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An Analysis of a Demand Charge Electricity Grid Tariff in the Residential Sector

Abstract:
This paper analyses the demand response from residential electricity consumers to a demand charge grid tariff. The tariff charges the maximum hourly peak consumption in each of the winter months January, February and December, thus giving incentives to reduce peak consumption. We use hourly electricity consumption data from 443 households, as well as data on their network and power prices, the local temperature, wind speed and hours of daylight. The panel data set is analysed with a fixed effects regression model. The estimates indicate a demand reduction between 0.07 and 0.27 kWh/h in response to the tariff. This is on average a 5 percent reduction, with a maximum reduction of 9 percent in hour 8. The consumers did not receive any information on their continuous consumption or any reminders when the tariff was in effect. It is likely that the consumption reductions would have been even higher with more information to the consumers.

Keywords: Electricity consumption, demand charge tariff, demand response.

JEL classification: D10, Q40

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1. Introduction

The debate on electricity rates is as old as the industry itself as illustrated by a paper from the end of the 19th century (Hopkinson, 1892).[1] The central issues in this debate have always been revenue adequacy, economic efficiency and distributional effects, both between sectors, like residential-services-industry, and between large and small consumers within each sector. With respect to the rate structure, the discussion is about the respective weights on the fixed part, the peak demand related part (demand charge) and the part related to consumption (energy rate). Many countries today have settled for a combined demand charge (or Hopkinson tariff) and energy rate for industry and services, and a pure energy rate for households (Berg and Savvides, 1983). Energy rates for all sectors may either be constant the entire year, or vary through the day or the year, with typically three or four different rate levels.

A number of developments appear to have initiated a renewed interest in rate structures:

- Unbundling of generation, supply and distribution of electricity.
- Increased cost awareness as a result of competition (in generation and supply) and stricter regulation (in distribution).
- Focus on demand flexibility as a requirement for well-functioning power markets.
- Focus on demand reduction as one of the measures to reduce GHG emissions.
- Dramatic decrease in the cost of metering technology.

These developments give motivation for more variable rates with stronger incentives to adapt demand to the varying conditions in the power system. Increased cost awareness should motivate suppliers to reduce peak demand, because their supply contracts normally only cover base load or expected peak load. In cases of extreme peak demand, the deficit must be bought in the day ahead or balancing markets at potentially very high prices. Cost awareness in distribution can make grid companies see peak demand reduction as an alternative to increased grid capacity. The importance of increased demand elasticity for well-functioning power markets has been acknowledged by Schweppe et al. (1988). It has been discussed in Stoft (2002) and in several other papers (e.g. Bompard et al., 2007 and Bruno et al., 2006). The issue of greenhouse gas emissions has generally increased the focus on demand efficiency. Finally, the decrease in the cost of technology has made hourly or

[1] An overview of the early debate is given in Hausman and Neufeld (1984) and a discussion is also found in Byatt (1963).

even shorter metering intervals a realistic option. While the cost of metering until recently was the major obstacle for the use of more dynamic and cost-reflective rates, several large and many small power companies and countries have now introduced Advanced Meter Reading (AMR) or plan to do so. The most notable example is Italy, with 30 million meters (Botte et al., 2006). Also Sweden, Norway and the Netherlands have decided to go for full scale AMR. As a result of these developments, soon there will be no technological or cost barriers against the introduction of more dynamic and cost-reflective rates.

Several alternative rate types that provide peak reducing incentives have been reported in the literature, such as the Time Of Use (TOU) pricing, Real-Time Pricing (RTP) and Critical-Peak Pricing (CPP) (Herter, 2007). With a TOU rate, prices vary across periods within a day or seasonally, but are predetermined and thus static and predictable. With RTP, the consumer price tracks the price in the power market, normally the day-ahead prices, and is therefore changing from hour to hour. CPP rates augment the static nature of a time-invariant or TOU rate structure with a state dependent "critical" price during periods of system stress, typically in a limited number of hours annually. CPP can be seen as a compromise between the static properties of TOU and the variability of RTP, and is increasingly implemented for business (Pacific Gas and Electric Company, 2008 and Southern California Edison, 2008) and residential consumers (Gulf Power, 2008). However, the lack of hourly metering has until recently been a major obstacle for the wide spread use of such tariffs.

Electricity consumers in the household sector in Norway have traditionally only paid for their energy consumption. However, the major share of the grid costs depends only on the maximum demand.[2] This is because most of the costs are directly related to the capacity of the grid, which must be large enough to transport the total demand peak, which occurs only during a couple of hours each year. In Norway this will be during severe colds, due to the high penetration of electrical heating. A cost reflective tariff would therefore include a term related to peak demand. This can reduce grid costs, if consumers reduce their peak demand by flattening their consumption pattern in response to the prices.

In the present research, we look at a demand charge (DC) grid tariff for residential consumers. Demand charges are of a static character, as they generally charge the highest demand peaks at a predetermined rate, and therefore do not convey the correct marginal price signals (Schweppe et al., 1988). However, they give a potentially strong incentive to reduce "needle peaks", i.e. relatively short periods of extreme demand, typically occurring

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[2] After the deregulation of the Norwegian electricity market in 1991, vertically integrated power companies were separated into generating, trading and grid divisions or split up in separate companies. Customers now face a grid tariff from their local grid company, and a power tariff from a power supplier, which can be freely chosen from a number of competing companies.

during periods of extremely low temperatures (in the case of electric heating). The general rationale for a demand charge tariff is that the dominating share of the grid costs are fixed costs that are directly dependent on peak demand. For a grid owner, it is therefore of interest to investigate the response of residential consumers to a DC tariff. DC tariffs are common in the commercial sector, but we are not aware of literature reporting their use in the residential sector.

This paper analyses data from a Norwegian grid company, Istad Nett AS (INAS), that introduced a DC tariff for its residential electricity customers in 2000. We estimate the consumption reductions from the households due to the DC tariff, using a panel data model with fixed effects. Such estimates are useful information for companies that want to anticipate the load reduction potential in their area. All the consumers had hourly automatic meter reading, and we use a panel data set of hourly consumption measurements from 443 households for 2006. We also control for other important factors that influence consumption, using data on the power price (spot prices) that the consumers paid with respect to their power contracts, the number of hours of daylight per day and measurements of hourly average temperatures and wind speeds. We find that the consumers reduce consumption with up to 9 percent as a response to the tariff. However, we suggest that the reductions could have been even higher if consumers had received more information on their continuous consumption levels, and if they had been reminded more frequently of the type of tariff they had, and in which periods they were charged if their consumption became too high.

The remainder of the paper is organized as follows: in Section 2 we describe the demand charge tariff and discuss the price signal given to the consumer. Section 3 describes the data that are analyzed and Section 4 describes the method and models that are used. The results from the regression analysis are evaluated in Section 5, and the last Section concludes.

2. The demand charge tariff

INAS has two grid tariff options for its residential consumers:

- An energy tariff, with a fixed annual charge of 2300 NOK[3] and a variable energy rate of 0.3366 NOK/kWh.
- A demand charge tariff with an annual charge of 765 NOK, a variable energy rate of 0.1789 NOK/kWh and a demand charge of 650 NOK/kW/year.

[3] 1 NOK ≈ 0.104 Euro (December 2008).

The demand charge is settled and billed on a monthly basis in the winter months December, January and February for highest registered hourly kilowatt consumption on working days between 7 am and 4 pm (hour 8 to 16). For the other months in the year, the average of the highest demand in each of the three winter months is billed.

The DC tariff was introduced on a voluntary (opt-in) basis in 2000. The tariff was designed in such a way that if all consumers chose this tariff without changing their demand patterns, revenues for the grid company would be unchanged. The intention however, is that consumers do change their demand patterns by lowering their peak demand, decreasing their costs and at the same time decreasing the costs of the grid company by making it possible to postpone investments. The DC tariff is therefore attractive for consumers that are able to lower their peak demand to obtain a lower electricity bill. Note that in addition to the grid tariff, consumers also pay their power supplier for the power they use. The rate structure and actual price depend on the actual supplier and rate each consumer chooses.

