Discussion Papers No. 479, October 2006
Statistics Norway, Research Department

Torgeir Ericson

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.

Keywords: Direct load control; Demand response; Load management; Water heaters

JEL classification: D10, Q41

Acknowledgement: I am very grateful to Kjetil Telle and Bente Halvorsen for advice and helpful discussions. I also appreciate comments on earlier drafts of this paper from Terje Skjerpen, Petter Vegard Hansen, Knut Reidar Wangen, Annegrete Bruvoll, Trond Gärtner, Hanne Sæle and Per Finden, and programming assistance from Hilde Madsen.

Address: Torgeir Ericson, Statistics Norway, Research Department. E-mail: toe@ssb.no

Discussion Papers comprise research papers intended for international journals or books. A preprint of a Discussion Paper may be longer and more elaborate than a standard journal article, as it may include intermediate calculations and background material etc.

Abstracts with downloadable Discussion Papers
in PDF are available on the Internet:
http://www.ssb.no
http://ideas.repec.org/s/ssb/dispap.html

For printed Discussion Papers contact:

Statistics Norway
Sales- and subscription service
NO-2225 Kongsvinger

Telephone: +47 62 88 55 00
Telefax: +47 62 88 55 95
E-mail: Salg-abonnement@ssb.no

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 14 kWh when all members are showering, which requires the heating element to operate for seven hours

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

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 Fig. 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.

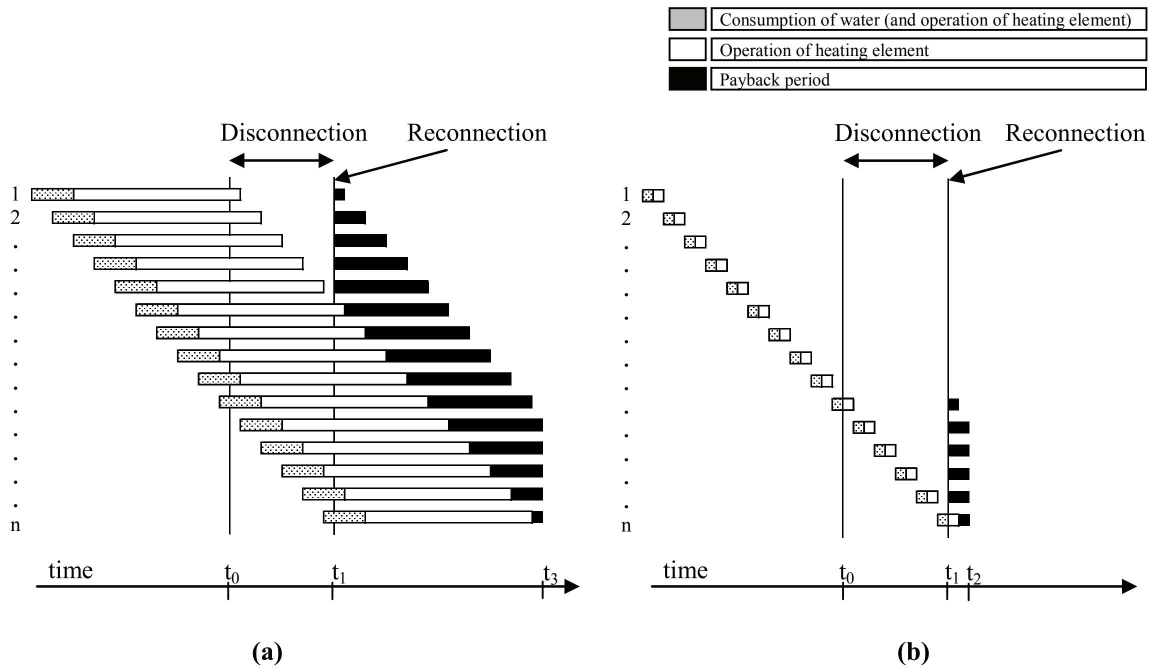


Fig. 1.

