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Short-term electricity demand response

Thesis for the degree doktor ingeniør

Trondheim, March 2007

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Torgeir Ericson

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Part 1:

Introduction

1 Background and research questions

Short-term demand response from electricity consumers is important for deregulated competitive electricity markets to function properly.[1] An active demand side that respond when wholesale prices vary, may contribute to efficiency and reliability, reduced price volatility, mitigation of exercise of market power, as well several other advantages in the electricity market. Despite this importance, many electricity markets are characterized by a rather low response from the demand side. One reason is that most consumers do not face time-differentiated prices that reflect the wholesale price variation; they have instead prices that are fixed for longer periods of time (weeks, months, years). Many of these consumers have chosen these fixed contracts voluntarily, for instance in order to ensure more stable and predictable prices. However, many consumers have not the possibility to choose differently if they are equipped with an electric metering system which can only measure accumulated electricity consumption. This metering system makes it impossible to charge the consumers by real-time prices corresponding to their actual real-time consumption. As a result, they lack incentives to respond to short-term market price fluctuations. This implies that their demand in the wholesale market is represented by price insensitive demand curves.

Lack of demand response may have adverse implications. Electric generators with high costs may be utilized to cover demand during short-term peak price periods, even though many consumers would use less electricity if they were faced with the actual cost of their consumption. Similarly, because consumers neither increase consumption during short-term off-peak price periods, some generators are not utilized even though they may offer electricity at costs below what many consumers would be willing to pay if they had the opportunity to do so. This short-term inefficiency in allocation of resources may also have long-term impacts through inefficient investments in generation capacity. Moreover, low demand response, accompanied with the special

[1] "Short-term" in this thesis refers to an hourly time-scale, and short-term demand response refers to electricity consumption adjustments to prices that vary within the day, or short-term consumption changes as a result of incentive payments designed to induce reductions when needed, for instance during high price periods or during periods when the system is constrained.

properties of electricity as a commodity; non-storability, capacity constraints and long lead times for new capacity expansions, also contributes to volatile prices. Low demand response may furthermore make it easier and more profitable to exercise market power, which exacerbates price volatility even more. Increased price volatility increases uncertainties regarding long-run average rate of return on capacity investments which in turn may reduce the investment level and thus reliability of supply. High and unpredictable prices and increased probability for shortage of supply increase the risk of political intervention in the market. The likelihood of political intervention may further reduce the propensity for investments.

Most Norwegian households are metered by their accumulated electricity consumption. This implies a disconnection between the wholesale market and the retail market in which households purchase their power. The rapidly changing costs of electricity are not signalled to the consumers, and, consumers' willingness to pay for electricity is not reflected in the market, in the short term. This disconnection may be of increasing concern as the overcapacity from the regulated period is diminishing, and as Norway and the other Nordic countries now enters a period where tighter conditions may be experienced. If consumers instead face prices that are closer to the marginal costs of supply through time-differentiated tariffs, and are metered automatically, they have incentives to adjust their demand to the varying prices. New enabling technologies that can control appliances automatically, such as direct load control of water heaters and energy management systems, may further enhance households' responsiveness to short-term price changes. With this infrastructure, information about wholesale prices is conveyed to the customers, they have incentives and increased ability to respond to the prices, and, information about their responses are conveyed back to the market. Increasing demand response in the electricity system by connecting the wholesale and the retail market this way may provide several benefits and mitigate the concerns described above.

This thesis encompasses several topics. With the objective of studying the importance of demand response in the electricity market, it first details the above discussion by examining the Norwegian electricity market and by reviewing relevant literature. It describes the present wholesale and the end-user market, and discusses why

there is a lack of short-term demand response from households, how it can be increased, and potential benefits from this. It argues that short-term demand response in the electricity market is an important contributor to obtain and maintain an efficient and well-functioning market. It also surveys demand response experiments around the world. This survey indicates that households do respond when exposed to time-differentiated prices, and that enabling technologies contribute to increase their responses.

Many of the benefits from demand response programs are influenced by the extent to which consumption is adjusted. Estimates of the potential increase in demand response that may be achieved are necessary to compare benefits with costs associated with the introduction of automatic meter reading, time-differentiated tariffs and direct load control. Indications and expectations of Norwegian households' demand response potential may be provided by examining other demand response programs and experiments. Such results and experiences enable evaluations on how tariffs, load control strategies, information and marketing campaigns, etc., may affect consumers' electricity consumption. However, as will be seen, these estimates may vary due to e.g. experimental or region/country specific differences. The results are therefore not necessarily transferable to Norwegian conditions. This suggests it is also important to conduct own experiments which give the opportunity to evaluate the Norwegian demand response potential, and to compare obtained results with results from other similar experiments. Together, this information provides a basis for the development of effective instruments forming new demand response programs.

The thesis further study Norwegian households' demand response potential by analysing households participating in a large-scale demand response experiment called "End-user flexibility by efficient use of information and communication technology". In this experiment, electricity consumers (mostly households) were equipped with automatic meter reading and they were offered time-differentiation of both network and power tariffs, as well as direct load control of their water heaters. Hourly metering of each household's electricity consumption and hourly measurements of temperature and wind speed, number of hours of daylight and household data from a survey, provide a large panel data set. In order to evaluate the households' demand response potential, these data are analysed with statistical and econometrical methods.

The most important research questions analyzed here are: What is the load reduction potential from direct load control of residential water heaters? Which customers will choose time-differentiated tariffs; those who will adjust their consumption as a result of the new tariff, or those who already have a consumption pattern which make it favourable to choose the new tariff even without adjusting consumption (sometimes called free-riders)? What is households' electricity consumption response to time-differentiated prices? And, how much can direct load control contribute to increase the responses?

The thesis consists of two parts, where Part 1 gives a summary of the analysis, which are presented in Part 2. Part 1 is organized as follows. Section 2 describes the large-scale experiment where the data analysed in the thesis are gathered. Section 3 briefly sums up the main results from four articles which constitute the main work of the thesis, and Section 4 discusses the implications of these results. This discussion evaluates how the tariffs and load control offered by the network and the power companies separately affect the households' consumption, as well as the combined effect on consumption from these measures. It attempts to discuss the results in light of the instruments utilized, and in light of experiences from other similar demand response experiments and programs, in order to offer suggestions for future demand response programs. Section 5 gives a conclusion. Part 2 presents the four articles, with an appendix at the end, describing the methods applied in the analyses in more detail.

2 The Norwegian large-scale experiment "End-user flexibility by efficient use of information and communication technology"

A large-scale project was established in 2001 to test automatic meter reading, direct load control technology and households' demand response to new tariffs. Three of the articles in this thesis analyses data from this project. This section describes the project and the data it provided.

"End-user flexibility by efficient use of information and communication technology (ICT)" was a large-scale Norwegian project running in the period 2001-2004.[2] The objective was to increase the end-user flexibility in periods with scarcity of electrical energy and power, by:

- Establishing a decision basis and suggest external conditions for a prioritised building of an infrastructure based on ICT-solutions for the future.
- Develop, test and evaluate different initiatives with basis in network tariff, power prices and other market solutions, based on ICT, which stimulates to flexibility in consumption.

EBL Kompetanse was the responsible institution towards the Norwegian Research Council, with SINTEF Energy Research as executing research establishment. Several participants in the Norwegian energy sector constituted a reference group.[3] The project contained six sub projects, including this doctorate study.

In the project, two network companies (Buskerud Kraftnett and Skagerak Energi Nett) installed automatic meter reading and direct load control technology at approximately 5,000 electricity consumers each, mostly residentials. The meters allowed for hourly metering of electricity consumption, and the direct load control enabled disconnection of load, mostly water heaters. The analyses in this thesis use data from one of the network companies, Buskerud Kraftnett.

Approximately 5,000 electricity customers in the grid area of Buskerud Kraftnett had automatic meter reading technology mandatory installed. These customers were offered several voluntary options with respect to new network tariffs, power tariffs and direct control of load. The tariffs and load control options studied in this thesis are:

- Customers were offered a discounted network tariff if they allowed for disconnection of their water heater in periods the network company defined as constrained.
- At the end of 2002, customers were offered a dynamic critical peak pricing (CPP) network rate to be in effect from 2003. This rate had a peak price that

[2] See also http://www.energy.sintef.no/prosjekt/Forbrukerflex/engelsk.

[3] The reference group consisted of representatives from Buskerud Kraftnett, Skagerak Energi Nett, Østfold Energi Nett/ Fortum Distribusjon, Trondheim Energiverk Nett, Helgelandskraft, Istad Nett, NVE, Statnett, EBL Kompetanse, Hafslund and Fjordkraft.

increased with 1 NOK, from a level of 0.15 NOK, in the peak hours from 7 to 11 am and from 4 to 8 pm on working days with temperatures lower than -8°C.[4]

- However, temperatures never fell below -8°C in 2003, so it was not possible to measure the customers' price response with this rate. Because of this, it was decided to offer a new time-of-use (TOU) tariff to all customers, also to those that did not have the CPP rate from before. The customers on the CPP rate were automatically transferred to the TOU rate, with the possibility of opting out if they did not want this new rate.[5] The TOU rate was offered in October 2003, and was in effect from November 2003. This rate was quite similar to the CPP rate, but the peak price was charged the peak hours independent of temperature.[6]
- Customers were offered an hourly spot price tariff from one power company (Hafslund).
- Customers who chose the hourly spot price tariff were offered the possibility of automatic disconnecting the water heaters in the normally two most expensive spot price hours of the morning and evening (8-10 am and 5-7 pm on working days).

All customers were offered all opportunities, and the customers spread from the standard network tariff and standard power tariffs to different combinations of the above mentioned options. This means that some customers had discounted network and standard power contracts, and allowed the network company to disconnect during shortage situations. Some had the CPP or the TOU network tariffs in combination with their standard power tariff. Some chose CPP or the TOU tariff, and in addition the spot price power tariff, with or without disconnection of the water heater in the peak spot price hours.

[4] The rate is described further in Article III.
[5] Approximately 10 percent of the customers opted out of the new TOU rate.
[6] The TOU rate is described in Article IV.

3 Summary of the thesis' main results

This section gives a brief presentation of the results found in each of the four articles in the thesis. The next section attempts to draw some implications based on these findings. The first article describes the present wholesale and end-user market in Norway, and discusses why there is a lack of short-term demand response from households in the electricity market, how it can be increased, potential benefits from this, and some evidences on households responsiveness found in demand response experiments around the world. The second article estimates the load reduction potential from direct load control of residential water heaters using the experimental data. The third article studies whether offering time-differentiated tariffs attracts demand responsive households, or mainly households who benefit because of their consumption pattern, even if they do not have a corresponding demand response. The fourth article estimates households' electricity consumption response to time-differentiated prices in three groups that differed with respect to their choice of network and power tariffs and direct load control.

3.1 Article I: Improving the power market performance by automatic meter reading and time-differentiated pricing

Because the electric meters installed in Norwegian households only measure accumulated electricity consumption, it is not possible for them to face time-differentiated electricity prices that vary frequently, for instance from hour to hour. Instead, the households have prices that are fixed for, at least, weeks at a time. Households do consequently not see the continuously varying costs of electricity consumption reflected in the wholesale prices, and have thus no incentives to respond to these prices. Because of this, households' short-term demand appears totally inelastic in the wholesale market.

If consumers face the marginal costs of supply through time-differentiated tariffs and are metered automatically, they have better incentives to adjust their demand to the varying prices. New technologies that can control appliances automatically may further assist households' response to prices. 40 percent of the annual Norwegian electricity consumption, where households' consumption constitute the main part, does not have automatic meter reading. If these consumers are provided with this technology, and if the consumers that today have monthly average spot price based contracts then continue on hourly spot price contracts, the share of Norwegian annual consumption by consumers with incentives to be short-term price responsive may double. It is also worth noticing that during cold peak periods, when demand response often is most needed, this percentage share is likely to be higher due to households' high temperature sensitivity as compared with for instance the large industry. Thus, there is a considerable potential for increased short-term demand response in the electricity market if these customers are provided with new metering technology.

Increasing demand response in the electricity system may provide several benefits such as improved efficiency, enhanced system reliability, reduced price volatility and mitigation of exercise of market power. It may therefore be important to exploit the demand response potential among households as we now enter a period where the Norwegian and the Nordic electricity consumption approach capacity.

Experiences from experiments and projects around the world indicates that households do respond to short-term changing price signals, and that assistant technologies contribute to increase the demand response.

3.2 Article II: Direct load control of residential water heaters

In this article, a regression model is developed to evaluate the effects on the load curve of disconnections and reconnections of residential water heaters. The analysis uses a panel data fixed effects regression method to estimate the load control impacts (this method is described in the appendix).

The results show that a disconnection of heaters from the electricity grid for the analyzed customer group give an hourly average reduction in load per household of between 0.18 kWh/h and 0.60 kWh/h dependent on which hour the disconnection occurred, with an average of approximately 0.5 kWh/h.

The interruption of the natural diversity between the water heaters' electricity consumption during a disconnection causes a payback effect, i.e. a higher consumption in a period after reconnection. For the first hour after reconnection, the average extra consumption was found to be up to 0.28 kWh/h, dependent on the hour. It is likely that the instantaneous demand at the moment of reconnection is higher than the hourly averaged estimates. By using the averaged hourly demand for the subsequent hours after reconnection, a simple methodology indicates the excess power demand at the moment of reconnection to be 0.36 kW (after disconnection in hour 10).

3.3 Article III: Households' self-selection of a dynamic electricity tariff

Customers may want to be exposed to higher prices in peak periods in return for lower prices in other periods if they are able to adjust their consumption, thus reducing their electricity bill. Another reason for choosing such a tariff may be that their consumption is normally low during peak price periods and/or high in off-peak price periods. With such a consumption pattern, they may reduce their electricity bill simply by choosing the differentiated rate, even without a corresponding price response (they may, of course, benefit further if they also adjust consumption). For the customers, this may be considered as fair as they no longer are subsidizing other customers' expensive peak consumption. However, from the perspective of those offering this tariff, attracting mainly the last group to the differentiated rate may not be desirable, since their intention often is to increase demand response. It may also lead to lower revenues. Thus, if the latter participation motive is prevailing among customers, it may be questioned whether companies will be likely to offer such tariffs.

The article uses a discrete choice model to analyze whether the customers chose the new rate because of a higher ability to respond to the price signals, or because of favorable consumption pattern (see the appendix for details of the statistical method).

The results suggest that, on average, the consumption pattern does not influence the households' decision of whether to select the time-differentiated critical-peak pricing (CPP) rate or the standard rate. On the other hand, ownership of energy management systems and wood-burning furnaces increased the probability to join the CPP program. Households can utilize such equipment to shift peak consumption to off-peak hours or to reduce peak consumption and thus reduce electricity expenditures. These results therefore indicate that the offering of CPP tariffs attract customers with potentially higher demand response compared to the general population, and the CPP tariff does not attract customers that may benefit without making consumption adjustments in a significant way, more than it attracts other customers.

3.4 Article IV: Time-differentiated pricing and direct load control of residential electricity consumption

The analysis in the third article does not reveal whether the consumers actually did respond to the prices when they were exposed to the new tariff. The demand response due to price changes is the topic of the fourth article. The focus is on three different household groups, which differed with respect to their choices of tariffs and direct load control:

- Group 1 (TOU/Std): *Time-of-use* network tariff and *standard* power tariff, *without* load control.
- Group 2 (TOU/spot): *Time-of-use* network tariff and *spot price* power tariff, *without* load control.
- Group 3 (TOU/spot/DLC): *Time-of-use* network tariff and *spot price* power tariff, *with* load control.

A fixed effect panel data regression model is used to measure the effect of TOU and spot pricing of electricity on the daily load curves for households' participating in the experiment (see the appendix for a description of the model and the method).[7] The contribution from direct load control of water heaters to automatically increase the price response is also estimated.

The results from Group 1 indicate modest consumption reduction to price signals (0.055 kWh/h electricity consumption reduction to a price increase of 1 NOK). The results from Group 2, show high price response (0.545 kWh/h reduction). Customers in Group 3, showed slightly higher responses than the first group (0.077 kWh/h), but not as high as one could expect considered they had automatic load control.

[7] Only consumers from which power price information exist are included, i.e., consumers from Hafslund.

4 Discussion and implications of the results

This section discusses the results from the articles. It attempts to discuss these results in connection with each other and in connection with results found elsewhere, and give some implications for the demand response potential in the electricity system. It first discusses the results regarding direct load control and time-differentiated pricing separately, and then the combined effect of these two measures.

4.1 Demand response and load control

The results in Article II suggest that disconnections of water heaters may be an effective way to reduce peak load, given some physical factors are taken into account. Using the estimated average load reduction per customer of approximately 0.5 kWh/h for hour 10, the total load reducing potential in Norway from disconnection of water heaters can be suggested. Assuming that half of the Norwegian households (approximately 1 million households) have allowed for disconnection of their water heater, and assuming a 0.2 percent loss in the grid in a peak load situation, the total load reduction potential is 600 MWh/h for the whole Norwegian system.[8] The results also indicate a payback effect when the heaters are reconnected. The average additional demand the first hour after reconnection is estimated to 0.24 kWh/h. This means that an average additional demand of 288 MWh/h can be expected in the electricity system the first hour after a one-hour disconnection. Also, because the heaters were reconnected simultaneously, it is likely that the initial peak taking place at the moment the heaters are reconnected is higher than the average for the entire hour after the reconnection. The result indicates an initial payback of approximately 0.36 kW power demand per household, or 432 MW at an aggregated level, at the moment when the heaters are reconnected.

It is illustrative to impose these numbers into the system load curve of 5 February, 2001, the day with the highest system peak in Norway so far. The load in the peak hour (hour 10) would then be reduced from 23,054 MWh/h to 22,454 MWh/h, i.e. a 2.6

[8] Assumptions are based on Graabak and Feilberg (2004).

percent reduction. The system load the following hour after reconnection (hour 11) would rise from 22,940 MWh/h to 23,228 MWh/h on average. Furthermore, the instantaneous payback effect would yield an instant total power demand of 23,432 MW (assuming the power demand at the reconnection moment was approximately the average of the load in hour 10 and 11; i.e. 23,000 MW). On this day, the new "post-peak" would thus be at a higher level than the peak that was the target for the load reduction. This indicates that direct load control of water heaters may also have an unfortunate payback effect that should be monitored and possibly controlled so that a new problematic peak is not created.

To avoid possible post-peak problems, one may disconnect for longer periods, in order to wait for lower system load. Then the payback effect may occur at a time when the new peak does not create a load problem. However, one should be aware of that the longer the disconnection period, the higher the payback effect. Rotational disconnections and reconnections of the heaters is another way to circumvent a problematic payback effect, as described in Article II. By using this method, the operators can better tailor the load control as they need.

4.2 Demand response and time-differentiated prices

The results in Article III show that the customers choosing the time-differentiated tariff were well equipped and held characteristics that made them suited to exploit the varying prices. The article suggests that the offering of time-differentiated tariffs is likely to increase demand response among residential consumers because the consumers choosing the tariff have higher flexibility with respect to the timing of their electricity consumption due to certain household characteristics, compared to the customers that did not choose the new tariff. In Article IV, the consumers' price response to the TOU tariff was estimated (Group 1 (TOU/Std)).[9] The result indicate that the price response was lower than the responses found for the two other groups also analysed in this article, and also compared to results in many other demand response programs (see the

[9] As explained in Section 2, the peak price of the CPP tariff were never activated due to temperatures that never fell below the activating threshold, and the customers did consequently not experience differentiation in their price. This group was transferred to the time-of-use (TOU) tariff, and actually constituted the main part of this group. Their price response to the TOU tariff was estimated in Article IV, in Group 1 (TOU/Std).

review of other programs in Article I). Even if the results in Article III indicate these customers' demand response *potential*, their *revealed* response found in Article IV suggests it still may not have been optimal for them to adjust consumption.

One reason for this may be that the customers found the benefits from adjustments in consumption too little compared with the inconvenience and costs. The economic incentive, i.e. the peak/off-peak price ratio, may have been too small to motivate a larger price response for this group. Experiences from other TOU experiments indicate that the largest consumption reductions are found where the price ratio are highest (Faruqui and Malko, 1983), and according to Braithwait (2000), the ratios need to be in the range of 4:1 or 5:1 to induce substantial price response. Although the TOU price ratio in the Norwegian experiment alone was high, the total price ratio (when adding the network and the power prices) was approximately 3.2:1, and may thus be one explanation why the demand response in this experiment is lower than in many other experiments analyzed in the literature. This suggests that higher price differentials may be considered in future programs utilizing TOU tariffs.[10]

The high economic incentive needed to induce customers to respond, further suggests that enabling technologies that control loads automatically are important for consumption adjustments. For instance, water heaters, heating cables or heating panels may be directly controlled without any effort from the customer. Allowing the customers to override a control event in case of too high inconvenience may increase customers' acceptance for the demand response program. Simple energy management systems such as timers (or more advanced systems) can also be offered along with the new tariffs. If such timers are already programmed, it makes it easier for the customers to take the device in use.[11] It is also worth noticing that signalling lamps or other price information systems have given higher responses than those without such assistant technology in experiments abroad (see Article I). Providing customers with such

[10] Whether this is consistent with a desire of designing the tariff to reflect expected time-varying network cost is another question and will not be dealt with here. A CPP tariff may be better suited for this than the more static TOU tariff, because CPP may have higher prices during critical peak periods and lower prices during more normal peak periods, while still allowing the average of the prices to reflect expected average costs (see Article I for a description of these rates).

[11] See also Hartway et al. (1999), attributing their large load response findings in a TOU program to the high price differential (6.5:1), and to customers' programming of their air conditioners, using an advanced energy management system.

equipment could possibly increase their awareness of the prices they face and contribute to increase their demand response.

Another aspect worth considering is the information and the educational material given the consumers on the various ways to exploit the price structure in order to reduce electricity expenditures. If this information was insufficient, it may have lead many customers to disregard possible ways to benefit and to believe it was little to gain from adjusting consumption. In two experiments that seem to display higher responses than in the one analyzed here, and where the enrollment and welcome packages offered the customers are available (which they rarely are), the educational material seems to be more comprehensive (see Norges Energiverksforbund,[12] 1989, Vaage, 1995 and CRA, 2005a, 2005b for the former, and Sæle and Grande, 2004 for the latter experiment). Although such a comparison across experiments of the information level and the achieved demand response results are complicated by other factors that also influence the results, it may serve as an indication of the importance of instructive educational information to consumers.[13]

Finally, it must be mentioned that the results are average over all the customers in each group. No attempts have been made to reveal whether there exist subgroups within the sample that exhibit higher price responsiveness. For instance is it likely that customers with energy management systems have higher response than those without such equipment. It may also be that consumers that differ with respect to their consumption pattern prior to the participation in the experiment, as discussed in Article III, display differing responses. The high response found in Group 2 (TOU/spot), i.e. those with a TOU network tariff and spot price tariff but no load control, also analysed in Article IV, indicates that there exist customers highly motivated and able to exploit the varying rates by adjusting their consumption.[14] This is also supported by several papers that find price responses to differ across customers, for instance due to differing stock of appliances (see Article I). Thus, designing marketing campaigns directed

[12] This is a former Norwegian time-differentiated pricing experiment conducted from 1984-1987.

[13] See also Hartway et al. (1999), paying especially high attention to the customer information aspect, and as already mentioned, achieving high responses.

[14] Note that this group consisted of very few households, so that drawing inferences from this group may questionable.

towards customer segments that are likely to yield high responses may give the highest response from those participating (see also Faruqui and George, 2005).

4.3 Demand response and load control combined with time-differentiated prices

It is interesting to study how load control combined with time-differentiated prices affected households' price responses. This is analyzed in Article IV, with Group 3 (TOU/spot/DLC), i.e. those with a TOU network tariff, and a spot price power contract combined with direct load control. The analysis estimates the total price response, from both the customers' own efforts to adjust consumption, and, from the assistance of the direct load control.[15]

The results indicate a total price response which is not as high as one could expect, compared with the other two groups analyzed, given the fact they had assistance from load control. This may both have to do with the way that the load control events were carried out, and with the efforts the customers did on their own to adjust consumption.

The spot price varied very little within the day in the experiment period, and since the water heater disconnections were carried out in conjunction with the peak periods of the spot price contract, the effect was that the customers received only small benefits when load was shifted from the spot price peak hours to the following off-peak hours. The main price differentiation of the customers' total price was therefore due to the TOU tariff. It will thus mainly be the consumption adjustments to the TOU price that drive the results in the analysis. The fact that disconnections occurred in the two middle hours of the TOU peak periods may thus explain the estimated response. The payback effect that occurred after reconnecting the heaters, as described in Article II, appeared when the TOU price was still high. This means that load was not shifted entirely out from the TOU peak hours to off-peak hours so that the load level during the high price period did not change much, with a low estimated response as the result. Although the spot price power tariff and the TOU network tariff were two separate products that were

[15] It may not be entirely correct to refer to load reductions due to automatic control as price response, since a reduction from a disconnected water heater is the same independent on the price level. However, this enables comparison between the analysed groups.

offered independently, the customers would have experienced higher benefits if the disconnections had been coordinated and timed in accordance with the price structure of both contracts. This is important to notice, since in a non-experimental setting, peak price periods of two tariffs may be defined in such a way that load control carried out in connection with the peak price period of one tariff could shift consumption from off-peak to peak price periods of the other tariff, and thus offset much of the gains that the disconnections can provide.

Group 3 (TOU/spot/DLC), had nevertheless a somewhat higher total price response than the other group discussed in the previous section; Group 1 (TOU/Std). The reason for this may be that the control events after all shifted some parts of the energy to the off-peak TOU period for some customers in Group 3.[16] This means that the customers' own efforts to adjust consumption probably were small in Group 3 too. This may have to do with similar conditions as suggested for Group 1.

5 Conclusions

This thesis analyses factors limiting household demand response in Norway, how to increase the response and benefits from that. It is argued that increasing demand response may be important to achieve a well-functioning, efficient and reliable electricity market. The thesis also analyses the demand response potential in households, using data from a large-scale Norwegian time-differentiated pricing and direct load control experiment. The results from these analyses indicate that load reductions from direct load control of residential water heaters have a potential which may contribute to decrease peak load when needed, given some physical factors are taken into account. Furthermore, the offering of time-differentiated tariffs seems to attract households with a higher potential to respond to price changes than those remaining on standard rates. Yet, the demand response from the customers' owns efforts to adjust consumption within the day generally seem to be on average low, although some customers display high price sensitivity.

[16] Water heaters that are affected more than one hour during the disconnection period would experience this. See Article II, Section 2 for a discussion of how load control affects water heaters.

This indicates a demand response potential among the analyzed customers that may be better exploited. The experiment and the analyses have pointed out possible ways to improve households' demand response. For instance, marketing campaigns, both before and during the demand response program with good information and guidance to the households on how to take advantage of the new tariff structures is likely to be important. Automatic load control is also an essential contributor. Both direct load control performed by external parties such as network or power companies, as well as energy management systems such as timers, are likely to contribute to increased demand response. The analysis have also pointed at the importance of a coordination between separate products such as time-differentiated network and power tariffs and direct load control if they are offered by different parties, so that they do not offset each other and the combined effect gives the consumers the highest possible benefits from participation.

When evaluating the results from the experiment, one should bear in mind that Norwegian customers traditionally have been provided with low electricity prices so that the focus on electricity saving may have been low. Changing behavior with respect to how and when electricity is used may take time. If the power and energy situation continue to tighten, this might change, as seen in the winter 2003/2003 and in 2006. Higher and more volatile prices may thus increase customers' incentives and awareness of potential ways to reduce their electricity expenditures by adjusting consumption.

In a situation where capacity becomes tighter, it may be valuable to have the necessary infrastructure in place in order to utilize the demand elasticity. The thesis has discussed that even a small increase in price responses may contribute to a well-functioning market by increasing efficiency, reducing price volatility, mitigating exercise of market power and contributing to a reliable power supply.

Whether the demand responses found in the analyses are sufficient for the benefits to exceed the costs associated with new metering infrastructure, tariffs and load control, is beyond the scope of this thesis. According to Kolbeinstveit and Tjeldflåt (2006), 60 % of the Norwegian annual consumption has now automatic meter reading and they amount to 100,000 measuring points out of a total 2.5 million. This means that the remaining consumers are many and small. Development of new meters to a higher share of this group may therefore provide less benefit compared with the cost from each consumer than what might have been the case for those already provided with this technology. However, one should note that many of the benefits come through the market, and may not directly benefit the one responsible for developing the infrastructure, or the customers, who now may require automatic meter reading technology but must pay for it (though limited to a maximum price). Although difficult to calculate, these benefits may be important to include when cost-benefit analysis are conducted and decisions of whether developing automatic meter reading to a higher share of the consumers are taken. This is important because the possible situation could exist, where cost-benefit analyses conducted by either the responsible institution (e.g. a network company) or by single customers show negative results, while an analysis including all costs and all benefits for all affected parties could show the opposite. If the latter is the case, there may be need for coordination of the development of the necessary infrastructure for remaining customers without automatic meter reading. Anyway, the costs of the necessary technology have declined recent years, and are likely to continue declining (Jørum et al., 2006). At some point, the benefits will probably exceed the costs.[17] This suggests it is important to continue the research and the experiments with demand response so that the infrastructure and the most efficient instruments at that time are prepared for implementation.

[17] According to Jørum et al. (2006), the benefits already exceed costs in Norway.

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Part 2:

Articles

Article I:
Improving the power market performance by automatic meter reading and time-differentiated pricing[*]

Abstract

In most electricity markets, households' electricity metering systems only allow prices that are fixed for long periods of time (weeks, months, years). Households can therefore not choose tariffs reflecting the continuously changing conditions and marginal costs in the electricity system. Thus, they have no incentive to adjust their electricity consumption in the short-term. This lack of demand response in the market may create inefficient allocation of resources in the short term and non-optimal investments in capacity in the long term. It may contribute to insufficient reliability of supply, higher price volatility and to an electricity system more exposed to exercise of market power. This paper discusses how automatic meter reading and direct load control technology combined with time-differentiated tariffs can increase demand response and improve the functioning of the electricity market.

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1 Introduction

In most electricity markets, the electric metering system installed in households can only measure accumulated electricity consumption. Households can consequently only choose between tariffs where prices in practice are fixed for longer periods of time.[1] Because these consumers do not, and can not, face the continuously varying costs of electricity consumption reflected in the wholesale prices, they have no incentives to respond to these prices by consumption adjustments. Because they do no restrict their demand if the wholesale price increases in the short-term, their retailers must bid price insensitive bids into the wholesale markets, and are thus forced to pay any price in order to serve their customers. This situation indicates a disconnection between the wholesale and the retail market; information about market conditions, communicated by the wholesale prices, is not conveyed to households. And, information about households' actual demand response and their actual willingness to pay for electricity is not reflected in the wholesale market, leading to artificially low price elasticities. [2]

This disconnection may contribute to an electricity market that performs less efficient than what is possible. When consumers face prices different from the short-term marginal cost of supply, electric generators with high costs may be utilized to cover demand during peak periods, even though many consumers would reduce their consumption if they were charged marginal costs. Furthermore, during off-peak periods, some generators are not utilized even though they may offer electricity at prices below what many consumers are willing to pay. The short-term inefficient allocation of resources may also have long-term impacts through inefficient investments in generation capacity. Low demand elasticity together with the special properties of electricity; non-storability, capacity constraints and long lead times for new expansions, may further contribute to volatile prices. This may also make it easier and more profitable to exercise market power, which exacerbates price volatility even more. Price

[1] This applies to all consumers without automatic meter reading, i.e. most of the household sector. Also consumers with "spot price" based contracts face a price that are fixed for months at a time, because they in reality only see the monthly average of the market based spot price.

[2] Demand response in this paper refers to electricity consumption adjustments to prices that vary within the day, or consumption changes as a result of incentive payments designed to induce reductions when needed, for instance during high price periods or during periods when the system is constrained.

volatility increases uncertainties regarding long-run average rate of return on capacity investments. Investors may thus be more reluctant to invest as they require higher prices to cover their risk-premium. This may in turn reduce reliability of supply and increase the risk of rationing in high-demand periods. High and unpredictable prices and higher probability for shortage of supply increase the risk of political intervention in the market, which, in turn, may further reduce the propensity for investments. As this paper describes, demand response is one important factor that may contribute to a well-functioning market with the ability of moderating volatility of prices, balancing demand and supply, and providing sufficient and timely investment in capacity.

Increased demand response may be achieved if consumers face prices that are closer to the marginal costs of supply through time-differentiated tariffs, and if they are metered automatically. Consumers will then have incentives to adjust their demand to the varying prices. Enabling technologies that can control appliances, such as direct load control of water heaters or energy management systems, may further enhance their price responsiveness. With these technologies, information about wholesale prices is conveyed to the customers, their incenctives and ability to respond to the prices increases, and information about their responses is brought back to the market. This connects the wholesale and the retail markets, and as will be described in this paper, provides for several benefits.

Many of these benefits are due to an improved electricity market performance, and are distributed among several of the participators in the market. However, the decision of whether to develop the new metering infrastructure may often hinge on individual (network) companies who may ignore benefits that are not utilized by them directly. If they find the costs too high, they may not carry out the development, even if the benefits for the society as a whole may exceed the costs. Thus, socially optimal decision on such may require governmental intervention. The discussion in this paper is exemplified using the Norwegian (and the Nordic) market. It aims to discuss benefits related to the introduction of the mentioned technologies, many of which would probably not be included in cost-benefit analysis conducted by individual companies, and many of which is not included in earlier cost-benefit evaluations in Norway (see for instance Grande and Graabak, 2004, Tjeldflåt and Vingås, 2004 and Jørum et al., 2006).