Although the DC tariff has only three parameters, its impact on the consumers' marginal cost is not evident. To illustrate this we describe the tariff below. Denote the highest consumption on working days between 7 am and 4 pm Q_i, the tariff fixed charge c_{grid}, demand charge m and energy rate h respectively, and monthly energy consumption q_i for each month i. Then the monthly grid cost DC_i is given by:

$$DC_i = c_{grid} + hq_i + mQ_i \qquad \text{for } i = 1,2,12$$

and (1)

$$DC_i = c_{grid} + hq_i + m\frac{Q_1 + Q_2 + Q_{12}}{3} \qquad \text{for } i = 3,\ldots,11,$$

where the tariff data are given by c_{grid} = 69.8 NOK/month, h = 0.1789 NOK/kWh, m = 60.4 NOK/kW/month[4].

As we can see, the marginal price effect from a demand increase in January, February or December not only influences the bill the existing month, but also influences the bill for the whole year. The cost of this is m in month i and 1/3 of m in the 9 months March-November, resulting in a marginal demand charge related cost of

$$C_{DC,i} = m + 9 \cdot \frac{1}{3} m = 4m\,, \tag{2}$$

[4] A tax rate equal to 0.115 NOK/kWh and VAT (24 percent) are included.

where the first term is caused by the immediate effects in the actual month for each of the three winter months, and the second by the effect this increase has in the nine other months. This means that if the maximum registered consumption increases by 1 kW in one of the winter months, the total price over the year does not increase by *m* (or 69.8 NOK), but with 4*m*, which equals 241.6 NOK.

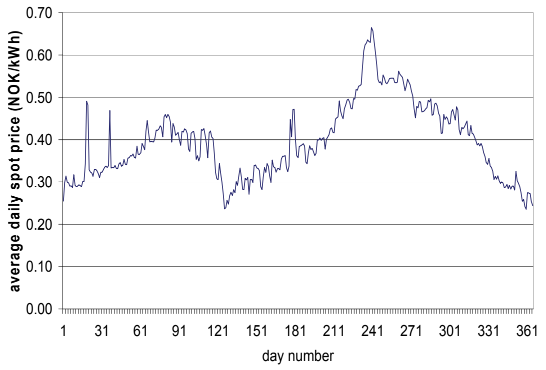
This high cost is not necessarily obvious to a consumer, as the consumer is not confronted immediately on the bill with the whole effect of a consumption that increases the maximum registered peak, because this cost is also paid for in the nine other months. The price signal is thus difficult to assess because it is delayed, blurred and diluted. In addition, it is difficult for a household to know whether consumption in an hour will contribute to a higher maximum registered consumption than is registered from before, because the consumers do not have any information on the level of consumption. So although the DC tariff gives a general indication that peak demand is "expensive", it is for most consumers probably not clear that the marginal cost of an increase in consumption during a few specific hours is as high 241.6 NOK/kWh.

3. Data

We use hourly electricity consumption data from a Norwegian grid company, INAX, that were collected from 1 January 2006 to 31 December 2006. Our sample consists of 443 consumers that have chosen both the network demand charge and a spot price power tariff.[5] In addition to the network demand charge tariff, we use data on the spot price, the temperature, hours of daylight per day and the wind speed. Figures 1 and 2 show the average daily spot prices in 2006, as well as the average hourly spot prices during the day for some selected months.[6] To indicate the temperature and how it relates to consumption, Figure 3 plots the average daily consumption vs. the average daily temperature for the customers that occur in the data set used in the analysis, and Figure 4 shows how average daily temperature and consumption changes during the year. Temperature and wind data were collected from a weather station situated in Molde, the largest town in INAS' supply area.

[5] Approximately 700 or about 5 percent of Istad Nett's customers have chosen the DC grid tariff. We restrict our analysis to the customers that also chose a spot price power tariff, and that were without erroneous data registrations, i.e., 443 customers. By using these customers we can include the power price as an explanatory variable in the regression, because we have data on this price.

[6] The spot price rate the consumers were confronted with refers to the hourly Nord Pool spot price plus 0.025 NOK/kWh.



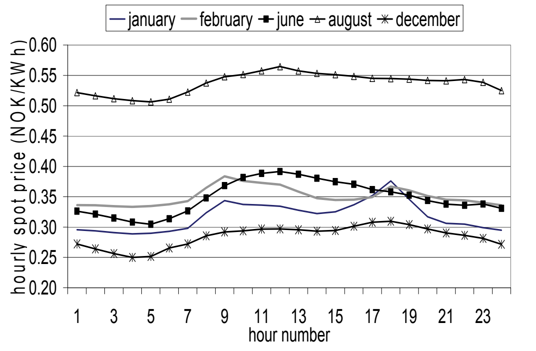
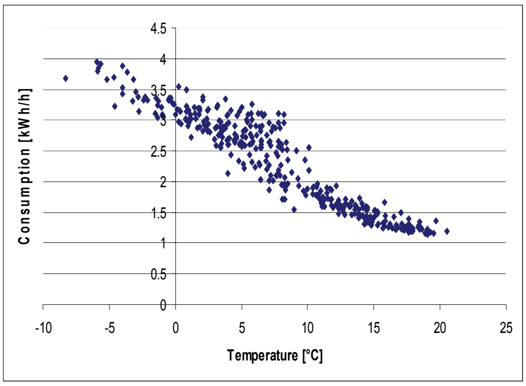


Figure 1. Average daily Nord Pool spot prices in 2006

Figure 2. Average hourly Nord Pool spot prices for selected months in 2006



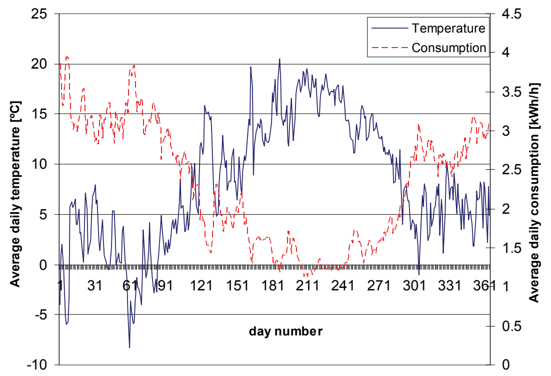


Figure 3. Average daily consumption per household [kWh/h] plotted against the average daily temperature [°C]

Figure 4. Average daily temperature [°C] and average daily consumption [kWh/h]

As we can see from Figures 1 and 2, the spot prices in august were very high. This was caused by an especially dry hydrological situation, and the price movements in 2006 were non-typical. Figures 3 and 4 clearly illustrate the importance of the ambient temperature for demand, showing that demand with an average daily temperature of –7 °C is about three times the demand with a temperature of 20 °C. In Figure 3 we can see a slight flattening at both ends of the temperature scale, which may indicate that when the temperature is very low, consumers tend to switch to alternative heating sources, and when it becomes high, there is no need for room heating and electricity is used only for lighting, food preparation, water heating etc.[7] This effect is further discussed in the next section. A summary of the temperature, wind speed, daylight and spot price data is shown in Table 1.

[7] The use of air conditioning is not common in this area with normally moderate summer temperatures.

Table 1. Summary statistics for consumption, spot price, temperature, wind speed and number of daylight hours

Variable	**Mean**	**Std dev.**	**Min.**	**Max.**
Energy [kWh/h]	2.7	1.6	0	18.0
Spot price [NOK]	0.39	0.09	0.1	1.15
Temperature [°C]	8.2	6.7	–11.8	29.2
Wind speed [m/s]	3.2	2.2	0	18.3
Daylight [hours]	12.7	0	5.7	20.2

The variation in all variables is high, with average hourly consumption from 0 to 18 kWh/h, spot prices from 0.1 NOK/kWh to 1.15 NOK/kWh, hourly temperatures from –12 to nearly 30 degrees Celsius (note that Figures 3 and 4 show average daily temperatures), Average hourly wind speeds up to 18 m/s are registered, and the number of hours of daylight per day varies between 6 hours up to 20 hours (INAS is situated in the middle of Norway which has long days during the summer). High wind speed tends to increase the need for room heating, while more hours of daylight reduce the need for lighting.

