Price elasticity of electricity demand in metropolitan areas – Case of Oslo

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***Abstract*— This paper investigates how the electricity demand in the main Norwegian metropolitan area Oslo responds to variable electricity prices and if it contributes to lower peak demand for electricity. The electricity demand in this area consists mainly of households and office buildings with electricity-based heating. A general linear model was used to estimate the short-term price elasticity from a historical data set. The analysis of different variables that influence demand concluded with that temperature is the most important explanatory variable when developing a model for estimating the short-term price elasticity. Model results show that no price elasticity is existent on the coldest days, and therewith days with highest peak demand for electricity. Significant price elasticity can only be observed in some other periods, with estimates between -0.011 and -0.075. However, this price elasticity does not contribute to lower peak demand and in conclusion, does not affect the need for transmission grid capacity.**

***Index Terms*-- Power demand, Econometrics**

I. Introduction

A. The role of short-term price elasticity in transmission grid development

All Norwegian electricity consumers are equipped with smart meters since the beginning of 2019. One expectation of this smart meter roll-out is that it will lead to larger price elasticity of electricity demand. In the long run, such a development should lead to lower peak demand and in consequence to lower grid investments. Especially the investments in transmission grid capacity towards the main Norwegian metropolitan areas should benefit from this anticipated development since these regions are growing and with it the peak demand for electricity.

However, this opportunity can only be exploited, if the right price elasticity is considered in grid development studies, and therewith in the long-term demand forecasts estimate the future peak demand. It is therefore from great importance to understand and quantify the short-term price elasticity in metropolitan areas. This paper investigates the historic price elasticity of the largest metropolitan region in Norway, namely the Oslo region, to have a first estimate and a lower limit of price elasticity that could be used in long term demand forecast studies.

B. Characteristics of electricity demand in Norwegian metropolitan areas with the example of Oslo

Norway is a highly electrified country and most consumers use electricity for space heating and producing hot water. Households and office buildings stand for the major share of electricity demand in metropolitan areas. In the region of Oslo, these consumer groups are related to 83 % of the electricity demand in 2015 [1]. In consequence, an estimate of the price elasticity in metropolitan areas describes mainly the price elasticity of households and offices.

C. The concept of price elasticity of electricity demand

In general, price elasticity of electricity demand is defined as a percentage change in electricity demand divided by the percentage change in electricity price that leads to the response in the demand. For example, a ratio of -0.1 means that a 1 % increase in electricity price leads to a reduction in the electricity demand with 0.1 %. Price elasticity can be distinguished in short-term and long-term elasticity and correspondents to the duration of time consumers have to respond. Here, we focus on short-term elasticity, which means that consumers, for example, have not the possibility to change their electrical appliances. Figure 1 illustrates how the market equilibrium is affected by changes in electricity price ΔQ_P, which is understood as price elasticity (black), and changes in electricity demand ΔQ_Q (grey). It shows a demand function with constant price elasticity and in this case, the demand function can be expressed with electricity demand Q, electricity price P and price elasticity β as

$$Q = \alpha P^{\beta}. \qquad (1)$$

The challenge of analyzing price elasticity is to be able to distinguish between these two effects. Otherwise, the results will always result in a positive relationship between price and demand, since this effect is far more prevalent. It is therefore important to control for all important variables which influence the electricity demand and can explain shifts in the demand. Comparison of almost equal situations, where only the price differs and all other variables are constant, results in

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an estimate of price elasticity and not only a description of the general correlation between price and demand.

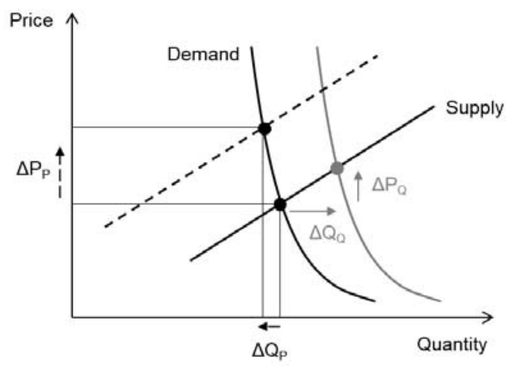

Figure 1. Effect of change in electricity price or electricity demand on the market equilibrium in the electricity market.

D. *Previous studies about price elasticity*

Several price elasticity studies have been performed in Norway and especially studies with households and office buildings are of interest since these consumer groups represent the majority of electricity demand in cities. A study of Statistics Norway [2] investigated the price elasticity of the aggregate Norwegian electricity market with hourly data and concluded that the short-term price elasticity due to variable spot prices is -0.02 in winter and zero in summer. Another Norwegian study [3] calculated the price elasticity on a monthly basis for Norwegian demand excluding electricity-intensive industry and concluded with an elasticity of – 0.05. Another study [4] estimated price elasticity for 24 countries, amongst others Norway. Based on yearly data, they estimated a price elasticity of -0.005 in Norway. Whereas these studies were focused on the price elasticity of the whole country, other studies analyzed also the price elasticity of specific consumer groups. [5] investigated the short-term price elasticity of large customers as office buildings. Based on historical electricity demand data with a monthly resolution, they concluded that no elasticity can be observed. Norwegian households were in focus of [6] and a short-term price elasticity between -0.02 and -0.26 was observed. In contrast to the other studies, which used historical data, the data for this study were obtained with a variable pricing experiment.