Quantifying, and weighing the benefits against related costs, both for the individual companies and for the society as a whole, is however beyond the scope of this paper.

Section 2 gives a short description of the wholesale and the end-user market in Norway as a basis for the other topics addressed in this paper. Section 3 discusses the performance of the market and why many consider the deregulated market to have performed well in terms of efficient operation until now, but also why there is a potential for improvement by fully integrating the wholesale and the retail market. It discusses the reasons for the lack of short-term demand response in the electricity market, and why automatic meter reading and time-differentiated tariffs are necessary prerequisites to increase short-term demand response. Section 4 discusses implications and benefits in the market of increasing demand response, such as improved efficiency and system reliability, reduced price volatility and mitigation of exercise of market power, and, in addition, several other benefits. Section 5 reviews results from the literature describing experiments where households' responses to short-term price changes have been tested. This is important knowledge since the extent of households' demand response has implications for the benefits from demand response programs. Section 6 sums up the discussion and concludes.

2 The Norwegian electricity market

During the years of the regulated electricity market, central decision makers were responsible for maintaining reliability of supply. Risk of shortages of supply was limited since the objective of the production capacity planning was to cope with demand under nearly all circumstances (Bye and Hope, 2005). Production investment risk was low since tariffs were designed to cover the costs, and inefficient investments decisions could be recovered by tariff modifications. However, there were indications of substantial over-investment in the power sector, and a lack of cost effectiveness in the networks.[3] One of the main objectives of the deregulation was to increase efficiency and achieve a better utilization of the total resources in the power sector by leaving investment decisions to the market players (decentralised decision making). The

[3] According to Bye and Halvorsen (1999), efficiency losses in the power market, power production and distribution were considerable, and may have added up to 2.5-3 percent of GDP in 1991.

Norwegian electricity market was deregulated in 1991. Sweden followed in 1996, and a common Norwegian and Swedish Exchange (Nord Pool) was established as the first multinational exchange for trade in power contracts in the world. Finland joined in 1998, Denmark West in 1999 and Denmark East in 2000. The Nordic countries are now connected in a common integrated electricity market. In 2005, Nord Pool Spot opened a new bidding area in the Vattenfall Europe Transmission control area in Germany (www.nordpool.com). This section presents the wholesale and the end-user market in Norway.

2.1 The wholesale market

Any producer in the Nordic area can deliver electricity to the common Nordic electricity market. The wholesale market includes power producers, power suppliers, retailers, industry and other large undertakings. In the wholesale market, the trade of electricity takes place at the Nord Pool exchange and bilaterally between different market players. About 40 percent of the physical deliveries are traded at the Nord Pool Spot (Glende et al. 2005). The exchange provides a financial market for trading contracts for price hedging and risk management, and an Elspot market for trading power contracts for next day's physical deliveries.

At the Nord Pool Elspot, the next day's hourly spot prices are settled on the basis of bids from the participators for purchase and sale (a day-ahead market). Each participant submits bids to Nord Pool Elspot on bidding forms, and the bids are aggregated to a demand and a supply curve for each of the next day's 24 hours. The intersection of the demand and the supply curve provides the Elspot system price. The price also determines the obligations for each participant to deliver or take power from the central grid (see for instance Flatabø et al., 2003, Nord Pool, 2006a).

The determination of the spot price may lead to a power flow from one area to another that exceeds the ability of the network to transfer the electricity. If there are bottlenecks, the market is divided into pricing areas and the prices in the surplus areas are lowered and the price in the deficit area is increased, until demand and production is in balance within each area (Rønningsbak, 2000).

Because electricity cannot be economically stored, balance between production and consumption must exist at every moment. However, operational difficulties, production fall out, bottlenecks in the grid, unexpected shift in temperature or other unforeseen events may lead to differences between forecasted deliveries/demand and real deliveries/demand. Imbalance between production and consumption is the result. The Norwegian system operator (Statnett) has the responsibility of maintaining the balance in the Norwegian electricity system and provide for sufficient capacity reserves at every time. Statnett uses the Regulating Power Market to keep a stable balance and frequency in the electricity system. In this market, producers as well as consumers can bid regulating power for either up regulation or down regulation.[4]

During cold periods there is a risk that all Norwegian generating capacity is sold in the Elspot market. In order to secure sufficient power reserves for the regulating power market, a Regulating Power Option Market was established in 2000 (see Walther and Vognild, 2005, Glende et al., 2005). Here, Statnett purchases the right to utilize generating and demand resources for regulating purposes if needed. Statnett chooses the cheapest bids up to the desired amount, which then must be offered in the Regulating Power Market the next week.

2.2 The end-user market

The end-user market includes all buyers of electricity for own consumption, for instance industry, commercial buildings, households, etc. Households' electricity consumption constitutes approximately 1/3 of Norway's total electricity demand (SSB, 2006a). Approximately 60 percent of the households have standard variable contracts (in the third quarter of 2006), 11 percent have fixed price contracts, and 29 percent have spot price based tariffs (SSB, 2006b). In the latter case, the consumers are confronted at the end of each month with the average hourly spot price, i.e. they do not face hourly varying prices. All consumers can change supplier every week. In the other Nordic countries, most end-users have fixed price contracts (Kristensen et al., 2004).

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[4] Since the Nordic countries have a connected grid, regulating power anywhere in the area can treat imbalances, given there are no bottlenecks (see for instance, Wibroe et al., 2002). From 2002, the Nordic system operators created a common regulating power market in order to utilize the resources in all countries optimal.

End-users in Norway with an annual consumption below 100,000 kWh have meters that measure accumulated consumption.[5] The consumers with this metering technology constitute approximately 40 percent of the total annual electricity consumption (Kolbeinstveit and Tjeldflåt, 2006). Since households on average use approximately 18,000 kWh per year (Halvorsen et al., 2005), i.e. well below the 100,000 kWh threshold, they constitute most of the consumers without automatic meter reading.[6] They are required to report their consumption a few times a year (but may report more often if they want) and are charged according to their accumulated consumption between the meter reading dates. The price these customers pay is a weighed average, over the so-called adjusted load profile from all non-hourly metered customers in the area for the relevant period.[7] Since one single customer has no significant impacts on this load profile, he or she will not receive the whole benefit if reducing consumption more than other customers do during a high price period. This means the efficient signal of hourly spot prices is substantially diluted (see also Fraser, 2001). The result is that at what time between the meter reading dates that the consumer uses electricity, does not matter for the total bill. The incentive is thus only to save energy for the whole period, independent on the time of day/week/month this saving is carried out. Note that this also applies to those with spot price based tariffs who only face the average of the hourly spot prices.

3 Potential for improvement in the electricity market

In general, the Nordic market has so far been working well (Flatabø et al., 2003, Bergman, 2005, von der Fehr et al., 2005). For instance, the deregulation have yielded a downward pressure on the electricity price as excess capacity has been exposed to competition in the market, and, prices between customer groups have equalized (Bye and Hope, 2005). Tjeldflåt (2005) considers the end-user market to function quite well, since customers seem to change retailer when the price differential between retailers is

[5] From 1 January 2005, all customers with an annual consumption above 100,000 kWh were required to have hourly metering of consumption.

[6] The households may require automatic meter reading but they must pay for it themselves, though with a maximum price.

[7] Consumers with fixed price contracts pay only according to their accumulated consumption.

high, and because the market share of the dominating retailers has declined recent years. Also, according to Statnett (2004), Norway has one of the most efficient and best utilized transmission systems for electricity in the world.

3.1 The disconnected wholesale and retail electricity markets

Increased integration between the retail and the wholesale market may improve the functioning of the market further. Figure 3.1 illustrates the existing situation in which most households now have no incentives to respond to short-term changes in wholesale prices by consumption adjustments. It shows the hourly spot prices in the Oslo pricing area during the winter 2002/2003, along with the prices offered through a standard variable contract from one of the larger suppliers in the Oslo region.

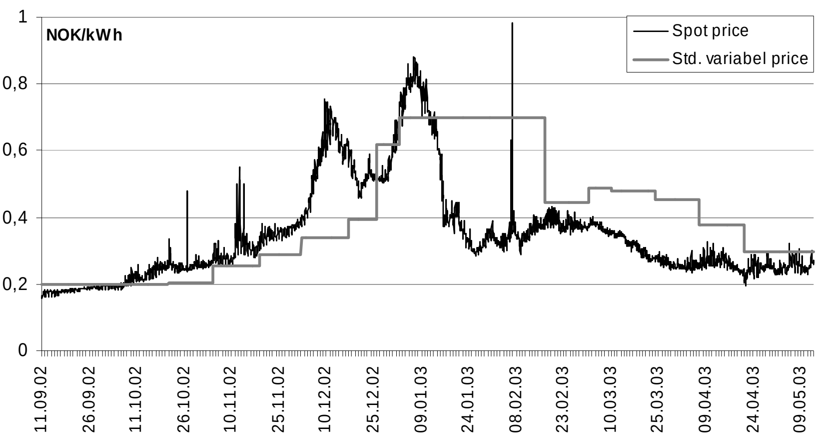

Figure 3.1. Hourly spot prices (in the Oslo region) and the price offered from a supplier through a standard variable price contract in the winter 2002/2003

As seen in the figure, the spot price rose to very high levels in December 2002 and the beginning of January 2003, due to a situation with scarcity of energy.[8] The standard price facing the customers, however, was in parts of this period lower, sometimes only about half of the market price. Furthermore, from mid-January until May, the customer price was high above the market price, sometimes more than twice. We can see here that the standard price did not bring the energy scarcity price signal to the customers at

[8] More on the 2002/03 winter can be found in for instance Bye et al. (2003b), Nordel (2003), Finon et al. (2004), von der Fehr et al. (2005), OED (2003).

the time the market considered the situation to be constrained. Neither did the standard price signal inform the customers when the market considered this situation to be over. Also important is the price spike 6 February 2003, where the peak price signalled a power shortage situation (see also Figure 3.3). The figure illustrates that consumers have little incentive to adjust consumption according to short-term changing market prices.[9] Because of this, their retailers must bid price insensitive bids into the wholesale markets, and are forced to pay any price in order to serve their customers. This is illustrated in Figure 3.2.

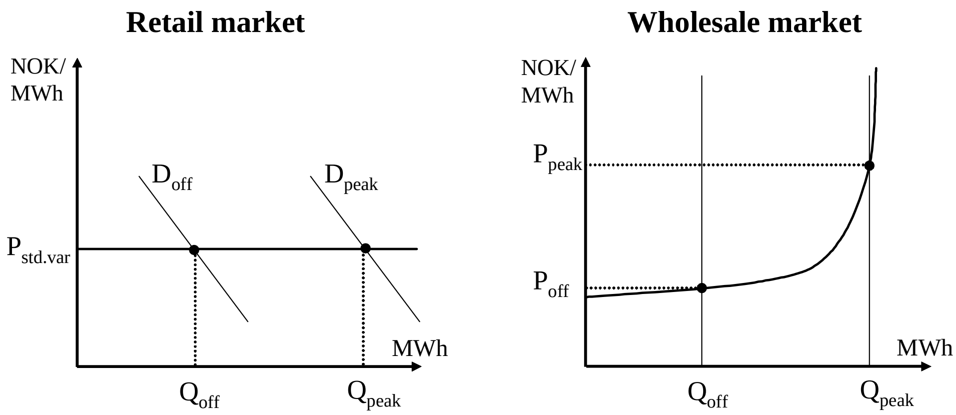

Figure 3.2. The disconnection between the wholesale and the retail markets

The left figure illustrates consumers' demand curves in off-peak and peak periods of the day (D_{off} and D_{peak}), and a standard variable price ($P_{std,var}$) offered by their retailer, which can not change in any of the periods. The elastic demand curves indicate that consumers are price responsive and willing to adjust consumption on a short notice if they were given this opportunity (the assumption that consumers are price responsive is supported in the review in Section 5). However, their price does not change in the short-term. Consequently, their demand appears inelastic in the wholesale market both in the off-peak as well as in the peak periods. The figure to the right illustrates this with two perfectly inelastic demand curves (assuming all customers are completely inelastic).

[9] We know that tacit collusion between consumers may give some market response, thus changing the load profile and costs for the consumers, while each consumer alone will not have this impact. However, it is questionable whether consumers will act like this, for instance due to lack of knowledge regarding the load profiling effects and due to free rider problems from consumers benefiting from others tacit collusive behaviour.

This situation indicates a disconnection between the wholesale and the retail market; information about short-term changing market conditions is not received by consumers. And, information about consumers' actual demand response and their willingness to pay for electricity is not reflected in their demand curves in the wholesale market.

The actual demand curves at the Nord Pool are however not as inelastic as they appear in Figure 3.2, because some customers with automatic meter reading and time-differentiated tariffs also are present in the wholesale market. However, Figure 3.3, showing the purchase and sales curves at Nord Pool Spot the 6 February 2003, hour 17:00-18:00, illustrates that the short-term price response still may be limited, as the purchase curve is nearly vertical at higher prices. [10]

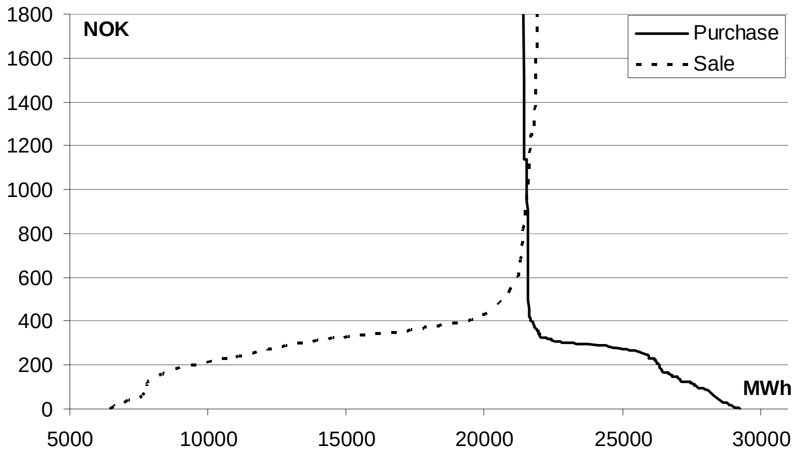

Figure 3.3. Elspot purchase/sales curves. Hour 17:00-18:00, 6. February 2003, System Price NOK 981,14. (Source: Nord Pool Spot AS)

That the demand response is low, is further supported in, for instance, Hansen and Bye (2006) who estimated low short-term demand elasticities in a simultaneous multimarket model for the Norwegian and the Swedish market. They found the price elasticity to be approximately -0.015 in Norway and even smaller in Sweden.[11]

[10] Note that the threshold for requirement of automatic meter reading was lowered from an annual consumption of 400,000 kWh to 100,000 kWh in 2005. This increased the amount of the Norwegian annual consumption on this metering technology from 50% to 60% (Tjeldflåt and Vingås, 2004). The elasticity may therefore be somewhat higher in today's market than what this figure illustrates.

[11] The elasticity may be somewhat higher now for the same reason as in the previous footnote.

The low elasticity may be a consequence of a too small amount of consumption with contracts tied to the spot price, and which also are hourly metered. It may also reflect low responses among those customers. For instance, the share of the Norwegian electricity consumption in the energy-intensive manufacturing and pulp and paper industry with contracts tied to the spot price constitute only approximately 0.2 % (in the 3rd quarter of 2006, SSB, 2006a, 2006b).[12] For mining, quarrying and other manufacturing industries this number is approximately 2.6 %. These sectors constitute about 45 % of the total Norwegian annual electricity consumption. In addition, households and others without automatic meter reading constitute around 40 % of the annual consumption.

The remaining part thus constitutes about 15 percent. A high share of this consumption is probably within the consumer group called "Other industry", i.e. for instance, trade, hotels and restaurants, public administration, education, health and social work and other service activities. Here, the share of customers tied to spot price contracts is a little above 70 percent, and then comprises approximately 10 percent of the Norwegian annual consumption.

Thus, the part of the Norwegian consumption on contracts tied to the spot price probably constitutes less than 13 %. Furthermore, some of this consumption probably only faces monthly average spot prices, which means this estimate probably is a maximum.[13] This means that the main part of the Norwegian consumption today has no incentives to be short-term responsive. Given the many long-term contracts in the other Nordic countries, the share of the total Nordic consumption (approximately 400 TWh) with hourly spot price contracts is thus probably only a few percent.

Since the consumption in "Other industry" constitute the highest share with spot price contracts, the elasticity for this group of customers will therefore be important for the total response in the Norwegian (and Nordic) market. This group's price elasticity is not known, but, according to Faruqui and George (2002) price elasticities for small to medium size commercial and industrial consumers are significantly smaller than for

[12] Assuming that the contracts are evenly distribution among the consumers.

[13] SSB (2006a and 2006b), only inform that the contracts are "tied to" the spot price, thus it is unknown whether the contracts are based on hourly prices or monthly average spot prices.

residential consumers, suggesting households could be important contributors to increase demand response in the market.

As mentioned, approximately 40 % of the annual consumption in Norway, with households as the largest share, can only choose tariffs with prices that do not reflect the short-term marginal cost of supply. Given that those on spot price based contracts today continue on hourly spot price contracts if they are provided with automatic meter reading, the share of the Norwegian annual consumption with incentives to be short-term demand responsive could more than double from today's level.[14]

Furthermore, these consumers' electricity consumption is likely to constitute a larger share than 40 % during cold periods due to their high temperature sensitivity (compared with for instance large industry). This means that a significant share of the market has no possibility to be responsive to prices in periods when demand response often is needed most.

3.2 Connecting the markets and increasing demand response with automatic meter reading and time-differentiated tariffs

The previous discussion indicates that there may be a considerable contribution to increased demand response by letting the customers without automatic meter reading to be fully integrated in the wholesale market. One way to achieve this is to provide customers with automatic meter reading so that they can choose electricity tariffs reflecting wholesale price variations. Furthermore, installation of notification systems able to signal the current price level on displays or by signal lamps, and possibilities for direct control of loads, may also increase consumers' demand response.

With such equipment installed, retailers can offer a range of new tariffs and products to the electricity customers.[15] For instance, a *spot price* contract may be popular among customers with a high risk tolerance who does not want to pay the "price

[14] Assuming the remaining part of the 40 % share is made up of consumers in the sector "Other industry".
[15] See also Mauldin, 1997, Eakin and Faruqui, 2000, Long et al., 2000, Camfield et al., 2002, Irastorza, 2005.

insurance premium" related to for instance a fixed price contract.[16] Customers with spot price contracts can expect a lower electricity bill than with a fixed price contract (Faruqui et al., 2002). Besides, if they can control and reduce their electricity consumption in peak hours, they may provide themselves with physical risk insurance towards the price volatility by being demand responsive (Hirst, 2002b).

In between the pure spot price contract, where most of the risk is placed on the consumer, and the fixed price contract where the main risk is placed on the supplier, there may emerge a variety of new kinds of contracts that fit different customers' tolerance for risk and ability to respond to time-differentiation in price. An example is the *time-of-use tariff* (TOU), which has prices that vary by blocks of time within the day, but are fixed and known by customers in advance independently of the conditions in the electricity system (see for instance Faruqui and George, 2002). This tariff is however quite static. If the system is unconstrained, the TOU peak price may be much higher than the wholesale price, and if the system is constrained, a higher price than the TOU peak price may be needed to signal the market condition and wholesale prices. A more dynamic tariff, able to reflect the spot price and the conditions in the electricity system more accurately, is the *critical-peak pricing* (CPP). This tariff can increase the peak price if the system is severely constrained, and is thus a hybrid between the TOU and the spot price tariff. The TOU and the CPP tariffs are more predictable for the consumers than the hourly spot price at the same time as they provide incentives for consumption adjustments. The CPP rate lessens the price and quantity risk for the retailer compared with the TOU rate because of the possibility to impose a critical peak price during special circumstances.

Another interesting tariff is a *two-part real-time pricing* (RTP) contract. This tariff offers consumers a fixed price for an agreed volume and the spot price for deviations from this volume. If the consumer uses less than what is agreed on, the consumer will be paid back the spot price for the deviation. If the consumer uses more, he pays the

[16] A *fixed price* contract ensures a known price a year or more in advance and protects customers from possible volatile prices in the wholesale market and reduces the risk for unforeseen expenditures during the contract period. However, offering a fixed price contract exposes the retailer for price and quantity risk, as procurement costs at the wholesale market and the customers' consumption level is unknown. Thus, the retailer charges more than the expected average wholesale price for the contract period to account for this uncertainty, or hedges at the financial market through for instance forward contracts. See for instance, Hirst, 2002b, Gersten, 1999, Woo et al., 2004, Nord Pool, 2006b, Deng and Oren, 2006.

spot price for the deviation. Other versions of this tariff may also price the deviation somewhere between the fixed price and the spot price (see for instance Braithwait and Eakin, 2002, Horowitz and Woo, 2006 or Hunt, 2002).[17] Consumers may also be offered a *spot price contract with a cap* at some level agreed on by the retailer and customer.

Both retailers and customers expose themselves for financial risk dependent on the electricity contract agreed on (Sioshansi, 2002, Solem et al., 2003a). Figure 3.4 summarizes some different tariffs and how they share risk between customer and retailer.

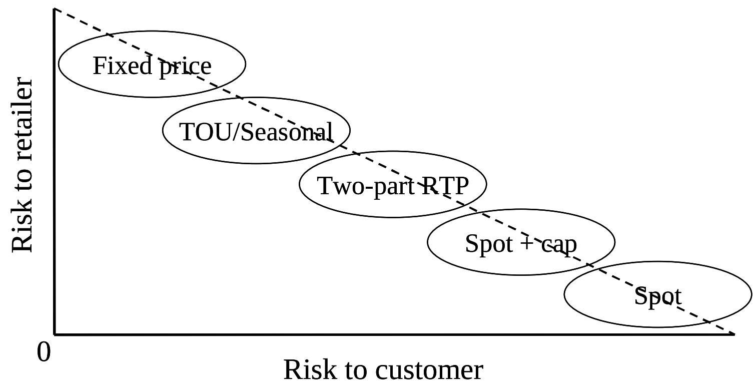

Figure 3.4. Electricity tariffs with differing risk on the customer or retailer. (Adapted from Eakin and Faruqui, 2000)

Due to differing risk taking preferences among the customers, they are likely to diversify to the different tariffs. The retailer can hedge some of its risk at the financial markets, thereby contributing to more predictable prices also for producers.

In addition, retailers may offer *direct load control* of appliances in order to assist end-users' price response, as a mean of attracting customers. Agreements can be made where load control is carried out at some predefined price levels, power consumption levels or in predefined periods in combination with any of the above mentioned contracts, to reduce or shift consumption when desired (see for instance Solem et al., 2003a,b).

[17] Trondheim Energiverk in Norway is currently offering a version of a two-part RTP tariff to residential customers, see www.tev.no.

When wholesale prices are conveyed to the customers and they adjust consumption to the varying prices, their retailers will bid price sensitive bids into the wholesale market. The two disconnected markets are then better integrated.

4 Benefits from increased demand response

There are a number of benefits that may be released with time-differentiated pricing, automatic meter reading and direct load control. This section discusses the following; improved economic efficiency in the electricity market, increased system reliability, reduced price volatility, mitigation of market power, and other benefits.

4.1 Improved economic efficiency in the electricity market

A market is most efficient when customers pay the marginal cost and make consumption decisions based on their marginal valuation of the commodity. For the electricity market, this means that consumers pay the wholesale hourly spot prices for their hourly consumption. The inefficiencies in the disconnection of the wholesale and the end-user markets arise when customer prices deviate from the wholesale prices. When customers pay less than the market price during peak periods, production technologies with high costs may be used to cover demand, even though many consumers would not find it worthwhile to consume electricity if they had been charged the marginal cost of this supply (see also Amundsen et al., 1996, Lafferty et al., 2001, Borenstein, 2002b, DOE, 2006). When customers pay more than the market price during off-peak periods, generators are not utilized even though many consumers would find the electricity production worth the costs.

Figure 4.1 illustrates demand and supply curves for two different periods of the day; one peak and one off-peak period, in an electricity market where the customers are metered hourly and charged wholesale prices.

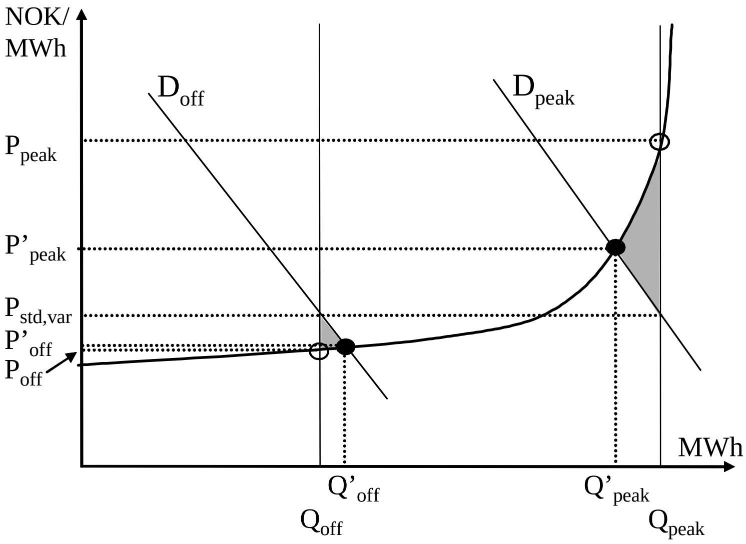

Figure 4.1. A connected market with demand responsive consumers with time-differentiated tariffs

The figure describes a connected market, as opposed to the situation in Section 3.1. Customers are confronted with the prices in the wholesale market and make consumption decisions according to their willingness to pay. Because the information about the customers' demand responsiveness is brought to the wholesale market, their demand curves will no longer appear vertical as is also shown in the figure. The market therefore clears at other consumption and price levels than before. During a high demand period, this occurs at a lower consumption and price level (Q'_{peak},P'_{peak}) than in the situation with no demand response (Q_{peak},P_{peak}). During a low demand period, the market clears at (Q'_{off},P'_{off}), i.e. at a higher consumption and price level than in the situation with no demand response (Q_{off},P_{off}). The efficiency gains that arise when customers face marginal prices rather than fixed prices are illustrated in the figure as the shaded areas (for two different periods of the day).[18]

As seen in Figure 3.1, there is almost always a divergence between the customer price and the wholesale price. In a tightening Norwegian and Nordic electricity market, where prices may fluctuate more, efficiency gains from time-differentiated tariffs and

[18] The standard variable tariff and the spot price based tariff are able to bring the customer price closer to the wholesale price than a fixed price contract for a year is. However, in today's market, the wholesale prices may rise without the prices in these contracts following closely. The deviation between customer price and wholesale price may thus be substantial, also for these contract types, as was described in Section 3.1 (see Figure 3.1). Furthermore, none of these contracts have the possibility to reflect short-term price spikes as the one exemplified 6 February 2003.

increased short-term demand response from households may thus have an increasing potential.

4.2 Increased system reliability

Reliability of supply in the power system is often characterised by system adequacy and security. Adequacy relates to the ability of the system to provide consumers' demand at all times, while security relates to the ability of the system to handle disturbances (Oren, 2005). The Norwegian electricity market organisation is often referred to as an energy-only market, which means that generators are paid only for their produced energy.[19] Under ideal conditions, energy-only markets are claimed to provide an adequate level of supply (Eltra et al., 2002, Oren, 2005). This level is where the cost of new capacity equals the willingness to pay for such capacity (von der Fehr et al., 2005).

However, there are concerns regarding the energy-only market's ability to provide sufficient investments.[20] It is argued that the markets may suffer from inadequate capacity levels due to a number of conditions which may contribute to inefficient market performance. As Morey (2001) puts it, the question seems not to be whether a competitive market can provide adequate capacity, but whether a competitive wholesale power market can be achieved. One of the conditions that may contribute to inefficient market performance is lack of demand response.

One of the reasons for this is that in the deregulated energy-only market framework, investments in generators (and demand side measures) are based on expectations of future energy prices (and maybe on income from the Regulating Power Market and Regulating Power Option Market). This means that the market model relies heavily on price signals, and consequently that the economic integrity of pricing mechanisms within the market rules is paramount (Fraser, 2001). Prices should provide the correct incentives for long-term investments decision and signal how much total capacity, and

[19] This is because no additional capacity mechanisms to ensure sufficient generation capacity exist. However, there may be payment for other services also, such as the Regulating Power Market or the Regulating Power Option Market. It may therefore not be entirely correct to refer to the Norwegian market as an energy-only market (Botterud and Korpås, 2004).

[20] See, for instance, Doorman, 2000, Agerholm et al., 2004, Botterud and Korpås, 2006, de Vries, 2003, 2004, Stoft, 2002, 2003, Eltra et al., 2002, Vázquez et al., 2002, Nordel, 2002.

which type of capacity, to build. However, when wholesale prices are not seen by the customers and their actual willingness to pay for supply of electricity is not reflected in the price in the market, the level of investments may consequently deviate from the most efficient one. Stoft (2003) argues that markets lacking demand responsiveness to prices learn nothing from high prices about consumer preferences for reliability. The required information simply does not exist when consumers' trade off between consuming and not consuming at different price levels is not revealed in the market.

Furthermore, because of the inelasticity of consumers and because it is impossible to prevent any customers from consuming electricity when they want, there is a chance that the demand and supply curve may fail to intersect (see Stoft, 2002, calling this a result of the two "Demand-Side Flaws": lack of metering and real-time billing, and, lack of real-time control of power flow to specific customers). Any actions directed towards reducing the probability of disruptions of supply will, according to Jaffe and Felder (1996), create positive externalities. They argue that resource adequacy is a public good and will be underprovided in the market. Others argue that uncertainties deteriorate the willingness to invest. For instance, Agerholm et al. (2004) point out uncertainties about the price of electricity, and whether price caps or other changes to the market framework might be imposed by regulators.[21] Stoft (2003) mentions the business risk associated with high price volatility as another factor. The long-run average rate of return is difficult to predict, so investors want a higher risk-premium on these risky investments. According to de Vries and Hakvoort (2004), it is not unlikely that investors will choose a risk-averse strategy, taken into account many of these (unquantifiable) uncertainties. Doorman (2000) argues that uncertainty is especially harmful for peaking

[21] Agerholm et al. (2004) also mention conditions which not necessarily are related to lack of demand response, for instance uncertainties about prices of other fuels and whether environmental restrictions (CO_2 targets and prices), taxes or other changes to the framework might be imposed by regulators. It has also been maintained that the electricity market does not perform efficiently if entry barriers are high enough to prevent investments by new entrants. Incumbent producers may exploit this by under-investing in capacity in order to raise prices (Vázquez et al., 2002, Eltra et al., 2002). High entry barriers may be the case in the Nordic countries since, according to for instance Bye et al. (2003a) and TU (2006), public regulations here make it very difficult to establish new capacity. Furthermore, according to for instance Nordel (2004b), one of the prerequisites for the market to work is that risk can be kept at a reasonable level. Risk may be overcome by hedging at the financial markets (Stoft, 2003). However, financial contracts at Nord Pool can not be purchased for more than four years ahead which may not be sufficient for investment hedging purposes given long lead times and life times of generators. Furthermore, existing standard financial instruments are based on a flat profile which means e.g. peaking units possibly may lack a hedging product that otherwise, according to Nordel (2004b), could have secured more predictable revenues during peak periods.

generators, since the generator with the highest marginal cost will have to cover its investment during a few short periods where all generators run at their capacity limits. Given risk-aversion among investors, investments may thus only occur when very high prices can be expected, and if there are no risks of price caps (see also Vázquez et al., 2002). However, as discussed in Finon et al. (2004), while high prices may be necessary to trigger investment, politicians may find them unacceptable. For instance, during the high-price period in 2002/03 politicians threatened to reregulate the Norwegian market (Bye and Hope, 2005). Politicians may especially find high prices unacceptable if they suspect high prices to be a result of abuse of market power by companies that are taking advantage of insufficient demand response (Oren, 2005, see also Section 4.4). And, if there is a risk that politicians may intervene in the price formation, investments may be postponed (Nordel, 2004a).

The above discussion indicates several conditions that may cause the investment level to deviate from the most efficient one. Whether this is the situation in Norway will not be evaluated here. However, as illustrated by Glende et al. (2005), we note that the peak load in Norway has been steadily increasing the last years, while the generating capacity has not increased to the same extent, resulting in a gradually deteriorating capacity balance. Others, for instance Bye and Hope (2005), Grande et al. (2001) and von der Fehr et al. (2005), have also emphasized the tighter market conditions that now may be seen, and that ensuring adequate capacity is an important challenge. Statnett (2006b) points out that the power sector in Norway has never before been on the way into an investment phase with the organization of the sector that we have today, which confronts the sector with new challenges. Statnett asserts that within the sector organization and the policy we have today, it is not likely that new overcapacity will systematically be built; a situation with little or scarce capacity will be persistent.

Some forecasts of the power balance in Norway and the whole Nordel area may further illustrate this. For the previous winter (2005/06), Norway as well as the whole Nordel area (the Nordic countries), were forecasted to have a deficit in the power balance in a very cold winter day, so that import to maintain balance between demand and supply could have been necessary (Statnett, 2005a, Nordel, 2005c). For the present winter (2006/07), both Norway and the Nordel area are forecasted to have a surplus in the power balance (Statnett, 2006a, Nordel, 2006b). Forecasts for the 2008/09 winter again indicates the need for import in case of a very cold winter day for Norway and the whole Nordel area, while the situation in 2009/10 indicates surplus for Norway but a deficit in the power balance for the Nordel area (Nordel, 2005a, 2006a). These forecasts indicate that the demand and supply levels the next years will alternate around what may be regarded as a tighter balance.