4. Method and model

The aim of this analysis is to quantify the effect of the DC tariff on household's electricity consumption. We use a regression model formulated on panel data, that is able to predict hourly electricity consumption, and thus also able to capture the effect of the DC tariff. The panel dataset is analyzed using a fixed effects regression model (see Greene, 2003, and Hsiao, 2003). The specification of the model is as follows:

$$
\begin{aligned}
y_{it} = {} & \sum_{k=8}^{16} \beta_{DC,k} D_{DC,k,t} + \beta_P P_t + \sum_{s \in S} \beta_{T,s} T_t D_{s,t} + \sum_{s \in S} \beta_{T^2,s} T_t^2 D_{s,t} + \\
& \sum_{s \in S} \beta_{TMA,s} TMA_t D_{s,t} + \sum_{s \in S} \beta_{TMA^2,s} TMA^2{}_t D_{s,t} + \sum_{s \in S} \beta_{W,s} W_t D_{s,t} + \\
& \sum_{s \in S} \beta_{WMA,s} WMA_t D_{s,t} + \sum_{m \in M} \beta_{DL,m} DL_t D_{m,t} + \sum_{p \in P} \sum_{wdh=1}^{24} \beta_{wd,p,wdh} D_{wd,p,wdh,t} + \\
& \sum_{s \in S} \sum_{weh=1}^{24} \beta_{we,s,weh} D_{we,s,weh,t} + \sum_{d \in D} \beta_d D_{d,t} + \sum_{m \in M \setminus \{nov\}} \beta_m D_{m,t} + \gamma_i + \varepsilon_{it},
\end{aligned}
\tag{3}
$$

$i = 1,\ldots,443$, $t = 1,\ldots,8760$, $D = \{\text{tue, wed, thu, fri, sat, sun}\}$, $M = \{\text{jan, feb, mar, apr, may, jun, aug, sep, oct, nov, dec}\}$, $S = \{\text{oct-apr, may-sep}\}$, P = {nov-mar, oct+apr, may-sep} where:

y_{it} =hourly electricity consumption [kWh/h] in hour t for household i;

$D_{DC,k,t}$ =dummy variable for the hours in January, February and December when the demand charge is active, i.e., 1 if t is in hour k, 0 otherwise;

P_t =spot price [NOK/kWh] in hour t;

T_t =temperature [°C] in hour t;

T^2_t =temperature, squared [°C]^2 in hour t;

TMA_t =moving average of temperature in the previous 24 hours [°C] in hour t;

TMA^2_t =moving average of temperature in the previous 24 hours, squared [°C]^2 in hour t;

W_t =wind speed [m/s] in hour t;

WMA_t =moving average of wind speed in the previous 24 hours [m/s] in hour t;

DL_t =daylight variable, 1 between sunrise and sunset, $0 < DL_t \leq 1$ in the actual hour of sunrise/sunset (dependent on the share of the hour with light), 0 otherwise;

$D_{s,t}$ =dummy variable, 1 if t is in season s, 0 otherwise;

$D_{wd,p,wdh,t}$ =dummy variable, 1 if t is in period p of the year and in hour *wdh* of a work day, 0 otherwise;

$D_{we,s,weh,t}$ =dummy variable, 1 if t is in season s of the year and in hour *weh* of a weekend or holiday, 0 otherwise;

$D_{d,t}$ =dummy variable, 1 if t is in day d of the week, 0 otherwise;

$D_{m,t}$ =dummy variable, 1 if t is in month m, 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. [8]

We use dummy variables to capture the average drop of consumption for each of the hours of the day when the DC tariff is active. Dummies are chosen for this because the

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

demand charge is constant and either active or non-active, dependent on the time of year and day. Thus, we expect consumers to respond with a non-continuous behaviour. The parameters of particular interest for our analysis are therefore $\beta_{DC8} - \beta_{DC16}$. To isolate the effect of the tariff, we also control for other important factors that may contribute to the customers' electricity consumption pattern, the electricity spot prices, temperature, daylight and wind speed. These factors are discussed below.

First, in addition to the households' network contract, the households also pay a bill according to their power contract. All consumers in our sample have chosen hourly changing spot prices for their power contract. The power price we include in the regression consists of the hourly spot price (see Figures 1 and 2) plus a small constant fee which is the supplier profit. Furthermore, we include temperature, as the electricity consumption is strongly influenced by temperature changes because of the high penetration of electrical heating. Figure 3 shows the average daily consumption plotted against the average daily temperature for the customers in the analysis. Figures 1 and 3 illustrate the importance of the temperature variable: the price in September (day 243-273) is more than 50 percent higher than the price in June (day 151-181). However, with temperatures in June above 15 °C and in September around 10 °C, demand is significantly higher in September. This suggests that even if the high price in September in isolation should give incentives to a lower consumption than in June when the price is lower, the temperature effect outweighs the price effect. We can also see from Figure 3 that the consumption flattens out when the temperatures exceed 15 °C. There is also a flattening tendency for low temperatures. The relationship between temperature and electricity consumption can therefore be described by an s-formed curve, where the changes in electricity consumption flatten out for low and high temperatures. Other studies also suggest this non-linear relation (Ericson, 2006b, Granger et al., 1979, and Ramanathan et al., 1997). These effects are controlled for in the model by two squared terms: one for the winter period and one for the summer period. To obtain the s-curve, the coefficients of these terms should enter the model with opposite signs. It is also likely that there will be a delayed effect on consumption from changes in temperature because of the natural thermal inertia of buildings. We therefore include 24-hour arithmetic moving average terms. Since the effects will be different for the summer and the winter we have two sets of variables, one for summer (May to September) and one for the winter (October to April).

Wind speed may also have an influence on the demand for heating. Increased wind, increases heat loss in the building, and both an hourly and a 24-hour moving average of the wind speed are included in the model. It is reasonable to believe that the wind has a different impact on consumption during the summer months compared with the winter months. We have therefore divided the wind terms into a winter and summer period, where the periods are defined as described before.

Finally, daylight has an influence on the electricity consumption as it decreases the need for electric light and electric heating. The hours with daylight are controlled for by dummy variables. We use one dummy variable for each month. The variable is 1 when the sun is up and 0 otherwise. We assume that all the customers face the same weather conditions, because they are situated in the same area.

Consumers have different needs for electricity at different times of the day due to the consumers' lifestyle, and this dependency is typically repetitive from day to day. In Norway there are huge variations in climate between summer and winter, and this has also an impact on people's lifestyle. As an example, many people go home from their work earlier during the summer. The consumption pattern of electricity and alternative fuel (typically wood-burning stoves) for heating purposes is also different during the year. A survey among about 1/3 of the households in this project revealed that 77 percent use both electricity and an alternative heating system, normally wood. It is well-known in Norway that people use wood in different ways. Some use wood as an additional source during the whole year, some only during the winter and others only during very cold periods as a "peaking" resource. The way the heating technologies are combined varies significantly between consumers, and the aggregate effect of this behaviour results in changes in the typical cyclical patterns. Due to these changes in cyclical patterns over the year, we have distinguished three separate sets of hourly dummy variables for the 24 hours of the working days and one for the 24 hours of the weekends and holidays. The three sets of dummy variables will control for: the winter season (November to March), the summer season (May to September) and the "transition" season, April and October. The transition period is modelled with separate dummies because this season is typically the time when people change their habits with respect to the use of their heating systems. To avoid perfect multicollinearity, the winter work day hour 01-, winter weekend hour 01-, Monday- and November dummy variables are excluded.

Seasonal changes such as humidity, rain, snow and others are controlled for by monthly dummy variables. The effects of type of household, type of heating technology and number of household members are captured by fixed effects.

5. Results

The impact of the DC tariff on the electricity consumption is analyzed using the model given by (3). Table 3 shows some of the results from the fixed effects regression using Stata, the rest is shown in the appendix (Statacorp, 2005).