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)

Fig. 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).

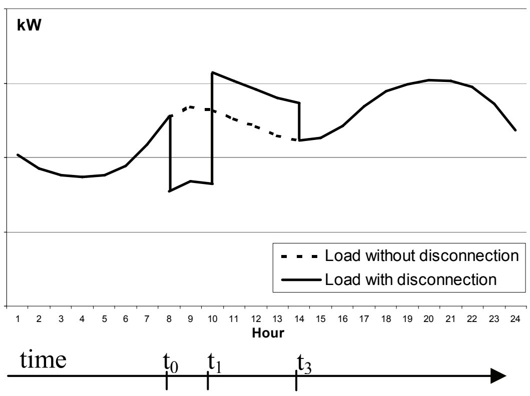
Fig. 1(a) shows households with a high level of hot water usage. It can be seen that the disconnection affects the first water heater only slightly. The heater has nearly finished recovering the energy loss when it is disconnected; the final part of its restoration of the energy must wait until the heater 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

[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.

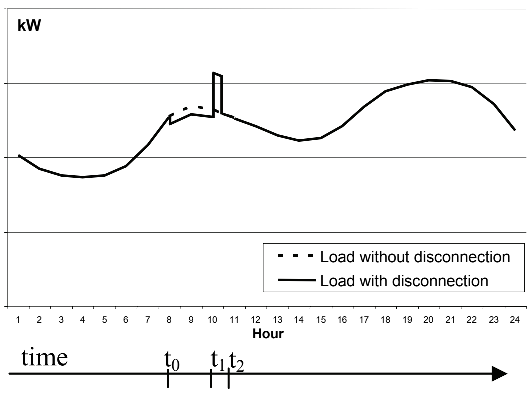
recovery period, their payback contribution occurs after t_1. At every moment during the disconnection period, it can be seen that the disconnection affects 10 heaters. When reconnected, only five heaters contribute to the payback effect at every moment until t_3. In this example the power demand added 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.

Fig. 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 Fig. 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 Fig. 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)

Fig. 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 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. 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 3.1.

[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: 1 NOK ≈ 0.12 EUR

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:

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

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.

---

[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.

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., 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. They were not squared, as we anticipate wind to affect only the linear part of the heat transfer processes from the buildings (Mills, 1995). 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 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

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

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

---

[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.

[7] Prices vary between households, due to differing types of contracts.

[8] In *X*, only price varies between households.

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.

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

where $\bar{y}_{\mathrm{i\cdot}}$, $\bar{X}_{\mathrm{i\cdot}}$, and $\bar{\varepsilon}_{\mathrm{i\cdot}}$ 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] Fig. 3 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. Fig. 4 illustrates the same for the evening load control events.

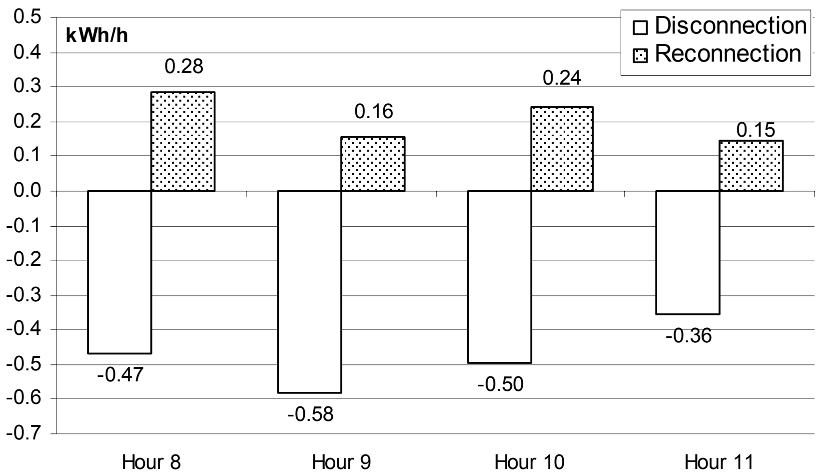


Fig. 3. Predicted effects (kWh/h) of disconnections and reconnections in the morning hours

[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.