Hunt (2002) and Fraser (2001) maintain that the lack of demand response is the reason for the worries about reliability and the need for capacity markets, installed capacity requirements, price caps and other holdovers from the period of regulation, seen in many countries.[22] Demand response is an important factor that may improve the functioning of the market and mitigate many of the concerns discussed above. One of the consequences with inelastic demand accompanied by increasing peak power consumption and lack of investments in supply, is that failure of market clearing in the day-ahead as well as in the regulating market may occur (Stridbæk, 2003). This is illustrated in Figure 4.2.

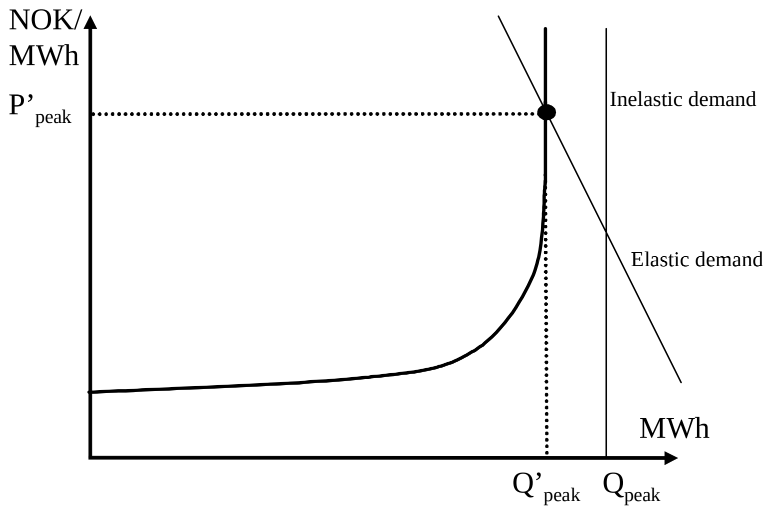

Figure 4.2. Demand response may avoid rationing

[22] Due to the concerns of the inability of the energy-only market to ensure adequate supply levels, additional instruments and different organizations of the market have been proposed and are in use in different markets around the world in order to meet the shortcomings of the energy-only market or in order to make the markets more complete. Capacity obligations, capacity payments, proxy market pricing or capacity subscription (see a discussion of these in Doorman, 2000), consumer response options (Stridbæk, 2003), and reliability contracts based on financial call options (Vázquez et al., 2002) are some examples.

The figure indicates two different situations. The first is where inelastic demand (Q_{peak}) exceeds available capacity (Q'_{peak}), for instance due to extreme cold, generator outages etc. With inelastic demand, involuntary disconnection of customers with the amount of Q_{peak}- Q'_{peak} may be necessary to maintain the power balance. This may lead to substantial loss of load costs, and may also be considered socially unacceptable. In addition, physical rationing is inefficient since all disconnected customers are equally affected, regardless of their willingness to pay for the electricity (Faruqui et al., 2002).[23]

Instead of resorting to involuntary rationing, this situation can therefore be managed by voluntary adjustments to high prices, as indicated in the second situation where demand response is present in the wholesale market with an elastic demand curve. Demand response ensures market clearing at Q'_{peak}, and thus helps balancing demand and supply. This implies that periods of under-investments of capacity in the market leads to higher prices rather than rationing of customers. As Fraser (2001) explains, if customers' willingness to pay is brought through to the wholesale market, each customer actually declares a maximum reservation price (i.e., each customer's value of lost load), which the customer is prepared to pay. The demand curve then becomes an ordered list of individual customer value of lost loads. Some argue that when customers ration themselves in this way, the public good characteristic of system adequacy is turned into a private one (IEA, 2003, Oren, 2005). The second situation also illustrates that the elastic demand curve may ensure clearing above marginal cost of the last unit, which may be necessary for generators to cover their fixed costs (see for instance Fraser, 2001 or Stoft, 2002).

According to Hunt (2002), California had to employ rolling blackouts with a shortage of only 300 MW in a system of 50,000 MW, which means that a very small reduction in demand was needed to avoid the blackouts. Others have also pointed out that one of the key factors of the problems in California's market was the absence of demand response (Faruqui and George, 2002, Fraser, 2001).

Increased demand response provides flatter daily load shapes, and a better utilization of the capacity for both generators and the networks. With lower peaks, the

[23] The average interruption cost for the total of Norwegian consumption is estimated at about 4 /kWh interrupted (Glende et al., 2005). Typically average outage cost used for system planning purposes in the US, range from $2.5 to $5/kWh (Boisvert et al., 2002, DOE, 2006).

transmission or generator capacity may not need to be dimensioned for the same extreme demand that may only occur for a few hours a year. The necessity of expanding the transmission system or building new peak power plants may thus be less, or deferred (Borenstein, 2002b, DOE, 2006, Earle and Faruqui, 2006).

Another advantage with demand responsive customers is that their bidding in the day-ahead market implies that demand during extreme situations is less than without demand response (see Figure 4.1). This may have reliability benefits since additional supplies become available for the Regulating Power Market to meet possible contingencies (see also Hirst, 2002a, Braithwait and Eakin, 2002). Some of these resources may be better suited for fast response in this market. Opportunities for retailers or network companies to aggregate reductions from certain types of load and sell this into the Regulating Power Market may also provide the system operator with more competition and cheaper prices in this balancing market (see Grande et al., 2000). Furthermore, as Braithwait and Eakin (2002) maintain, when the market performance is improved and load becomes more stable, the desired or needed reserve requirement may decrease.

It may also be less expensive and less time consuming to activate demand response and strengthen the peak load balance compared to investment in generating capacity (Earle and Faruqui, 2006, Nordel 2004a). Furthermore, Earle and Faruqui argue how implementing the necessary infrastructure for demand response, before an actual capacity shortage situation occurs, may have an option value. As they put it; it might be valuable to pay an insurance premium today as a hedge against future outages (see also Stridbæk (2003), arguing in the same line).

Finally, demand response may reduce price volatility, thus contributing to reduce investors' uncertainty regarding investments in new capacity which may contribute to more timely investments. This will be discussed in the next section.

Overall, we can see that demand response may contribute to benefits and reduced costs of maintaining a reliable and well-functioning electricity system. Those savings may eventually be distributed among several participators in the electricity market and may benefit all customers; those on time-differentiated tariffs and those on traditional tariffs.

4.3 Reduced prices and price volatility

Highly volatile spot prices in the day-ahead market may occur due to the inelasticity of demand in the wholesale market, the non-storable property of electricity, uncertainty regarding demand that vary by time of year, week and day, available production and transmission capacity, bottlenecks and possible exercise of market power. Figure 4.3 show some examples of daily spot price patterns in the Oslo area.

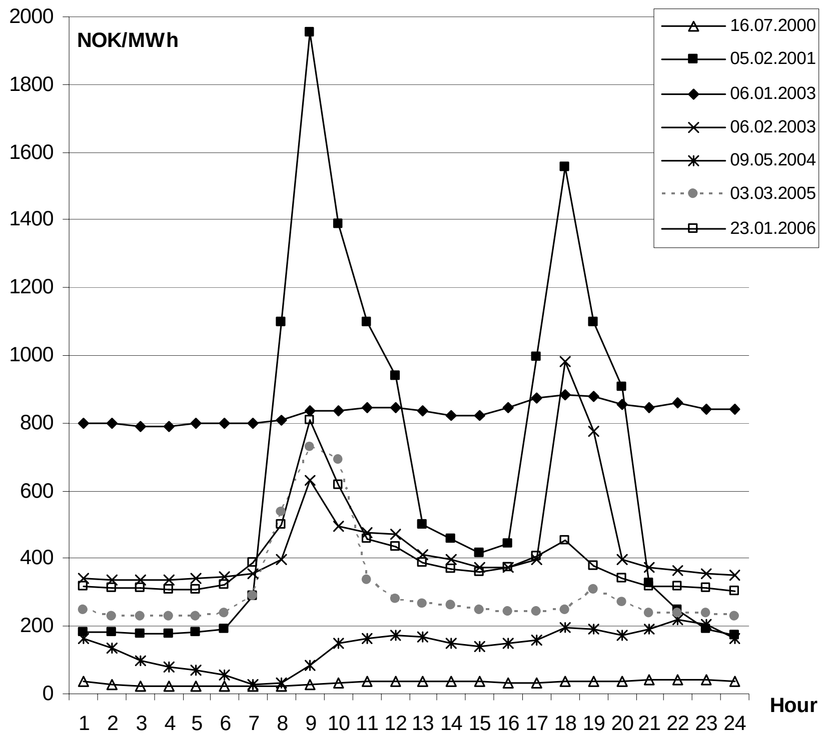

Figure 4.3. Different hourly spot prices for different days in the Oslo area

As seen in the figure, prices may vary significantly during the day and between seasons. For instance, during 5 February 2001, prices increased substantially, indicating a power capacity shortage situation. We also see that prices were constantly high during 6 January 2003 due to the energy scarcity situation. Also shown is the peak price situation 6 February 2003, discussed in Section 3.1. Examples of low prices are 16 July 2000 and 9 May 2004. Although these examples indicate significant price variation, prices traditionally vary little within the day in Norway. This may however change if the capacity situation continues to tighten, and also as a result of new transmission capacity to countries with thermal power production.

Several analyses and simulations support that demand responsiveness provides lower prices during peak periods, as illustrated in Figure 4.1. For instance, Boisvert et al. (2002) analyses how price responsive load contributed to relieve the electricity system at a time when electricity peak demand reached all time high levels, using data from demand response programs in the state of New York. They found that the increase in demand response reduced prices and price volatility in both the day-ahead market and the real-time market. The authors claim that only a little price responsive load can go a long way toward reducing prices and price volatility. Caves et al. (2000) simulated the market impacts of demand and supply shocks in the Midwest in the USA under a scenario where only 10 percent of the load had a spot price based contract. The simulations show that prices would be reduced by as much as 73 percent from the highest prices. Jaske (2002) reported results from an experiment performed by CalPX, which operated a day-ahead market in the USA. By re-simulating market prices with hypothetical load reductions from price responsive load, they found the price to decrease by approximately 28, 58 and 75 percent for load reductions of 5, 10 and 15 percent in the peak price hour, respectively. Simulations performed by Nordel have shown that demand response in one region of the Nordic countries will contribute to stabilize the spot prices also in other regions (Kristensen et al., 2004). See also Braithwait and Faruqui (2001) or Hirst (2002b) for similar computations.

Furthermore, with respect to Figure 3.3 showing the market cross for the hour 17:00-18:00, 6 February; if for instance 600 MW less demand (approximately 3 percent of the total cleared demand) were bid into the Elspot market at some predefined level because of customers demand response, let’s say at prices above 500 NOK, this could have been enough to clear the market at nearly half the price this hour. Pettersen (2004) also shows how demand response may even out prices, not only between peak and off-peak periods of the day, but also between seasons.

As described in the previous section, investments in peaking units are highly risky because they need market clearing above their marginal cost, which occurs in constrained situations only. The length and height of the price peaks must be high enough to recover the investment costs. The more elastic demand is, the less volatile are the price, and the less is the uncertainties with respect to future income from investments in generators. Increasing demand response may therefore contribute to increased propensity to invest. Since the likelihood of extreme prices also is reduced, the chance for political interventions in the market by for instance imposing price caps may also be less. This further reduces investors' uncertainty. Reduced volatility further reduces the retailers' price risk, which may lead to lower hedging costs at the financial markets. This provides benefits that in the next turn may be passed on to the consumers through lower tariff rates (Boisvert et al., 2002, Braithwait and Eakin, 2002, DOE, 2006). Lowering peak prices may ultimately also lower average prices, which may benefit also consumers who choose standard variable or fixed price contracts (Boisvert et al., 2002, Hirst, 2002b). However, as pointed out by Ruff (2002), bill reductions due to lower peak prices are rent transfers, not necessarily social benefits. Notwithstanding, many (for instance politicians) regard lower peak prices as benefits.

4.4 Mitigation of market power

In periods when peak demand approaches the limits of the production capacity, the market may clear at the steep part of the supply curve, as happened 6 February 2003 (see Figure 3.3). Then, producers with a significant market share may withhold enough power from the market to shift the supply curve to the left, and achieve higher price levels.[24] Taking 6 February 2003 as an example; if less than 3 percent of the total supply bid at the Nord Pool Spot was held back between 17:00-18:00, the price could have been doubled. However, the gains for producers of such attempts to exercise market power depend on the trade-off between selling less power to a higher price and selling more power to a lower price. The gain is higher if raising the price has little short-term impact on the demand. That is, with a significant share of consumption coming from consumers facing prices that do not vary by time of the day, the incentive for exercising market power is higher. On the other hand, with time-differentiated prices conveying real-time prices to demand responsive customers, companies holding back power from the market will have smaller impacts on the wholesale price. This reduces the

[24] Bye and Hope (2005) points out that any producer on the margin (in restricted price areas), even a small firm, may also exercise market power.

profitability of exercising market power (see also Borenstein, 2000, Borenstein et al., 2000, DOE, 2006).

Another point is that when firms exercise market power, prices deviate from the cost of production. Reducing market power therefore contributes not only to reduced price volatility and price spikes, it reduces wealth transfer from customers to suppliers, and reduces efficiency losses in the market that occur from the difference of what the customers pay and the marginal production cost (Borenstein, 2002a, Lafferty et al, 2003). Besides, artificially high prices may lead firms, which are dependent on electricity, not to establish new businesses (Borenstein et al. 2000). De Vries (2003) and Twomey et al. (2005) further remark that since exercise of market power may distort prices, investment decisions with respect to new capacity may also be distorted. Mitigating market power by increasing demand response can thus also reduce uncertainties and improve the basis on which investors make their investment decisions.

4.5 Other benefits

With automatic meter reading and direct load control technology, the opportunities for a retailer to differentiate its products from those of its competitors' is enhanced. Customers get more opportunities to choose from and can select the tariffs or products that are best designed for their specific wants and needs, and then tolerance for risk.

More accurate meter reading and billing of the customers, also prevent possible tactic meter reading by customers, and reduce the costs for customers as they no longer need to read and report their consumption manually.

Environmental benefits may also arise if increased demand response leads to a reduction in peak period emission that weighs up against possible increases in off-peak production emissions (Holland and Mansur, 2004, 2006). Holland and Mansur find that the impact on the emissions of SO_2, NO_X and CO_2 depends on the generation technology characteristics of the region they analyses. Another benefit is that new power plants or transmission lines with environmental impacts may not be needed if peak load is reduced.

In addition, some claim that energy efficiency may follow from demand response programs. For instance, Faruqui (1983) surveyed 12 TOU experiments and found that overall reduction in daily consumption generally occurs. In Puget Sound Energy Time-of-Use pilot program (PSE, 2003) it was documented a 1 percent average decline in total monthly energy use by TOU pricing participants. An IEA (2003) publication suggests that typical residential programs deliver approximately 2 percent reductions in energy consumed.

Since increased demand response provides a less varying demand, it will give more continuous utilization of generators, hence reducing starting and stopping of peak production, which tend to increase wear and tear for the generators (TU, 2005). Reduced demand during peak periods also reduces losses in the grid (Haugen et al., 2004).

Finally, under the existing load profile billing system, customers with little electricity consumption during peak periods and much electricity in the off-peak periods actually subsidize those with "the opposite" consumption pattern (Borenstein, 2002b, Borenstein, 2005). Instead of mainly paying the off-peak prices, as the customers would do with a time-differentiated price, a part of the customers' off-peak consumption is also charged the peak price, according to the adjusted load profile. Hunt (2002) remarks, “It is hard to think of any other industry where products whose price varies so widely are bundled together for sale”. Many customers consider this unfair, and may therefore want to be charged by time-differentiated tariffs.

5 Evidences of households’ demand responsiveness

The release of many of the benefits depends on the consumers’ demand responsiveness. It has therefore been important to quantify price elasticities by conducting time-differentiated pricing experiments. This section reviews some of the literature analysing data from these experiments.

In some European countries, time-differentiated electricity rates have been tested or been in use for some decades, while the U.S.' interest for demand response programs grew in the 1970's, partly due to the oil crisis and a growing environmental concern (Eto, 1996). [25]

Papers analysing consumers' responses to time-differentiated prices were few before researchers analysed a series of 16 experiments carried out in the US in the late 1970's and 80's. Two annuals of *Journal of Econometrics* were in its entirety devoted to many of these analyses (Aigner, 1984, Lawrence and Aigner, 1979). Since then, an extensive literature has developed on residential consumer response to variable pricing. Also, literature on load control of e.g. water heaters has been published, although not to the same extent. This review will therefore mainly focus on the time-differentiated pricing literature, but will also describe some experiments including load control. Furthermore, this review focuses on residential electricity consumers only.[26]

The first experiments usually featured the TOU rate. However, due to the static properties of this rate as described in Section 3.2 (it is constant in each time block regardless of varying conditions in the electricity system), more dynamic rates, such as real-time market prices or the CPP rate, have been tested recently. Most of the papers on customers' responses to time-differentiated pricing have therefore analyzed TOU programs. Very few papers where end-users at the household level have been offered spot price tariffs, are published.

Usually, the results from analyses of consumers' responses are reported in terms of elasticities. The most common is the own price elasticity (usually only referred to as the price elasticity) and the elasticity of substitution. The own price elasticity is defined as the percentage change in quantity demanded, divided by the percentage change in price. The elasticity of substitution is the negative of the percentage change in the ratio of peak to off-peak consumption, divided by the percentage change in the ratio of the peak to the off-peak price.[27]

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[25] For instance, time-of-use (TOU) rates have been reported in use as early as 1913 (Mountain and Lawson, 1995), and water heater load control as early as 1934 (Hastings, 1980). Since 1965, French households have been offered the choice between a standard flat rate and a rate with two daily pricing periods (Aubin et al., 1995), in the UK a large TOU tariff experiment was conducted in 1966/67 (Hawdon, 1992) and Finland has offered consumers a TOU rate since 1970 (Kärkkäinen, 2005).

[26] For papers analyzing or reviewing commercial and industrial customers, see for instance Aigner and Hirschberg (1985), Aigner et al. (1994), Faruqui and George (2005), Ham, Mountain and Chan (1997), Hopper et al. (2006), Mak and Chapman (1993), Schwarz et al. (2002).

[27] According to King and Chatterjee (2003), an elasticity of substitution of 0.17 is consistent with a peak-period own price elasticity of approximately -0.3.

5.1 TOU experiments

The results from the analyses of the 16 U.S. projects conducted in the 1970/80's differed, and questions were raised how to transfer the results to other regions, which was one of the intentions with the experiments (Aigner, 1984, Lawrence and Aigner, 1979). Initiatives were therefore taken to investigate whether consistency could be found across the experiments if the differences between the experimental characteristics where controlled for. Caves et al. (1984) reviewed several of the experiments and selected five with sufficiently high quality that could be used to pool the data. Their analyses found consistent price responses across the experiments when the effects from weather, appliance holdings and household characteristics were controlled for. They found the substitution elasticity to vary depending on the stock of electric appliances in the homes. For a typical customer the elasticity was 0.14, for a household with no major appliances it was 0.07, while a household with all major electric appliances had a substitution elasticity of 0.21. Baladi et al. (1998) report similar findings from a later U.S. experiment.

A Norwegian TOU electricity pricing experiment took place during the period from 1984 to 1987 and included 374 households that volunteered for the experiment. Vaage (1995) found the results to be quite comparable with the results from the U.S. experiments. The elasticity of substitution varied between 0.13 in the winter and 0.24 in the spring, with an average over the whole period of 0.18. Hence, price responses were highest in the part of the year that is considered as off-peak period. Furthermore, nighttime consumption was more elastic than daytime consumption. Vaage also tested whether the elasticity changed during the two years the consumers faced the TOU rate. Although the substitution elasticity showed a slight increase from the first to the second year, he evaluated it to be too small to be given any weigh. Hauge (1993) analyzed data from the same experiment, and found somewhat higher responses, and also that responses were higher in households with a higher total consumption of electricity, living in detached houses and with alternative heating sources.

In Great Britain, a TOU pricing experiment took place from April 1989 to March 1990. Henley and Peirson (1998) analyzed data from this project, and found that consumers reduced daytime consumption in response to the prices and that the price response was dependent on temperature (price elasticity was highest at 10°C). They reported price elasticities of -0.10 and -0.25 at 10°C. In an earlier work, Henley and Peirson (1994) found that responses were different depending on the customers' consumption strata, with higher responses in the highest strata.

Train and Mehrez (1994) analysed a TOU tariff experiment in California in 1985 and 1986. They estimated price elasticities of –0.15 in the peak and –0.25 in the off-peak period, and also found that peak and off-peak consumption are substitutes because of positive cross-price elasticities.

Filippini (1995a) analyzed panel data from 21 cities in Switzerland, from the period 1987 to 1990, where consumers faced a time-of-use tariff or a two-part tariff. Unlike most other studies, which use micro data, this study was based on aggregated cross-sections data at city or state level. Filippini found elasticities that are much higher than in most other studies. He found peak elasticities to range from -1.29 to -1.50 and off-peak elasticities from -2.36 to -2.42. Another analysis by Filippini (1995b), this time using micro data, confirmed the previous results with estimated elasticities in the same range.

In a Japanese TOU experiment in Japan, Matsukawa (2001) found price elasticities close to those in Filippini (1995). However, contrary to the Swiss results, Matsukawa found peak elasticities (-0.70 to -0.77) to exceed off-peak elasticities (-0.51 to -0.72).

A residential TOU program carried out by Puget Sound Energy in the USA in 2001/2002 showed a shifting of 5 – 6 percent of the customers' consumption out of high-priced periods (Williamson, 2002). This result must be seen in light of very low price differentials in the experiment, which gave limited incentives for the consumers to shift their energy use.

These results indicate that customers do respond to time-differentiated prices, but the extent to which they respond varies between the experiments. According to Braithwait and Eakin (2002), the average elasticity of substitution from traditional TOU programs is about 0.15. According to King and Chatterjee (2003), the average own price elasticity from all types of programs (including CPP and automated thermostat control programs, discussed in the next section) is -0.3.

5.2 Dynamic pricing and direct load control experiments

Dynamic rates have often been combined with signal lamps or enabling technologies. For instance, Räsänen et al. (1995) analysed data from a voluntary dynamic pricing experiment in Finland during 1988-1993. A yellow signal lamp warned the customers one day in advance that the critical peak price could be charged their usage, and a red lamp signaled the customers during the peak hours that the critical peak price was actually in effect. Räsänen et al. found it important to analyze impacts of the rates at an individual customer level, since the customers' responses differ. In their data they found an active and a passive response group. The passive group reduced their consumption in peak period with 16 to 26 percent while the active group showed strong responses with 60 to 71 percent reductions.

Elecricité de France has for a long time offered their electricity consumers time-of-use tariffs. From 1996 the French electric utility also introduced critical-peak price tariffs for its residential consumers. Prior to this introduction, from 1989 to 1992, they conducted an experiment with this so-called tempo-tariff. With this tariff, the year is divided into 22 red, 43 white and 300 blue days, and each day has a peak and an off-peak period. The red days charged electricity consumption the highest prices and the largest peak/off-peak price ratios, and the white days the lowest prices and smallest ratios. As in the Finnish experiment, the end-users were notified with a signal lamp of the next day's price structure at the end of each day. The prices accompanied with each of the days were fixed and known for the customers, but the colour of the days was unknown until the evening before. Aubin et al. (1995) found high elasticities in this experiment, with a peak price elasticity of -0.79 and off-peak elasticity of -0.28.

A large-scale project in the USA tested a real-time market price on households, with a notification by e-mail or phone if the next day's price exceeded USD 0.10. The analysis of the data found price elasticity of -0.04. This somewhat low result must be seen in light of prices that were not particularly high in the test period (Summit Blue Consulting, 2004).

The above experiments did not assist the consumers' load reductions by automatically controlling loads. Other experiments have done this by offering enabling technologies such as direct load control, combined with time-differentiated pricing in order to enhance the consumers' price response. King (2004) made a survey of programs with dynamic pricing of electricity and/or with automated control. The intention of the survey was to compare the peak demand reducing performance of programs with only dynamic pricing or with only automated control, with programs that combined those two demand response measures. He found load reductions for programs that integrated dynamic pricing with automated load control to be on average 53 percent larger than load reductions in programs with only load control. He further found the integrated programs to give 102 percent larger reductions compared with programs with only dynamic pricing.

An example of one such project is a program in the USA that used a critical-peak price tariff together with an interactive communication system. This system allowed the utility to send a signal to the consumers when critical prices were expected and also allowed the customers to program and schedule some of their appliances in order to modify the consumption according to the prices. Braithwait (2000) analyzed data from the project and found elasticities of substitution of approximately 0.3.

Hartway et al. (1999) found load reductions of up to 1.95 kW (approximately 35 percent reduction) in another program in the USA. They attributed these high responses to the high price differential (6.5:1), and to customers' programming of their air conditioners using an advanced energy management system.

The results from the recently finished Statewide Pricing Pilot in California (Faruqui and George, 2005, CRA, 2005) further illustrate the same results. Although comparisons between the different customer groups in the program should be made with care, the results showed that customers with enabling technologies responded more than customers without this equipment.

6 Conclusions

Increasing short-term demand response in the Norwegian electricity market may increase efficiency, improve system reliability, decrease price volatility and mitigate exercise of market power. These market performance improvements may contribute to lessen uncertainties for investors of new capacity due to a market framework that may become more predictable, thus providing more timely and correct investments decisions. These benefits may prove valuable as the Norwegian and the Nordic market now enter a period with tighter conditions and with uncertainties regarding new investments in electricity production.

Approximately 40 percent of the *annual* electricity consumption, and probably more than 40 percent of the power consumption during cold peak periods, is metered by technologies that can only measure accumulated consumption. This prohibits the use of time-differentiated electricity tariffs that reflect wholesale prices because such tariffs require automatic meter reading. Consequently, households only face prices that are fixed for long periods of time, and have no incentives to adjust consumption according to the short-term varying market conditions signalled in the wholesale prices. This consumer group will therefore to a limited extent contribute to achieve the benefits described in this paper. Experiences from around the world have shown that households are responsive to the price. This suggests that households better integrated into the electricity market can be important contributors to increase demand response, and thus to improve the functioning and increase the efficiency of the Norwegian and the Nordic market.

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Article II:
Direct load control of residential water heaters*

Abstract

In Norway there is a growing concern that electricity production and transmission may not meet the demand in peak-load situations. It is therefore important to evaluate the potential of different demand side measures that may contribute to reduce peak load. This paper analyses data from an experiment where residential water heaters were automatically disconnected during peak periods of the day. A model of hourly electricity consumption is used to evaluate the effects on the load of the disconnections. The results indicate an average consumption reduction per household of approximately 0.5 kWh/h during disconnection, and an additional average increase in consumption the following hour, due to the payback effect, of approximately 0.2 kWh/h.

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1 Introduction

Peak electricity consumption in Norway has been increasing, and is expected to continue to increase in the years to come (Glende et al., 2005). However, since deregulation of the electricity market in 1991, new investment in power generation has been at a low level (Bye and Hope, 2005). Periods with extreme cold weather have revealed a vulnerable production and distribution system, as consumption in such peak situations has been close to capacity. This calls for a flexible demand side with the potential of reducing loads in peak situations to relieve the constrained system. Demand response may consequently defer the need for costly augmentation of the electricity grid or power production.

Direct load control and time-differentiated tariffs are two measures to obtain demand response that have been tested and used worldwide. A direct load control programme often involves customers who are willing to offer electricity-consuming appliances for load reduction if they are compensated economically. Traditional interruptible programmes have paid their customers in advance for participating, for example, through rate discounts. An example is an air conditioner and water heater load programme in the USA, where customers are provided with discounts on their electricity bill if they participate in the programme (Xcel Energy, 2005). The customers receive $US6 for each month in the summer if they allow 15–20 minutes cycling of their air conditioner in the hot summer months and an additional $US2 each month for the whole year if they allow their water heaters to be disconnected for six-hour periods on hot summer days or cold winter days. The utility is only allowed to control the appliances for a maximum of 300 hours per year. In 2001, when approximately 280,000 residential customers were on the programme, electricity consumption was reduced by 330 MW in peak situations. Another example where water heaters are under direct control is an Australian programme involving 355,000 water heaters. This control reduces peak electricity consumption by 389 MW. The incentive for the customers to participate in the programme is lower rates for their water heating (Charles River Associates, 2003). A direct load control programme in the USA controls air conditioning, central electric heaters, electric water heaters and swimming pool pumps. A total of 800,000 controlled points provides 1,000 MW of demand reduction in normal operation, and 2,000 MW in emergency situations (Malemezian, 2004).

Direct load control is often combined with time-differentiated pricing, such as time-of-use or dynamic pricing, to assist reduction of consumption during high-priced peak periods. King (2004) found load reductions for programmes that integrated dynamic pricing with automated load control to be on average 53% larger than load reductions in programmes with load control alone. He further found the integrated programmes give 102% larger reductions than programmes with only dynamic pricing, i.e., over twice the reduction.

Water heaters constitute approximately 10% of the electricity consumption in Norwegian households (Larsen and Nesbakken, 2005). Direct load control of water heaters may therefore have a large demand response potential which is important to quantify. This paper provides such estimates by studying data from a large-scale Norwegian project where load control of residential water heaters was applied. Hourly measurement of the electricity consumption from 475 households, number of hours of daylight each day, and the local temperature and wind speed in a six-month period from November 2003 to May 2004, provide a large panel data set that we analyse with statistical methods. We develop a fixed effects regression model of hourly electricity consumption and use it to evaluate the impact of the water heater control on households' load curves.

The results from the analysis show significant electricity consumption reductions during disconnections of the water heaters. The results also indicate additional consumption when the heaters are reconnected due to the so-called "payback" or "cold load pickup" effect (which is explained in the next section) which may cause a new peak in the electricity system, suggesting cycling the control events may be necessary.

Section 2 describes factors that may influence the load reducing potential and the payback effect experienced when applying direct load control of water heaters, Section 3 describes the experiment and the data that are analysed and Section 4 describes the method and the models that are used. The results are evaluated in Section 5 and the last section concludes.

2 Water heaters and load control

When water heaters are used for direct load control, essentially all of the energy not supplied to the heaters when they are disconnected from the electricity supply will be required when they are reconnected. When switched on, all affected heaters that were supposed to be on during the control period, will start recovering from the interruption at the same time. Unless handled properly, this payback effect may have the undesired effect of creating a new peak in the electricity system. It is thus useful to discuss some causes for the effects experienced when water heaters are used for load control. This section describes some of these factors.

A water heater is used to heat and store hot water. A typical Norwegian residential water heater holds 200 litres and has a rated heating element capacity of 2 kW. The heat loss from a tank is approximately 0.1 kWh/h at a temperature of 75°C (HiO, 2005). It takes approximately 2.3 hours for a full heated tank to drop in temperature by 1°C in stand-by mode, i.e., when no hot water is drawn from the tank. The water heater's thermostat is usually a bimetallic strip with a dead-band of approximately 4°C. This means that the heating element will start operating when temperature falls below 73°C and stop operating when the temperature exceeds 77°C. Due to the thermostat's dead-band, a full heated tank in stand-by mode will require approximately nine hours before the thermostat activates the heating element as a result of heat loss. Orphelin and Adnot (1999) found that most heaters are operating due to the households' usage of water rather than due to heat losses.

When a household uses hot water, the water is drawn from the top of the tank. At the same time, cold water refills at the bottom of the tank. The thermostat is placed a few centimetres above the bottom, and will respond to a temperature drop by activating the heating element. A hand wash may use only a few litres of hot water. The energy use is accordingly low, and a heater will need to operate for only a few minutes to restore the energy used.[1] A large family may use all the hot water, approximately 14 kWh, when all members are showering, which requires the heating element to operate

[1] However, small amounts of water use may not activate the heating element. This is explained below.

for seven hours afterwards. Those two examples may represent a range of energy use due to hot water use during morning hours in different households.

Because hot water can be stored for long periods of time without significant heat loss in a well-insulated tank, it is well suited to heat water at one period of the day and use this water at another period. Direct load control of water heaters has therefore been widely applied to reduce peak load. The idea is to turn off the electricity supply to a large number of heaters during peak periods. If all heaters have elements of 2 kW-rated capacity, the maximum theoretical load reduction achievable is 2 kWh/h per heater. However, the average reduction of load per household is likely to be less, due to diversity with respect to the timing of the hot water usage between households.

Two principle outlines of energy recover in water heaters, with and without disconnections of the heaters, in hypothetical household groups with different usage (high and low) of hot water are shown in parts (a) and (b) of Figure 2.1. The heating element capacity is assumed to be the same for all households. For illustrative purposes it is assumed that the starting point for hot water usage is distributed uniformly over the hours around the control event.