Table 3. Selected results from the fixed effects regression using (3) [9]

Coeff.	Variables	Explanation	Estimate	t-value	p-value
$\beta_{DC,8}$	DC_8	Dummy, demand charge, hour 8	-0.269	-22.61	0.000
$\beta_{DC,9}$	DC_9	Dummy, demand charge, hour 9	-0.253	-20.22	0.000
$\beta_{DC,10}$	DC_{10}	Dummy, demand charge, hour 10	-0.159	-12.36	0.000
$\beta_{DC,11}$	DC_{11}	Dummy, demand charge, hour 11	-0.106	-8.24	0.000
$\beta_{DC,12}$	DC_{12}	Dummy, demand charge, hour 12	-0.075	-6.04	0.000
$\beta_{DC,13}$	DC_{13}	Dummy, demand charge, hour 13	-0.068	-5.48	0.000
$\beta_{DC,14}$	DC_{14}	Dummy, demand charge, hour 14	-0.066	-5.38	0.000
$\beta_{DC,15}$	DC_{15}	Dummy, demand charge, hour 15	-0.081	-6.79	0.000
$\beta_{DC,16}$	DC_{16}	Dummy, demand charge, hour 16	-0.124	-10.21	0.000
β_P	P	Spot price	-0.048	-3.45	0.001
$\beta_{T,oct\text{-}apr}$	$D_{oct\text{-}apr}\ T$	Temperature, oct-apr	-0.045	-84.18	0.000
$\beta_{T^2,oct\text{-}apr}$	$D_{oct\text{-}apr}\ T^2$	Temperature, oct-apr, squared	0.000	1.92	0.055
$\beta_{TMA,oct\text{-}apr}$	$D_{oct\text{-}apr}\ TMA$	Temperature, moving average, oct-apr	-0.033	-51.22	0.000
$\beta_{TMA^2,oct\text{-}apr}$	$D_{oct\text{-}apr}\ TMA^2$	Temperature, moving average, oct-apr, squared	-0.001	-22.91	0.000
$\beta_{T,may\text{-}sep}$	$D_{may\text{-}sep}\ T$	Temperature, may-sep	-0.029	-23.79	0.000
$\beta_{T^2,may\text{-}sep}$	$D_{may\text{-}sep}\ T^2$	Temperature, may-sep, squared	0.000	8.40	0.000
$\beta_{TMA,may\text{-}sep}$	$D_{may\text{-}sep}\ TMA$	Temperature, moving average, may-sep	-0.071	-37.84	0.000
$\beta_{TMA^2,may\text{-}sep}$	$D_{may\text{-}sep}\ TMA^2$	Temperature, moving average, may-sep, squared	0.001	16.34	0.000
$\beta_{W,oct\text{-}apr}$	$D_{oct\text{-}apr}\ W$	Wind speed, oct-apr	0.020	42.41	0.000
$\beta_{W,may\text{-}sep}$	$D_{may\text{-}sep}\ W$	Wind speed, may-sep	0.009	19.39	0.000
$\beta_{WMA,oct\text{-}apr}$	$D_{oct\text{-}apr}\ WMA$	Wind speed, moving average, oct-apr	0.032	55.14	0.000
$\beta_{WMA,may\text{-}sep}$	$D_{may\text{-}sep}\ WMA$	Wind speed, moving average, may-sep	0.014	16.91	0.000
$\beta_{DL,jan}$	$D_{jan}\ DL$	Daylight: January	-0.114	-14.86	0.000
$\beta_{DL,feb}$	$D_{feb}\ DL$	Daylight: Febary	-0.110	-16.21	0.000
$\beta_{DL,mar}$	$D_{mar}\ DL$	Daylight: March	-0.098	-15.86	0.000
$\beta_{DL,apr}$	$D_{apr}\ DL$	Daylight: April	-0.004	-0.76	0.448
$\beta_{DL,mai}$	$D_{may}\ DL$	Daylight: May	-0.032	-5.69	0.000
$\beta_{DL,jun}$	$D_{jum}\ DL$	Daylight: June	-0.020	-3.22	0.001
$\beta_{DL,jul}$	$D_{jul}\ DL$	Daylight: July	-0.052	-8.74	0.000
$\beta_{DL,aug}$	$D_{aug}\ DL$	Daylight: August	-0.071	-14.02	0.000
$\beta_{DL,sep}$	$D_{sep}\ DL$	Daylight: September	-0.047	-10.07	0.000
$\beta_{DL,okt}$	$D_{oct}\ DL$	Daylight: October	0.003	0.43	0.669
$\beta_{DL,nov}$	$D_{nov}\ DL$	Daylight: November	-0.034	-4.93	0.000
$\beta_{DL,des}$	$D_{dec}\ DL$	Daylight: December	-0.041	-5.47	0.000
	Constant		2.495	311.27	0.000

R-sq: within=	0.3739	F test that all u_i=0:
between=	0.0001	F(169, 3876081)=12947.23
overall=	0.2812	Prob > F= 0.0000

[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 3 shows that most of the explanatory variables enter (3) very significantly. An F-statistic is used to test whether all the coefficients, except the intercept, are jointly zero or not. The hypothesis that they are jointly zero are rejected, indicating that the model has substantial explanatory power.

The main parameters of interest are $\beta_{DC8} - \beta_{DC16}$. These parameters indicate the effect of the demand charge tariff on consumption in each of the hours 8 to 16, on working days in January, February and December. Their estimates are all significant and negative. The demand reduction in the different hours is presented in Figure 5.

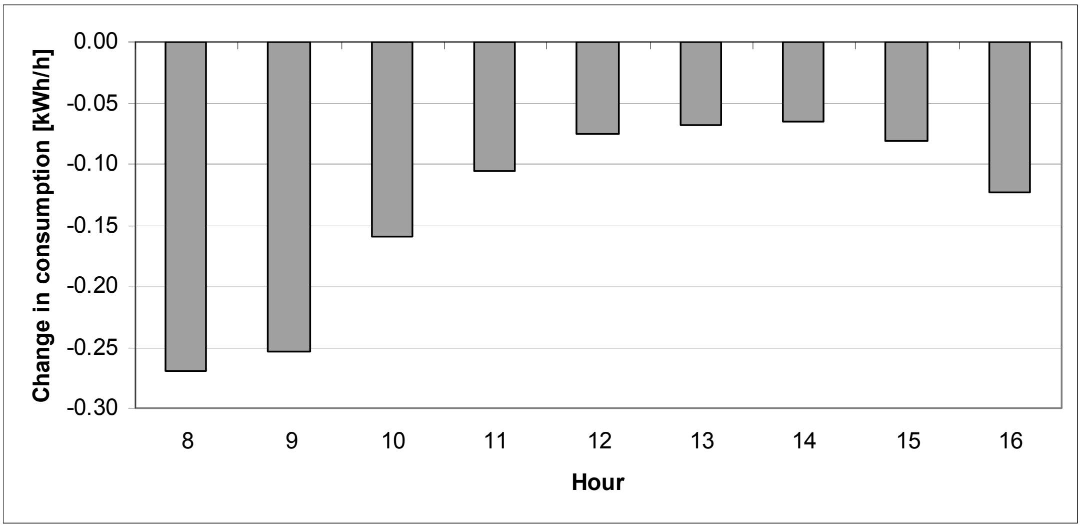


Figure 5. The average change in consumption per customer for each hour within the active window

Figure 5 shows that the average reduction per household varies between 0.07 and 0.27, kWh/h dependent on the hour. The largest load reductions occur in hour 8 and 9 in the morning. The result in hour 8 implies a reduction of 9 percent of the average consumer's demand in that hour. The average reduction of demand due to the DC tariff for all the nine hours in the active window is 5 percent.

We can also see from the figure that the effect of the DC tariff decreases in the middle of the day before it again rises in hour 15 and 16. There may be several explanations for this result. One possible explanation is that most people work during the day and that there is nobody present during the middle of the day, resulting in a smaller potential for demand reduction for these hours. Another possibility is that people are aware that their consumption is higher during the morning and afternoon, resulting in a higher potential saving.