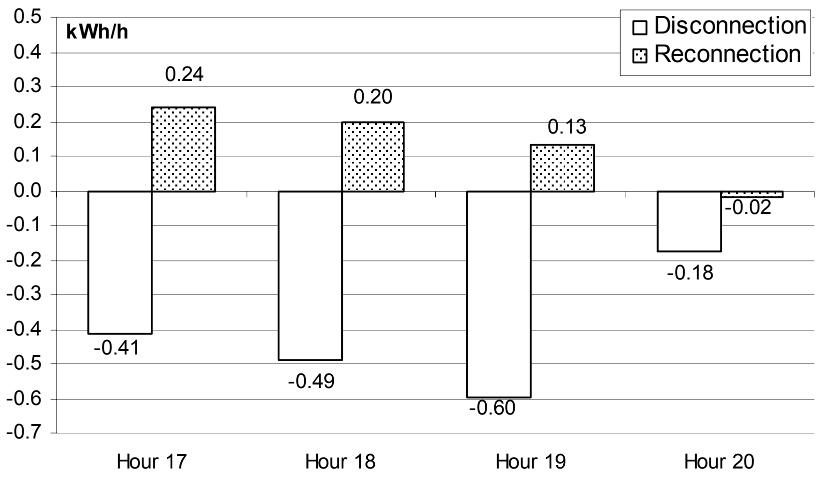


Fig. 4. Predicted effects (kWh/h) of disconnections and reconnections in the evening hours

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, Fig. 5 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.

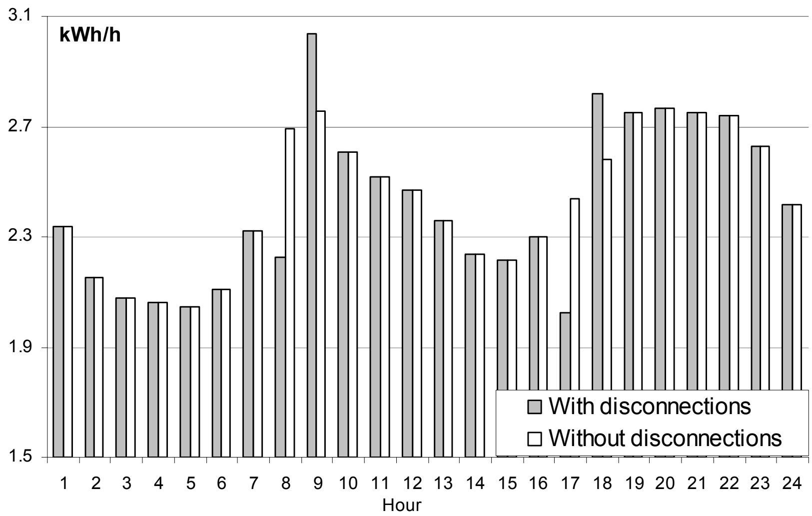


Fig. 5. Predicted consumption for one day with disconnection in hour 8 and 17, with and without predicted disconnection and reconnection terms

---

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 Fig. 5, 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.

However, 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.

Fig. 6 illustrates the hourly averaged estimates for the subsequent four hours after a disconnection and the fitted line suggests the real-time payback power demand.

