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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.

Keywords: Time-differentiated pricing, TOU, direct load control

JEL classification: D10, Q41

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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 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).

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[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.

[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).

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 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 et al. (2004) 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

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

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 small 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.

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 cus-

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[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).

tomers' 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.

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 1 shows average, minimum, and maximum daily spot prices during the test period.

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[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 1. Average, minimum, and maximum daily spot prices from November 2003 to May 2004

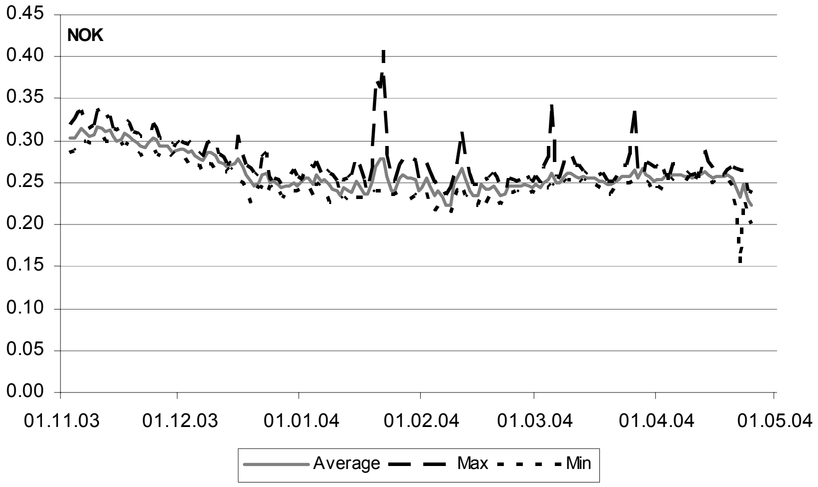
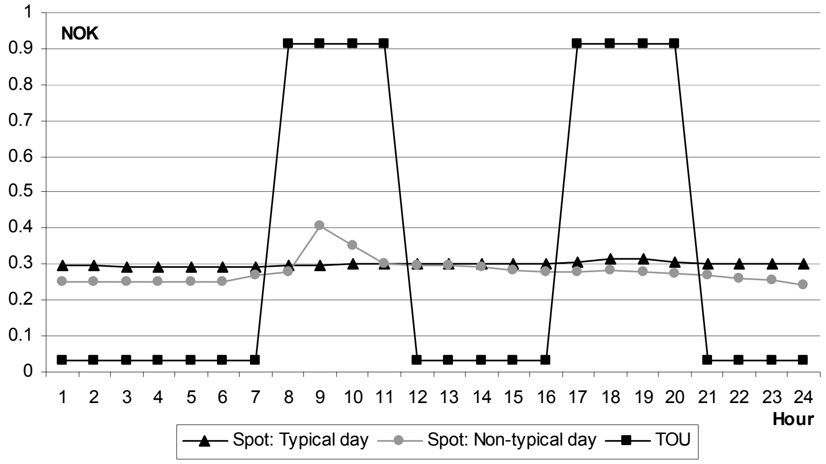


Figure 1 reveals two important characteristics of the spot price during the test period. First, the average daily level was quite stable. Over the first 1½ months, the price remained at a level of about NOK 0.30 and, for the rest of the period, it remained at a level of approximately NOK 0.25. Second, 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 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 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).

Figure 2. Hourly spot price on a typical (15 November) and non-typical day (22 January), and the TOU tariff



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).

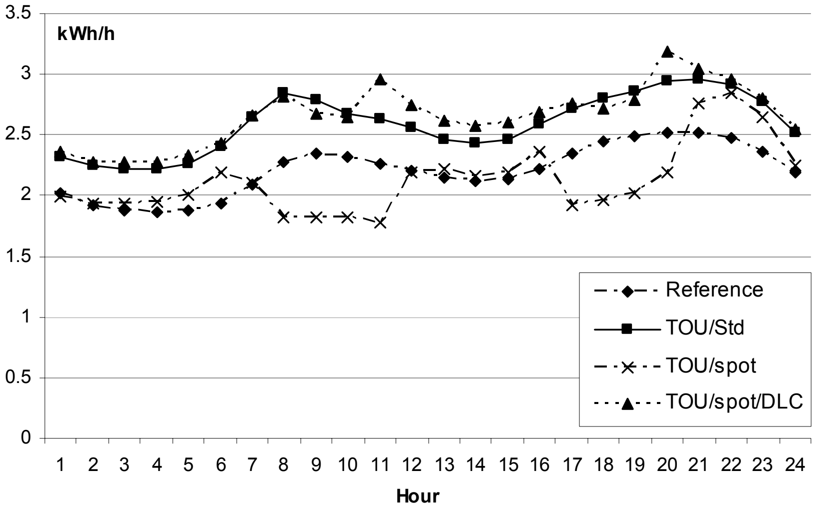
The load control events were not timed in accordance with the network TOU tariff. Because the water heaters were reconnected at the beginning of the last hour of the TOU peak price period, the water heater energy restoration for the first hour after re-connection did not take place when the TOU price 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 with respect to the TOU tariff. If the recovery period normally took one hour or less, all consumption would 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 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 to enable visual comparisons between the groups.

Figure 3. Average daily load curve for the groups with time-differentiated rates and a reference group



As seen in Figure 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 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

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[7] Consumption will 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).

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) 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.

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). 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:

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

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 $\sin(\pi h/6)$, $\sin(\pi h/8)$, $\sin(\pi h/12)$, $\cos(\pi h/6)$, $\cos(\pi h/12)$, for $j=1,\ldots,5$, 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. These are not squared as wind is anticipated to affect the heat transfer processes from buildings in a linear way (Mills, 1995). 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 daylight's

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

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. 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

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[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.

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 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.[11] 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 weak 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

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

various ways they could exploit the electricity rate structures. As 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 weak response, but it was somewhat stronger 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 1 NOK 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 small but 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

$$\underline{X}_j = \left[X_{j1}, \quad X_{j2}, \quad ..., \quad X_{jT}\right]^{/}.$$

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

$$\underline{X}_j = \left[B_{j1}^{/}, \quad B_{j2}^{/}, \quad ..., \quad B_{jK}^{/}\right]^{/},$$

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

$$B_{j1} = \left[X_{j1}, \quad X_{j2}, \quad ..., \quad X_{j24}\right]^{/},$$

$$B_{j2} = \left[X_{j,25}, \quad X_{j,26}, \quad ..., \quad X_{j,48}\right]^{/} \text{ and}$$

$$B_{jK} = \left[X_{j,T-23}, \quad X_{j,T-22}, \quad ..., \quad X_{j,T}\right]^{/}.$$

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:

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

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

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

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

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

We consider the following vectors

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

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

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

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

Coefficients	Variables	Explanation	Estimate	t-value	p-value
$\beta_{trig,1}$	$trig_1$	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

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