Assuming that 5 percent of the consumers in Istad Nett's area that chose the DC tariff reduce consumption with 9 percent, the grid company may anticipate a total load reduction in their area of up to nearly 0.5 percent.[10] It would probably be possible to achieve a significantly higher response by providing the consumers with more information. The grid company did little effort to inform consumers because they hoped to find out if it was possible to reduce peak demand with low costs. It was hoped that the fact that consumers knew that prices were high during the daytime was sufficient to obtain a large reduction in demand. More and better information beyond what was implicit in the prices could have given stronger reactions. Examples are updated information on demand on the Internet or the actual expected marginal price through a display that could be placed at a central place in the home. With the DC tariff the price signal can be quite strong, as demonstrated in Section 2, but it is difficult for the consumers to know the real marginal price at any instant. If this price signal could be conveyed to the consumer, this would probably result in a much stronger response.

For the other variables we find that the estimated power price coefficients indicate that if the price increases with 1 NOK, the consumption decreases with 0.05 kWh/h. This gives a power price elasticity approximately equal to –0.02.[11] Ericson (2006a), also analysing Norwegian households' price responses, found price elasticities in the interval –0.02 to –0.03 for customers with a TOU grid tariff and standard or spot price power contracts. Our result is thus quite similar.

For the other parameters we can see that all the estimated temperature coefficients are significant. All the linear terms have negative signs. This indicates that consumption will increase if the temperature or the average temperature for the previous 24 hours drops from one hour to the next. Both the squared summer terms enter with positive estimates, resulting in a flattening out of demand at high temperatures, as expected. The squared average temperature for the previous 24 hours in the winter term enters with a negative estimate, which means that the consumption levels out when the average temperature the previous 24 hours drops from one hour to another, which also corresponds to the physical reality. However, the sign of the estimate of the squared term for hourly winter temperatures is counterintuitive, although it is insignificant. The explanation may lie in the use of alternative fuel as discussed with respect to Figure 3. Probably a number of consumers actually use electricity in addition to an alternative fuel only when temperatures are low.

The wind coefficient estimates are all positive and significant which indicates that electricity consumption increases with the wind speed. Furthermore, we see that the estimated effect of the wind is greater in the winter than in the summer, which is reasonable.

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[10] This assumes that also the customers that did choose the DC tariff, but did not choose the spot price tariff and those that had erroneous data (which are not included in the regression), respond similar to our findings. There could be some selections problems related to this, so this attempt to aggregate our findings is only indicative.

[11] We have assumed a linear price response and calculated the price elasticity by using average price (0.81 NOK) and electricity consumption (2.3 kWh/h) values.

Daylight variables enter negatively except in October, when the estimate is positive and significant. This indicates that more daylight will decrease electricity consumption as expected.

6. Conclusions

We have analysed the effect of a demand charge grid tariff on the electricity consumption for 443 Norwegian households. The tariff charges the maximum hourly peak consumption in each of the winter months, thus giving incentives to reduce peak consumption. We use a panel data model with fixed effects that is able to predict hourly electricity consumption, and to quantify the effect of the demand charge tariff. The analysis indicates a consumption reduction between 0.07 and 0.27 kWh/h, with the strongest effect in hour 8, and the weakest effect in the middle of the day. This variation is probably due to the fact that there normally are few or no people at home in many Norwegian households during the daytime. In hour 8, where the effect is strongest, the reduction is approximately 9 percent, while the average reduction for all hours is approximately 5 percent. From all consumers in the grid company's area choosing the DC tariff, this could represent up to nearly a 0.5 percent reduction of total load.

The consumers did not receive any information on the continuous level of consumption they had. Neither were they provided with any reminders that the tariff was in effect and would charge their consumption if it was high enough. Presumably, the impact on the consumers' behaviour could have been much stronger if the equipment had been set up differently, by for instance bringing the price signal and consumption level information to the consumers by a display.

References

Baladi, M. S., Herriges, J. A., Sweeney, T. J., 1998. Residential response to voluntary time-of-use electricity rates. Resource and Energy Economics 20, 225–244.

Berg, S.V., Savvides, A., 1983. The theory of maximum kW demand charges for electricity. Energy Economics 5 (4), 258–266.

Bompard, E., Ma, Y., Napoli, R., Abrate, G., 2007. The Demand Elasticity Impacts on the Strategic Bidding Behavior of the Electricity Producers. IEEE Transactions on Power Systems 22 (1), 188–197.

Botte, B., Cannatelli, V., Rogai, S., 2006. The Telegestore project in ENEL's metering system. 18th International Conference and Exhibition on Electricity Distribution, Turin, Italy. 6-9 June 2005.

Bruno, S., De Benedictis, M., La Scala, M., Wangensteen, I.,2006. Demand elasticity increase for reducing social welfare losses due to transfer capacity restriction: A test case on Italian cross-border imports. Electric Power Systems Research 76 (6-7), 557–566.

Byatt, I.C.R., 1963. The Genesis of the Present Pricing System in Electricity Supply, Oxford Economic Papers 15 (1), 8–18.

Faruqui, A., George, S., 2005. Quantifying Customer Response to Dynamic Pricing. The Electricity Journal 18 (4), 53–63.

Ericson T., 2006a. Time-differentiated pricing and direct load control of residential electricity consumption. Discussion papers no. 461, Statistics Norway, Oslo.

Ericson T., 2006b. Direct load control of residential water heaters. Discussion papers no. 479, Statistics Norway, Oslo.

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

Gulf Power, 2008. http://www.gulfpower.com/residential/specialrate.asp.

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.

Greene H. William, 2003. Econometric Analysis. Prentice Hall.

Hausman, W.J., Neufeld, J.L., 1984. Time-of-Day Pricing in the U.S. Electric Power Industry at the Turn of the Century. The RAND Journal of Economics 15 (1), 116–126.

Herter, K., 2007. Residential implementation of critical-peak pricing of electricity, Energy Policy 35 (4), 2121–2130.

Hopkinson, J., 1892. The Cost of Electric Supply. Transactions of' The Junior Engineering Society, 33–46.

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

Pacific Gas and Electric Company, 2008. http://www.pge.com/mybusiness/energysavingsrebates/demandresponse/cpp.

Ramanathan, R., Engle, R., Granger, C.W.J., Vahid-Araghi, F., Brace, C., 1997. Short-run Forecasts of Electricity Loads and Peaks. International Journal of Forecasting 13, 161–174.

Schweppe, F.C., Caramanis, M.C., Tabors, R.D., Bohn, R.E., 1988. Spot pricing of electricity, Springer.

Stoft, S., 2002. Power System Economics, IEEE Press, Wiley-Interscience.

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

Southern California Edison , 2008. Internet, http://www.sce.com/RebatesandSavings/LargeBusiness/CPP/.