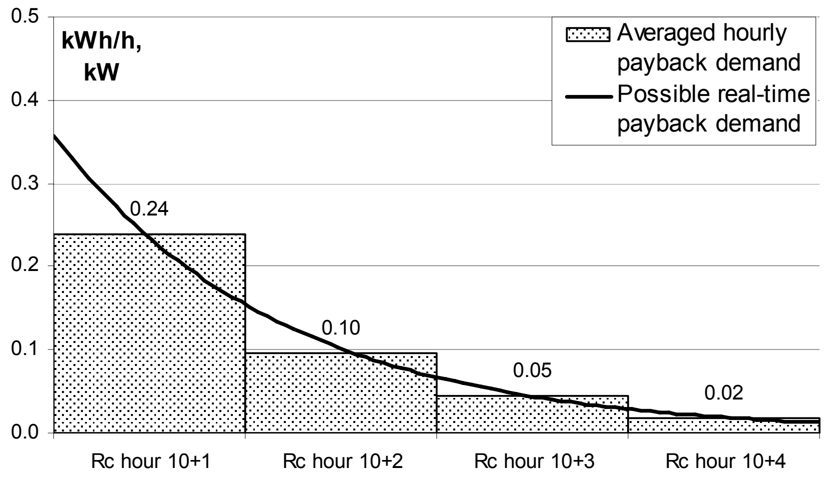


Fig. 6. Estimated average payback consumption for four hours following a disconnection, and a fitted exponential trend curve, the potential real-time payback power demand

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 heater electricity consumption 15 minutes after a one-hour disconnection would be nearly twice the size that would have occurred if

[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.

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 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 reconnecting on a first-off first-on basis when the load is sufficiently low again, load reductions can be achieved

---

[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).

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.

References

Al-Zayer, J., Al-Ibrahim, A.A., 1996. Modelling the impact of temperature on electricity consumption in the eastern province of Saudi Arabia. Journal of Forecasting 15, 97–106.

Bische, R.F., Sella, R.A., 1985. Design and controlled use of water heater load management. IEEE Transactions on Power Apparatus and Systems PAS–104 (6), 1290–1293.

Bye, T., Hope, E., 2005. Deregulation of electricity markets. The Norwegian experience. Economic and Political Weekly. December 10, 5269–5278.

Charles River Associates, 2003. DM programs for Integral Energy, Final report.

Glende, I., Tellefsen T., Walther, B., 2005. Norwegian system operation facing a tight capacity balance and severe supply conditions in dry years. www.statnett.no.

Gomes, A., Martines, A.G., Figueiredo, R., 1999. Simulation-based assessment of electrical load management programs. International Journal of Energy Research 23, 169–181.

Gould, W., 2001. Interpreting the intercept in the fixed-effects model. http://www.stata.com/support/faqs/stat/xtreg2.html.

Graabak, I., Feilberg, N., 2004. Forbrukerfleksibilitet ved effektiv bruk av IKT. Analyseresultater. SINTEF, TR A5980. (In Norwegian).

Granger, C.W.J., Engle, R., Ramanathan, R., Andersen, A., 1979. Residential load curves and time-of-day pricing: An econometric analysis. Journal of Econometrics 9 (1), 13–32.

Gustavson, M.W., Baylor, J.S., Epstein, G., 1993. Direct water heater load control – estimating program effectiveness using an engineer model. IEEE Transactions on Power systems 8 (1), 137–143.

Harvey, A., Koopman, S.J., 1993. Forecasting hourly electricity demand using time-differentiated splines. Journal of the American Statistical Association 88 (424), 1228–1336.

Hendricks, W., Koenker, R., Poirier, D.J., 1979. Residential demand for electricity. An Econometric Approach. Journal of Econometrics 9 (1), 33–57.

Henley, A., Peirson, J., 1997. Non-linearities in electricity demand and temperature: parametric versus non-parametric methods. Oxford Bulletin of Economics and Statistics 59 (1), 149–161.

Henley A, Peirson, J., 1998. Residential energy demand and the interaction of price and temperature: British experimental evidence. Journal of Energy Economics 20 (2), 157–171.

Hsiao, C., 2003. Analysis of panel data, 2nd ed. Cambridge University Press, Cambridge.