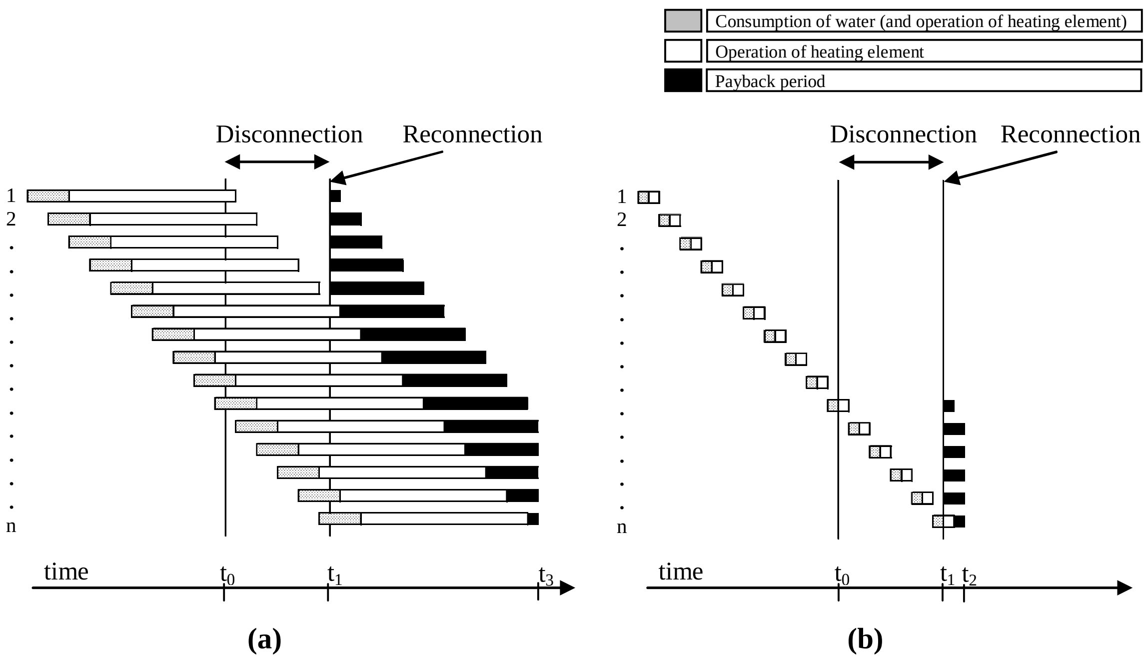


Figure 2.1. Energy recovering of water heaters with and without disconnections for households with a high level of hot water consumption, 1,…,n (a), and low level of hot water consumption, 1,…,n (b)

Figure 2.1 shows water heaters of two household groups with *n* households in each group. There is one heater at each "line". The shaded and the white areas indicate the operating period for the heaters under normal conditions if a disconnection *is not* made. The shaded area indicates the period of hot water use (it is assumed that the heaters start operating immediately after hot water is drawn, i.e., at the beginning of the shaded area). The households use hot water at different times; in each group, number 1 starts consuming hot water first and number *n* last. A disconnection starts at t_0 and finishes at t_1, when the heaters are reconnected. The black area indicates the period when the heaters recover energy in the situation where a disconnection *has occurred*. The black area is simply the part of the energy recovery period that could not be accomplished due to the disconnection and which is postponed compared to the normal situation, without the disconnection. Approximately the same amount of energy that would normally be consumed during a disconnection will be consumed after the heater is reconnected.[2] This demand will be added to the system load and give rise to consumption that would normally not exist if load control did not occur. This payback effect is therefore the result of a disturbance in the natural diversity of the heaters used for load control (see for example Rau and Graham (1979) and van Tonder and Lane (1996) for a similar discussion).

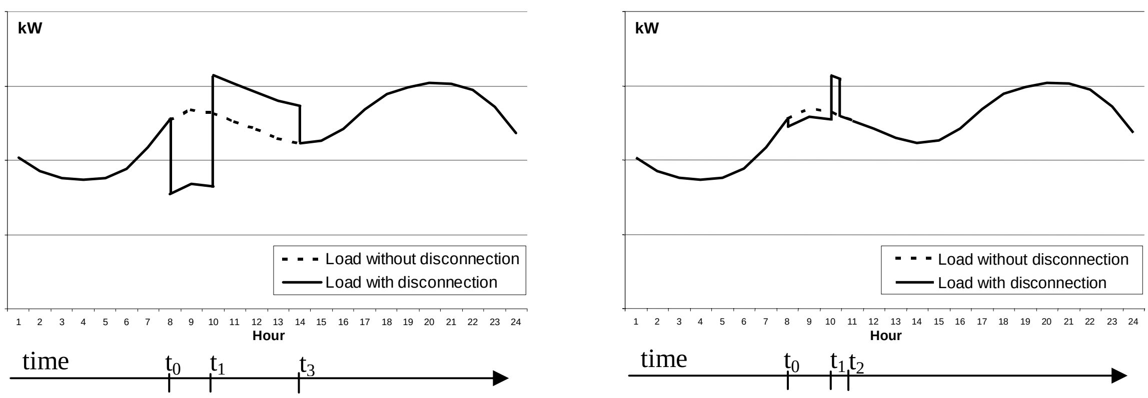
Figure 2.1(a) shows households with a high level of hot water usage. It can be seen that the disconnection affects the first water heater only slightly. The heater has nearly finished recovering the energy loss when it is disconnected; the final part of its restoration of the energy must wait until the heater is reconnected. Disconnection of this water heater will contribute little to load reduction in the electricity system. Nevertheless, the heater will contribute with its full-rated capacity at the time of reconnection, although only for a short time. To some extent, this will also be the case for the second and third heaters. The heaters in the middle of the figure will, however, contribute to a reduction with their rated capacity during the entire disconnection period. In addition, as these heaters start operating close to the time of disconnection and have a long recovery period, their payback contribution occurs after t_1. At every

[2] There will be a very small energy saving effect as the heaters are left for a period at a lower temperature than they otherwise would have been.

moment during the disconnection period, it can be seen that the disconnection affects 10 heaters. When reconnected, only five heaters contribute to the payback effect at every moment until t_3. In this example the power demand added to the system load after a disconnection is therefore only half the size of the reduced power demand during the disconnection. The system load curve will return to normal shape after t_3, when all heaters affected by the load control have restored the energy consumed by the hot water use.

Figure 2.1(b) shows households with a low level of hot water consumption. Their contribution to load reduction in the electricity system is small, and the disconnection has no effect on most of the heaters. For those that are affected, only one heater is disconnected in a certain time interval whereas five heaters will start operating simultaneously when reconnected, giving a payback effect from t_1 to t_2. The power demand added to the system load after a disconnection is five times the size of the reduced power demand during the disconnection. Furthermore, the size of the payback is the same as from the high hot water consumers in Figure 2.1(a). The system load curve will however quickly return to normal shape (after t_2), when all heaters affected by the load control have restored the energy consumed by the hot water usages.

Parts (a) and (b) of Figure 2.2 illustrate the discussion above with load curves during a day with and without disconnection of water heaters for the two customer groups.



(a) **(b)**

Figure 2.2. Load curves with and without disconnection for households with a high level of hot water consumption (a), and low level of hot water consumption (b)

These simplified examples indicate some effects experienced when water heaters are used in load control programmes. Consumption is shifted out of the disconnection period to a later period. The payback effect will then give rise to extra consumption in the system load that would not have taken place otherwise. The figure illustrates that the low hot water consumers contribute little to reducing the load during the disconnection, but still create a high, although brief, peak when reconnected. This suggests that households with the highest consumption of hot water may be the target group in a direct load control programme.

The above discussion illustrates some effects that may occur due to *differing amounts of hot water consumption among households* in a direct water heater load control programme. Further, the *capacity of the heating elements of the water heaters* will influence the effects. Given two consumer groups of equal size and with similar amounts of hot water consumption distributed equally over time, heaters with a low-rated heating element capacity will require a longer time to restore energy than those with high capacity, and the demand during restoration will be smaller. The group of heaters with a high heating element capacity will contribute the same demand reduction during the disconnection as those with the low-element capacity, but will yield a higher payback demand, although over a shorter period of time, before water temperature is restored.

The *inlet temperature of water to the tanks* also influences the impact on the load curve from control events. Low inlet temperature will contribute to longer heating periods and vice versa.

The *frequency of hot water use* may contribute to different impacts from load control, depending on the region where it is applied. A survey of Norwegians' showering habits revealed that the frequency of showers differed between regions. For example, the percentages of citizens showering daily differed from 31% in one region to 66% in another region (Pettersen, 2006).

The *timing of the households' hot water consumption* may also be important. Most people in Norway start their day from 5 to 8 am (Vaage, 2002). This suggests that a large share of the water heaters in Norway are operating around these morning hours (around 7 to 9 am). For the evening, the proportion of people that are home from work and have a meal is highest around 4 to 5 pm. The proportion of households performing household work is highest around 6 pm. Disconnections occurring around those two periods of the day (morning and afternoon) may then give the largest consumption reductions since this will probably affect a high proportion of the households' heaters.

The *design of the heater* may also be important. A tank will always contain a volume of water below the heating element that remains unheated, and this unheated volume will be larger if the heating element is installed horizontally than if it is tilted downwards inside the tank (the thermostat is placed above the element for both designs). When hot water is drawn, the unheated water will be pushed upwards and activate the thermostat. Therefore, because the unheated water is just below the thermostat in the horizontal design, use of even small volumes of hot water will activate the thermostat. In the downward-tilted design, the unheated water is further below and larger volumes of hot water use are allowed before the cold water reaches and activates the thermostat. Furthermore, some heaters are designed with a cold-water distributor, which decreases the velocity of the inlet water so that the water at the bottom is blended to a lesser degree. This allows larger volumes of hot water to be drawn without activating the heater.

The *length of a disconnection* will also influence the size of the initial payback demand from all households affected by the control event, since a longer disconnection period affects more heaters.

Therefore, load control carried out in different areas may give different load reductions and different payback effects if, for example, hot water consumption behaviour, types of water heaters, etc., differ between areas due to differing demographic characteristics of the households (see also Gustavson et al. (1993), for a discussion of some of these factors).

3 Experimental data

The project "End-user Flexibility by Efficient Use of Information and Communication Technology" (2001–2004) was a Norwegian large-scale project where automatic meter reading and direct load control technology were installed at electricity consumers' premises (chiefly residential). We used data from this project to study the effect on households' loads caused by direct load control of their water heaters.

3.1 Direct load control of water heaters

The automatic meter reading and direct load control technology enabled hourly metering of each household's electricity consumption throughout the test period and direct control of their water heaters. The automatic load disconnections were performed by a common signal from the network company to a relay in each household's fuse box. The relay disconnected the heaters from the electricity until a new signal was sent for reconnection. This was tested on 12 different test days in hour 10 (9–10 am). There were also two test weeks with disconnections at different hours in the morning and the afternoon in order to study the load control impact for different hours. For two days disconnections were tested in hour 8 (7–8 am) and hour 17 (4–5 pm), two days in hour 9 and hour 18, two days in hour 10 and hour 19, and two days in hour 11 and hour 20. If the households in the sample inquired, they were told they could find information on the timing of the tests on a web page, but no information was given directly. One can therefore assume that most did not know when the tests occurred, and therefore did not take any precautionary actions to compensate for the electricity being disconnected.

3.2 The data

We used a sample of households that had been exposed to automatic disconnection of their water heaters but had not faced time-differentiated tariffs. The households could voluntarily choose whether they wanted to participate. The sample consisted of 475 households where hourly electricity consumption for each customer had been metered in the period from 3 November 2003 to 30 April 2004 (which corresponds to 180 days or 4,320 hours). Totally, the panel data set (unbalanced) consists of approximately 1.4 million hourly observations.[3]

In addition to electricity prices and individual consumption data, we use information on numbers of hours of daylight each day, and temperature and wind on an hourly basis. Summary statistics of the data are shown in Table 1.

[3] Missing observations occurred due to technical problems with the metering system.

Table 1. Summary statistics of the data

Variable	Mean	Std. dev.	Min	Max
Energy [kWh/h]	2.8	1.6	0.1	17.3
Price [NOK]	0.6	0.1	0.4	0.6
Temp [°C]	0.5	5.6	–16.3	16.7
Wind [m/s]	1.5	0.8	0.3	6.6
Daylight [hours]	9.0	2.8	5.9	15.2

Note: NOK 1 ≈ EUR 0.12

The variation in the weather variables was high with temperatures from –16 to +16°C, and wind speed approaching 7 m/s (hourly average). This variation captures much of the temperature and wind conditions that are often experienced in these seasons in Norway. The number of hours of daylight each day varies from 5.9 (in December) to 15.2 (in April), with an average of nine hours.

4 Method and model

The aim of the analysis was to quantify the average load reducing potential from load control of the households' water heaters and the size of the payback effect due to simultaneous reconnection of the heaters.

We used a regression model capable of predicting the average residential consumption for every hour throughout the test period. The disconnection and payback effects were captured by dummy variables for the hours in question. The households' price response and the effect on consumption from variations in outside temperature and wind speed, number of hours of daylight, and the cyclical consumption patterns due to times of day, week and year are also accounted for in the regression.

4.1 Econometric specification

We assumed the following specification for the hourly residential consumption of electricity:

$$
\begin{aligned}
y_{it} = {} & \sum_{h\in H}\delta_{Dc,h}Dc_{h,t} + \sum_{h\in H\setminus\{10\}}\delta_{Rc,h+1}Rc_{h+1,t} + \sum_{j=1}^{5}\delta_{Rc,10+j}Rc_{10+j,t} + \beta_p p_{it} + \\
& \beta_T T_t + \beta_{T^2}T_t^2 + \beta_{TMA}TMA_t + \beta_{TMA^2}TMA_t^2 + \beta_W W_t + \beta_{WMA}WMA_t + \\
& \sum_{m\in M}\beta_{dl,m}D_{m,t}dl_t + \sum_{wdh=2}^{24}\beta_{wd,wdh}D_{wd,wdh,t} + \sum_{weh=2}^{24}\beta_{we,weh}D_{we,weh,t} + \\
& \sum_{d\in D}\beta_d D_{d,t} + \sum_{m\in M\setminus\{nov\}}\beta_m D_{m,t} + \beta_{Hd}D_{Hd,t} + \sum_{dlc\in C}\beta_{dlc}D_{dlc,t} + \gamma_i + \varepsilon_{it},
\end{aligned}
\tag{4.1}
$$

i = 1,…,475, t= 1,....,4296, C = {17nov–21nov,18dec,19dec,14jan–16jan,15mar–18mar,26apr–29apr}, D = {tue,wed,thu,fri,sat,sun}, H = {8–11,17–20}, M = {nov,dec,jan,feb,mar,apr},

where:

y_{it}	=	hourly electricity consumption [kWh/h] at time *t* for household *i*;
$Dc_{h,t}$	=	dummy variables for the hour of disconnection, i.e., 1 if *t* is disconnection hour *h*, 0 otherwise;
$Rc_{h+1,t}$	=	dummy variables for the hour following a disconnection, i.e., 1 if *t* is in reconnection hour *h + 1*, 0 otherwise;
$Rc_{10+j,t}$	=	dummy variables for the five hours following a disconnection in hour 10, i.e., 1 if *t* is in reconnection hour *10 + j*, *j = 1,…,5*, 0 otherwise;
p_{it}	=	electricity price [NOK] for household *i* at time *t* ;
T_t	=	temperature [ºC] at time *t*;
T_t^2	=	temperature, squared [ºC]^2 at time *t*;
TMA_t	=	moving average of temperature in the previous 24 hours [ºC] at time *t*;
TMA_t^2	=	moving average of temperature in the previous 24 hours, squared [ºC]^2 at time *t*;
W_t	=	wind [m/s] at time *t*;
WMA_t	=	moving average of wind last 24 hours [m/s] at time *t*;

dl_t	=	daylight variables; 1 between sunrise and sunset, 0 otherwise;
$D_{wd,wdh,t}$	=	dummy variables; 1 if t is in hour wdh of a weekday, 0 otherwise;
$D_{we,weh,t}$	=	dummy variables; 1 if t is in hour weh of a weekend or holiday, 0 otherwise;
$D_{d,t}$	=	dummy variables; 1 if t is in day d of the week, 0 otherwise;
$D_{m,t}$	=	dummy variables; 1 if t is in month m of the year, 0 otherwise;
$D_{Hd,t}$	=	dummy variables; 1 if t is in a holiday, 0 otherwise;
$D_{dlc,t}$	=	dummy variable is 1 if t is in a day dlc where direct load control is carried out, 0 otherwise;
γ_i	=	fixed time-invariant effect for household i; and
ε_{it}	=	a genuine error term, assumed to be independently distributed across i and t with a constant variance.[4]

To capture the drop in consumption caused by a disconnection we used dummy variables for the period in question. In addition, to capture the size of the expected payback effect in the hour of reconnection, we included a dummy variable for these hours. For the 12 days with disconnection in hour 10 we also included dummy variables for each of the five hours after the reconnection to study how long the payback effect lasts, and its size.[5] The parameters of interest are therefore the coefficients for the disconnection (δ_{Dc}) and reconnection (δ_{Rc}) variables. The estimates of the coefficients related to the dummy variables may be interpreted as deviations from the normal consumption and they indicate directly the difference in kWh/h from the alternative of no disconnection. To isolate these effects it is important to control any other factors that may interfere with the dummy variables. The most important factors influencing electricity consumption included in the model are described briefly below.

A fixed periodic/cyclical pattern, that often is assumed caused by the lifestyle of the households, can be modelled using dummy variables (Granger et al., 1979; Pardo et al.,

[4] The Huber/White/sandwich estimator was used to obtain robust estimates of the asymptotic variance–covariance matrix of the estimated parameters (StataCorp, 2005).

[5] The ability to estimate accurately the load control impact with the chosen model depends on the accuracy of the predictions of the load curve for the days of the load control events. We found that the model fits very well for the average of the 12 days with disconnections in hour 10, but has a somewhat poorer fit for the two test weeks with disconnections at other hours. Therefore, we only used the former days to study the length of the payback effect.

2002) or trigonometric terms (Al-Zayer and Al-Ibrahim, 1996; Granger et al., 1979), or by the use of splines (Hendricks et al., 1979; Harvey and Koopman, 1993). We modelled the cyclical patterns with dummy variables; one set with dummy variables for the 24 hours of the working days and one set for the 24 hours of the non-working days. In addition, we controlled for the possible different levels in use between the different days of the week with day dummy variables, and with the same argument for the months we introduce monthly dummy variables. To avoid multicollinearity, the weekend hour 01–, Monday–, and November dummy variables were excluded. Dummy variables were also included for each of the days where load control was applied to adjust the consumption curve level for those days to obtain a better fit.

A rich literature on the temperature's effect on electricity consumption suggests that the impact of a temperature change has non-linear, as well as delayed effects; see, for example, Henley and Peirson (1997, 1998), Granger et al. (1979), Harvey and Koopman (1993), Ramanathan et al. (1997) and Pardo et al. (2002). Following Granger et al. (1979) we allowed for the current temperature by one term and its possible non-linear influence by a squared term. To account for the delayed effect of a temperature change we introduced a 24-hour moving average term, and also the square of this variable. Although most of the above studies have focused on temperature as the key weather variable, wind may also be important as it can increase a building's heat loss (SINTEF, 1996). Both a current term and a 24-hour moving average term were included. Because the customers in the sample are located within the same area (Drammen), we assumed all dwellings to be exposed to the same weather conditions.

Daylight is also likely to influence the consumption of electricity, as it decreases the need for electric lights and electric heating (see, for example, Johnsen (2001)). To allow for varying impact of daylight over the seasons, one variable for each month is included. Each variable was given the value 1 in the hours between sunrise and sunset for the existing month, and 0 otherwise.[6]

Other seasonal changes, such as the change in humidity, rain or other seasonal factors, are picked up by the monthly dummy variables. In addition, because electricity

[6] In the sunrise or sunset hour, the value of a daylight variable is equal to the share of the hour that it is daylight, i.e., between 0 and 1.

prices are expected to influence behaviour when they vary, a price variable was included in the model.[7]

Differing time-invariant characteristics of the households may cause different consumption patterns. Such variables can be assumed constant during the six months the experiment lasted. We do not comment on their impact on consumption because our choice of model presented in the next section allows for such time-invariant variables.

4.2 Fixed effects estimation

It is likely that the consumption pattern of the households will differ due to differences in, for example, dwelling size, age and standard of the dwelling, heating systems, number of members in the families, income, education, attitude to environmental issues, etc. All such variables cannot possibly be obtained, and omission of some in the model may influence the estimates of the other parameters of interest. The cross section time series dimension of the data invites us to take the household-specific factors into consideration by the use of a fixed-effects model. To present this idea, consider the simple model

$$y_{\mathrm{it}} = X_{\mathrm{it}}\beta + \gamma_{\mathrm{i}} + \varepsilon_{\mathrm{it}} , \qquad (4.2)$$

where y_{it} represents consumption of electricity, X_{it} the vector of explanatory variables from (4.1), β is the vector of coefficients for the variables, and γ_i can be interpreted as fixed unobserved time-invariant household-specific effects.[8] If the covariance between X_{it} and γ_i is non-zero, an ordinary least-squares estimation, where household-specific effects are neglected, will give biased estimators of β (Hsiao, 2003). However, by subtracting from each observation its household-specific mean, we can eliminate the effect of the unobserved household-specific effects.

$$\left(y_{\mathrm{it}} - \bar{y}_{\mathrm{i\cdot}}\right) = \left(X_{\mathrm{it}} - \bar{X}_{\mathrm{i\cdot}}\right)\beta + \left(\varepsilon_{\mathrm{it}} - \bar{\varepsilon}_{\mathrm{i\cdot}}\right) , \qquad (4.3)$$

[7] Prices vary between households, due to differing types of contracts.
[8] In *X*, only price varies between households.

where $\bar{y}_{i\cdot}$, $\bar{X}_{i\cdot}$, and $\bar{\varepsilon}_{i\cdot}$ indicate the mean value of the variables for each household. The transformation removes the household-specific effects. β can then be estimated consistently without bias by ordinary least squares on the transformed variables. The use of ordinary least squares on (4.3) is therefore robust to correlation between X_{it} and γ_i, which is not the case when ordinary least squares is used on (4.2) and γ_i is omitted from the equation. The resulting estimator is called the fixed effects estimator, or the within estimator.[9]

5 Results

The results from the fixed effects regression using Stata are shown in Table 2 (StataCorp, 2005).

[9] Note that the regressions are performed with the software Stata, which uses an alternative but equivalent formulation by introducing an intercept (see StataCorp, 2005 and Gould, 2001). The intercept represents the average value of the fixed effects.

Table 2. Results from the fixed effects (within) regression

Variables	Estimate	t-value	p-value
Dc hour 8	–0.466	–14.62	0.000
Dc hour 9	–0.580	–18.69	0.000
Dc hour 10	–0.497	–33.91	0.000
Dc hour 11	–0.355	–10.70	0.000
Dc hour 17	–0.414	–11.57	0.000
Dc hour 18	–0.489	–14.00	0.000
Dc hour 19	–0.596	–17.85	0.000
Dc hour 20	–0.178	–4.47	0.000
Rc hour 8+1	0.284	7.23	0.000
Rc hour 9+1	0.158	4.12	0.000
Rc hour 10+1	0.239	13.60	0.000
Rc hour 10+2	0.097	5.48	0.000
Rc hour 10+3	0.045	2.61	0.009
Rc hour 10+4	0.019	1.12	0.262
Rc hour 10+5	0.002	0.10	0.918
Rc hour 11+1	0.147	3.78	0.000
Rc hour 17+1	0.240	5.80	0.000
Rc hour 18+1	0.196	4.83	0.000
Rc hour 19+1	0.134	3.14	0.002
Rc hour 20+1	–0.017	–0.41	0.679
Price	–0.246	–9.23	0.000
Temp	–0.024	–65.18	0.000
$Temp^2$	–0.001	–25.22	0.000
TempMA	–0.043	–101.74	0.000
$TempMA^2$	0.000	0.38	0.706
Wind	0.014	11.03	0.000
WindMA	0.069	31.59	0.000
Daylight: November	–0.072	–10.75	0.000
Daylight: December	–0.043	–6.83	0.000
Daylight: January	–0.084	–13.20	0.000
Daylight: February	–0.147	–25.72	0.000
Daylight: March	–0.128	–24.97	0.000
Daylight: April	–0.056	–10.57	0.000
Constant	2.529	123.13	0.000
R^2: within = 0.2251		F(109,1498051) = 3740.91	
between = 0.0047		Prob > F = 0.0000	
overall = 0.1124			

Note: the effects of the holiday, control day, cyclical hour, day and month dummy variables are reported in the Appendix. Dc = Disconnection, Rc = Reconnection

The results show that most of the explanatory variables are highly significant. The hypothesis that all the slope coefficients are jointly 0, which is tested using an F-statistic, is rejected (see the bottom of the table).

First we comment on the results for the load control in the two test weeks with control in different morning and afternoon hours, then we examine the impact of load control for the 12 days with disconnections in hour 10.

5.1 Results for load control in different hours in two test weeks

The estimates reported in Table 2 for the automatic load disconnection dummy variables all show the expected negative signs indicating consumption reductions, and all the reconnection dummies but the estimate for hour 20 are positive, indicating a payback effect in the first hour after a disconnection.[10] Figure 5.1 plots the estimates from Table 2 for the morning disconnections and the hour immediately after the disconnection when the water heaters are reconnected to the electricity supply. Figure 5.2 illustrates the same for the evening load control events.

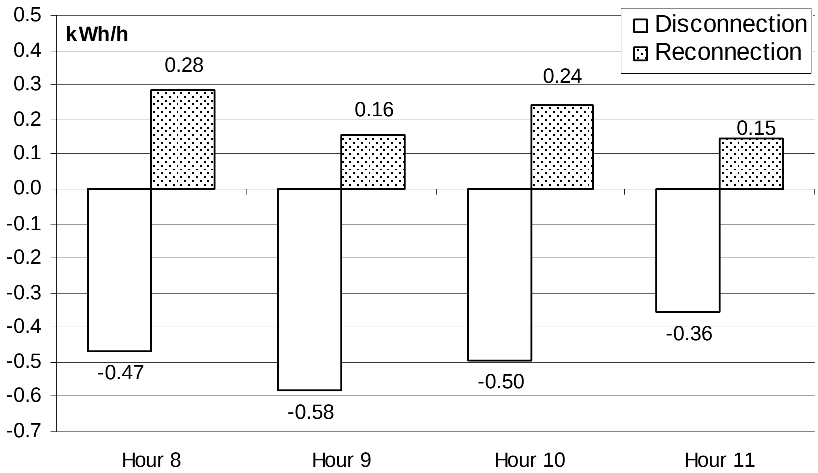


Figure 5.1. Predicted effects (kWh/h) of disconnections and reconnections in the morning hours

[10] The positive reconnection estimate of hour 20 is an anomaly and probably due to a small deviation between the predicted and the real load curve. However, the estimate is far from significant.

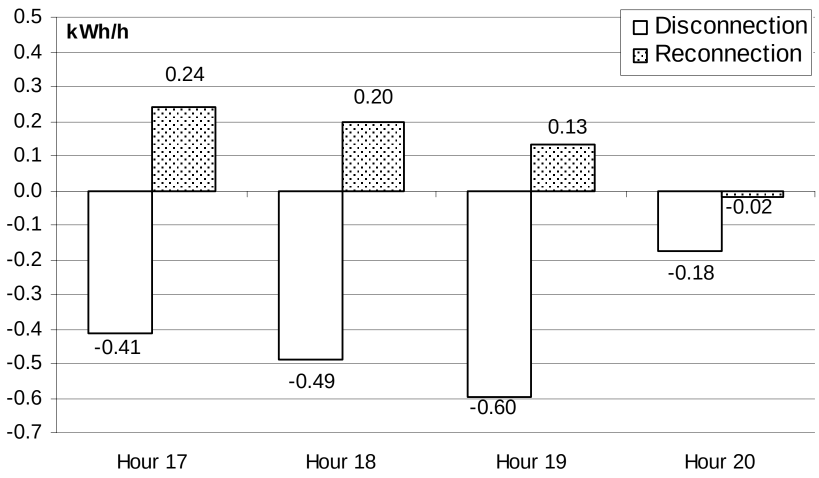


Figure 5.2. Predicted effects (kWh/h) of disconnections and reconnections in the evening hours

Our findings suggest that when a common signal for automatic disconnection of the water heaters is sent, one can anticipate an average load reduction of between 0.36 and 0.58 kWh/h per household for the morning hours, depending on the hour, and between 0.18 and 0.60 kWh/h in the afternoon, depending on which hour disconnections occur. Graabak and Feilberg (2004), analysing the impact of load control in one of the test weeks, found similar, but somewhat smaller effects.[11] Our results show that disconnection in hour 9 in the morning and in hour 19 in the evening give the largest load reductions.

Assuming an average load reduction per customer of 0.5 kWh/h, the total load reducing potential in Norway from this measure can be inferred. Given that half of the Norwegian households (approximately 1 million) have their water heaters disconnected, and assuming 20% losses in the grid in a peak load situation, the potential is 0.5 kWh/h * 1,000,000 * 1.2 = 600 MWh/h reduction of load for the whole Norwegian system (assumptions correspond to those used by Graabak and Feilberg, 2004). For comparison, the maximum measured load in Norway is 23,054 MWh/h in hour 10, 5 February 2001. This suggests that consumption could be lowered to 22,454 MWh/h this hour.

[11] The differences between their results and ours may be due to different analysis methods (they compared load curves with those of a reference group) and they studied only one of the two test weeks.

The positive coefficients for the hour following a reconnection of the water heaters indicate the size of the payback effect, i.e., the electricity use that will be added to the system load curve after load control has occurred. We see that disconnections lead to surplus consumption of between 0.15 and 0.28 kWh/h in the morning and between 0[12] and 0.24 kWh/h in the evening, when the heaters are reconnected.[13] Assuming the payback effect to be 0.24 kWh/h, the aggregated extra average demand for the Norwegian system can be inferred using a similar calculation to the above; 288 MWh/h for the first hour after the disconnection in hour 10. Imposing this value into the same day as above suggests that consumption could increase from 22,940 MWh/h (the load in hour 11 in the Norwegian system 5 February 2001) to approximately 23,230 MWh/h, that is, to a higher level than the previous peak.

To illustrate how the automatic load control may affect the daily load curve for the households in this study, Figure 5.3 shows the predicted mean hourly electricity use for one of the test days with disconnection in hour 8 and in hour 17. The payback effect is only indicated for the first hour following a disconnection.

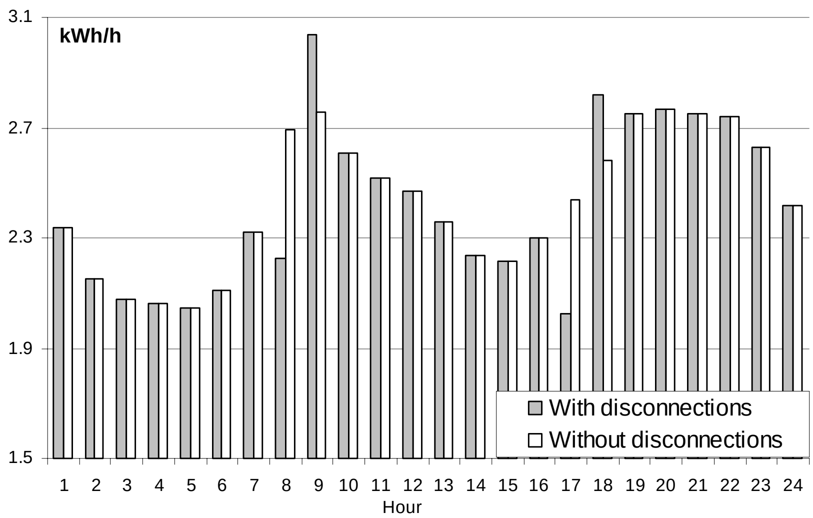


Figure 5.3. Predicted consumption for one day with disconnection in hour 8 and 17, with and without predicted disconnection and reconnection terms

[12] Assuming the negative estimate of –0.017 is not logical. It is likely to be at least 0.

[13] Graabak and Feilberg (2004) found payback effects of between 0.09 and 0.29 kWh/h for the morning hours, and between 0.06 and 0.37 kWh/h for the evening hours.

As shown in Figure 5.3, disconnections cause significant reductions in consumption. In addition, the post-peak in the hour after the water heaters have been reconnected is evident.

5.2 Results for load control in hour 10 in twelve test days

Section 2 indicates that the size of the post-peak is likely to be largest in the first minutes after reconnection and then diminish. However, since our data are measured with an hourly sampling frequency, we only know the average effects over hourly intervals and not the instantaneous power demand at the moment the heaters are reconnected, or the following evolvement of the payback effect. Nevertheless, we know the likely range for the instantaneous power demand. Since most heaters in Norway have heating elements with rated capacities of 2 kW, the maximum possible average payback demand at reconnection is likely not to be higher than 2 kW. In addition, using hour 10 as an example, we know from the estimated hourly average payback demand for the first hour after a disconnection, that the additional power demand is not likely to be less than 0.239 kW.

Nevertheless, our estimates for the five hours after the hour 10 disconnections allow us to indicate the payback size at the time of reconnection. From Table 2 we can see that the hourly payback is highest in the first hour and diminishes over the following hours. The estimates for the fourth and fifth hours are not significantly different from 0. We can then anticipate that it will take at least three hours before all energy is restored, on average, in all the water heaters affected by the disconnection. This supports our description in Section 2 regarding the distribution of the time the water heaters use to restore the energy in the tanks; some heaters use a short time to recover from an energy loss, whereas others require a longer time.