Appendix: The rest of the results from the fixed effects regression

Coeff.	Variables	Explanation	Estimate	t-value	p-value
$\beta_{wd,\ nov\text{-}mar,\ 2}$	$D_{wd,\ nov\text{-}mar,\ 2}$	Dummy, workday, November to March, hour 2	-0.187	-28.25	0.000
$\beta_{wd,\ nov\text{-}mar,\ 3}$	$D_{wd,\ nov\text{-}mar,\ 3}$	Dummy, workday, November to March, hour 3	-0.272	-42.49	0.000
$\beta_{wd,\ nov\text{-}mar,\ 4}$	$D_{wd,\ nov\text{-}mar,\ 4}$	Dummy, workday, November to March, hour 4	-0.273	-42.64	0.000
$\beta_{wd,\ nov\text{-}mar,\ 5}$	$D_{wd,\ nov\text{-}mar,\ 5}$	Dummy, workday, November to March, hour 5	-0.257	-40.59	0.000
$\beta_{wd,\ nov\text{-}mar,\ 6}$	$D_{wd,\ nov\text{-}mar,\ 6}$	Dummy, workday, November to March, hour 6	-0.150	-23.19	0.000
$\beta_{wd,\ nov\text{-}mar,\ 7}$	$D_{wd,\ nov\text{-}mar,\ 7}$	Dummy, workday, November to March, hour 7	0.159	22.99	0.000
$\beta_{wd,\ nov\text{-}mar,\ 8}$	$D_{wd,\ nov\text{-}mar,\ 8}$	Dummy, workday, November to March, hour 8	0.689	65.85	0.000
$\beta_{wd,\ nov\text{-}mar,\ 9}$	$D_{wd,\ nov\text{-}mar,\ 9}$	Dummy, workday, November to March, hour 9	0.588	52.86	0.000
$\beta_{wd,\ nov\text{-}mar,\ 10}$	$D_{wd,\ nov\text{-}mar,\ 10}$	Dummy, workday, November to March, hour 10	0.452	40.55	0.000
$\beta_{wd,\ nov\text{-}mar,\ 11}$	$D_{wd,\ nov\text{-}mar,\ 11}$	Dummy, workday, November to March, hour 11	0.336	30.49	0.000
$\beta_{wd,\ nov\text{-}mar,\ 12}$	$D_{wd,\ nov\text{-}mar,\ 12}$	Dummy, workday, November to March, hour 12	0.234	21.69	0.000
$\beta_{wd,\ nov\text{-}mar,\ 13}$	$D_{wd,\ nov\text{-}mar,\ 13}$	Dummy, workday, November to March, hour 13	0.191	17.93	0.000
$\beta_{wd,\ nov\text{-}mar,\ 14}$	$D_{wd,\ nov\text{-}mar,\ 14}$	Dummy, workday, November to March, hour 14	0.197	18.65	0.000
$\beta_{wd,\ nov\text{-}mar,\ 15}$	$D_{wd,\ nov\text{-}mar,\ 15}$	Dummy, workday, November to March, hour 15	0.288	27.73	0.000
$\beta_{wd,\ nov\text{-}mar,\ 16}$	$D_{wd,\ nov\text{-}mar,\ 16}$	Dummy, workday, November to March, hour 16	0.561	54.72	0.000
$\beta_{wd,\ nov\text{-}mar,\ 17}$	$D_{wd,\ nov\text{-}mar,\ 17}$	Dummy, workday, November to March, hour 17	1.034	124.56	0.000
$\beta_{wd,\ nov\text{-}mar,\ 18}$	$D_{wd,\ nov\text{-}mar,\ 18}$	Dummy, workday, November to March, hour 18	1.158	138.87	0.000
$\beta_{wd,\ nov\text{-}mar,\ 19}$	$D_{wd,\ nov\text{-}mar,\ 19}$	Dummy, workday, November to March, hour 19	1.187	144.79	0.000
$\beta_{wd,\ nov\text{-}mar,\ 20}$	$D_{wd,\ nov\text{-}mar,\ 20}$	Dummy, workday, November to March, hour 20	1.175	146.23	0.000
$\beta_{wd,\ nov\text{-}mar,\ 21}$	$D_{wd,\ nov\text{-}mar,\ 21}$	Dummy, workday, November to March, hour 21	1.142	144.74	0.000
$\beta_{wd,\ nov\text{-}mar,\ 22}$	$D_{wd,\ nov\text{-}mar,\ 22}$	Dummy, workday, November to March, hour 22	1.072	137.59	0.000
$\beta_{wd,\ nov\text{-}mar,\ 23}$	$D_{wd,\ nov\text{-}mar,\ 23}$	Dummy, workday, November to March, hour 23	0.838	112.45	0.000
$\beta_{wd,\ nov\text{-}mar,\ 24}$	$D_{wd,\ nov\text{-}mar,\ 24}$	Dummy, workday, November to March, hour 24	0.429	59.50	0.000
$\beta_{wd,\ oct+apr,\ 1}$	$D_{wd,\ oct+apr,\ 1}$	Dummy, workday, October plus April, hour 1	-0.007	-0.75	0.450
$\beta_{wd,\ oct+apr,\ 2}$	$D_{wd,\ oct+apr,\ 2}$	Dummy, workday, October plus April, hour 2	-0.079	-9.07	0.000
$\beta_{wd,\ oct+apr,\ 3}$	$D_{wd,\ oct+apr,\ 3}$	Dummy, workday, October plus April, hour 3	-0.091	-10.45	0.000
$\beta_{wd,\ oct+apr,\ 4}$	$D_{wd,\ oct+apr,\ 4}$	Dummy, workday, October plus April, hour 4	-0.089	-10.48	0.000
$\beta_{wd,\ oct+apr,\ 5}$	$D_{wd,\ oct+apr,\ 5}$	Dummy, workday, October plus April, hour 5	-0.023	-2.65	0.008
$\beta_{wd,\ oct+apr,\ 6}$	$D_{wd,\ oct+apr,\ 6}$	Dummy, workday, October plus April, hour 6	0.235	25.65	0.000
$\beta_{wd,\ oct+apr,\ 7}$	$D_{wd,\ oct+apr,\ 7}$	Dummy, workday, October plus April, hour 7	0.658	63.56	0.000
$\beta_{wd,\ oct+apr,\ 8}$	$D_{wd,\ oct+apr,\ 8}$	Dummy, workday, October plus April, hour 8	0.581	53.32	0.000
$\beta_{wd,\ oct+apr,\ 9}$	$D_{wd,\ oct+apr,\ 9}$	Dummy, workday, October plus April, hour 9	0.503	46.66	0.000
$\beta_{wd,\ oct+apr,\ 10}$	$D_{wd,\ oct+apr,\ 10}$	Dummy, workday, October plus April, hour 10	0.423	39.42	0.000
$\beta_{wd,\ oct+apr,\ 11}$	$D_{wd,\ oct+apr,\ 11}$	Dummy, workday, October plus April, hour 11	0.352	33.02	0.000
$\beta_{wd,\ oct+apr,\ 12}$	$D_{wd,\ oct+apr,\ 12}$	Dummy, workday, October plus April, hour 12	0.318	30.11	0.000
$\beta_{wd,\ oct+apr,\ 13}$	$D_{wd,\ oct+apr,\ 13}$	Dummy, workday, October plus April, hour 13	0.302	29.06	0.000
$\beta_{wd,\ oct+apr,\ 14}$	$D_{wd,\ oct+apr,\ 14}$	Dummy, workday, October plus April, hour 14	0.363	34.58	0.000
$\beta_{wd,\ oct+apr,\ 15}$	$D_{wd,\ oct+apr,\ 15}$	Dummy, workday, October plus April, hour 15	0.525	48.30	0.000
$\beta_{wd,\ oct+apr,\ 16}$	$D_{wd,\ oct+apr,\ 16}$	Dummy, workday, October plus April, hour 16	0.807	71.92	0.000
$\beta_{wd,\ oct+apr,\ 17}$	$D_{wd,\ oct+apr,\ 17}$	Dummy, workday, October plus April, hour 17	0.920	82.33	0.000
$\beta_{wd,\ oct+apr,\ 18}$	$D_{wd,\ oct+apr,\ 18}$	Dummy, workday, October plus April, hour 18	0.989	87.90	0.000
$\beta_{wd,\ oct+apr,\ 19}$	$D_{wd,\ oct+apr,\ 19}$	Dummy, workday, October plus April, hour 19	1.041	92.68	0.000