HiO (Høgskolen i Oslo), 2005. Testrapport. Måling av varmetap fra varmtvannsberedere. Rapport nr. OIH 15091–2005.1.B. Oslo. (In Norwegian).

Johnsen, T.A., 2001. Demand, generation, and price in the Norwegian market for electric power. Energy Economics 23, 227–251.

King, C., 2004. Integrating residential dynamic pricing and load control: The literature. EnergyPulse. www.energypulse.net.

Larsen, M.B., Nesbakken, R, 2005. Formålsfordeling av husholdningenes elektrisitetsforbruk i 2001. Sammenligning av formålsfordelingen i 1990 og 2001, Rapport 2005/18, Statistics Norway. (In Norwegian).

Lee, S.H., Wilkins, C.L., 1983. A practical approach to appliance load control analysis: a water heater case study. IEEE Transactions on Power Apparatus and Systems PAS–102 (4), 1007–1013.

Malemezian, E., 2004. Largest 2-Way, direct load control program? Association of Energy Services Professionals Member Newsletter, January.

Mills, F.A., 1995. *Heat and Mass Transfer*. Chicago: Richard D. Irwing, INC.

Orphelin, M., Adnot, J., 1999. Improvement of methods for reconstructing water heating aggregated load curves and evaluating demand-side control benefits. IEEE Transactions on Power Systems 14 (4), 1549–1555.

Pardo, A., Meneu, V., Valor, E., 2002. Temperature and seasonality influence on Spanish electricity load. Energy Economics 24, 55–70.

Pettersen, T.E., 2006. Vår daglige dusj. Dagbladet, Magasinet, 14 January, 42–45. (In Norwegian).

Ramanathan, R., Engle, R., Granger, C.W.J., Vahid-Araghi, F., Bracey, C., 1997. Short-run forecasts of electricity loads and peaks. International Journal of Forecasting 13, 161–174.

Rau, N.S., Graham, R.W., 1979. Analysis and simulation of the effects of controlled water heaters in a winter peaking system. IEEE Transactions on Power Apparatus and Systems PAS-98 (2), 458–464.

Reed, J.H., Thompson, J.C., Broadwater, R.P., Chandrasekaran, A., 1989. Analysis of water heater data from Athens load control experiment. IEEE transactions on Power Delivery 4 (2), 1232–1238.

Ryan, N.E., Braithwait, S.D., Powers, J.T., Smith, B.A., 1989. Generalizing direct load control program analysis: implementation of the duty cycle approach. IEEE Transactions on Power Systems 4 (1), 293–299.

Salehfar, H., Patton, A.D., 1989. Modeling and evaluation of the system reliability effects of direct load control. IEEE Transactions on Power Systems 4 (3), 1024–1030.

SINTEF, 1996. Enøk i bygninger. Effektiv energibruk. Oslo: Universitetsforlaget AS. (In Norwegian).

StataCorp, 2005. Stata Statistical Software: Release 9. StataCorp LP, College Station, TX.

Vaage, O.F., 2002. Til alle døgnets tider. Tidsbruk 1971–2000. Statistical Analyses. Statistics Norway. (In Norwegian).

van Tonder, J.C., Lane, I.E., 1996. A load model to support demand management decisions on domestic storage water heater control strategy. IEEE Transactions on Power Systems 11 (4), 1844–1849.

Weller, G.H., 1988. Managing the instantaneous load shape impacts caused by the operation of a large-scale direct load control system. IEEE Transactions on Power Systems 3 (1), 197–199.

Xcel Energy, 2005. www.xcelenergy.com/XLWEB/CDA/0,3080,1–1–2_738_23162–212–11_192_352–0,00.html and http://tdworld.com/ar/power_xcel_energys_savers.