We indicate a possible real-time power demand curve after reconnection by plotting the estimates for four hours after reconnection and fitting a simple exponential trend line to the hourly estimates (the fifth hour is excluded as it is highly insignificant). The intersection with the y-axis for the trend line will indicate the size of the instantaneous water heater demand at the moment of reconnection. There is a high degree of uncertainty related to this curve and its intersection, so one must be cautious about transferring our results from the hour 10 disconnections to other hours of the day or to other customer areas. Nonetheless, it is useful as a starting point for discussion and as an illustration of how the real payback demand curve may look. In addition, bear in mind that we use averaged data for 12 days to indicate the instantaneous payback effect, which makes it likely that some of these 12 days experienced higher instantaneous peaks.

Figure 5.4 illustrates the hourly averaged estimates for the subsequent four hours after a disconnection and the fitted line suggests the real-time payback power demand.

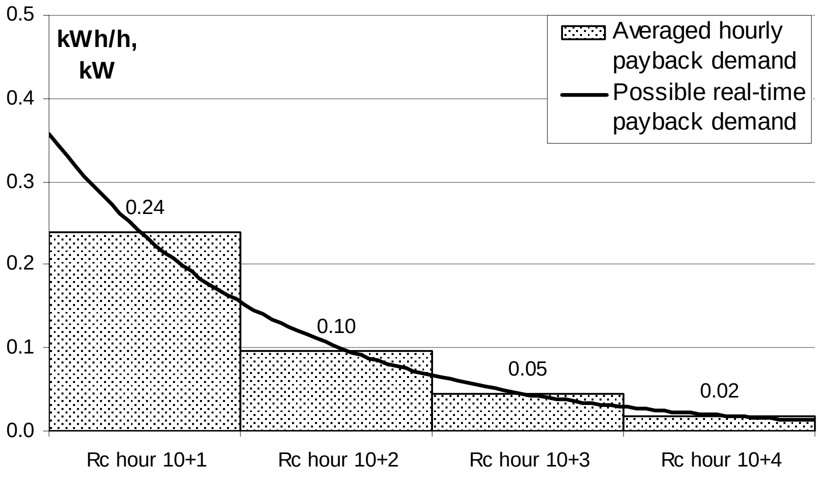


Figure 5.4. Estimated average payback consumption for four hours following a disconnection, and a fitted exponential trend curve, the potential real-time payback power demand

Using the four estimates to fit the exponential trend line, we find the power demand at the time of reconnection to be approximately 0.36 kW.[14] By visual inspection, the area (i.e., the energy use) under the trend line for each hour is quite similar to the area under the hourly estimates. This indicates that the trend line is sensible.

In the literature, the payback effect has been described using data from actual field tests and by simulation models. For example, Bische and Sella (1985) found that a load shedding of 25 MW of water heaters can build up to an initial payback demand of 80–90 MW. Another example is found in Lee and Wilkins (1983). Using their model, water

[14] Using only the three estimates that are significant at the 10% level, we find it to be 0.35 kW, and if all five estimates are used, the intersection is at 0.57 kW.

heater electricity consumption 15 minutes after a one-hour disconnection would be nearly twice the size that would have occurred if no load control had been applied, and three times the size after a two-hour disconnection.[15] The plots in Reed et al. (1989) indicate that the percentage of water heaters operating can be approximately 2.5 times higher immediately after a two-hour disconnection than if no disconnection is applied. In Ryan et al. (1989), the payback effect is approximately three to four times higher than the normal water heater load, after a four-hour disconnection.

Compared with the instantaneous power demand at the moment of reconnection found in this literature, our indication of the water heater power demand immediately after a reconnection seems to be quite low. The size of the payback demand found is approximately 0.7 times higher than water heater electricity consumption during normal operation, while the examples from the literature range from two to four times higher.[16] One reason may be that the rated power of the heating elements in water heaters used in experiments abroad is higher than in Norway. For example, heating elements with rated power of 4.5 kW are common in the USA (Orphelin and Adnot, 1999). Norwegian households, which usually have 2 kW heating elements, will then have comparably lower instantaneous power demand and longer recovering periods for the same amount of hot water use. Another reason is probably that some of the disconnections referred to have a longer disconnection period.

Whether payback effects due to load control of residential water heaters induce new so-called post-peaks in the electricity system higher than the targeted peak depends on the total load in the system. If the total load curve has a pattern such that the load is low enough in the same period as the post-peak appears, it may offset the payback effect. However, this may vary from day to day, depending on a number of variables, as, for example, temperature. A strategy to control the payback effect is to divide the heaters into groups and cycle the control events between the groups, i.e., disconnect and reconnect the groups at different times during the control period. The principle is that when some heaters are reconnected, others will be allowed to recover. By disconnecting one or more groups of heaters when the system load reaches a pre-defined level and

[15] Displaced energy during disconnection is assumed to be 0.5 kWh/h.

[16] The value 0.7 is found by dividing the power demand (0.36 kW) by the disconnected demand (0.5 kWh/h) for hour 10 (assuming the water heater power demand to be a constant 0.5 kW).

reconnecting on a first-off first-on basis when the load is sufficiently low again, load reductions can be achieved while a critical post-peak can be avoided (van Tonder and Lane, 1996; see also Bische and Sella (1985), Lee and Wilkins (1983), Rau and Graham (1979), Salehfar and Patton (1989), Weller (1988) and Gomes et al. (1999) for descriptions of cycling strategies).

5.3 Results for temperature, wind and daylight

From the other results shown in Table 2 we first see the importance of controlling for the current and moving average temperature, as the estimates are highly significant. There is a decreasing impact from a temperature change on electricity consumption for the current term when temperature falls. The moving average of temperature influences consumption only linearly because the squared term is insignificant. Second, the wind speed coefficients are highly significant, indicating that increased wind speed increases energy use, as expected. Third, the estimates attached to the hours of daylight variables are negative, which indicates that more daylight reduces electricity consumption, as expected. Fourth, the price coefficient indicates that a price increase of 0.01 NOK/kWh will decrease consumption by 0.003 kWh/h.

6 Conclusions

Estimates of the impact of load reduction indicate that direct load control of households' water heaters can be an effective tool in decreasing peak load consumption. Disconnection of the heaters from the electricity grid for the sample of households analyzed in this paper can be expected to give an average reduction in load per household of between 0.36 kWh/h and 0.58 kWh/h in the morning hours and between 0.18 kWh/h and 0.60 kWh/h in the evening hours. As described in this paper, the interruption of the natural diversity of the water heater electricity consumption during a disconnection gives rise to a payback effect, which leads to an additional consumption in a period after reconnection. For the first hour after a reconnection we found that the average extra consumption can reach up to 0.28 kWh/h per household. Note that the data are measured on an hourly sampling frequency, and that the instantaneous demand at the instant of reconnection is likely to be higher than the hourly estimates of the payback effect. By using the hourly payback demand estimates for the subsequent hours after disconnection in hour 10, we have indicated an average power demand per household at the instant of reconnection to be 0.36 kW more than it would be if no load control had been applied. This payback demand may have the adverse consequence of causing a new peak in the system, which suggests it may be necessary to re-establish the diversity of the loads in a controlled manner by cycling the control events.

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Appendix

Table A1. Results from the fixed effects regression

Coefficient	Variable	Explanation	Estimate	t-value	p-value
$\delta_{Dc,8}$	Dc_8	Dummy, disconnection, hour 8	–0.466	–14.62	0.000
$\delta_{Dc,9}$	Dc_9	Dummy, disconnection, hour 9	–0.580	–18.69	0.000
$\delta_{Dc,10}$	Dc_{10}	Dummy, disconnection, hour 10	–0.497	–33.91	0.000
$\delta_{Dc,11}$	Dc_{11}	Dummy, disconnection, hour 11	–0.355	–10.70	0.000
$\delta_{Dc,17}$	Dc_{17}	Dummy, disconnection, hour 17	–0.414	–11.57	0.000
$\delta_{Dc,18}$	Dc_{18}	Dummy, disconnection, hour 18	–0.489	–14.00	0.000
$\delta_{Dc,19}$	Dc_{19}	Dummy, disconnection, hour 19	–0.596	–17.85	0.000
$\delta_{Dc,20}$	Dc_{20}	Dummy, disconnection, hour 20	–0.178	–4.47	0.000
$\delta_{Rc,8+1}$	Rc_{8+1}	Dummy, reconnection, hour 8+1	0.284	7.23	0.000
$\delta_{Rc,9+1}$	Rc_{9+1}	Dummy, reconnection, hour 9+1	0.158	4.12	0.000
$\delta_{Rc,10+1}$	Rc_{10+1}	Dummy, reconnection, hour 10+1	0.239	13.60	0.000
$\delta_{Rc,10+2}$	Rc_{10+2}	Dummy, reconnection, hour 10+2	0.097	5.48	0.000
$\delta_{Rc,10+3}$	Rc_{10+3}	Dummy, reconnection, hour 10+3	0.045	2.61	0.009
$\delta_{Rc,10+4}$	Rc_{10+4}	Dummy, reconnection, hour 10+4	0.019	1.12	0.262
$\delta_{Rc,10+5}$	Rc_{10+5}	Dummy, reconnection, hour 10+5	0.002	0.10	0.918
$\delta_{Rc,11+1}$	Rc_{11+1}	Dummy, reconnection, hour 11+1	0.147	3.78	0.000
$\delta_{Rc,17+1}$	Rc_{17+1}	Dummy, reconnection, hour 17+1	0.240	5.80	0.000
$\delta_{Rc,18+1}$	Rc_{18+1}	Dummy, reconnection, hour 18+1	0.196	4.83	0.000
$\delta_{Rc,19+1}$	Rc_{19+1}	Dummy, reconnection, hour 19+1	0.134	3.14	0.002
$\delta_{Rc,20+1}$	Rc_{20+1}	Dummy, reconnection, hour 20+1	–0.017	–0.41	0.679
β_p	p	Price	–0.246	–9.23	0.000
β_T	T	Temperature	–0.024	–65.18	0.000
$\beta_T^{\ 2}$	T^2	Temperature, squared	–0.001	–25.22	0.000
β_{TMA}	TMA	Temperature, moving average	–0.043	–101.74	0.000
$\beta_{TMA}^{\ \ 2}$	TMA^2	Temperature, moving average, squared	0.000	0.38	0.706
β_W	W	Wind	0.014	11.03	0.000

β_{WMA}	WMA	Wind, moving average	0.069	31.59	0.000
$\beta_{dl,nov}$	$D_{nov}\ dl$	Daylight: November	–0.072	–10.75	0.000
$\beta_{dl,dec}$	$D_{dec}\ dl$	Daylight: December	–0.043	–6.83	0.000
$\beta_{dl,jan}$	$D_{jan}\ dl$	Daylight: January	–0.084	–13.20	0.000
$\beta_{dl,feb}$	$D_{feb}\ dl$	Daylight: February	–0.147	–25.72	0.000
$\beta_{dl,mar}$	$D_{mar}\ dl$	Daylight: March	–0.128	–24.97	0.000
$\beta_{dl,apr}$	$D_{apr}\ dl$	Daylight: April	–0.056	–10.57	0.000
$\beta_{wd,2}$	$D_{wd,2}$	Dummy, weekday, hour 2	–0.138	–23.67	0.000
$\beta_{wd,3}$	$D_{wd,3}$	Dummy, weekday, hour 3	–0.191	–33.32	0.000
$\beta_{wd,4}$	$D_{wd,4}$	Dummy, weekday, hour 4	–0.195	–34.29	0.000
$\beta_{wd,5}$	$D_{wd,5}$	Dummy, weekday, hour 5	–0.175	–30.63	0.000
$\beta_{wd,6}$	$D_{wd,6}$	Dummy, weekday, hour 6	–0.073	–12.49	0.000
$\beta_{wd,7}$	$D_{wd,7}$	Dummy, weekday, hour 7	0.163	26.21	0.000
$\beta_{wd,8}$	$D_{wd,8}$	Dummy, weekday, hour 8	0.477	70.06	0.000
$\beta_{wd,9}$	$D_{wd,9}$	Dummy, weekday, hour 9	0.538	75.55	0.000
$\beta_{wd,10}$	$D_{wd,10}$	Dummy, weekday, hour 10	0.505	64.08	0.000
$\beta_{wd,11}$	$D_{wd,11}$	Dummy, weekday, hour 11	0.429	54.08	0.000
$\beta_{wd,12}$	$D_{wd,12}$	Dummy, weekday, hour 12	0.374	47.27	0.000
$\beta_{wd,13}$	$D_{wd,13}$	Dummy, weekday, hour 13	0.308	39.31	0.000
$\beta_{wd,14}$	$D_{wd,14}$	Dummy, weekday, hour 14	0.286	36.57	0.000
$\beta_{wd,15}$	$D_{wd,15}$	Dummy, weekday, hour 15	0.343	43.36	0.000
$\beta_{wd,16}$	$D_{wd,16}$	Dummy, weekday, hour 16	0.458	61.53	0.000
$\beta_{wd,17}$	$D_{wd,17}$	Dummy, weekday, hour 17	0.617	86.13	0.000
$\beta_{wd,18}$	$D_{wd,18}$	Dummy, weekday, hour 18	0.699	98.69	0.000
$\beta_{wd,19}$	$D_{wd,19}$	Dummy, weekday, hour 19	0.708	101.48	0.000
$\beta_{wd,20}$	$D_{wd,20}$	Dummy, weekday, hour 20	0.707	102.31	0.000
$\beta_{wd,21}$	$D_{wd,21}$	Dummy, weekday, hour 21	0.685	102.03	0.000
$\beta_{wd,22}$	$D_{wd,22}$	Dummy, weekday, hour 22	0.627	95.62	0.000
$\beta_{wd,23}$	$D_{wd,23}$	Dummy, weekday, hour 23	0.473	74.43	0.000
$\beta_{wd,24}$	$D_{wd,24}$	Dummy, weekday, hour 24	0.240	38.62	0.000
$\beta_{we,2}$	$D_{we,2}$	Dummy, weekend, hour 2	–0.143	–17.10	0.000

$\beta_{we,3}$	$D_{we,3}$	Dummy, weekend, hour 3	–0.214	–26.01	0.000
$\beta_{we,4}$	$D_{we,4}$	Dummy, weekend, hour 4	–0.247	–30.42	0.000
$\beta_{we,5}$	$D_{we,5}$	Dummy, weekend, hour 5	–0.257	–31.86	0.000
$\beta_{we,6}$	$D_{we,6}$	Dummy, weekend, hour 6	–0.229	–28.31	0.000
$\beta_{we,7}$	$D_{we,7}$	Dummy, weekend, hour 7	–0.158	–19.14	0.000
$\beta_{we,8}$	$D_{we,8}$	Dummy, weekend, hour 8	–0.033	–3.84	0.000
$\beta_{we,9}$	$D_{we,9}$	Dummy, weekend, hour 9	0.185	20.11	0.000
$\beta_{we,10}$	$D_{we,10}$	Dummy, weekend, hour 10	0.451	44.60	0.000
$\beta_{we,11}$	$D_{we,11}$	Dummy, weekend, hour 11	0.620	58.78	0.000
$\beta_{we,12}$	$D_{we,12}$	Dummy, weekend, hour 12	0.663	62.28	0.000
$\beta_{we,13}$	$D_{we,13}$	Dummy, weekend, hour 13	0.641	60.34	0.000
$\beta_{we,14}$	$D_{we,14}$	Dummy, weekend, hour 14	0.600	56.42	0.000
$\beta_{we,15}$	$D_{we,15}$	Dummy, weekend, hour 15	0.605	57.00	0.000
$\beta_{we,16}$	$D_{we,16}$	Dummy, weekend, hour 16	0.628	61.63	0.000
$\beta_{we,17}$	$D_{we,17}$	Dummy, weekend, hour 17	0.660	65.81	0.000
$\beta_{we,18}$	$D_{we,18}$	Dummy, weekend, hour 18	0.686	68.50	0.000
$\beta_{we,19}$	$D_{we,19}$	Dummy, weekend, hour 19	0.700	70.16	0.000
$\beta_{we,20}$	$D_{we,20}$	Dummy, weekend, hour 20	0.675	68.73	0.000
$\beta_{we,21}$	$D_{we,21}$	Dummy, weekend, hour 21	0.599	63.55	0.000
$\beta_{we,22}$	$D_{we,22}$	Dummy, weekend, hour 22	0.500	54.53	0.000
$\beta_{we,23}$	$D_{we,23}$	Dummy, weekend, hour 23	0.362	40.58	0.000
$\beta_{we,24}$	$D_{we,24}$	Dummy, weekend, hour 24	0.175	19.56	0.000
β_{tue}	D_{tue}	Dummy, Tuesday	0.013	4.06	0.000
β_{wed}	D_{wed}	Dummy, Wednesday	0.023	7.47	0.000
β_{thu}	D_{thu}	Dummy, Thursday	–0.001	–0.28	0.782
β_{fri}	D_{fri}	Dummy, Friday	–0.007	–2.19	0.028
β_{sat}	D_{sat}	Dummy, Saturday	0.055	6.95	0.000
β_{sun}	D_{sun}	Dummy, Sunday	0.095	12.09	0.000
β_{dec}	D_{dec}	Dummy, December	0.085	22.65	0.000
β_{jan}	D_{jan}	Dummy, January	0.156	36.39	0.000
β_{feb}	D_{feb}	Dummy, February	0.036	8.43	0.000

β_{mar}	D_{mar}	Dummy, March	–0.046	–10.43	0.000
β_{apr}	D_{apr}	Dummy, April	–0.249	–48.23	0.000
β_{Hd}	D_{Hd}	Dummy, Holiday	0.096	11.94	0.000
β_{17nov}	D_{17nov}	Dummy, control day, 17 November	–0.064	–5.19	0.000
β_{18nov}	D_{18nov}	Dummy, control day, 18 November	–0.047	–3.83	0.000
β_{19nov}	D_{19nov}	Dummy, control day, 19 November	0.033	2.84	0.004
β_{20nov}	D_{20nov}	Dummy, control day, 20 November	0.004	0.35	0.729
β_{21nov}	D_{21nov}	Dummy, control day, 21 November	0.040	3.21	0.001
β_{18dec}	D_{18dec}	Dummy, control day, 18 December	0.010	1.05	0.295
β_{19dec}	D_{19dec}	Dummy, control day, 19 December	0.081	8.19	0.000
β_{14jan}	D_{14jan}	Dummy, control day, 14 January	–0.044	–4.28	0.000
β_{15jan}	D_{15jan}	Dummy, control day, 15 January	–0.115	–10.52	0.000
β_{16jan}	D_{16jan}	Dummy, control day, 16 January	–0.141	–11.05	0.000
β_{15mar}	D_{15mar}	Dummy, control day, 15 March	0.031	2.95	0.003
β_{16mar}	D_{16mar}	Dummy, control day, 16 March	0.026	2.48	0.013
β_{17mar}	D_{17mar}	Dummy, control day, 17 March	–0.041	–3.96	0.000
β_{18mar}	D_{18mar}	Dummy, control day, 18 March	–0.066	–6.22	0.000
β_{26apr}	D_{26apr}	Dummy, control day, 26 April	0.084	7.03	0.000
β_{27apr}	D_{27apr}	Dummy, control day, 27 April	0.151	12.89	0.000
β_{28apr}	D_{28apr}	Dummy, control day, 28 April	0.030	2.61	0.009
β_{29apr}	D_{29apr}	Dummy, control day, 29 April	–0.060	–5.24	0.000
		Constant	2.529	123.13	0.000

Article III: Households' self-selection of a dynamic electricity tariff*

Abstract

Offering electricity consumers time-differentiated tariffs may increase demand responsiveness, thereby reducing peak consumption. However, one concern is that time-differentiated tariffs may also attract consumers who benefit because of their consumption pattern, even without a corresponding demand response. A discrete choice model applied to data from a residential dynamic pricing experiment indicates that higher demand flexibility increases the propensity of a household to select dynamic tariffs, while consumption patterns do not influence the tariff choice. The offering of dynamic time-differentiated tariffs is then likely to increase the demand response among residential consumers.

* An earlier version of this paper can be found in the Proceedings of the 28th Annual IAEE International Conference, Taipei, 3-6 June. A later version is published in the Statistics Norway's Discussion Paper series (see www.ssb.no/publikasjoner/DP/pdf/dp446.pdf). This version has been selected for presentation at the EcoMod Conference on Energy and Environmental Modeling in Moscow, Russia on September 13 – 14, 2007. I am grateful to Bente Halvorsen, Kjetil Telle, Petter Vegard Hansen, Terje Skjerpen, Hanne Sæle, Runa Nesbakken, Annegrete Bruvoll for help and discussions

1 Introduction

Deregulation of the Norwegian electricity market in 1991 improved efficiency (Bye and Halvorsen, 1999), but the continued reliance on tariffs with prices fixed for long periods of time lessens demand response among end-users and may prevent the realisation of further efficiency gains. Increased demand response may decrease consumption during constrained peak periods and flatten load curves, deferring or avoiding the need for costly investment in production and transmission capacity. It may also reduce average power prices, stabilize volatile spot prices, improve system reliability, and decrease the likelihood of exercise of market power (Caves et al., 2000, Braithwait and Eakin, 2002, Schwartz, 2003, Kristensen et al., 2004).

A number of different approaches can be used to increase demand response. One is to offer residential electricity consumers time-differentiated tariffs. These tariffs charge electricity consumers high prices in peak-load periods and low prices in off-peak periods, i.e., they better reflect wholesale real-time price variations than flat rates. Examples of tariffs are the time-of-use (TOU) rate, where prices vary by hours-of-the-day blocks. Another is the more dynamic critical peak pricing (CPP) rate, where higher prices may be imposed if the system is severely constrained as in cold winter periods. In these instances, end-users have incentives to respond to short-term price variations by reducing peak consumption or by shifting peak consumption to off-peak periods.

An important question is the extent to which voluntary time-differentiated rates attract price responsive customers. One would expect responsive customers to choose rates according to their ability to shift or reduce consumption, and thereby reduce electricity expenditure (Caves et al., 2000). Experiments with optional TOU rates have indicated that customers choosing this rate are more price responsive than the rest of the population as a whole (Aigner and Ghali, 1989, Train and Mehrez, 1994, Caves et al., 1989).

However, one concern with voluntary time-differentiated rate programs is that customers who benefit without any demand response also may choose to participate. Typically, these are customers with low electricity consumption in peak-price periods and high electricity consumption during off-peak periods. If most participating customers have such favourable consumption patterns and little price response, differentiated rates may not be an efficient tool to increase demand response. Furthermore, revenues for the utility offering the rate may decrease because the participating customers pay less for electricity than before, while the cost of providing electricity remains the same. In turn, revenue losses are imposed on the utility or its shareholders, or shifted to the remaining customers through an increase in the general rate (Train and Mehrez, 1994). Such an outcome may well be justified as consumers selecting the differentiated rates are released from subsidizing other customers' expensive peak consumption (PLMA, 2002). However, if an increase in the standard rate is the result, it may be politically difficult to implement because of opposition from customers harmed through the rate increase (Williamson, 2002).[1]

Aigner and Ghali (1989) found evidence of participation based on favourable consumption patterns in their analyses of five TOU experiments. High peak-period consumption in the pre-experiment period resulted in a lower participation rate and higher off-peak consumption resulted in the opposite. Train et al. (1987) found similar results. Their results indicated that the probability of choosing TOU rates decreased if the electricity costs under these rates increased compared with the costs on a standard rate. Patric (1990), Train and Mehrez (1994) and Matsukawa (2001) also found that consumers volunteering for TOU rates possessed more favourable load shapes than consumers on standard rates.

However, the literature is inconclusive regarding customer participation as based on favourable load patterns. Caves et al. (1989), for example, found that consumption patterns do not influence the customers' choice of a TOU rate. Analysing data from a voluntary TOU experiment, and comparing their findings with earlier mandatory TOU programs, they found that volunteers do not take greater advantage of participation without shifting usage than the rest of the population. In a Canadian TOU program, Mountain and Lawson (1995) calculated monetary savings and losses for customers choosing TOU rates and standard rates, assuming no change in consumption patterns. They found no difference with respect to the distribution of savings. Baladi et al. (1998)

[1] MacKie-Mason (1990) and Train (1991) have shown that optional TOU rates can be designed that require those choosing the rate to adjust consumption in order to benefit, while others will not be negatively influenced by introduction of the new rate. However, designing such rates requires knowledge of all customers' consumption patterns, which utilities may not always have.

compared consumption patterns of volunteers and non-volunteers from a pre-test period in a TOU experiment, and concluded that on-peak consumption shares were indistinguishable.

The lack of consensus concerning participation and consumption patterns calls for further study in new tariff programs. Further, to the author's knowledge, the extent of participation in time-differentiated programs based on load patterns and/or price responsiveness has only been investigated in the context of TOU programs. Compared with traditional TOU pricing, dynamic pricing schemes may entail more uncertainty for end-users with respect to the frequency and the timing of high peak prices. Consequently, it is more difficult for electricity consumers to assess whether they will benefit from the dynamic rate without load shifting. It may be hypothesized that this uncertainty will reduce the extent of customer participation based on consumption patterns, and increase instead the extent of participation based on the customers' ability and willingness to respond to the price signals. Since dynamic pricing (e.g. critical peak pricing) of electricity has recently been the subject of much interest (see, for instance, Faruqui and George (2002, 2005), Herter (2007)), there is a need for further examination of dynamic rate programs.

This paper investigates these questions using data from a Norwegian residential dynamic pricing experiment. A qualitative response model is used to test whether the customers' choice between the dynamic rate and the standard rate was influenced by their consumption patterns. The model is also used to test whether the group that chooses the dynamic rate differs from the group that retains a standard rate with respect to the ownership of appliances suited for load reduction or shifting. In addition, socio-economic characteristics of the households are included in the econometric model in order to reveal other important factors that may help explain customers' choices.

2 The dynamic pricing experiment

In a Norwegian experiment in 2003, households with annual electricity consumption above 8,000 kWh had new technology installed that enabled hourly automatic metering of consumption. These households were offered a critical peak pricing (CPP) network rate, and could choose between this and the standard rate already in place.[2]

The CPP network rate had a two-level structure. It was dynamic in the sense that *peak periods* were defined as the hours 8–11 and the hours 17–20 on working days, *only when temperatures fell below –8°C* (during winter). The peak price was approximately 1.15 NOK/kWh.[3] *Off-peak periods* were defined as all other hours of the year. The off-peak price was approximately 0.15 NOK/kWh. Summer was defined as the months May to October, and winter as November to April. The standard network price was approximately 0.20 NOK/kWh; that is, somewhat higher than the off-peak CPP price and substantially lower than the peak CPP price.

The CPP tariff was designed to be revenue neutral for the network company. The peak and off-peak prices were chosen so that if the *average* customer, as defined by the average consumption pattern, did not change his or her consumption pattern under the CPP rate, electricity revenues would be unchanged, as compared to revenues from the average customer on a standard rate. Based on statistical data, peak periods were assumed to occur in eighteen days during the winter. Few electricity consumers actually have an average consumption pattern. This means that if all customers chose the CPP rate, while not changing load patterns, many customers would gain while the rest would lose. Williamson (2002), analyzing a TOU rate program found that about half would pay less while the other half would pay more than on the fixed rate.

3 Who will choose the dynamic rate?

This section discusses the factors that may have influenced customers' choice between the CPP and the standard rate, i.e., the customers' load patterns and their ability to adjust consumption to the prices.

[2] The total electricity price facing the consumer consists of the network price plus the power price (plus taxes and VAT).

[3] NOK 1 ~ EUR 0.12 / USD 0.16

3.1 Consumers' utility functions

Consider two utility maximizing households, A and B, with utility functions U^A and U^B, shown in Figure 3.1. Their budgets for electicity under the standard tariff are assumed equal, and are illustrated by the budget line m^{std}. The figure shows their different consumption bundles of peak and off-peak electricity.

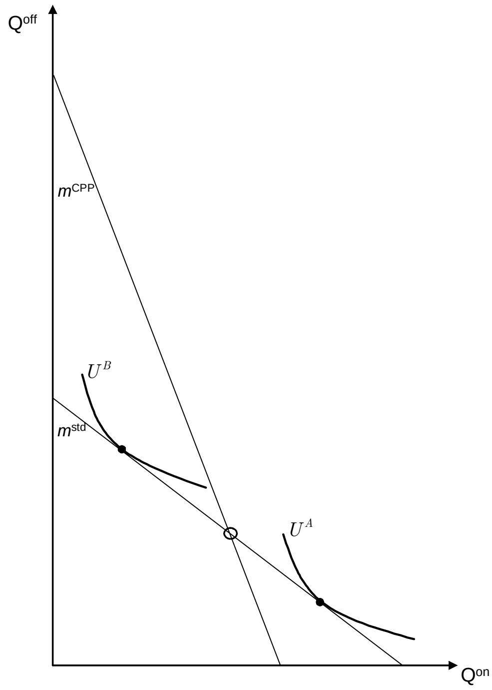


Figure 3.1. Two consumers' indifference curves and their option between the standard and the CPP tariff

Let us assume that the consumers are offered the new CPP tariff. Since the tariff is constructed to be revenue neutral for the average consumer (given that consumption is not changed under the new tariff), the budget line, m^{CPP}, will pivot around the peak/off-peak consumption bundle of this consumer, illustrated in the figure by the circle. This means that any consumption bundle along m^{std} under the standard tariff costs the same as any consumption bundle along m^{CPP} under the CPP tariff. The question is: which consumers will have incentives to select the new tariff? The answer to this question depends on the consumer's consumption pattern, i.e. the ratio of the peak to off-peak consumption, and on the ability of the consumer to respond to prices.

From Figure 3.1 we see that consumer B has a peak/off-peak consumption ratio which is lower than for the average consumer. It is clear that consumer B will benefit by simply choosing the new rate, even without adjusting consumption. By selecting the CPP tariff, consumer B can, for instance, continue consuming the same amount of peak and off-peak electricity as under the standard tariff and spend the profit on other goods (not shown in this figure), or the consumer may increase peak and/or off-peak electricity consumption until the new budget constraint is reached at a higher utility level than before. Consumer A, however, has a peak/off-peak consumption ratio which is higher than for the average consumer. Whether the consumer may benefit from switching tariff depends on the utility function, i.e. how price responsive the consumer's consumption is. Let us examine consumer A and B in more detail. First, in Figure 3.2, we look at consumer A.

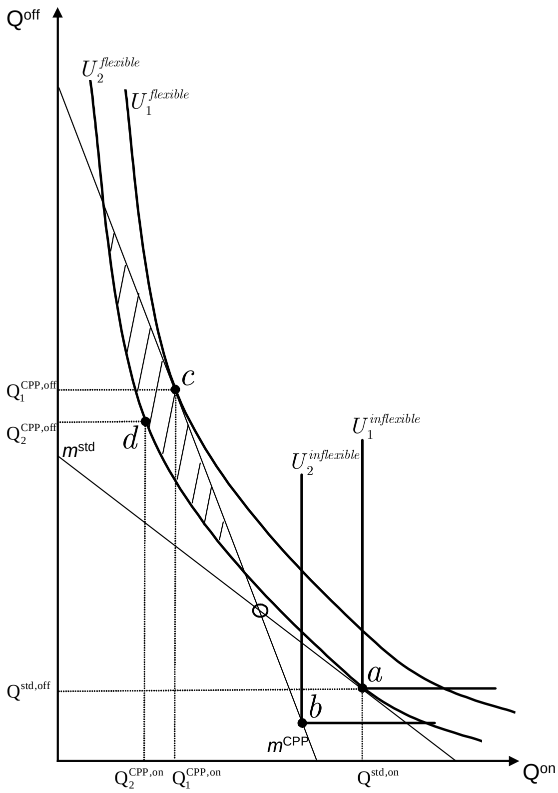


Figure 3.2. The choice of tariffs for consumer A, with two possible sets of indifference curves indicating flexible and inflexible consumption

As we can see at point *a* in the figure, consumer A consumes $Q^{std,off}$ in the the off-peak period and $Q^{std,on}$ in the peak period under the standard tariff. If the consumer does not have the ability to adjust consumption, this consumption pattern does not induce the consumer to be better off by simply choosing the CPP tariff. Whether the consumer is flexible in consumption is revealed by his or hers indifference curve. The figure illustrates two alternative sets of indifference curves that consumer A may have; one set where peak and off-peak consumption are perfect complements ($U^{inflexible}$), i.e., the consumer has no possibility to shift load from peak to off-peak periods, and another set where peak and off-peak consumption are substitutes ($U^{flexible}$), i.e. the consumer is price responsive.

We can see that with the price inresponsive indifference curves, $U_1^{inflexible}$ and $U_2^{inflexible}$, consumer A can not benefit from choosing the CPP rate, because the new utility maximizing consumption bundle would be at a lower utility level (point *b*), while expenditures remain unchanged.

However, with the price responsive indifference curves $U_1^{flexible}$ and $U_2^{flexible}$, the consumer can adjust consumption by shifting peak consumption to off-peak periods, and increase or decrease peak and off-peak consumption. For instance, by selecting the CPP tariff, the consumer may choose to remain at the same expenditure level in order to achieve a higher utility level, by consuming $Q_1^{CPP,off}$ and $Q_1^{CPP,on}$ (point *c*), or the consumer may choose to remain at the same utility level in order to achieve lower electricity expenditures, by consuming $Q_2^{CPP,off}$ and $Q_2^{CPP,on}$ (point *d*), and instead spend the profit on other goods. The shaded area indicates the possible peak and off-peak consumption bundles where the consumer will benefit on sticking to the CPP rate instead of switching to the standard rate. Which consumption bundle the consumer actually chooses, also depend on the trade-off between electricity and all other goods. Note that the consumption at point *d* represents the compensated (Hicksian) demand and that the difference between the consumption expenditures in point *c* and *d* equals the compensating variation (see e.g. Varian, 1992).