Coeff.	Variables	Explanation	Estimate	t-value	p-value
$\beta_{wd,\ oct+apr,\ 20}$	$D_{wd,\ oct+apr,\ 20}$	Dummy, workday, October plus April, hour 20	1.084	96.96	0.000
$\beta_{wd,\ oct+apr,\ 21}$	$D_{wd,\ oct+apr,\ 21}$	Dummy, workday, October plus April, hour 21	1.088	99.48	0.000
$\beta_{wd,\ oct+apr,\ 22}$	$D_{wd,\ oct+apr,\ 22}$	Dummy, workday, October plus April, hour 22	0.930	88.90	0.000
$\beta_{wd,\ oct+apr,\ 23}$	$D_{wd,\ oct+apr,\ 23}$	Dummy, workday, October plus April, hour 23	0.594	59.18	0.000
$\beta_{wd,\ oct+apr,\ 24}$	$D_{wd,\ oct+apr,\ 24}$	Dummy, workday, October plus April, hour 24	0.249	25.95	0.000
$\beta_{wd,\ may\text{-}sep,\ 1}$	$D_{wd,\ may\text{-}sep,\ 1}$	Dummy, workday, may-sep, hour 1	0.108	8.54	0.000
$\beta_{wd,\ may\text{-}sep,\ 2}$	$D_{wd,\ may\text{-}sep,\ 2}$	Dummy, workday, may-sep, hour 2	0.025	1.99	0.046
$\beta_{wd,\ may\text{-}sep,\ 3}$	$D_{wd,\ may\text{-}sep,\ 3}$	Dummy, workday, may-sep, hour 3	-0.007	-0.60	0.547
$\beta_{wd,\ may\text{-}sep,\ 4}$	$D_{wd,\ may\text{-}sep,\ 4}$	Dummy, workday, may-sep, hour 4	0.004	0.32	0.750
$\beta_{wd,\ may\text{-}sep,\ 5}$	$D_{wd,\ may\text{-}sep,\ 5}$	Dummy, workday, may-sep, hour 5	0.046	3.69	0.000
$\beta_{wd,\ may\text{-}sep,\ 6}$	$D_{wd,\ may\text{-}sep,\ 6}$	Dummy, workday, may-sep, hour 6	0.239	19.12	0.000
$\beta_{wd,\ may\text{-}sep,\ 7}$	$D_{wd,\ may\text{-}sep,\ 7}$	Dummy, workday, may-sep, hour 7	0.567	44.75	0.000
$\beta_{wd,\ may\text{-}sep,\ 8}$	$D_{wd,\ may\text{-}sep,\ 8}$	Dummy, workday, may-sep, hour 8	0.521	41.10	0.000
$\beta_{wd,\ may\text{-}sep,\ 9}$	$D_{wd,\ may\text{-}sep,\ 9}$	Dummy, workday, may-sep, hour 9	0.484	38.13	0.000
$\beta_{wd,\ may\text{-}sep,\ 10}$	$D_{wd,\ may\text{-}sep,\ 10}$	Dummy, workday, may-sep, hour 10	0.453	35.51	0.000
$\beta_{wd,\ may\text{-}sep,\ 11}$	$D_{wd,\ may\text{-}sep,\ 11}$	Dummy, workday, may-sep, hour 11	0.421	33.05	0.000
$\beta_{wd,\ may\text{-}sep,\ 12}$	$D_{wd,\ may\text{-}sep,\ 12}$	Dummy, workday, may-sep, hour 12	0.397	31.10	0.000
$\beta_{wd,\ may\text{-}sep,\ 13}$	$D_{wd,\ may\text{-}sep,\ 13}$	Dummy, workday, may-sep, hour 13	0.395	30.93	0.000
$\beta_{wd,\ may\text{-}sep,\ 14}$	$D_{wd,\ may\text{-}sep,\ 14}$	Dummy, workday, may-sep, hour 14	0.438	34.29	0.000
$\beta_{wd,\ may\text{-}sep,\ 15}$	$D_{wd,\ may\text{-}sep,\ 15}$	Dummy, workday, may-sep, hour 15	0.583	45.21	0.000
$\beta_{wd,\ may\text{-}sep,\ 16}$	$D_{wd,\ may\text{-}sep,\ 16}$	Dummy, workday, may-sep, hour 16	0.783	60.52	0.000
$\beta_{wd,\ may\text{-}sep,\ 17}$	$D_{wd,\ may\text{-}sep,\ 17}$	Dummy, workday, may-sep, hour 17	0.830	63.92	0.000
$\beta_{wd,\ may\text{-}sep,\ 18}$	$D_{wd,\ may\text{-}sep,\ 18}$	Dummy, workday, may-sep, hour 18	0.827	63.93	0.000
$\beta_{wd,\ may\text{-}sep,\ 19}$	$D_{wd,\ may\text{-}sep,\ 19}$	Dummy, workday, may-sep, hour 19	0.856	66.36	0.000
$\beta_{wd,\ may\text{-}sep,\ 20}$	$D_{wd,\ may\text{-}sep,\ 20}$	Dummy, workday, may-sep, hour 20	0.913	70.92	0.000
$\beta_{wd,\ may\text{-}sep,\ 21}$	$D_{wd,\ may\text{-}sep,\ 21}$	Dummy, workday, may-sep, hour 21	0.926	72.05	0.000
$\beta_{wd,\ may\text{-}sep,\ 22}$	$D_{wd,\ may\text{-}sep,\ 22}$	Dummy, workday, may-sep, hour 22	0.850	65.83	0.000
$\beta_{wd,\ may\text{-}sep,\ 23}$	$D_{wd,\ may\text{-}sep,\ 23}$	Dummy, workday, may-sep, hour 23	0.633	49.15	0.000
$\beta_{wd,\ may\text{-}sep,\ 24}$	$D_{wd,\ may\text{-}sep,\ 24}$	Dummy, workday, may-sep, hour 24	0.332	25.95	0.000
$\beta_{we,\ oct\text{-}apr,\ 2}$	$D_{we,\ oct\text{-}apr,\ 2}$	Dummy, weekend/holiday, oct-apr, hour 2	-0.225	-32.37	0.000
$\beta_{we,\ oct\text{-}apr,\ 3}$	$D_{we,\ oct\text{-}apr,\ 3}$	Dummy, weekend/holiday, oct-apr, hour 3	-0.330	-48.70	0.000
$\beta_{we,\ oct\text{-}apr,\ 4}$	$D_{we,\ oct\text{-}apr,\ 4}$	Dummy, weekend/holiday, oct-apr, hour 4	-0.365	-54.61	0.000
$\beta_{we,\ oct\text{-}apr,\ 5}$	$D_{we,\ oct\text{-}apr,\ 5}$	Dummy, weekend/holiday, oct-apr, hour 5	-0.361	-54.27	0.000
$\beta_{we,\ oct\text{-}apr,\ 6}$	$D_{we,\ oct\text{-}apr,\ 6}$	Dummy, weekend/holiday, oct-apr, hour 6	-0.312	-46.56	0.000
$\beta_{we,\ oct\text{-}apr,\ 7}$	$D_{we,\ oct\text{-}apr,\ 7}$	Dummy, weekend/holiday, oct-apr, hour 7	-0.218	-31.50	0.000
$\beta_{we,\ oct\text{-}apr,\ 8}$	$D_{we,\ oct\text{-}apr,\ 8}$	Dummy, weekend/holiday, oct-apr, hour 8	-0.085	-11.29	0.000
$\beta_{we,\ oct\text{-}apr,\ 9}$	$D_{we,\ oct\text{-}apr,\ 9}$	Dummy, weekend/holiday, oct-apr, hour 9	0.168	20.27	0.000
$\beta_{we,\ oct\text{-}apr,\ 10}$	$D_{we,\ oct\text{-}apr,\ 10}$	Dummy, weekend/holiday, oct-apr, hour 10	0.445	48.36	0.000
$\beta_{we,\ oct\text{-}apr,\ 11}$	$D_{we,\ oct\text{-}apr,\ 11}$	Dummy, weekend/holiday, oct-apr, hour 11	0.617	65.42	0.000
$\beta_{we,\ oct\text{-}apr,\ 12}$	$D_{we,\ oct\text{-}apr,\ 12}$	Dummy, weekend/holiday, oct-apr, hour 12	0.634	66.71	0.000
$\beta_{we,\ oct\text{-}apr,\ 13}$	$D_{we,\ oct\text{-}apr,\ 13}$	Dummy, weekend/holiday, oct-apr, hour 13	0.603	63.84	0.000
$\beta_{we,\ oct\text{-}apr,\ 14}$	$D_{we,\ oct\text{-}apr,\ 14}$	Dummy, weekend/holiday, oct-apr, hour 14	0.573	60.53	0.000
$\beta_{we,\ oct\text{-}apr,\ 15}$	$D_{we,\ oct\text{-}apr,\ 15}$	Dummy, weekend/holiday, oct-apr, hour 15	0.595	64.67	0.000
$\beta_{we,\ oct\text{-}apr,\ 16}$	$D_{we,\ oct\text{-}apr,\ 16}$	Dummy, weekend/holiday, oct-apr, hour 16	0.668	73.26	0.000