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

Table A1. (continued)

Coefficient	Variable	Explanation	Estimate	t-value	p-value
$\beta_{wd,2}$	$D_{wd,2}$	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

Table A1. (continued)

Coefficient	Variable	Explanation	Estimate	t-value	p-value
$\beta_{we,18}$	$D_{we,18}$	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

Recent publications in the series Discussion Papers

387 G. H. Bjertnæs and T. Fæhn (2004): Energy Taxation in a Small, Open Economy: Efficiency Gains under Political Restraints

388 J.K. Dagsvik and S. Strøm (2004): Sectoral Labor Supply, Choice Restrictions and Functional Form

389 B. Halvorsen (2004): Effects of norms, warm-glow and time use on household recycling

390 I. Aslaksen and T. Synnestvedt (2004): Are the Dixit-Pindyck and the Arrow-Fisher-Henry-Hanemann Option Values Equivalent?

391 G. H. Bjønnes, D. Rime and H. O.Aa. Solheim (2004): Liquidity provision in the overnight foreign exchange market

392 T. Åvitsland and J. Aasness (2004): Combining CGE and microsimulation models: Effects on equality of VAT reforms

393 M. Greaker and Eirik. Sagen (2004): Explaining experience curves for LNG liquefaction costs: Competition matter more than learning

394 K. Telle, I. Aslaksen and T. Synnestvedt (2004): "It pays to be green" - a premature conclusion?

395 T. Harding, H. O. Aa. Solheim and A. Benedictow (2004). House ownership and taxes

396 E. Holmøy and B. Strøm (2004): The Social Cost of Government Spending in an Economy with Large Tax Distortions: A CGE Decomposition for Norway

397 T. Hægeland, O. Raaum and K.G. Salvanes (2004): Pupil achievement, school resources and family background

398 I. Aslaksen, B. Natvig and I. Nordal (2004): Environmental risk and the precautionary principle: “Late lessons from early warnings” applied to genetically modified plants

399 J. Møen (2004): When subsidized R&D-firms fail, do they still stimulate growth? Tracing knowledge by following employees across firms

400 B. Halvorsen and Runa Nesbakken (2004): Accounting for differences in choice opportunities in analyses of energy expenditure data

401 T.J. Klette and A. Raknerud (2004): Heterogeneity, productivity and selection: An empirical study of Norwegian manufacturing firms

402 R. Aaberge (2005): Asymptotic Distribution Theory of Empirical Rank-dependent Measures of Inequality

403 F.R. Aune, S. Kverndokk, L. Lindholt and K.E. Rosendahl (2005): Profitability of different instruments in international climate policies

404 Z. Jia (2005): Labor Supply of Retiring Couples and Heterogeneity in Household Decision-Making Structure

405 Z. Jia (2005): Retirement Behavior of Working Couples in Norway. A Dynamic Programming Approch

406 Z. Jia (2005): Spousal Influence on Early Retirement Behavior

407 P. Frenger (2005): The elasticity of substitution of superlative price indices

408 M. Mogstad, A. Langørgen and R. Aaberge (2005): Region-specific versus Country-specific Poverty Lines in Analysis of Poverty

409 J.K. Dagsvik (2005) Choice under Uncertainty and Bounded Rationality

410 T. Fæhn, A.G. Gómez-Plana and S. Kverndokk (2005): Can a carbon permit system reduce Spanish unemployment?

411 J. Larsson and K. Telle (2005): Consequences of the IPPC-directive’s BAT requirements for abatement costs and emissions

412 R. Aaberge, S. Bjerve and K. Doksum (2005): Modeling Concentration and Dispersion in Multiple Regression

413 E. Holmøy and K.M. Heide (2005): Is Norway immune to Dutch Disease? CGE Estimates of Sustainable Wage Growth and De-industrialisation

414 K.R. Wangen (2005): An Expenditure Based Estimate of Britain's Black Economy Revisited

415 A. Mathiassen (2005): A Statistical Model for Simple, Fast and Reliable Measurement of Poverty

416 F.R. Aune, S. Glomsrød, L. Lindholt and K.E. Rosendahl: Are high oil prices profitable for OPEC in the long run?

417 D. Fredriksen, K.M. Heide, E. Holmøy and I.F. Solli (2005): Macroeconomic effects of proposed pension reforms in Norway