Now, let us look at consumer B, who is analogously illustrated with two sets of indifference curves, in Figure 3.3.

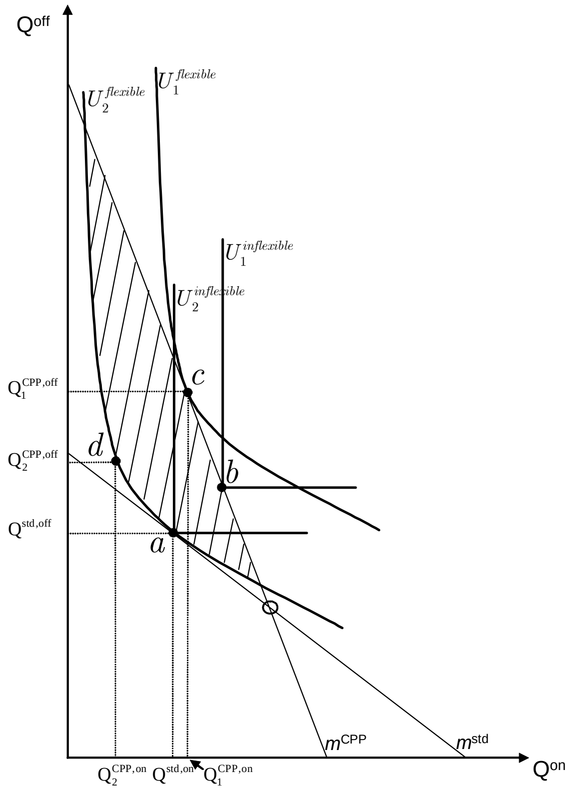


Figure 3.3. The choice of tariffs for consumer B, with two possible sets of indifference curves indicating flexible and inflexible consumption

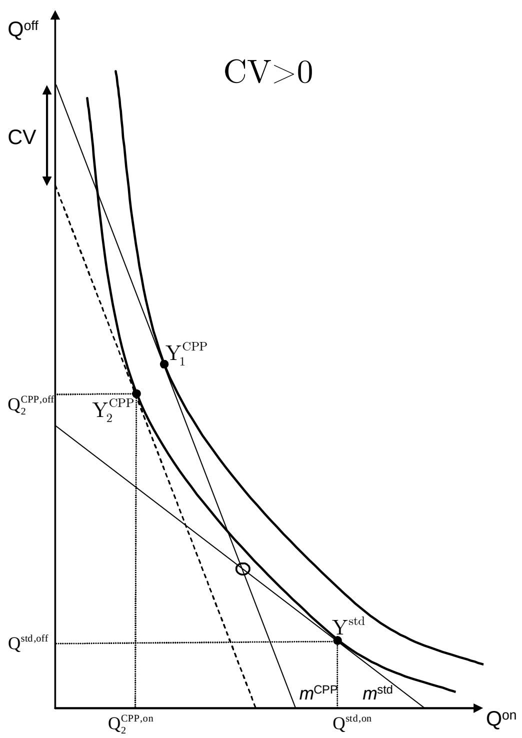
Consumer B consumes $Q^{std,off}$ and $Q^{std,on}$ under the standard tariff in the off-peak and peak periods, respectively (point *a*). We see that by simply choosing the CPP tariff, the consumer will benefit independent of the shape of the indifference curves, i.e., the consumer will benefit even with completely inflexible consumption.

Notice that this consumer may actually increase peak consumption (as well as off-peak consumption) compared with the case under the standard tariff due to the decrease in electricity expenditures (income effect). For instance, the consumer may increase peak and off-peak consumption so that the expenditures under the CPP tariff are unchanged from what they were under the standard tariff (point *b* or *c*, dependent on the utility function). If most of the consumers selecting the CPP tariff behave like this, the network company may experience an increase, instead of a decrease, in peak consumption, while the revenue from the consumers remains unchanged. However, the final consumption bundle for the consumer when maximizing utility, given the new prices, also depends on the trade-off between electricity and all other goods, and will be somewhere within the shaded area.

3.2 Compensating variation

The discussion above suggests it is important to understand which kind of consumer that will choose the CPP tariff since this has implications for the result from a time-differentiated pricing program. Let V^{CPP} and V^{std} indicate the indirect utility for a household choosing either the CPP rate or the standard rate, respectively, and $\Delta V = V^{CPP} - V^{std}$ the difference in indirect utility between the two tariffs. The consumers' decision criteria are that they will choose the CPP rate if the indirect utility exceeds indirect utility under the standard rate, i.e. they select the CPP rate if $\Delta V>0$. As a measure of the change in indirect utility, we use the compensating variation which measures how much money the consumer would need when facing CPP peak/off-peak prices to be as well off as the consumer was at the standard price tariff (see Varian, 1992). The compensating variation measures the income that the consumer needs to be compensated for the change of tariff. By using this measure, we can find the sign of the difference between indirect utility on the CPP and the standard rate. If the compensating variation is positive, the consumer is better off choosing the CPP rate. If it is negative, the consumer will choose the standard rate.[4] This is illustrated in Figure 3.4, for consumer A with positive and negative compensating variation (CV) in the left and right picture, respectively. The sign of the CV thus depends on the sign of the indirect utility change in the choice between the different tariffs. For consumer B, the compensating variation will always be positive, and the consumer will always be better off choosing the CPP.

[4] Other costs related to the selection of the CPP rate, such as differences in the fixed costs of the two rates, or transaction costs related to the inconvenience of switching to the new rate, may also influence the choice. However, the rates had equal fixed costs, and for simplicity, we disregard transaction and other costs.



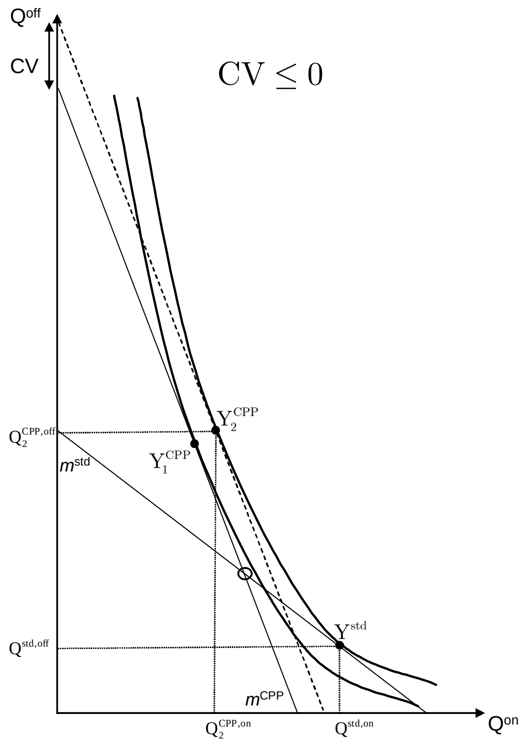


Figure 3.4. Compensating variation for consumer A with two different shapes of indifference curves. The left diagram illustrates the consumer with flexible consumption and a positive compensating variation (CV). The right diagram illustrates the consumer with a less flexible consumption and negative CV

In the figure, Y^{std} denotes the expenditures under the standard rate, Y_1^{CPP} denotes the expenditures if the consumer maximizes utility under the CPP rate assuming expenditures on electricity to remain unchanged, and Y_2^{CPP} denotes the expenditures at the new CPP rate assuming the utility to be at the same level as on the standard tariff. The difference between Y_1^{CPP} and Y_2^{CPP} equals the compensating variation by definition.

In the following we assume that Y_1^{CPP} equals Y^{std}, because electricity expenditures under each tariff alternative are equal along the two budget lines of the two rates, and, for simplicity, we drop the subscripts and write $Q^{CPP,on}$ instead of $Q_2^{CPP,on}$ and $Q^{CPP,off}$ instead of $Q_2^{CPP,off}$.

The consumer will select the CPP rate if he gain utility from changing, that is if CV>0, i.e. ΔV >0. Thus, the CPP rate is selected if:

$$\begin{aligned} CV &= Y_1^{CPP} - Y_2^{CPP} = Y^{std} - Y_2^{CPP} \\ &= p^{std}\left(Q^{std,off} + Q^{std,on}\right) - \left(p^{CPP,off}Q^{CPP,off} + p^{CPP,on}Q^{CPP,on}\right) > 0, \end{aligned} \tag{3.1}$$

where p^{std} is the standard rate electricity price, $p^{CPP,off}$ is the CPP off-peak price and $p^{CPP,on}$ is the CPP peak price. $Q^{std,off}$ and $Q^{std,on}$ denote annual consumption under the standard rate in the off-peak and peak periods, respectively, $Q^{CPP,off}$ and $Q^{CPP,on}$ denote annual consumption under the CPP rate in the off-peak and peak periods, respectively.

The consumer's choice between the tariffs is based on the consumption pattern they normally have under the standard rate, and on the ability to adjust consumption to the CPP tariff structure. Thus, when considering the CPP option, the consumers anticipate their consumption pattern under this rate to be similar to what it is under the standard rate, with the exception that consumption may be adjusted to the price variations. Consumption under the CPP rate will then be given as:

$$Q^{CPP,off} = Q^{std,off} + \Delta Q^{CPP,off} \quad \text{and} \quad Q^{CPP,on} = Q^{std,on} + \Delta Q^{CPP,on}, \tag{3.2}$$

i.e., consumption under the CPP rate equals consumption under the standard rate, plus adjustments in consumption to the CPP prices ($\Delta Q^{CPP,off}$ and $\Delta Q^{CPP,on}$), in off-peak and peak periods, respectively. Inserting (3.2) in (3.1) and rearranging suggests that the CPP rate will be selected if:

$$CV = \left(p^{std} - p^{CPP,off}\right)Q^{std,off} - \left(p^{CPP,on} - p^{std}\right)Q^{std,on} - \left(p^{CPP,off}\Delta Q^{CPP,off} + p^{CPP,on}\Delta Q^{CPP,on}\right) > 0. \tag{3.3}$$

The different terms in expression (3.3) imply that whether the consumer selects the CPP rate depends on the expenditure savings if off-peak consumption is charged by the CPP off-peak price instead of the standard price ($\left(p^{std} - p^{CPP,off}\right)Q^{std,off}$), the extra expenditure if peak consumption is charged by the CPP peak price instead of the standard price ($\left(p^{CPP,on} - p^{std}\right)Q^{std,on}$), and on the household's ability to shift, increase and reduce consumption in order to benefit ($p^{CPP,off}\Delta Q^{CPP,off} + p^{CPP,on}\Delta Q^{CPP,on}$). The last two terms are collected into a single 'adjustment' term:

$$adj^{CPP} = p^{CPP,off}\Delta Q^{CPP,off} + p^{CPP,on}\Delta Q^{CPP,on}. \tag{3.4}$$

Inserting (3.4) in (3.3) and rearranging, we find that the consumer will choose the CPP tariff if:

$$\frac{\left(p^{std} - p^{CPP,off}\right)}{\left(p^{CPP,on} - p^{std}\right)} > \frac{Q^{std,on}}{Q^{std,off}} + \frac{adj^{CPP}}{\left(p^{CPP,on} - p^{std}\right)Q^{std,off}}. \tag{3.5}$$

The inequality (3.5) conveniently expresses the fact that the consumer's choice depends on the ratio of the differences between the standard price and the off-peak CPP price to the difference between the peak price and the standard price (first term), the ratio of consumption in peak hours to the consumption in off-peak hours (second term), and the customer's ability to adjust consumpion (third term). This means that the consumer will consider all prices (i.e. the price ratio), and then select the CPP rate if: i) the consumption ratio is small enough; and/or ii) if the benefits related to consumption adjustment are sufficiently high.

We now discuss the *consumption ratio* term and the *consumption adjustment* term on the right hand side of the inequality (3.5) in further detail to evaluate which customers may benefit from choosing the CPP rate, and which may not. We will also discuss whether it is likely that the customers' knowledge and *information level* is adequate to make the calculations necessary for accurate comparisons between the rate alternatives.

3.3 The consumption ratio

As discussed, peak consumption consists of the sum of consumption in the hours 8–11 and 17–20 on working days in the winter when the temperature is below –8 °C. Off-peak consumption then consists of total electricity consumption in other winter hours and in all summer hours.

A household will benefit from the CPP rate, given an unchanged consumption pattern, if its consumption ratio is lower than the price ratio. As the price ratio is calculated using the consumption pattern of an average customer, we may also put this differently; a household will benefit if its consumption ratio is lower than the consumption ratio of the average customer. It is clear that low on-peak consumption or high off-peak consumption contributes ceteris paribus to a consumption ratio that may be smaller than that of the average consumer.

It is likely that certain household electricity consumption behaviour affects normal load patterns. For instance, households who normally lower their electricity consumption during night hours may not benefit, unless they change their consumption pattern. This is because the off-peak consumption in night hours in the winter will be smaller, thereby giving a higher ratio. If these households are unwilling to change their way of using electricity for heating, the probability they will not choose the CPP rate increases. Likewise, lower electricity use during off-peak weekends in winter will contribute to a higher ratio. Households who normally use little electricity during daytime are likely to have ratios in their favour, and thus benefit from choosing the CPP rate, even without changing their pattern of consumption.

3.4 Consumption adjustments

Consider a customer with an equal or larger peak/off-peak consumption ratio than the average customer. The only way this customer can benefit from the CPP rate is by shifting peak consumption to the off-peak period, and/or reducing and/or increasing consumption in the off-peak and peak period.[5] Of course, customers with smaller

[5] We disregard other possible benefits such as automatic meter reading, which is both convenient and time-saving.

consumption ratios than price ratios may benefit further from consumption adjustments if they choose the CPP rate. However, whether consumption is flexible enough and suited for adjustment to the price will vary across households as illustrated by the two kinds of indifference curves for consumer A in Figure 3.2 and 3.4. Accordingly, it is likely that certain household characteristics will increase their propensity to select the new rate offered, and vice versa.

For instance, consumers with energy management systems can program their electric heaters in order to shift peak consumption to off-peak hours. These households can more easily take advantage of the CPP rate and save money on their electricity bill than other households. One can then expect ownership of energy management systems to increase the propensity of households to choose the CPP rate.

Another way of taking advantage of the price structure is to reduce peak electricity consumption through heating the dwelling with a wood-burning stove instead of electricity. Some households do not normally use oil/paraffin/gas furnaces, even if already owned, and may decide to do so once they select the CPP rate. Ownership of alternative heating equipment may therefore increase a household's interest in the alternative rate.

Furthermore, households who only use electricity for space heating may find it easier to adjust consumption than those without electricity for heating at all, as a higher consumption level may increase flexibility (for instance, Mountain and Lawson (1995) found price responses to be larger for households with electric heating, air conditioning and electric water heating, compared with households without these appliances). Such households may have a higher probability of choosing the CPP rate.

The timing of use of electric appliances, such as washing machines, dishwashers, vacuum cleaners, televisions, personal computers, electric cookers, outdoor electric ground heating, engine heaters, etc., may easily be shifted from peak to off-peak hours. Consequently, we may expect households with a large stock of electric appliances to be more interested in the CPP rate than those with fewer appliances. This is supported by studies elsewhere that have found households with relatively more appliances to have higher price responses (see, for instance, Caves et al. 1984, Baladi et al., 1998).

The income of the household can also influence the willingness to participate in the CPP rate program. Households in the highest income groups may care less about their electricity bill if it constitutes only a small part of total expenditure. Hence, we may expect customers in the lowest income groups to have the highest propensity to choose the CPP tariff since they are likely to be most price responsive (see for instance Reiss and White (2005)).

3.5 Information level

All things considered, the decision on selecting the CPP rate is a difficult task for consumers. The uncertainty with respect to how many peak hours will be charged the peak price during the winter season introduces a problem for the household when trying to calculate which rate will yield most benefits. Moreover, customers do not usually have any information on how much electricity they normally use each day, week or year. This makes it difficult in practice to undertake the necessary calculations. Besides, it is unlikely that every household will actually undertake these calculations. On the other hand, customers may rely on a rule of thumb to assess whether they wish to use the CPP rate. If they know their consumption is small during the hours of the day when the peak price may be activated, they may believe that they will benefit from choosing the rate. However, such consumers may be a minority in the population, as electricity consumption may not be of major concern to most households. It may be more likely that most customers will base their decision on information and knowledge they actually have, i.e. their ability and willingness to adjust consumption according to varying prices.

4 Econometric specification

The households' decision to select the CPP rate or the standard rate is formulated with a discrete choice participation model. This statistical model is used to test whether there are statistically significant differences between two groups that have chosen differently between the rates, with respect to their characteristics.

Let the indirect utility V for a customer under each of the rates depend on the consumption pattern of the customer (i.e. consumption in the off-peak and peak periods), electricity prices, income, and other household characteristics. Then $\Delta V = V^{CPP} - V^{std}$ indicates the difference in a household's indirect utility between choosing the CPP rate and the standard rate. A household will choose the CPP rate if $\Delta V>0$, i.e. if the indirect utility on the CPP rate is higher than on the standard rate. The utilities are unobservable, but in a linear random utility framework we observe the choice between the two rate alternatives, and this choice is assumed to reveal the one with the greatest utility (see e.g. Greene, 2003). Let

$$CPP = \begin{cases} 1 & \text{if } \Delta V > 0 \\ 0 & \text{otherwise} \end{cases}, \qquad (4.1)$$

and $V^{CPP}= X\beta^{CPP}-\varepsilon^{CPP}$, $V^{std}= X\beta^{std}-\varepsilon^{std}$, so that $\Delta V=X(\beta^{CPP} - \beta^{std}) - (\varepsilon^{CPP}-\varepsilon^{std}) = X\beta-\varepsilon$, where X is the deterministic component, ε is the stochastic component which, for instance, may represent unobserved preferences for comfort (indoor temperature, lighting, amount of hot water spent on showering or bathing, etc.), environmental concerns (if they regard peak consumption reductions as an environmental measure), transaction costs of a shift of tariff (such as time and effort spent on understanding the new rate alternative). β are unknown coefficients to be estimated. As described in Section 3, the systematic part of ΔV depends on the difference in expenditures between the two rates, $CV = Y^{std} - Y^{CPP}$. Then customer *i*'s probability of choosing the CPP rate is given by:

$$P\left(CPP_i = 1\right) = P\left(\Delta V_i > 0\right) = P\left(\varepsilon_i < X_i\beta\right) = P\left(\varepsilon_i < \alpha + \beta_1 Q_i^{std,off} + \beta_2 Q_i^{std,on} + Z_i^{CPP}\gamma\right), \qquad (4.2)$$

where $\beta_1 Q_i^{std,off}$ and $\beta_2 Q_i^{std,on}$ gives the effect on utility of consumption in off-peak and peak periods under the standard rate. As discussed in Section 3 regarding the indifference curves and the consumption ratio, a consumer with high off-peak consumption will have a low consumption ratio, and one may expect such a consumer to select the CPP rate. The sign of β_1 is then hypothesised to be positive. The opposite is likely to be true for β_2, which is attached to the on-peak consumption variable. The consumption variables in (4.2) will thus pick up the impact of peak and off-peak consumption on the propensity to participate separately, instead of in a single ratio term. $Z_i^{CPP}\gamma$ gives the effect on the utility of consumption adjustments to the prices for each household. The vector Z_i^{CPP} is approximated by variables indicating the households' ability or willingness to reduce or shift consumption in peak periods, i.e. the substitability of peak and off-peak consumption revealed by the indifference curves. γ is expected to be positive/negative for variables that are likely to increase/decrease a household's likelihood of selecting the CPP rate. The stochastic error term (ε_i) is assumed to be logistic and independently distributed. The unknown parameters in (4.2) are estimated using a bivariate logit model (see, for instance, Greene, 2003).

5 The data

In the experiment, automatic meter reading technology provided measurements of each customer's hourly electricity consumption. All customers were asked to answer a survey by post or Internet that requested socio-demographic information about the household. Twenty percent of households responded to the survey (see Andersen et al., 2004, and Sæle, 2004, for details). The consumption and survey data are used in this analysis to investigate systematic differences between households choosing the CPP rate and those retaining the standard rate. This section describes the data and the variables included in the analysis.

One objective of the analysis is to study whether the customers' consumption patterns have affected their choice of tariff. Data from the experiment period is used as an indicator of the consumption pattern before the participation decision was made.[6] In November and December 2003 (during the experiment period), temperatures never fell below –8°C and the peak price was never activated. Hence, customers that chose the CPP tariff faced flat off-peak prices, and had no incentive to adjust their daily load

[6] Metering of the households' electricity consumption commenced at the beginning of the experiment period.

patterns.[7] It is then reasonable to assume that the CPP group (as well as the standard group) behaved in the same manner in this period with respect to their consumption patterns, as they did prior to the experiment period.

Consumption during the hours 8–11 and 17–20 in the coldest days in November and December are therefore used to approximate peak consumption, while the remaining consumption in these months is used to approximate off-peak consumption. The number of peak hours used is approximately the same as the number of hours with temperatures below –8°C that normally would occur in November and December.[8] Although consumption behaviour for temperatures below –8°C is not measured, temperatures lay below zero for several days. This makes it likely that the data still reflects any consumption differences between the households.

The other objective of the analysis is to investigate whether customers who selected the CPP rate did so because they are more flexible in consumption when prices vary. As indicators of flexibility, characteristics of the households and residences are used, as these may influence price responsiveness and the decisions to select the CPP rate (Train et al., 1987, Caves et al., 2000). Dummy variables are included to indicate households with an energy management system, households with electricity as their only space-heating source, households with electricity and wood-heating furnaces, households with electricity and oil/gas/paraffin and households with oil/gas/paraffin as their only space-heating source. Dummy variables also indicate whether the household is a single-member family (zero otherwise), whether there is at least one family member living at home (zero otherwise), and whether the total annual income of the household belongs to one of four income intervals (zero otherwise). In addition, dwelling size and age are included in the analysis as continuous variables.

Descriptive statistics for 107 households in the group choosing the CPP rate and 167 households choosing to remain on the standard rate are given in Table 1.

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[7] The consumers' total prices consist of the network plus the power prices plus taxes and VAT. The small difference in total price due to the difference between the off-peak CPP price and the standard price is assumed to be negligible (total price under the CPP and the standard tariff depends on the power tariff, but as an approximation, it would be about 0.60 NOK/kWh and 0.65 NOK/kWh, respectively). Moreover, it should not influence the shape of the load curve, since none of the rates varies across the day.

[8] Data from the remainder of the experiment period could not be used due to technical problems with the metering system and missing data.

Table 1. Summary statistics of household electricity consumption and characteristics for CPP and standard rate.

		Critical peak pricing				Standard rate		
Number of households				107			167	
Binary variables				*Percent*			*Percent*	
Energy management system				25.2			10.8	
Heating: No electricity				3.7			10.2	
Heating: Electricity + oil/gas/paraffin				46.7			55.7	
Heating: Electricity + wood				39.3			26.9	
Heating: Only electricity				10.3			7.2	
Dwelling: Detached				75.7			56.3	
Dwelling: Semi-detached				11.2			13.8	
Dwelling: Undetached				8.4			9.6	
Dwelling: Flat				4.7			20.4	
Income: 0–250,000 [NOK]				15.0			26.9	
Income: 250,000–500,000 [NOK]				38.3			30.5	
Income: 500,000–750,000 [NOK]				32.7			25.7	
Income: 750,000– [NOK]				14.0			16.8	
Single-member family				10.3			26.9	
Living at home				45.3			52.0	
Continuous variables	*Mean*	*Std. dev.*	*Min*	*Max*	*Mean*	*Std.*	*Min*	*Max*
Peak consumption [kWh]	104	43	15	216	91	44	5	235
Off-peak consumption	4326	1789	652	8497	3801	1875	243	10161
Peak/Off-peak cons. ratio	0.024	0.002	0.021	0.029	0.024	0.002	0.017	0.032
Age of dwelling [in years]	28.5	18.4	4	131	52.0	29.0	9	155
Dwelling size [m^2]	146.3	51.5	40	275	143.8	65.8	40	350

NOK 1 ~ EUR 0.12 / USD 0.16

Table 1 shows that both mean peak and off-peak electricity consumption is higher for the CPP group. However, peak/off-peak consumption ratio is almost the same. The share of households with an energy management system in the CPP group (25.2 percent) is also larger than in the standard group (10.8 percent).

Households are divided into four groups with respect to their heating equipment: dwellings with no electric heating (which means they use oil, gas or paraffin instead); dwellings with electricity and oil/gas/paraffin heating systems; dwellings with electricity heating and wood-burning furnaces; and finally, dwellings with electricity heating only. The percentage share of households with electricity heating only is somewhat larger for the CPP group, and the share of customers with oil/gas/paraffin heating in addition to electricity heating is somewhat larger for the group choosing the standard rate. The share of households with electricity heating and wood-burning stoves is nearly fifty percent larger in the CPP group, and the share of households without electricity heating in the CPP group is only a third of the share in the standard group.

In terms of dwelling type, about three quarters of CPP households, and only about half of the households in the standard group, are living in detached houses. The share of the households living in flats in the CPP group is about a quarter of the share in the standard group. The share of households living in semi-detached and undetached houses is quite similar for the two groups. With respect to the total annual income of households, we can see the share in the lowest income group (income less than NOK 250,000) is nearly half in the CPP group compared to the standard group, and somewhat larger in the two middlemost income groups. We also see that the two groups do not differ significantly for the highest income level.

The share of households in the CPP group living as a single-member family is nearly one third of the standard group. Households where at least one of the family members is living at home during the daytime do not differ much between the two groups, though the share is somewhat lower in the CPP rate group. Finally, we can see that the average age of dwellings for the CPP group is nearly half that of the standard group, but the average dwelling size is approximately the same.

6 Estimation results

As shown in the previous section, the summary statistics indicate differences between households choosing the CPP rate and those choosing to remain on the standard rate. A cross-section logit model is used to analyse the joint impact of the variables on the participation decision. Results from the estimated logit model, using Stata 8.0 (StataCorp, 2003), are presented in Table 2.[9]

Table 2. Estimated logit model results.

Variable	Coef.	Robust Std. Err.	P>|z|
Energy management system	0.9873	0.4201	0.019
Peak consumption	–0.0272	0.0232	0.241
Off-peak consumption	0.0007	0.0005	0.187
Heating: Electricity + oil/gas/paraffin	0.4444	0.6618	0.502
Heating: Electricity + wood	1.1778	0.7162	0.100
Heating: Only electricity	1.6842	0.9033	0.062
Dwelling: Semi-detached	–0.8183	0.5157	0.113
Dwelling: Undetached	–1.3333	0.5966	0.025
Dwelling: Flat	–2.3886	0.6804	0.000
Income: 0–250,000 [NOK]	0.4991	0.6433	0.438
Income: 250,000–500,000 [NOK]	0.9920	0.5709	0.082
Income: 500,000–750,000 [NOK]	0.3358	0.5226	0.521
Single-member family	–0.8991	0.5485	0.101
Living at home	–0.3007	0.3441	0.382
Dwelling size [m^2]	–0.0081	0.0040	0.043
Age of dwelling [in years]	–0.0468	0.0107	0.000
Constant	1.5554	1.1796	0.187
Log pseudo-likelihood =	–130.14876	Wald chi2(16) =	49.95
Pseudo R^2 =	0.2863	Prob>chi2 =	0.0000

Note: The left-hand side binary variable is one for households choosing the CPP rate and zero for households choosing to remain on the standard rate. Detached dwelling, Heating with only oil/gas/paraffin, Multi-member family and Income 750,000– are omitted to avoid multicollinearity.

A positive sign on an estimated coefficient in this table indicates the increased propensity of a household to select the CPP rate; negative signs indicate greater reluctance to select the CPP rate.

The peak and off-peak consumption parameter estimates display a negative and a positive sign, respectively. This indicates reluctance of consumers with large peak and/or low off-peak consumption to choose the CPP rate. Alternatively, it indicates the interest of consumers with small peak and/or large off-peak consumption to take

[9] To correct for possible misspecification in the model, the Huber/White/sandwich estimator is used to obtain a robust estimate of the asymptotic variance-covariance matrix of the estimated parameters (StataCorp, 2003).

advantage of their consumption pattern by choosing the CPP rate. However, none of the estimated coefficients is significant. Jointly testing the two variables' significance with an F-test also fails to indicate any statistical significance. This suggests that with respect to electricity consumption patterns, households selecting the CPP rate do not differ significantly from the households who do not.

One reason may be that the consumers do not have accurate information about their consumption during the day, in either peak or off-peak periods. This complicates the task of calculating how their consumption during different parts of the day across a year affects expected expenditure. One should also recall the dynamic feature of the CPP rate; that is, the peak price is only charged when the temperature is below –8°C. Although the customers were informed how often these temperatures normally occur, it introduces additional uncertainty, which further complicates the calculation of peak and off-peak consumption and its related costs. These uncertainties and difficulties may be the main reason why the consumption differences in peak and off-peak periods are insignificant. Baladi et al. (1998) suggests another explanation for similar findings: instead of making decisions based on accurate consumption information, customers may rely on perceived usage patterns, which are not necessarily correct.

In this case, instead of choosing between rate alternatives based on consumption patterns, households may have based their decision on their ability and willingness to adjust usage. Estimates for the remaining variables indicate whether this was the case.

The effect of the energy management system variable, as expected, is positive and significant (at the 2 percent level). Since these households display a higher ability to shift consumption between peak and off-peak periods, this is likely to be the reason why their probability of choosing the CPP rate is higher than other households. This implies that the group of customers selecting the rate has greater potential to be demand responsive than those selecting the standard rate. However, and as shown in Table 1, there are still some households with energy management systems who did not choose the CPP rate, even though they possibly could have benefited. This suggests that the marketing campaign for the CPP tariff could have focused more on the saving potential of energy managing systems. This could then have increased the demand response potential from the households on the CPP rate.

The results also indicate that households with electricity heating only and households with wood-burning furnaces in addition to electricity are significantly more interested (at the 10 percent level) in the CPP rate than households without electricity heating (those with only oil, gas, paraffin heating). The interest of the former may be explained by their higher potential for changing consumption, as they use more electricity for heating and then have greater consumption to reduce or shift. The latter may be explained by the ability to substitute electricity consumption in peak-price hours with wood. The group with electricity heating in addition to oil, gas or paraffin is not significantly different from the group with oil/gas/paraffin heating only. These groups may be reluctant to participate because their electricity usage is not as flexible as households who use electricity, or electricity and wood, to heat their residences.

The results also indicate that customers living in detached houses are more likely to select the CPP rate than households living in other house types. Households living in flats were least likely to select the CPP rate. One reason may be that detached houses usually have more rooms, which makes it easier to reduce consumption in parts of the house that are not frequently in use. Another reason is that households living in detached houses are more likely to own more electric appliances than those living in other and smaller dwellings (some examples of appliances are listed in Section 3). With more appliances, it should be easier to alter the time of usage between price periods. If we interpret dwelling types as a proxy for electric appliances excluded in the estimation, this may explain why house type significantly affects the choice of CPP.

In terms of total annual income, the results indicate that households in the second-to-lowest and lowest income groups are most likely to select the CPP rate, when compared with the highest income group. The reason why households with the highest income have a lower interest may be that they do not care about saving the relatively small share of income used on electricity consumption. However, only the coefficient for the second-to-lowest income group differs significantly from that for the highest income group.

The coefficient for single-member families displays a negative sign. Singles are assumed less likely to select the CPP rate, as compared to families of two or more members. One possible explanation may be that the adjustments in consumption necessary to take advantage of the rate may be more easily accomplished if there are more people in the household, i.e., the time budget spent on making consumption adjustments is shared across household members. Another explanation is that more members infers higher consumption and with that, higher adjustment potential. The estimate is nearly significant at the 10 percent level.

The effect of the variable that indicates whether people are home during the daytime is negative. The reason for this reluctance to choose the CPP rate may be an unwillingness to reduce consumption during colder periods during the day as the household may have small children or elderly occupants. The estimate is, however, not significant. The significant negative estimate of the coefficient for net floor space indicates that larger dwellings decrease the likelihood of participation. The size of the dwelling (in square metres) is likely correlated with both income and dwelling type, which are controlled for in the regression. However, income is defined in quite broad intervals, and the income dummy variables may therefore not have picked up all of the explanatory power related to the income effect. The negative coefficient may be thought of as a further support for higher income groups' low interest in the CPP rate.

We further show that the age of the dwelling is highly significant with a negative sign. This indicates that households in newer dwellings are more likely to choose the CPP rate. This variable picks up standard and energy efficiency differences between dwellings, e.g., electric floor heating is more common in newer dwellings. With electric floor heaters, energy is stored in the floor due to its higher heating capacity. Households with these heating systems are more time-of-use flexible, and hence better suited for switching consumption between price periods. Newer dwellings also tend to be better insulated. This decreases heat loss from the dwelling and lessens the loss of comfort if, for instance, electric heaters are turned off during high price periods.

Finally, the Wald-statistic (which is χ^2-distributed with the degrees of freedom equal to the number of slope coefficients) is used to test the hypothesis that all coefficients (except the intercept) are jointly equal to zero. This hypothesis is rejected at a high level. This indicates that the model explains outcomes quite well.

7 Conclusions

This analysis indicates that, on average, the consumption pattern does not influence the households' decision on whether to select the critical peak price (CPP) rate or the standard rate. Ownership of energy management systems and wood-burning furnaces increases the probability of joining the CPP program. Households can use this equipment to shift peak consumption to off-peak hours, or to reduce peak consumption and reduce electricity expenditures. The results indicate that the offering of CPP tariffs may increase the demand response among residential electricity consumers since the tariff appears to attract customers with a higher ability to respond to varying prices than the population as a whole. Moreover, the CPP tariff does not, on average, appear to attract customers that may benefit without making any consumption adjustments significantly more than the tariff attracts other consumers.