Coeff.	Variables	Explanation	Estimate	t-value	p-value
$\beta_{we,\ oct\text{-}apr,\ 17}$	$D_{we,\ oct\text{-}apr,\ 17}$	Dummy, weekend/holiday, oct-apr, hour 17	0.783	84.69	0.000
$\beta_{we,\ oct\text{-}apr,\ 18}$	$D_{we,\ oct\text{-}apr,\ 18}$	Dummy, weekend/holiday, oct-apr, hour 18	0.860	93.17	0.000
$\beta_{we,\ oct\text{-}apr,\ 19}$	$D_{we,\ oct\text{-}apr,\ 19}$	Dummy, weekend/holiday, oct-apr, hour 19	0.896	97.45	0.000
$\beta_{we,\ oct\text{-}apr,\ 20}$	$D_{we,\ oct\text{-}apr,\ 20}$	Dummy, weekend/holiday, oct-apr, hour 20	0.870	96.94	0.000
$\beta_{we,\ oct\text{-}apr,\ 21}$	$D_{we,\ oct\text{-}apr,\ 21}$	Dummy, weekend/holiday, oct-apr, hour 21	0.779	90.24	0.000
$\beta_{we,\ oct\text{-}apr,\ 22}$	$D_{we,\ oct\text{-}apr,\ 22}$	Dummy, weekend/holiday, oct-apr, hour 22	0.635	77.74	0.000
$\beta_{we,\ oct\text{-}apr,\ 23}$	$D_{we,\ oct\text{-}apr,\ 23}$	Dummy, weekend/holiday, oct-apr, hour 23	0.430	55.08	0.000
$\beta_{we,\ oct\text{-}apr,\ 24}$	$D_{we,\ oct\text{-}apr,\ 24}$	Dummy, weekend/holiday, oct-apr, hour 24	0.150	19.85	0.000
$\beta_{we,\ may\text{-}sep,\ 1}$	$D_{we,\ may\text{-}sep,\ 1}$	Dummy, weekend/holiday, may-sep, hour 1	-0.020	-2.18	0.030
$\beta_{we,\ may\text{-}sep,\ 2}$	$D_{we,\ may\text{-}sep,\ 2}$	Dummy, weekend/holiday, may-sep, hour 2	-0.119	-12.98	0.000
$\beta_{we,\ may\text{-}sep,\ 3}$	$D_{we,\ may\text{-}sep,\ 3}$	Dummy, weekend/holiday, may-sep, hour 3	-0.157	-17.69	0.000
$\beta_{we,\ may\text{-}sep,\ 4}$	$D_{we,\ may\text{-}sep,\ 4}$	Dummy, weekend/holiday, may-sep, hour 4	-0.159	-18.06	0.000
$\beta_{we,\ may\text{-}sep,\ 5}$	$D_{we,\ may\text{-}sep,\ 5}$	Dummy, weekend/holiday, may-sep, hour 5	-0.148	-16.93	0.000
$\beta_{we,\ may\text{-}sep,\ 6}$	$D_{we,\ may\text{-}sep,\ 6}$	Dummy, weekend/holiday, may-sep, hour 6	-0.112	-12.77	0.000
$\beta_{we,\ may\text{-}sep,\ 7}$	$D_{we,\ may\text{-}sep,\ 7}$	Dummy, weekend/holiday, may-sep, hour 7	-0.052	-5.86	0.000
$\beta_{we,\ may\text{-}sep,\ 8}$	$D_{we,\ may\text{-}sep,\ 8}$	Dummy, weekend/holiday, may-sep, hour 8	0.109	11.73	0.000
$\beta_{we,\ may\text{-}sep,\ 9}$	$D_{we,\ may\text{-}sep,\ 9}$	Dummy, weekend/holiday, may-sep, hour 9	0.299	30.51	0.000
$\beta_{we,\ may\text{-}sep,\ 10}$	$D_{we,\ may\text{-}sep,\ 10}$	Dummy, weekend/holiday, may-sep, hour 10	0.425	41.63	0.000
$\beta_{we,\ may\text{-}sep,\ 11}$	$D_{we,\ may\text{-}sep,\ 11}$	Dummy, weekend/holiday, may-sep, hour 11	0.409	39.56	0.000
$\beta_{we,\ may\text{-}sep,\ 12}$	$D_{we,\ may\text{-}sep,\ 12}$	Dummy, weekend/holiday, may-sep, hour 12	0.371	35.84	0.000
$\beta_{we,\ may\text{-}sep,\ 13}$	$D_{we,\ may\text{-}sep,\ 13}$	Dummy, weekend/holiday, may-sep, hour 13	0.337	32.62	0.000
$\beta_{we,\ may\text{-}sep,\ 14}$	$D_{we,\ may\text{-}sep,\ 14}$	Dummy, weekend/holiday, may-sep, hour 14	0.339	32.66	0.000
$\beta_{we,\ may\text{-}sep,\ 15}$	$D_{we,\ may\text{-}sep,\ 15}$	Dummy, weekend/holiday, may-sep, hour 15	0.351	33.56	0.000
$\beta_{we,\ may\text{-}sep,\ 16}$	$D_{we,\ may\text{-}sep,\ 16}$	Dummy, weekend/holiday, may-sep, hour 16	0.399	37.77	0.000
$\beta_{we,\ may\text{-}sep,\ 17}$	$D_{we,\ may\text{-}sep,\ 17}$	Dummy, weekend/holiday, may-sep, hour 17	0.463	43.31	0.000
$\beta_{we,\ may\text{-}sep,\ 18}$	$D_{we,\ may\text{-}sep,\ 18}$	Dummy, weekend/holiday, may-sep, hour 18	0.504	46.96	0.000
$\beta_{we,\ may\text{-}sep,\ 19}$	$D_{we,\ may\text{-}sep,\ 19}$	Dummy, weekend/holiday, may-sep, hour 19	0.527	49.15	0.000
$\beta_{we,\ may\text{-}sep,\ 20}$	$D_{we,\ may\text{-}sep,\ 20}$	Dummy, weekend/holiday, may-sep, hour 20	0.580	54.64	0.000
$\beta_{we,\ may\text{-}sep,\ 21}$	$D_{we,\ may\text{-}sep,\ 21}$	Dummy, weekend/holiday, may-sep, hour 21	0.537	51.83	0.000
$\beta_{we,\ may\text{-}sep,\ 22}$	$D_{we,\ may\text{-}sep,\ 22}$	Dummy, weekend/holiday, may-sep, hour 22	0.445	43.86	0.000
$\beta_{we,\ may\text{-}sep,\ 23}$	$D_{we,\ may\text{-}sep,\ 23}$	Dummy, weekend/holiday, may-sep, hour 23	0.311	31.37	0.000
$\beta_{we,\ may\text{-}sep,\ 24}$	$D_{we,\ may\text{-}sep,\ 24}$	Dummy, weekend/holiday, may-sep, hour 24	0.122	12.57	0.000
β_{tue}	D_{tue}	Dummy, Tuesday	-0.003	-1.58	0.115
β_{wed}	D_{wed}	Dummy, Wednesday	-0.018	-8.68	0.000
β_{thu}	D_{thu}	Dummy, Thursday	-0.023	-10.97	0.000
β_{fri}	D_{fri}	Dummy, Friday	-0.014	-6.50	0.000
B_{sat}	D_{sat}	Dummy, Saturday	0.236	40.27	0.000
β_{sun}	D_{sun}	Dummy, Sunday	0.258	43.94	0.000
β_{dec}	D_{dec}	Dummy, January	0.384	100.71	0.000
β_{jan}	D_{jan}	Dummy, February	0.198	51.26	0.000
β_{feb}	D_{feb}	Dummy, March	0.100	22.00	0.000
β_{mar}	D_{mar}	Dummy, April	-0.135	-25.24	0.000
β_{apr}	D_{apr}	Dummy, May	-0.305	-20.62	0.000
β_{may}	D_{may}	Dummy, June	-0.331	-21.21	0.000

Coeff.	Variables	Explanation	Estimate	t-value	p-value
β_{jul}	D_{jul}	Dummy, July	-0.379	-24.07	0.000
β_{jun}	D_{jun}	Dummy, August	-0.425	-26.96	0.000
β_{aug}	D_{aug}	Dummy, September	-0.382	-24.40	0.000
β_{sep}	D_{sep}	Dummy, October	-0.300	-57.56	0.000
β_{oct}	D_{oct}	Dummy, December	0.160	42.45	0.000