418 D. Fredriksen and N.M. Stølen (2005): Effects of demographic development, labour supply and pension reforms on the future pension burden

419 A. Alstadsæter, A-S. Kolm and B. Larsen (2005): Tax Effects on Unemployment and the Choice of Educational Type

420 E. Biørn (2005): Constructing Panel Data Estimators by Aggregation: A General Moment Estimator and a Suggested Synthesis

421 J. Bjørnstad (2005): Non-Bayesian Multiple Imputation

422 H. Hungnes (2005): Identifying Structural Breaks in Cointegrated VAR Models

423 H. C. Bjørnland and H. Hungnes (2005): The commodity currency puzzle

424 F. Carlsen, B. Langset and J. Rattsø (2005): The relationship between firm mobility and tax level: Empirical evidence of fiscal competition between local governments

425 T. Harding and J. Rattsø (2005): The barrier model of productivity growth: South Africa

426 E. Holmøy (2005): The Anatomy of Electricity Demand: A CGE Decomposition for Norway

427 T.K.M. Beatty, E. Røed Larsen and D.E. Sommervoll (2005): Measuring the Price of Housing Consumption for Owners in the CPI

428 E. Røed Larsen (2005): Distributional Effects of Environmental Taxes on Transportation: Evidence from Engel Curves in the United States

429 P. Boug, Å. Cappelen and T. Eika (2005): Exchange Rate Rass-through in a Small Open Economy: The Importance of the Distribution Sector

430 K. Gabrielsen, T. Bye and F.R. Aune (2005): Climate change- lower electricity prices and increasing demand. An application to the Nordic Countries

431 J.K. Dagsvik, S. Strøm and Z. Jia: Utility of Income as a Random Function: Behavioral Characterization and Empirical Evidence

432 G.H. Bjertnæs (2005): Avioding Adverse Employment Effects from Energy Taxation: What does it cost?

433. T. Bye and E. Hope (2005): Deregulation of electricity markets—The Norwegian experience

434 P.J. Lambert and T.O. Thoresen (2005): Base independence in the analysis of tax policy effects: with an application to Norway 1992-2004

435 M. Rege, K. Telle and M. Votruba (2005): The Effect of Plant Downsizing on Disability Pension Utilization

436 J. Hovi and B. Holtsmark (2005): Cap-and-Trade or Carbon Taxes? The Effects of Non-Compliance and the Feasibility of Enforcement

437 R. Aaberge, S. Bjerve and K. Doksum (2005): Decomposition of Rank-Dependent Measures of Inequality by Subgroups

438 B. Holtsmark (2005): Global per capita CO_2 emissions - stable in the long run?

439 E. Halvorsen and T.O. Thoresen (2005): The relationship between altruism and equal sharing. Evidence from inter vivos transfer behavior

440 L-C. Zhang and I. Thomsen (2005): A prediction approach to sampling design

441 Ø.A. Nilsen, A. Raknerud, M. Rybalka and T. Skjerpen (2005): Lumpy Investments, Factor Adjustments and Productivity

442 R. Golombek and A. Raknerud (2005): Exit Dynamics with Adjustment Costs

443 G. Liu, T. Skjerpen, A. Rygh Swensen and K. Telle (2006): Unit Roots, Polynomial Transformations and the Environmental Kuznets Curve

444 G. Liu (2006): A Behavioral Model of Work-trip Mode Choice in Shanghai

445 E. Lund Sagen and M. Tsygankova (2006): Russian Natural Gas Exports to Europe. Effects of Russian gas market reforms and the rising market power of Gazprom