One possible explanation for the results is that customers' lack of information and knowledge of when and how electricity is used prevents decisions being taken with respect to consumption patterns. Instead, their decisions appear to be based on the knowledge they have in place, such as their own motivation and ability to be price responsive. The data also show that a larger share of households with energy management systems and with wood-burning furnaces could have been attracted to the CPP rate. This suggests that marketing campaigns may attain a higher share of possible price responsive households if a greater effort was made to inform them about the expenditure saving potential of the CPP rate.

Technologies supplying hourly consumption data to households will probably be more common in the future. Such technologies may ease the comparison of expenditure with different rate alternatives. With such information, it is likely that the customers' selection of time-differentiated rates will increasingly be taken on the basis of consumption patterns. If customers with advantageous consumption patterns mainly choose differentiated tariffs, this may in turn erode the benefits associated with demand response programs based on time-differentiated tariffs. On the other hand, new technologies are also likely to manage electricity usage in more advanced ways, and may offer automatic calculation of the possible savings from price adjustment. This may increase the participation of price responsive customers, which in turn will increase the benefits of demand response programs.

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Article IV:
Time-differentiated pricing and direct load control of residential electricity consumption*

Abstract

Time-of-use and real-time spot pricing tariffs in conjunction with direct load control of water heaters was offered to residential electricity consumers in a large-scale demand response experiment. Hourly data from the experiment on consumption, temperature, wind, and hours of daylight comprise a large panel data set, which are analysed with a fixed effects regression model. Price responses are estimated for three customer groups, which differ with respect to their choices of tariffs and requests for direct load control. The results indicate differing responses between the groups depending on their tariff combination.

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1 Introduction

Measures to increase demand response in the power system may contribute to improve efficiency, maintain reliability and mitigate exercise of market power (DOE, 2005). Presently, most Norwegian households face electricity prices that might be constant over weeks or seasons, and they are charged their energy consumption accumulated between meter reading dates occurring only a few times a year. This does not encourage consumption reductions during constrained peak periods. If instead households face time-differentiated prices, and are metered automatically, they will be provided with incentives to reduce electricity usage in peak price periods.

Time-differentiated tariffs can be designed in various ways. With *time-of-use* (TOU) rates, prices vary by blocks of time within the day and are fixed and known by customers in advance. However, the TOU pricing scheme remains quite static because the prices in each time block are constant and independent of the conditions in the electricity system. With *dynamic rates*, prices can be adjusted in accordance with the system situation. An example of a dynamic rate is *critical-peak pricing*. This is related to the TOU rate, but has the possibility of increasing the peak price to an extra high level if the system is severely constrained. Even more dynamic is *real-time pricing*. With this rate, the price can change frequently, e.g., on an hourly basis, to better reflect real-time system conditions. The market-based spot price is an example of this (see, for instance, Faruqui and George (2002) for a description of these rates).

Several experiments using time-differentiated pricing of electricity have been carried out in recent decades to quantify the responsiveness of end users. A series of experiments were conducted in the USA in the late 1970s and early 1980s. Although results differ, the general findings from the analyses of these experiments are that consumers respond to the varying prices (Lawrence and Aigner, 1979, Aigner, 1984). Caves et al. (1984) pooled data from five of the experiments and calculated a substitution elasticity of about 0.14.[1] Later analyses of similar experiments indicate the

[1] The elasticity of substitution is a measure of the percentage change in the ratio of the peak to off-peak consumption as a result of a percentage change in the ratio of the peak to the off-peak price.

same result: customers do respond to short-term price signals. For instance, Filippini (1995) found high price elasticities ranging from –1.25 to –1.41,[2] Vaage (1995) found elasticities of substitution of about 0.18, Henley and Peirson (1998) reported price elasticities of –0.102 and –0.249, Baladi et al. (1998) estimated substitution elasticities from 0.127 to 0.173, and Matsukawa (2001) found price elasticities of about –0.7.

However, despite the fact that customers respond to price signals, the resulting benefits have not normally been sufficiently large to justify investment in the costly equipment needed for implementing the new tariff schemes (Hawdon, 1992, Braithwait, 2000).

This has motivated projects using enabling technologies designed to motivate or aid an increase in the price response. This is done either by continuously informing consumers of the current price level, or by helping them to reduce consumption by, for example, controlling loads automatically. An example is a Finnish dynamic pricing experiment that used indicator lamps to warn customers that peak price periods were possibly forthcoming or in effect. Räsänen et al. (1995) found customers responded to this price signal by reducing consumption during peak periods by up to 71%. The “tempo tariff” offered by Electricité de France is an example of an approach using critical-peak pricing along with notification to the households of the next day’s prices. The price level is signalled to customers by colour signals on their meters. Aubin et al. (1995) found high responses in an experiment using the tempo tariff (price elasticity of –0.79). A project conducted in the USA used a critical-peak price tariff together with an interactive communication system. The system allowed the utility to send a signal to the consumers during critical high-price periods. In addition, it allowed customers to program and schedule some of their appliances to adjust consumption according to prices. Braithwait (2000) analysed data from this project, and found an elasticity of substitution of approximately 0.3, considered to be higher than what has been found in most other studies of traditional TOU programs. The results from the recently finished Statewide Pricing Pilot in California (Faruqui and George, 2005) further illustrate the same results. Although comparisons between different customer groups in the

[2] The (own) price elasticity is a measure of the percentage change in consumption as a result of a percentage change in the price. A price elasticity of –0.3 is comparable to an elasticity of substitution of 0.17 (Faruqui and George, 2002).

experiment should be made with care, the results showed that customers with enabling technologies responded more than customers without this equipment.

A Norwegian residential large-scale experiment combined time-differentiated tariffs with automatic meter reading and direct load control. The consumers were offered a time-of-use tariff and real-time spot prices as incentives to adjust electricity consumption according to varying prices. In addition, they were offered price-response assistance by direct load control of their water heaters. Ericson (2006b) investigated the effect of the automated water heater control on the daily load shape in this experiment. The data analysis showed that disconnecting water heaters reduced the load by approximately 0.5 kWh/h per household on average.[3]

This paper investigates new data from the Norwegian experiment. It aims to estimate price responses for three groups of households, which differ in their choice of tariffs and requests for direct load control. The panel data set, analysed with a fixed effects regression model, was collected over a six-month period. It consists of hourly metered data on electricity consumption from 312 households (nearly 800,000 data points), along with the number of hours of daylight per day and measurements of local temperatures and wind speeds.

The results indicate that customers with TOU and spot prices, *without* direct load control, were most responsive to the price variation. Customers with TOU and standard power tariffs, *without* direct load control, and customers with TOU and spot prices *and* direct load control of water heaters had smaller responses to the prices.

2 Experiment and data

"End-user Flexibility by Efficient Use of Information and Communication Technology" (2001–2004) was a Norwegian project where automatic meter reading and direct load control technology was installed in residential dwellings. The project developed and tested the use of time-differentiated network and power tariffs, and direct load control of water heaters. The electricity consumption of each household was metered every hour from 3 November 2003 to 25 April 2004, i.e., for 4200 hours.

[3] A typical water heater in Norway has a capacity of 200 litres and a heating element of 2 kW.

2.1 Samples

Before the test period started, all customers had standard flat network tariffs and standard power tariffs.[4] The project was a voluntary “opt-in” program, and the customers were given different participation choices. They could choose a TOU tariff from the network company and/or the market based spot price tariff from a power company. If they chose the spot price alternative, they had the further option of direct load control of their water heaters. The disconnections of the heaters would normally occur in the two most expensive spot price hours, every morning and evening. Depending on the customers’ choices, they divided into groups with differing combinations of standard and/or new tariffs, and with/without direct load control of water heaters.

This paper studies three different samples from the panel of customers. The samples are grouped according to their choice of tariff and their choice regarding water heater disconnection. Table 1 shows the customer groups, the number of households in each group, and the total number of observations in each group.

[4] After the deregulation of the Norwegian electricity market in 1991, vertically integrated power companies were separated into generating or trading divisions and network divisions. Customers now face one network tariff from their local net supplier, and one power tariff from a power supplier, which can be freely chosen from competing companies. Therefore, a consumer's total electricity price will be made up of the network price plus the power price (plus taxes and VAT).

Table 1. Customer groups (abbreviations in parentheses), the number of households in each group, and the total number of observations in each group

Customer group		No. of households	No. of observations
TOU net tariff & standard power tariff	(TOU/Std)	171	415,841
TOU net tariff & spot price power tariff	(TOU/spot)	7	19,289
TOU net tariff & spot price power tariff & direct load control	(TOU/spot/DLC)	134	343,138

Note: Approximately 150 of the households in the TOU/Std group are only "semi-volunteers". They originally chose a dynamic tariff that activated high peak prices only when temperatures fell below –8 °C. This tariff was terminated at the beginning of January 2004 and the customers were automatically transferred to the normal TOU tariff, with the option of opting out if they refused this rate (approximately 10 percent refused the new tariff). Only observations from the period with the normal TOU tariff (later than 5 January 2004) are included in the analysis of those customers.

2.2 Tariffs

The TOU network tariff had a two-level rate structure with a peak price of approximately NOK[5] 0.91 in hours 8–11 (7 am–11am) and hours 17–20 (4 pm–8 pm) on working days, and an off-peak price of approximately NOK 0.03 in all other hours of working days, weekends, and holidays.[6] The power tariff was the next day's hourly spot prices, settled in the day-ahead market at Nord Pool. Figure 2.1 shows average, minimum, and maximum daily spot prices during the test period.

[5] NOK 1 ≈ EUR 0.12 and USD 0.15

[6] Tax and VAT (24%) are not included. In 2003, a tax of approximately NOK 0.10 was added to the power price. In 2004, this tax was shifted to the network price.

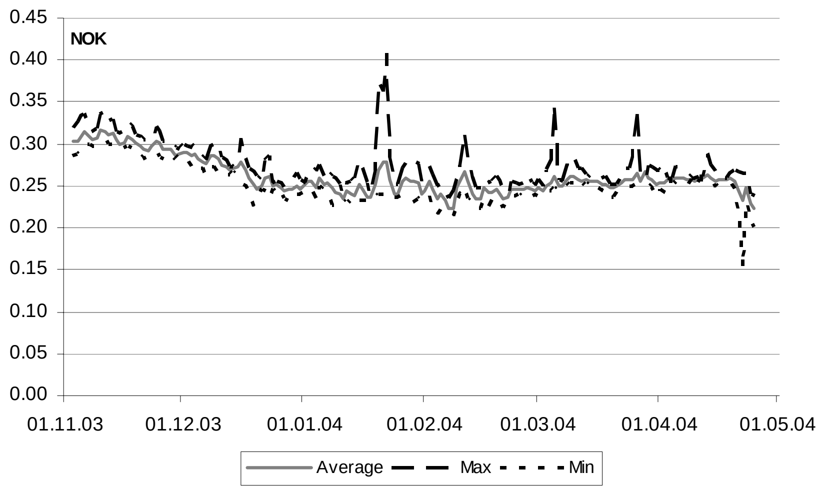

Figure 2.1. Average, minimum, and maximum daily spot prices from November 2003 to May 2004

Figure 2.1 reveals two important characteristics of the spot price during the test period. First, the average daily level was quite stable. Over the first 1½ months, the price remained at a level of about NOK 0.30 and, for the rest of the period, it remained at a level of approximately NOK 0.25. Second, the average difference between the minimum and maximum hourly spot price for each day was below NOK 0.03. Only on nine days did the difference exceed NOK 0.05 and, on four of those days, the difference exceeded NOK 0.10. To exemplify the hourly price variation the consumers were faced with, Figure 2.2 shows the spot price for one typical day (15 November) and one non-typical day (22 January), along with the TOU rate for working days.

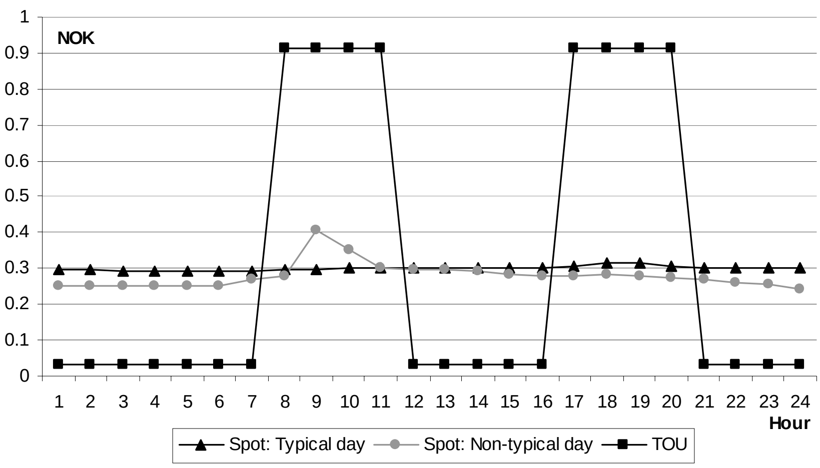

Figure 2.2. Hourly spot price on a typical (15 November) and non-typical day (22 January), and the TOU tariff

Figure 2.2 clearly shows that, on most days, the spot price provided only small incentives for consumers to alter their consumption. In other words, the TOU tariff was by far the most powerful price signal when it came to encouraging intra-daily changes in electricity consumption, for all three consumer groups. The price ratio (peak price/off-peak price) of the TOU rate, disregarding the power rate and taxes, is very high. However, as the total price faced by the consumers consists of the network price plus the power price plus taxes and VAT, the average total price ratio that the consumers actually face is lower (approximately 3.2:1).

2.3 Direct load control

The disconnections and reconnections of the water heaters' electricity circuits were carried out by direct contact with a relay in each household's fuse box. The load control was a service accompanied with the spot price tariff, and performed in conjunction with the hours when the spot price was expected to be highest (hours 9, 10, 18, and 19).

The load control events were not timed in accordance with the network TOU tariff. Because the water heaters were reconnected at the beginning of the last hour of the TOU peak price period, the water heater energy restoration for the first hour after reconnection did not take place when the TOU price was low, but when the price was still high. Thus, the length of a heater's normal recovery period, without any interruption, determined whether a household gained from the disconnection, also with respect to the TOU tariff. If the recovery period normally took one hour or less, all consumption would only be shifted to the hour when the TOU price was high and these consumers would probably not gain from the load control. On the other hand, if the recovery period normally took more than one hour, some of the hot water recovery would take place in the low-price period. Consequently, these consumers would shift parts of their consumption from TOU peak to off-peak price hours, and gain from the load control, not only with respect to the spot price power tariff, but also with respect to the TOU network tariff.

2.4 Household electricity consumption

The time-differentiated tariffs are intended to provide customers with incentives to adjust their electricity consumption patterns throughout the day. Figure 2.3 shows the average daily load curve (average consumption per hour) in the test period for the three groups with differentiated rates and a reference group. The reference group consists of 754 households that did not volunteer for the new rates. They had no incentives to alter their daily load curve, and are included in the figure to enable visual comparisons between the groups.

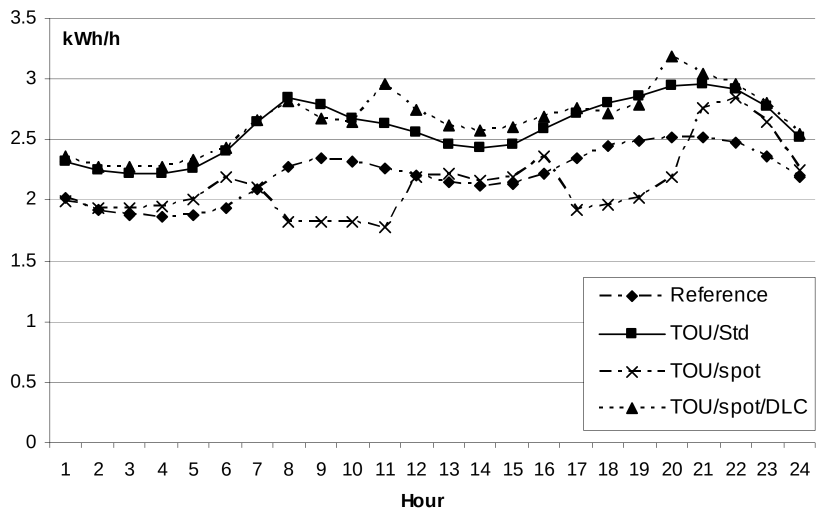

Figure 2.3. Average daily load curve for the groups with time-differentiated rates and a reference group

As seen in Figure 2.3, the reference group with standard network and power tariffs has a smooth daily load curve. There are morning and afternoon peaks corresponding to the hours when people are usually at home, and off-peak periods in the middle of the day and at night, which correspond to the hours when people are at work or asleep. This load curve reflects the typical consumption pattern for households that do not face variations in price during the day, and thus have no incentive to change their electricity consumption behaviour.

The groups with TOU and standard power tariffs *without* direct load control (TOU/Std) and with TOU and spot prices *with* direct load control (TOU/spot/DLC) have higher overall consumption levels than the reference group. In addition, it appears that these two groups consume more electricity in the early morning hours, when the price is low, compared with the reference group. This is illustrated by their consumption curve which seems to increase more in those hours. Following the same argument, it does not appear that these two groups have reduced their consumption in hour 8, which is a high-price hour. For the TOU/spot/DLC group, we see the effect of the disconnections in hours 9, 10, 18, and 19, when consumption drops. The effect of the reconnections is seen in hours 11 and 20. Consumption increases in these hours owing to the postponed water heater recovery.[7]

The group with TOU and spot price *without* direct load control (TOU/spot) differ from the other two test groups, as overall consumption level is lower. In addition, their consumption pattern is well adjusted to the TOU peak and off-peak prices. Their consumption seems to fall substantially in high-price periods and to increase in the low-price periods.

As Figure 2.3 shows, the consumption curves of all three groups differ from the reference group in their consumption level and/or in their pattern during the day. As the customers participated on a voluntarily basis, one could argue that the time-differentiated tariffs were chosen either by households that could easily alter their consumption pattern or by households with a favourable load profile. If the sample consisted purely of the former type of customers, the utility could expect a demand response from its customers. However, if the sample consisted only of the latter type, reductions might actually not have taken place because these customers simply could continue their prior consumption behaviour during the experiment, and gain from the tariff without changing their consumption. Thus, it is important to know whether this type of self-selection is prevalent among the customers. Ericson (2005, 2006a) investigated this issue among customers in the TOU/Std group and found that the load pattern of this group did not differ significantly from a group that chose to remain on their standard tariff. This indicates that self-selection based on favourable load patterns is not prevailing and that any load reductions measured in the analyses in the present paper is a result of adjustments to the price, at least for the TOU/Std group.

Summary statistics for electricity consumption for working days are given in Table 2.

[7] Consumption may remain high in subsequent hours also, but will not be as high as in the first hour after reconnection. Among other factors, consumption depends on the level of hot water used in each household and the time required to recover lost energy from the hot water consumption. This so-called payback or cold load pickup effect resulting from simultaneous reconnections is discussed in, e.g., Gomes et al. (1999), Orphelin and Adnot (1999), and van Tonder and Lane (1996).

Table 2. Summary statistics of electricity consumption [kWh/h] for the groups with time-differentiated tariffs and the reference group (working days)

Customer group		Period	Mean	Std dev.	Median	Min.	Max.
Reference		Off-peak	2.12	1.43	1.8	0.1	17.6
		Peak	2.38	1.59	2.0	0.1	25.8
TOU net tariff & standard power tariff	(TOU/Std)	Off-peak	2.50	1.48	2.2	0.1	14.7
		Peak	2.78	1.63	2.5	0.1	14.9
TOU net tariff & spot price power tariff	(TOU/spot)	Off-peak	2.23	1.24	2.1	0.1	9.6
		Peak	1.92	0.98	1.7	0.1	8.3
TOU net tariff & spot price power tariff & direct load control	(TOU/spot/DLC)	Off-peak	2.58	1.44	2.3	0.1	16.8
		Peak	2.81	1.56	2.5	0.1	15.9

Note: Peak (hours 8–11, 17–20 in working days) and off-peak (the remaining hours) are related to the high and low TOU rate periods, respectively.

2.5 Temperature and wind data

In addition to the electricity consumption data, hourly observations of average outdoor temperature and wind speed, and hours of daylight each day are available. These data are shown in Table 3. Temperature and wind data are measured at a central point in the vicinity of the customers.

Table 3. Summary statistics for temperature, wind, and number of daylight hours (all days)

Variable	Mean	Std dev.	Min.	Max.
Temp [°C]	0.5	5.6	–16.3	16.7
Wind [m/s]	1.5	0.8	0.3	6.6
Daylight [hour]	9.0	2.8	5.9	15.2

The variation in the weather variables was high with temperatures from –16 to +16 ºC and wind speeds reaching up to 6 m/s. This variation captures much of the temperature and wind conditions often experienced in these seasons in Norway. The number of hours of daylight each day varied from 5.9 (in December) to 15.2 (in April), with an average of nine hours.

3 Method and model

The regression model presented in this section is developed to predict the electricity consumption of customers at every hour during the whole test period. Analyses will be performed simultaneously on the three groups with the time-differentiated tariffs: the TOU/spot, TOU/Std, and TOU/spot/DLC groups. The goal is to find the extent to which the groups responded to the varying prices by adjusting consumption. The price responses will be captured in price coefficients, one for each of the three groups, and are measured as changes in kWh/h to changes in price (where the hourly price is the sum of the network and the power price in each hour, and taxes and VAT).

Variations in outside temperature and wind speed, number of hours of daylight each day, household specific characteristics, and time of day, week, and year are controlled for in the regression. As described earlier, self-selection based on an advantageous load pattern in the TOU/Std group did not appear to be prevalent, as indicated by the results in Ericson (2005, 2006a). This is assumed to be the case for the TOU/spot and the TOU/spot/DLC groups also. Hence, no measure for testing or controlling for this is included.

3.1 Econometric specification

In this analysis, the households' utility is assumed to depend on their consumption of electricity and all other goods and services. The consumption of electricity depends on the stock of electrical appliances because electricity does not give the household utility per se, but has to be used along with such equipment to obtain utility (for instance, when preparing hot meals, washing clothes, watching television, and heating water or rooms). The households are assumed to maximize their utility given all prices and income. This gives the households' demand for electricity and other goods as a function of all prices, incomes, their stock of appliances, and other household characteristics. Households' demand for electricity is approximated by:

$$y_{it} = \sum_{g \in G} \delta_g D_{i,g} p_{it} + \sum_{m \in M} \beta_{dl,m} D_{m,t} dl_t + \beta_T T_t + \beta_{T^2} T_t^2 +$$
$$\beta_{TMA} TMA_t + \beta_{TMA^2} TMA_t^2 + \beta_W W_t + \beta_{WMA} WMA_t + \sum_{h=2}^{24} \beta_h D_{h,t} + \tag{1}$$
$$\sum_{j=1}^{5} \beta_{trig,j} trig_{j,t} + \sum_{d \in D} \beta_d D_{d,t} + \sum_{m \in M \setminus \{nov\}} \beta_m D_{m,t} + \beta_{Hd} D_{Hd,t} + \gamma_i + \varepsilon_{it}$$

i = 1,…, N, t = 1,…,T, D={tue,wed,thu,fri,sat,sun},
G={TOU/spot,TOU/Std,TOU/spot/DLC}, M={nov,dec,jan,feb,mar,apr},

where:

y_{it}	=	hourly electricity consumption [kWh/h], at time *t* for household *i*;
p_{it}	=	electricity price [NOK] for household *i,* at time *t* ;
dl_t	=	daylight; 1 between sunrise and sunset, 0 else;
T_t	=	temperature [ºC], at time *t*;
T_t^2	=	temperature, squared, at time *t*;
TMA_t	=	moving average of temperature last 24 hours, at time *t*;
TMA_t^2	=	moving average of temperature last 24 hours, squared, at time *t*;
W_t	=	wind [m/s], at time *t*;
WMA_t	=	moving average of wind last 24 hours, at time *t*;
$trig_{j,t}$	=	trigonometric terms, taking the value sin(*πh*/6), sin(*πh*/8), sin(*πh*/12), cos(*πh*/6), cos(*πh*/12), for *j*=1,…,5, respectively, if *t* is in hour *h* of the day, for weekends and holidays (see Appendix A for more detailed information);
$D_{i,g}$	=	dummy variables; 1 if household *i* belongs to group *g*, 0 else;
$D_{h,t}$	=	dummy variables; 1 if *t* is in hour *h* of the day, 0 else;
$D_{d,t}$	=	dummy variables; 1 if *t* is in day *d* of the week, 0 else;
$D_{m,t}$	=	dummy variables; 1 if *t* is in month *m* of the year, 0 else;

$D_{Hd,t}$ = dummy variable; 1 if *t* is in a holiday, 0 else;

γ_i = fixed time invariant effect for household *i*; and

ε_{it} = an error term, assumed to be independently distributed over *i* and *t* with a constant variance.[8]

N represents the sum of all households *i*. T is the same for all groups (4200), although missing data will make some time series incomplete (an unbalanced panel).

The price responses will be captured by one price coefficient for each group as the effect of price changes is assumed to be different for the three groups. Further, it is necessary to control for other important factors influencing electricity consumption. They are discussed briefly below.

The influence of temperature on energy use is particularly important in countries with substantial climatic variations. The effect is well described in the literature, although no uniform way of including temperature in the models has been established. The different analyses have found that temperature changes may have non-linear, as well as delayed effects on electricity consumption. These findings are covered by, e.g., Henley and Peirson (1997, 1998), Granger et al. (1979), Harvey and Koopman (1993), and Ramanathan et al. (1997). Following Granger et al. (1979), the contemporary temperature is controlled for by one term, and its possible non-linear influence by a squared term. To account for the delayed effect of a temperature change, a 24-hour arithmetic moving average term as well as its squared value in another term is used.

Wind might influence energy use as it increases a building's heat loss (SINTEF, 1996). Both a contemporary term and a 24-hour moving average term are included. Because the households in the sample are located within the same area, all dwellings are assumed to be exposed to the same weather conditions over the data collection period.

Daylight is likely to influence the consumption of electricity because it decreases the need for electric lights and heating (see, for instance, Johnsen, 2001). To allow for different impacts of daylight over the seasons, variables intended to pick up the

[8] The Huber/White/sandwich estimator is used to obtain robust estimates of the asymptotic variance-covariance matrix of the estimated parameters (StataCorp, 2003).

daylight's impact in each month is included. Each variable takes the value one in the hours between sunrise and sunset in the existing month, and zero otherwise.[9]

In high-frequency data like those used here, a large part of the variation in the data is caused by seasonal and cyclical patterns. Seasonal factors (e.g. rain, snow, humidity), or special periods such as Christmas and New Year, might lead to different consumption levels, depending on the season. Cyclical patterns over the week might appear if, e.g., consumption is higher on weekends compared with weekdays. Also important, are the cyclical patterns of the day. Most people sleep at night, make breakfast and leave for work in the morning, and come home for dinner in the afternoon in a more or less similar pattern every day, and the electricity consumption reflects this behaviour. All the variables explaining these cycles cannot possibly be obtained, but they should still be accounted for in the model. Different approaches have been used in the literature to control for these patterns. Seasonal and weekly cycles can be controlled for by dummy variables (Pardo et al., 2002). Cycles within the day have been treated with dummy variables, one dummy for each hour (Granger et al., 1979, Ramanathan et al., 1985), by trigonometric terms (Granger et al., 1979), or by cubic splines (Hendricks et al., 1979, Harvey and Koopman, 1993). In the current paper, the cyclical patterns are modelled with dummies; one set with dummies for the 24 hours of the day.[10] As weekends and holidays have different consumption patterns compared with working days, trigonometric terms are included to allow for shifts in the consumption pattern.[11] After some experimentation, five variables were found to represent the daily cycle for these days; they are defined as $\sin(\pi h/6)$, $\sin(\pi h/8)$, $\sin(\pi h/12)$, $\cos(\pi h/6)$, and $\cos(\pi h/12)$, where h is the hour of the day. They do not enter on other days (see Appendix A for a more detailed explanation). Possible different levels in usage between the different days of the week or months are controlled for by day and month dummies. In addition, a

[9] In the sunrise or sunset hour, the value of a daylight variable is equal to the share of the hour which it is daylight, i.e. between 0 and 1.

[10] Consumption patterns for different working days were found to differ slightly. Regressions with inclusions of separate hour dummies for each weekday were tested, and found to increase the estimates of the price responses, but only to a small extent. Because such a specification is not very parsimonious, and it is computationally heavy, it was not considered worth the extra effort.

[11] Regressions with inclusions of separate hour dummies for the weekends were also tested. This was found to decrease the price response estimates, but only to a small extent. Inclusions of the extra variables were, for the same reasons as in the previous footnote, not considered worth the extra effort.

holiday dummy is included. To avoid multicollinearity, the hour-01, Monday, and November dummies are excluded.

The households' specific characteristics (income, stock of appliances, type of dwelling, etc.) are important factors that can account for differences in electricity consumption behaviour. Such variables are not included in the model, but heterogeneity between the households is accounted for by fixed (unobserved) effects with the estimation procedure presented in the next session. Therefore, their impact on electricity consumption is not commented on further.

The errors may have an autoregressive structure, where for instance special attention is devoted to residual autocorrelation at lag 1 (corresponding to the previous period), at lag 24 (corresponding to the same hour the previous day) and at lag 168 (corresponding to the same hour one week ago). No specification of autoregressive structures is done, since our software, Stata, only allow specifications of first-order for panel data. The estimators will anyway be consistent, but they are not efficient (Baltagi, 2001).

3.2 Estimation method

It is likely that the consumption patterns vary between customers with different demographic or household characteristics. For instance, it is likely that households with larger dwellings, higher incomes, more electrical appliances, or more family members will use more electricity than others. As the experiment lasted only six months, such characteristics are assumed to be constant during the test period. The cross section time series dimension of the data gives the opportunity to control for such household specific time-invariant explanatory variables by the use of a fixed effects panel data model. The fixed effects model controls for factors that are anticipated to not change within the timeframe of this experiment (see, e.g., Baltagi, 2001). This reduces heteroskedasticity and gives more efficient results.

4 Results

The analysis of the three groups' price responses is performed in one regression, with one separate price variable for each group to estimate the response to the total hourly price facing the customers. Table 4 shows the results from the fixed effects regression using Stata (StataCorp, 2005).

Table 4. Results from the fixed effects regression

Variables		Estimate	t-value	p-value
Price: TOU/spot		-0.5453	-35.94	0.000
Price: TOU/Std		-0.0556	-8.58	0.000
Price: TOU/spot/DLC		-0.0771	-11.57	0.000
Daylight: November		-0.0698	-5.54	0.000
Daylight: December		0.0118	0.88	0.380
Daylight: January		-0.0450	-5.48	0.000
Daylight: February		-0.1277	-17.36	0.000
Daylight: March		-0.1229	-18.28	0.000
Daylight: April		-0.0716	-10.06	0.000
Temp		-0.0286	-58.41	0.000
$Temp^2$		-0.0008	-20.91	0.000
TempMA		-0.0342	-61.24	0.000
$TempMA^2$		0.0001	1.87	0.061
Wind		0.0109	6.08	0.000
WindMA		0.0463	15.25	0.000
Constant		2.2923	233.33	0.000
	R^2: within	= 0.2024	F(71,777907)	= 2674.74
	between	= 0.0022	p-value for F-test	= 0.0000
	overall	= 0.1065		

Note: The results for the holiday and cyclical dummy variables for hours, days, and months, and the trigonometric terms are reported in Appendix B.

Table 4 shows that the price-response coefficients for the three groups are all significantly different from zero. Furthermore, F-tests indicate that the different price coefficients are significantly different from each other.

The results from the TOU/spot group are much higher than those for the other two groups. The estimated price response indicates a reduction in electricity usage of 0.545 kWh/h in response to an increase in price of 1 NOK. Assuming a linear price response and calculating the peak price elasticity using average price and electricity consumption values, the price elasticity is approximately –0.26.[12] Thus, the result is of the same magnitude as many of the findings from TOU experiments described in the Introduction. This group seems to have a higher ability and willingness to respond to the price variations than the other groups analysed in this paper. The TOU/spot group chose two independent rates that exposed them to the possibility of high volatility in prices, and high prices in the peak periods when consumption usually is higher. They did not choose direct load control with its prospective load reducing assistance. An explanation for their stronger response might be that these customers chose this riskier combination of tariffs because they relied on their own energy-controlling systems that could be programmed to exploit the tariff structure. Although this group consisted only of a few customers, their response gives an indication of the potential that might exist in households that are motivated and able to adjust consumption to varying price signals.

The estimated coefficients for the other two groups are smaller than for the TOU/spot group. For the TOU/Std group, we can see that electricity consumption declines by 0.055 kWh/h in response to a price increase of 1 NOK. Thus, the price elasticity is calculated to be –0.02. An explanation for the weaker response might be that households generally do not give their electricity consumption much attention, and want to take intra-daily price changes into account to a small extent only. The result may simply reflect that the end users in general are not very price responsive. However, it might be that a higher degree of information and frequent reminders of the tariff they have chosen are required for customers with a low interest in adjusting their electricity consumption. The customers received little information before and during the experiment about the various ways they could exploit the electricity rate structures. As

[12] The average off-peak and peak prices, including taxes and VAT, were approximately NOK 0.50 and NOK 1.60, respectively.

these types of rates were new and unknown to the customers, more attention and guidance on how to benefit from the varying prices may have increased the price response. Another explanation might be that the peak/off-peak price ratio was too small to motivate price-responsive behaviour from this group. Experience from earlier TOU experiments indicates that the largest consumption reductions are found when the peak to off-peak price ratio is highest (Faruqui and Malko, 1983) and that peak to off-peak price ratios should be in the range of 4:1 to 5:1 to induce substantial price responses (Braithwait, 2000). The price ratio in this experiment was approximately 3.2:1. Therefore, it may not have been sufficiently high to motivate the consumers to make consumption adjustments.