446 T. Ericson (2006): Households' self-selection of a dynamic electricity tariff

447 G. Liu (2006): A causality analysis on GDP and air emissions in Norway

448 M. Greaker and K.E. Rosendahl (2006): Strategic Climate Policy in Small, Open Economies

449 R. Aaberge, U. Colombino and T. Wennemo (2006): Evaluating Alternative Representation of the Choice Sets in Models of Labour Supply

450 T. Kornstad and T.O. Thoresen (2006): Effects of Family Policy Reforms in Norway. Results from a Joint Labor Supply and Child Care Choice Microsimulation Analysis

451 P. Frenger (2006): The substitution bias of the consumer price index

452 B. Halvorsen (2006): When can micro properties be used to predict aggregate demand?

453 J.K. Dagsvik, T. Korntad and T. Skjerpen (2006): Analysis of the disgouraged worker phenomenon. Evidence from micro data

454 G. Liu (2006): On Nash equilibrium in prices in an oligopolistic market with demand characterized by a nested multinomial logit model and multiproduct firm as nest

455 F. Schroyen and J. Aasness (2006): Marginal indirect tax reform analysis with merit good arguments and environmental concerns: Norway, 1999

456 L-C Zhang (2006): On some common practices of systematic sampling

457 Å. Cappelen (2006): Differences in Learning and Inequality

458 T. Borgersen, D.E. Sommervoll and T. Wennemo (2006): Endogenous Housing Market Cycles

459 G.H. Bjertnæs (2006): Income Taxation, Tuition Subsidies, and Choice of Occupation

460 P. Boug, Å. Cappelen and A.R. Swensen (2006): The New Keynesian Phillips Curve for a Small Open Economy

461 T. Ericson (2006): Time-differentiated pricing and direct load control of residential electricity consumption

462 T. Bye, E. Holmøy and K. M. Heide (2006): Removing policy based comparative advantage for energy intensive production. Necessary adjustments of the real exchange rate and industry structure

463 R. Bjørnstad and R. Nymoen (2006): Will it float? The New Keynesian Phillips curve tested on OECD panel data

464 K.M.Heide, E. Holmøy, I. F. Solli and B. Strøm (2006): A welfare state funded by nature and OPEC. A guided tour on Norway's path from an exceptionally impressive to an exceptionally strained fiscal position

465 J.K. Dagsvik (2006): Axiomatization of Stochastic Models for Choice under Uncertainty

466 S. Hol (2006): The influence of the business cycle on bankruptcy probability

467 E. Røed Larsen and D.E. Sommervoll (2006): The Impact on Rent from Tenant and Landlord Characteristics and Interaction

468 Suzan Hol and Nico van der Wijst (2006): The financing structure of non-listed firms

469 Suzan Hol (2006): Determinants of long-term interest rates in the Scandinavian countries

470 R. Bjørnstad and K. Øren Kalstad (2006): Increased Price Markup from Union Coordination - OECD Panel Evidence.

471 E. Holmøy (2006): Real appreciation as an automatic channel for redistribution of increased government non-tax revenue.

472 T. Bye, A. Bruvoll and F.R. Aune (2006): The importance of volatility in inflow in a deregulated hydro-dominated power market.

473 T. Bye, A. Bruvoll and J. Larsson (2006): Capacity utilization in a generlized Malmquist index including environmental factors: A decomposition analysis

474 A. Alstadsæter (2006): The Achilles Heel of the Dual Income Tax. The Norwegian Case

475 R. Aaberge and U. Colombino (2006): Designing Optimal Taxes with a Microeconometric Model of Household Labour Supply

476 I. Aslaksen and A.I. Myhr (2006): “The worth of a wildflower”: Precautionary perspectives on the environmental risk of GMOs

477 T. Fæhn and A. Bruvoll (2006): Richer and cleaner - at others’ expense?

478 K.H. Alfsen and M. Greaker (2006): From natural resources and environmental accounting to construction of indicators for sustainable development

479 T. Ericson (2006): Direct load control of residential water heaters