The TOU/spot/DLC group had a somewhat stronger response than that of the TOU/Std group. Electricity usage was reduced by 0.077 kWh/h in response to a price increase of 1 NOK (indicating a price elasticity of approximately –0.03, again assuming linear price responses). The estimate must be seen in the light of that the households in this group were exposed to automated load control. As was the case for the TOU/spot group, customers in this group chose two tariffs, which in combination could expose them to substantial price variations within the day. This might suggest that they had a high willingness and ability to be price responsive, as was seen in the TOU/spot group. However, instead of relying on their own energy-controlling systems to yield benefits from the price structure, they may have anticipated that the direct load control offered in conjunction with the spot price tariff would take care of their price response. Therefore, these customers may have taken little action on their own to respond to the price signals (regressions that control for the impact of the load control indicate slightly lower responses than for the TOU/Std group, thus indicating that the customers have done little efforts to respond to the price changes manually). That the estimate for the TOU/spot/DLC group is low, despite the fact that they had load control, may be due to that the spot price did not vary much within the day during the experiment. Thus, there was little to gain from shifting consumption from peak spot price hours to off-peak spot price hours. It may further indicate that a large share of the load was shifted only within the TOU peak price periods. It is probable that greater effects for the customers would have been experienced if the water heaters had been reconnected at the end of the TOU peak price periods instead of when the TOU price was still high. This could be achieved if, e.g., the water heaters had been disconnected for the entire TOU peak price periods. If this had occurred, the customers could have achieved benefits from shifting consumption out of possible high spot prices as well as the TOU peak prices. The result suggests that, if customers have two separate time-differentiated electricity tariffs from their network and power supplier, the timing of the load control measures in one of the tariffs might take into account the price structure of the other tariff in order to increase the benefits for the customers.

For the other estimates, we can see that the temperature coefficients are all significant. The negative contemporary linear and squared terms indicate that consumption will increase if the temperature drops from one hour to the next, but a temperature drop will have less impact as the weather becomes colder. The negative linear and positive squared moving average term indicates that, if the average temperature for the previous 24 hours drops, consumption will increase and the increase will be greater the colder it is.

The wind coefficient estimates are both positive and significant. As expected, wind increases electricity consumption.

All daylight variables except that for December are negative and significant. However, the December variable is not significant. This means that more daylight will decrease electricity consumption, as expected. We see that daylight has a greater impact during the months with more hours of light. The reason why daylight in April is estimated to cause less of a reduction in consumption as daylight in, say, February or March, may be that people heat their dwellings to a lesser degree at that time of the year. Thus, daylight does not replace electricity for heating in April to the same extent as it does in February and March.

The F-statistic test related to the hypothesis that all the coefficients except the intercept are jointly zero, is reported in Table 4. The hypothesis is clearly rejected, which suggests that the model has substantial explanatory power.

Finally, we mention that regressions were run for each of the groups separately to see whether this had an impact on the estimates. These results show price responses of –0.627 kWh/h for the TOU/spot group, –0.067 kWh/h for the TOU/Std group, and –0.066 kWh/h for the TOU/spot/DLC group. Thus, the estimates can be said to be robust as the responses are small and in the same range regardless of the specification for the

TOU/Std and TOU/spot/DLC groups, and high and in the same range for the TOU/spot group.

5 Conclusions

A fixed effects panel data model uses data from a Norwegian residential experiment to estimate price responses to TOU and spot pricing as well as direct load control of water heaters.

The results show that the customers with TOU and spot price tariffs *without* direct load control responded to a NOK 1 increase in price with a 0.545 kWh/h consumption reduction. Customers with a TOU network tariff and standard power tariff *without* disconnections responded to changes in price with a smaller adjustment in consumption (0.055 kWh/h). The customers with TOU and spot price tariffs *with* disconnections of water heaters had a somewhat higher response than the latter group (0.077 kWh/h).

These results indicate that the residential electricity consumers analysed were not very price responsive, as only one group with a few customers had a substantial response to the prices. However, the results indicate only the average response for all customers within each group and no attempts were made to reveal whether there existed subgroups with higher price responsiveness. The response found in one of the groups indicates that some customers are highly motivated and able to exploit the varying rates by adjusting consumption. For instance, it is likely that customers with equipment suited to taking advantage of the price structure by reducing or shifting consumption would have shown higher responses.

It may be that the provision of more information to the participating customers before and during the experiment on how they could have benefited from the rates could have increased the response. Furthermore, the direct load control would most likely have resulted in a higher response had the timing of the control events been conducted not only in accordance with the spot price power tariff but also in accordance with the TOU tariff. This suggests that, if customers have two separate time-differentiated electricity tariffs (network and power tariffs), one may consider taking into account the price structure of those two contracts when deciding the timing of load control measures in order to increase customers' economic savings from participation in time differentiated pricing programs.

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Appendix A

This appendix explains how the trigonometric variables accounting for weekend and holiday effects are constructed.

Let X_j be an arbitrary household invariant variable for which one has observations X_{j1}, X_{j2}, ..., X_{jT}. The variable is measured on an hourly basis. Let us assume that $X_{j,1}$ and $X_{j,T}$ correspond to the value of the variable X_j in the first hour of a Monday (the initial day) and the last hour of a Sunday (the last day), such that we consider complete weeks. Let us collect the observations in a vector, that is

$$\underline{X}_j = \begin{bmatrix} X_{j1}, & X_{j2}, & ..., & X_{jT} \end{bmatrix}'.$$

$\underline{X}$ may be partitioned in blocks corresponding to the different days, that is

$$\underline{X}_j = \begin{bmatrix} B'_{j1}, & B'_{j2}, & ..., & B'_{jK} \end{bmatrix}',$$

where B_{jk} is a column vector with 24 elements, corresponding to the hours of an arbitrary day, and where K=T/24. We have for instance

$$B_{j1} = \begin{bmatrix} X_{j1}, & X_{j2}, & ..., & X_{j24} \end{bmatrix}',$$

$$B_{j2} = \begin{bmatrix} X_{j,25}, & X_{j,26}, & ..., & X_{j,48} \end{bmatrix}' \text{ and}$$

$$B_{jK} = \begin{bmatrix} X_{j,T-23}, & X_{j,T-22}, & ..., & X_{j,T} \end{bmatrix}'.$$

For all the cases below one has that $B_{jk} = B_j \; \forall \; k = 1, 2, ..., K$. This means that we may write

$$\underline{X}_j = e_N \otimes B_j,$$

where e_K is a column vector with K elements, which all are equal to 1 and where $\otimes$ denotes the Kronecker-product. We will consider the five following B_j vectors:

$$B_1 = [\sin(1\pi/6), \quad \sin(2\pi/6), \quad ..., \quad \sin(24\pi/6)]^{/},$$

$$B_2 = [\sin(1\pi/8), \quad \sin(2\pi/8), \quad ..., \quad \sin(24\pi/8)]^{/},$$

$$B_3 = [\sin(1\pi/12), \quad \sin(2\pi/12), \quad ..., \quad \sin(24\pi/12)]^{/},$$

$$B_4 = [\cos(1\pi/6), \quad \cos(2\pi/6), \quad ..., \quad \cos(24\pi/6)]^{/} \text{ and}$$

$$B_5 = [\cos(1\pi/12), \quad \cos(2\pi/12), \quad ..., \quad \cos(24\pi/12)]^{/}.$$

Let furthermore D be a dummy variable with values $D_1, D_2, ..., D_T$ such that D_t is one if the hour corresponds to an hour on a Saturday, a Sunday or a holiday and zero in all other cases. We define the vector $\underline{D}$

$$\underline{D} = [D_1, \quad D_2, \quad ..., \quad D_T]^{/}.$$

We consider the following vectors

$$\underline{Z}_j = \underline{X}_j \odot \underline{D}, \; j = 1, ..., 5,$$

where $\odot$ denotes the Hadamard-product (that is elementwise multiplication). We may write

$$\underline{Z}_j = [Z_{j,1}, \quad Z_{j,2}, \quad ..., \quad Z_{j,T}]^{/}.$$

The total effect of the five Z-variables in period *t* may be written as $\sum_{j=1}^{5} \kappa_j Z_{j,t}$, which corresponds to $\sum_{j=1}^{5} \beta_{trig,j} trig_{j,t}$ in Eq. (1).

Appendix B

Table 5. Results from the fixed effects regression

Coefficients	Variables	Explanation	Estimate	t-value	p-value
$\delta_{TOU/spot}$	$D_{TOU/spot}\, p$	Price: TOU/spot	-0.5453	-35.94	0.000
$\delta_{TOU/Std}$	$D_{TOU/Std}\, p$	Price: TOU/Std	-0.0556	-8.58	0.000
$\delta_{TOU/spot/DLC}$	$D_{TOU/spot/DLC}\, p$	Price: TOU/spot/DLC	-0.0771	-11.57	0.000
$\beta_{dl,nov}$	$D_{nov}\, dl$	Daylight: November	-0.0698	-5.54	0.000
$\beta_{dl,dec}$	$D_{dec}\, dl$	Daylight: December	0.0118	0.88	0.380
$\beta_{dl,jan}$	$D_{jan}\, dl$	Daylight: January	-0.0450	-5.48	0.000
$\beta_{dl,feb}$	$D_{feb}\, dl$	Daylight: February	-0.1277	-17.36	0.000
$\beta_{dl,mar}$	$D_{mar}\, dl$	Daylight: March	-0.1229	-18.28	0.000
$\beta_{dl,apr}$	$D_{apr}\, dl$	Daylight: April	-0.0716	-10.06	0.000
β_T	T	Temp	-0.0286	-58.41	0.000
β_{T^2}	T^2	Temp, squared	-0.0008	-20.91	0.000
β_{TMA}	TMA	Temp, moving average	-0.0342	-61.24	0.000
β_{TMA^2}	TMA^2	Temp, moving average, squared	0.0001	1.87	0.061
β_W	W	Wind	0.0109	6.08	0.000
β_{WMA}	WMA	Wind, moving average	0.0463	15.25	0.000
β_2	D_2	Dummy, hour 2	-0.0955	-14.14	0.000
β_3	D_3	Dummy, hour 3	-0.1193	-17.47	0.000
β_4	D_4	Dummy, hour 4	-0.0991	-14.42	0.000
β_5	D_5	Dummy, hour 5	-0.0410	-5.95	0.000
β_6	D_6	Dummy, hour 6	0.0932	13.14	0.000
β_7	D_7	Dummy, hour 7	0.3004	39.10	0.000
β_8	D_8	Dummy, hour 8	0.5345	51.39	0.000
β_9	D_9	Dummy, hour 9	0.5512	50.67	0.000
β_{10}	D_{10}	Dummy, hour 10	0.5520	47.84	0.000
β_{11}	D_{11}	Dummy, hour 11	0.6368	54.67	0.000
β_{12}	D_{12}	Dummy, hour 12	0.4650	47.33	0.000
β_{13}	D_{13}	Dummy, hour 13	0.3572	36.92	0.000
β_{14}	D_{14}	Dummy, hour 14	0.3358	34.57	0.000

β_{15}	D_{15}	Dummy, hour 15	0.3832	39.04	0.000
β_{16}	D_{16}	Dummy, hour 16	0.4895	50.81	0.000
β_{17}	D_{17}	Dummy, hour 17	0.6348	58.32	0.000
β_{18}	D_{18}	Dummy, hour 18	0.6477	60.73	0.000
β_{19}	D_{19}	Dummy, hour 19	0.6807	64.94	0.000
β_{20}	D_{20}	Dummy, hour 20	0.8283	78.68	0.000
β_{21}	D_{21}	Dummy, hour 21	0.6974	85.37	0.000
β_{22}	D_{22}	Dummy, hour 22	0.5966	77.34	0.000
β_{23}	D_{23}	Dummy, hour 23	0.4416	61.07	0.000
β_{24}	D_{24}	Dummy, hour 24	0.2099	29.26	0.000
$\beta_{trig,1}$	$trig_1$	Trigonometric term, Sin(πh/6)	0.1120	29.17	0.000
$\beta_{trig,2}$	$trig_2$	Trigonometric term, Sin(πh/8)	0.2089	11.82	0.000
$\beta_{trig,3}$	$trig_3$	Trigonometric term, Sin(πh/12)	-0.0991	-29.02	0.000
$\beta_{trig,4}$	$trig_4$	Trigonometric term, Cos(πh/6)	0.2003	19.10	0.000
$\beta_{trig,5}$	$trig_5$	Trigonometric term, Cos(πh/12)	-0.2611	-18.78	0.000
β_{tue}	D_{tue}	Dummy, Tuesday	0.0408	10.08	0.000
β_{wed}	D_{wed}	Dummy, Wednesday	0.0238	5.86	0.000
β_{thu}	D_{thu}	Dummy, Thursday	-0.0131	-3.20	0.001
β_{fri}	D_{fri}	Dummy, Friday	-0.0048	-1.18	0.239
β_{sat}	D_{sat}	Dummy, Saturday	-0.0066	-1.12	0.261
β_{sun}	D_{sun}	Dummy, Sunday	0.0324	5.40	0.000
β_{dec}	D_{dec}	Dummy, December	0.2032	24.60	0.000
β_{jan}	D_{jan}	Dummy, January	0.1410	19.29	0.000
β_{feb}	D_{feb}	Dummy, February	0.0047	0.66	0.509
β_{mar}	D_{mar}	Dummy, March	-0.0422	-5.91	0.000
β_{apr}	D_{apr}	Dummy, April	-0.2086	-25.90	0.000
β_{Hd}	D_{Hd}	Dummy, Holiday	0.0345	5.02	0.000
		Constant	2.2923	233.33	0.000

Appendix:
Methods and models*

Article II, III and IV in this thesis analyse observed data from households in the experiment "End-user flexibility by efficient use of information and communication technology (ICT)". The articles use econometric/statistical methods to study the relation between variables of interest. Article II and IV utilize fixed effects panel data models to estimate the relation between electricity consumption and variables assumed to have explanatory power with respect to the consumption. Article III uses a discrete choice logit model to investigate to which extent households' choices of a new electricity tariff are influenced by some household characteristic variables. This Appendix will describe the econometric methods in more detail.

* I would like to thank Erik Biorn and Bente Halvorsen for comments and help.

1 Panel data models

When N households are observed over T time periods, one obtain a cross-section time-series dimensional data set, also called a panel data set. See, for instance, Biorn (2000), Hsiao (2003), Greene (2003) or Wooldridge (2002) for good descriptions of panel data models and more details on estimation methods.

Consider a simple model:

$$y_{it} = \alpha^* + x_{it}\beta + z_{it}\rho + u_{it} \qquad \begin{array}{l} i = 1,\ldots,N, \\ t = 1,\ldots,T, \end{array} \tag{1}$$

where x_{it} and z_{it} are scalars of exogenous variables, α^* is a constant, β and ρ are coefficients (the variables and the coefficients are generalized to vectors in Section 1.2). u_{it} is assumed to be independently, identically distributed over i and t, with mean zero and variance σ^2.

An ordinary least-squares estimation gives unbiased and consistent estimators of α^*, β and ρ. However, if z_{it} is unobserved, and if the covariance between x_{it} and z_{it} are nonzero, the ordinary least-squares regression of y_{it} on x_{it} will give biased estimators α^* and β (Hsiao, 2003).

1.1 Advantages with panel data

Panel data allows more complicated models than pure cross-sectional or time-series data, and may give the opportunity to control for the effects of missing or unobserved/unobservable variables. For instance, if the z values are constant through time for each household, but vary across households ($z_{it} = z_i$), the effect of z can be controlled for. This can be achieved by for instance subtracting the individual means from each observation

$$(y_{it} - \bar{y}_{i\cdot}) = (x_{it} - \bar{x}_{i\cdot})\beta + (u_{it} - \bar{u}_{i\cdot}) \qquad \begin{matrix} i = 1,\dots,N, \\ t = 1,\dots,T, \end{matrix} \qquad (2)$$

where $\bar{y}_{i\cdot} = (1/T)\sum_{t=1}^{T} y_{it}$, $\bar{x}_{i\cdot} = (1/T)\sum_{t=1}^{T} x_{it}$ and $\bar{u}_{i\cdot} = (1/T)\sum_{t=1}^{T} u_{it}$. The time invariant z variable is then swept away, and a least-squares regression of (2) will now give unbiased and consistent estimates of β. The utilization of ordinary least squares on (2) is therefore robust to correlation between x_{it} and z_i, which is not the case when ordinary least squares is used on (1) and z_i is omitted from the equation (since it is unobserved). The transformation of the data performed is not possible with only cross-sectional observations (where T = 1).

1.2 The fixed effects model

This section will discuss the fixed effects model which is utilized in Article II and IV.

Let us assume a regression equation with K right hand side variables:

$$\begin{cases} y_{it} = \alpha_i^* + \boldsymbol{x}_{it}\boldsymbol{\beta} + u_{it}, \\ u_{it} \sim \mathrm{IID}(0,\sigma^2), \end{cases} \qquad \begin{matrix} i = 1,\dots,N, \\ t = 1,\dots,T, \end{matrix} \qquad (3)$$

where $\boldsymbol{\beta} = (\beta_1, \beta_2, \dots, \beta_K)'$ is the column vector of coefficients for the K right hand side variables in the regression equation, $\boldsymbol{x}_{it} = (x_{1it}, x_{2it}, \dots, x_{Kit})$ is the row vector with observations of the K right hand side variables for household i in period t, and where u_{it} and $\boldsymbol{x}_{it}$ are independently distributed for all i and t.[1] In the context of this thesis, y_{it} is the hourly consumption of electricity for household i, $\boldsymbol{x}_{it}$ can for instance represent electricity price or temperature, and α_i^* represents the effect of all household specific variables which can be assumed unchanged for each household during the 6 months observation period; for instance income, size of dwelling, members in the household, education, attitude to for instance environmental issues, cognitive ability, motivation,

[1] IID(0,σ^2) is an abbreviation for independently, identically distributed variables with expectation 0 and variance σ^2.

etc. It is assumed that differences across households are captured in these household specific constant terms. Let us define the following vectors and matrices for household *i* of dimension (T × 1), (T × K) and (T × 1)

$$\boldsymbol{y}_i = \begin{bmatrix} y_{i1} \\ y_{i2} \\ \vdots \\ y_{iT} \end{bmatrix}, \qquad \boldsymbol{X}_i = \begin{bmatrix} \boldsymbol{x}_{i1} \\ \boldsymbol{x}_{i2} \\ \vdots \\ \boldsymbol{x}_{iT} \end{bmatrix} = \begin{bmatrix} x_{1i1} & x_{2i1} & \cdots & x_{Ki1} \\ x_{1i2} & x_{2i2} & \cdots & x_{Ki2} \\ \vdots & \vdots & & \vdots \\ x_{1iT} & x_{2iT} & \cdots & x_{KiT} \end{bmatrix}, \qquad \boldsymbol{u}_i = \begin{bmatrix} u_{i1} \\ u_{i2} \\ \vdots \\ u_{iT} \end{bmatrix},$$

and let $\boldsymbol{e}_T = (1,...,1)'$ be the (T × 1) vector with all elements equal to 1, $\boldsymbol{I}_T$ the identity matrix (all diagonal elements are 1, the rest of the elements are 0) of the order (T × T), and $\boldsymbol{0}_{T,1}$ the zero vector of dimension (T × 1). Then (3) can be written as

$$\begin{cases} \boldsymbol{y}_i = \boldsymbol{e}_T \alpha_i^* + \boldsymbol{X}_i \boldsymbol{\beta} + \boldsymbol{u}_i, \\ \boldsymbol{u}_i \sim \mathrm{IID}(\boldsymbol{0}_{T,1}, \sigma^2 \boldsymbol{I}_T), \end{cases} \qquad i = 1,\ldots, N. \tag{4}$$

The coefficients in (4), α_i^* and $\boldsymbol{\beta}$, can be found by minimizing the sum of the squared error terms

$$S = \sum_{i=1}^{N} (\boldsymbol{u}_i' \boldsymbol{u}_i) = \sum_{i=1}^{N} \left(\boldsymbol{y}_i - \boldsymbol{e}_T \alpha_i^* - \boldsymbol{X}_i \boldsymbol{\beta} \right)' \left(\boldsymbol{y}_i - \boldsymbol{e}_T \alpha_i^* - \boldsymbol{X}_i \boldsymbol{\beta} \right). \tag{5}$$

by first taking the partial derivate of S with respect to α_i^* and setting them equal to zero, which gives

$$\hat{\alpha}_i^* = \hat{\alpha}_i^* (\boldsymbol{\beta}) = \frac{\boldsymbol{e}_T'}{T} (\boldsymbol{y}_i - \boldsymbol{X}_i \boldsymbol{\beta}) = \bar{y}_{i\cdot} - \bar{\boldsymbol{x}}_{i\cdot} \boldsymbol{\beta}, \qquad i = 1,\ldots, N. \tag{6}$$

where

$$\bar{y}_{i\cdot} = \frac{1}{T}\sum_{t=1}^{T} y_{it}\ , \qquad\qquad \bar{\boldsymbol{x}}_{i\cdot} = \frac{1}{T}\sum_{t=1}^{T} \boldsymbol{x}_{it}\ .$$

Inserting for $\alpha_i^* = \hat{\alpha}_i^*$ from (6) into (5) and taking the partial derivative of *S* with respect to $\boldsymbol{\beta}$, we get

$$\hat{\beta}_W = \left[\sum_{i=1}^{N}\sum_{t=1}^{T}\left(\boldsymbol{x}_{it} - \bar{\boldsymbol{x}}_{i\cdot}\right)'\left(\boldsymbol{x}_{it} - \bar{\boldsymbol{x}}_{i\cdot}\right)\right]^{-1}\left[\sum_{i=1}^{N}\sum_{t=1}^{T}\left(\boldsymbol{x}_{it} - \bar{\boldsymbol{x}}_{i\cdot}\right)'\left(y_{it} - \bar{y}_{i\cdot}\right)\right] \qquad (7)$$

which is called the least-squares dummy-variable (LSDV) estimator, because it may be implemented by interpreting $\alpha_i^*,\ldots,\alpha_N^*$ as coefficients of dummy variables for individuals 1,…*N*. With many households (large *N*), as is the case for the regressions in this thesis, the computational burden when the dummy variables are included in the matrix of explanatory variables, is high. It is however not necessary to include the household specific dummy variables in the regression in order to estimate the $\boldsymbol{\beta}$'s (which are the coefficients of our interest), as shown by (7).

An alternative way of deriving (7) is the following: First, by premultiplying equation (4) by a (T × T) idempotent transformation matrix

$$\boldsymbol{B}_T = \boldsymbol{I}_T - \frac{\boldsymbol{e}_T\boldsymbol{e}_T'}{T} \qquad (8)$$

we obtain

$$\begin{aligned}\boldsymbol{B}_T\boldsymbol{y}_i &= \boldsymbol{B}_T\boldsymbol{e}_T\alpha_i^* + \boldsymbol{B}_T\boldsymbol{X}_i\boldsymbol{\beta} + \boldsymbol{B}_T\boldsymbol{u}_{it} \\ &= \boldsymbol{B}_T\boldsymbol{X}_i\boldsymbol{\beta} + \boldsymbol{B}_T\boldsymbol{u}_{it},\end{aligned} \qquad i = 1,\ldots, N. \qquad (9)$$

In (9), the observations are transformed so that the means of each household's time-series are subtracted from the observed variables, and the household specific effects (α_i^*) are swept out ($\boldsymbol{B}_T\boldsymbol{e}_T = \boldsymbol{0}_{T,1}$, since $\boldsymbol{B}_T$ and $\boldsymbol{e}_T$ are orthogonal). Second, by applying ordinary least-squares on (9), we get

$$\hat{\boldsymbol{\beta}}_W = \left[\sum_{i=1}^{N} \boldsymbol{X}_i' \boldsymbol{B}_T \boldsymbol{X}_i \right]^{-1} \left[\sum_{i=1}^{N} \boldsymbol{X}_i' \boldsymbol{B}_T \boldsymbol{y}_i \right] \tag{10}$$

which is the same estimator as was found in (7). The estimator is also often referred to as the *within-individual estimator* or the *fixed effects estimator*. It utilizes only the variation in the variables within each individual (in this thesis: household). The β's represent the impact on y of an increase in its corresponding variable, given all other variables are kept constant. For instance, a positive β related to the wind variable then tells how much consumption increases with a small increase in wind. A negative β related to the price variable tells how much consumption is reduced with a small increase in price.

The estimator $\hat{\beta}_W$ is unbiased, and when either N or T or both goes to infinity it is also consistent. Its covariance matrix is equal to

$$\mathrm{Var}\left(\hat{\boldsymbol{\beta}}_W\right) = E\left[\left(\hat{\boldsymbol{\beta}}_W - \boldsymbol{\beta}\right)\left(\hat{\boldsymbol{\beta}}_W - \boldsymbol{\beta}\right)'\right] = \sigma^2 \left[\sum_{i=1}^{N} \boldsymbol{X}_i' B_T \boldsymbol{X}_i \right]^{-1} \tag{11}$$

It should be noted that the regressions are performed with the software Stata, which uses an alternative but equivalent formulation of (3), by introducing an intercept μ (see StataCorp, 2005 or Gould, 2001)

$$y_{it} = \mu + \boldsymbol{x}_{it}\boldsymbol{\beta} + \alpha_i + u_{it} \tag{12}$$

In order to identify both μ and α_i, a restriction $\sum_{i=1}^{N} \alpha_i = 0$ is imposed. The intercept, μ, then represent the average value of the fixed effects, and α_i the deviations from this mean.

Stata runs ordinary least-squares on

$$\left(y_{it} - \bar{y}_{i\cdot} + \bar{\bar{y}}\right) = \mu + \left(x_{it} - \bar{x}_{i\cdot} + \bar{\bar{x}}\right)\beta + \left(u_{it} - \bar{u}_{i\cdot} + \bar{\alpha}\right) + \bar{\bar{u}} \tag{13}$$

where $\bar{\bar{y}} = (1/NT)\sum_{i=1}^{N}\sum_{t=1}^{T} y_{it}$, $\bar{\bar{x}} = (1/NT)\sum_{i=1}^{N}\sum_{t=1}^{T} x_{it}$, $\bar{\bar{u}} = (1/NT)\sum_{i=1}^{N}\sum_{t=1}^{T} u_{it}$ and $\bar{\alpha} = (1/NT)\sum_{i=1}^{N}\sum_{t=1}^{T} \alpha_{it} = 0$. This formulation has however no effect on the estimated β_W's.

2 Discrete choice models

In the regression models used in article II and IV, the regressand, i.e. the left hand dependent variable *y* was quantitative, and the right hand explanatory variables *X* were quantitative and qualitative (dummy variables). In article III, the dependent variable is qualitative. The model used is called a discrete choice model or a qualitative response regression model, because the dependent variable takes either of two values, which we conveniently set to 1, or 0. In this thesis, these values depend on a household's choice between a new tariff and the old tariff. This choice is assumed to depend on explanatory household characteristic variables, as for instance the households' ownership of energy management system, the electricity consumption pattern, income, etc. The objective of the model is to estimate how the probability that a household chooses the tariff, is affected by these characteristics (the model is also often referred to as a probability model). There are several approaches to develop a probability model for a qualitative binary response variable, the one used in article III is a logit model. For descriptions of the logit model, see for instance Biorn (2003), Gujarati (2003) or Green (2003).

2.1 The logit model

Article III aims at modelling households' choices between selecting a new tariff and not selecting the new tariff that was offered in the experiment "End-user flexibility by efficient use of information and communication technology (ICT)". Let us assume *n* households are observed, and let[2]

[2] This corresponds to Eq. (4.1) in Article III if y_i equals CPP_i.

$$y_i = \begin{cases} 1 \text{ if household } i \text{ selects the new tariff} \\ 0 \text{ if household } i \text{ does not select the new tariff} \end{cases} \qquad i = 1,\ldots, n.$$

We also assume that the households are observed independently of each other. Let us then say that P_i is the probability that a household selected the new tariff offered in the experiment ($y_i = 1$). Also, say ($1 - P_i$) is the probability that the household did not select the new tariff ($y_i = 0$). We do not observe P_i, but we observe whether each household chose the new tariff or not. Let

$$P_i = F\left(x_i\beta\right) \tag{14}$$

where the probability P_i is represented by a function F, with a vector of explanatory variables $x_i = (1, x_{1i}, x_{2i}, ..., x_{Ki})$ and parameters $\beta = (\beta_{0,}\beta_1, ..., \beta_K)'$.

The probability must lie between 0 and 1, and it is likely that P_i is nonlinearly related to the explanatory variables x_i. Furthermore, the function must be monotonically increasing in its argument. The strategy is to choose F such that its domain is (-∞, +∞) and its range is (0, 1), that is

$$F(-\infty) = 0 \qquad F(+\infty) = 1 \qquad F'(x_i\beta) \quad 0$$

The households' probability for choosing the new tariff can be represented by the logistic cumulative distribution function[3]

$$P_i = P\left(y_i = 1\right) = F\left(x_i\beta\right) = \frac{1}{1+e^{-x_i\beta}} = \frac{e^{x_i\beta}}{1+e^{x_i\beta}} \tag{15}$$

which satisfies the desired model properties just discussed. The response mechanism described in (15) is called the logit model. The probability of not choosing the new tariff can thus be expressed as

[3] This correspond to Eq. (4.2) in Article III.

$$1 - P_i = E\left(y_i = 0\right) = 1 - F\left(x_i\beta\right) = \frac{1}{1 + e^{x_i\beta}} = \frac{e^{-x_i\beta}}{1 + e^{-x_i\beta}} \tag{16}$$

2.2 Maximum likelihood estimation

Maximum likelihood is used to estimate the logit model. For the households i = 1,…,n, we have the sample of observations (y_i, x_i) = (y_i, 1, x_{1i}, x_{2i},…, x_{Ki}). We assume that ($y_1|x_1$), ($y_2|x_2$),…, ($y_n|x_n$) are stochastically independent, and let

$$L_i = P_i^{y_i}\left(1 - P_i\right)^{1-y_i} = \begin{cases} P_i & \text{for } y_i = 1, \\ 1 - P_i & \text{for } y_i = 0. \end{cases} \tag{17}$$

i.e., L_i is equal to the response probability if individual i respond positively and the non-response probability if he responds negatively. Then, the joint probability, L, of observing the sample is given as the product of the individual probabilities

$$L = \prod_{i=1}^{n} L_i = \prod_{i=1}^{n} P_i^{y_i}\left(1 - P_i\right)^{1-y_i} = \prod_{\{i:y_i=1\}} P_i \prod_{\{i:y_i=0\}} \left(1 - P_i\right) \tag{18}$$

where $\prod$ is the product operator, and $\prod_{\{i:yi=1\}}$ and $\prod_{\{i:yi=0\}}$ denotes the product taken over all i where y_i = 1 and where y_i = 0, respectively. The joint probability in Eq. (18) is called the likelihood function. By taking the natural logarithm, we obtain the log likelihood function

$$\ln\left(L\right) = \sum_{i=1}^{n} \ln\left(L_i\right) = \sum_{i=1}^{n} \left[y_i \ln\left(P_i\right) + \left(1 - y_i\right)\ln\left(1 - P_i\right)\right], \tag{19}$$

The Maximum Likelihood problem is to maximize the likelihood or the log likelihood function with respect to the β's. Put differently, the objective is to find the unknown β's that makes the observed sample most probable. The maximization is performed on (19) since this is the easiest mathematical problem. Differentiate (19) partially with respect to each unknown gives

$$\frac{\partial \ln(L)}{\partial \beta_k} = \sum_{i=1}^{n} (y_i - P_i) x_{ki} = \sum_{i=1}^{n} \left(y_i - \frac{e^{x_i \beta}}{1 + e^{x_i \beta}} \right) x_{ki} \qquad (20)$$

where k = 0, 1,…,K. By setting this expression equal to zero ((ln(L))/(β_k) = 0), we obtain the first-order conditions for the maximum likelihood problem

$$\sum_{i=1}^{n} y_i x_{ki} = \sum_{i=1}^{n} \left(\frac{e^{x_i \beta}}{1 + e^{x_i \beta}} \right) x_{ki}, \qquad k = 0, 1, \ldots, K. \qquad (21)$$

which are nonlinear equations that requires an iterative solution.

The sign of the β's tell whether a change in its corresponding variable increases of decreases the probability to select the tariff (a positive sign means an increase in the probability, and the other way round). The estimated parameters can be used in Eq. (15) and (16) to estimate the probability of a household to select the new tariff, or not to select the tariff, given the household's x-vector of characteristics. By differentiating (15) and (16) we get

$$\frac{\partial P_i}{\partial x_{ki}} = P_i (1 - P_i) \beta_k, \qquad \frac{\partial (1 - P_i)}{\partial x_{ki}} = -P_i (1 - P_i) \beta_k \qquad (22)$$

and by putting the estimates into these equations, we can find the changes in the probabilities if there is a change in one of the variables (given the other variables are kept at a chosen constant level, for instance at the sample mean).

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