Many international studies on price elasticity have been performed and these can be used for comparing the Norwegian values that are affected by the high degree of electrification in Norway with typical international values. A recent meta-analysis [7] reviewed price elasticities from 428 papers and reported an average short-time price elasticity of electricity demand of -0.201. Another study [8] reviewed 175 literature sources and, even they focused on the short-term price elasticity of residential demand, they got similar values with an average of -0.228, and a large spread of the values with a minimum of -0.948 and a maximum of 0.61.

Many international pricing experiments have been performed with residential demand to investigate if peak demand can be reduced by different variable electricity price rates. Three review articles ([9]–[11]) report that residential demand is price sensitive and that a clear relationship exists between the reduction in peak demand and the peak to off-peak price ratio. Peak demand reductions between 5 % and 16 % were achieved in the experiments reviewed by [11] and up to circa 15 % for a peak to off-peak price ratio of 10 in the review of [9], [10]. These values correspond to an elasticity of approximately 0.15 and were obtained in experiments without enabling technologies like smart meters and should be therefore most comparable to the price elasticity in Oslo before the introduction of smart meters.

E. *Aim of the work*

The purpose of this paper is to analyze how the electricity demand in metropolitan areas, mainly consisting of households and services, responds to variable electricity prices and if they, by doing so, contribute to lower peak demand for electricity. It will answer two scientific questions. First, which explanatory variables are important to include when estimating the short-term price elasticity of electricity demand in metropolitan areas with electricity-based heating? Secondly, can a short-term price elasticity be observed in peak hours in historical data of Oslo and does it differ dependent on parameters as for example seasons?

II. DATA DESCRIPTION

The dataset consists of hourly observations for weather, electricity spot prices and aggregated electricity demand of the metropolitan area of Oslo. The data are obtained from the Norwegian Meteorological Institute[1], Nordpool[2], and Statnett. A reduced dataset had to be created to allow for the inclusion of sunshine as a variable, due to missing values for some days. The main features of the dataset are described in Table 1 with the values of reduced data set in parentheses. The hourly observations are transformed into average values for each day, the 6 peak hours and the peak hour of each day.

TABLE I. MAIN CHARACTERISTICS OF THE DATA SET

Time span covered: 2013-01-01 to 2017-03-28
Observations: 1548 (1415)

Average values …	*Min*	*Median*	*Max*
… per day			
Demand (MW)	987 (*)	2005 (1963)	3757 (*)
Electricity price (NOK/MWh)	33 (*)	241 (235)	837 (*)
Temperature (°C)	-13.5 (*)	6.4 (6.6)	25.2 (*)
Wind speed (m/s)	0.6 (*)	2.5 (*)	7.4 (6.9)
Humidity (%)	31 (*)	78 (77)	100 (99)
Sunshine (min/h)	n/a (0)	n/a (13)	n/a (41)
… in the 6 peak hours per day			
Demand (MW)	1024 (*)	2251 (2201)	4103 (*)
Electricity price (NOK/MWh)	58	256 (251)	1961 (*)
Value in the peak hour per day			
Demand (MW)	983	2325 (2292)	4169
Electricity price (NOK/MWh)	61	263 (259)	2076

(*) same values

[1] eKlima.met.no
[2] https://www.nordpoolgroup.com/Market-data1/#/nordic/table

Figure 2 shows that there is a negative correlation between temperature and electricity demand due to electric heating. The positive correlation between demand and electricity price is, as explained in the introduction section C, due to the relationships in the electricity market. It is also a reminder of the modelling challenge since one wants to show that price has a negative effect on the demand, everything else equal.

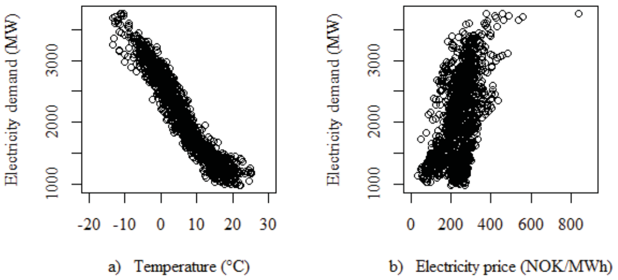

Figure 2. The relation between average daily values of electricity demand and a) temperature and b) electricity price in the data set.

III. Method

A. Modeling approach towards finding price elasticities

A general linear model was used to estimate the short-term price elasticity from the data set. The analysis approach is divided into two steps. First, different model formulations have been tested to understand what explanatory variables must be included in the model since they have a significant effect on the electricity demand. In this step, electricity price was excluded from the model formulation to find important variables besides the electricity price. In the second step, the short-term price elasticity is estimated with the final model which includes the electricity price and is corrected for all other relevant influences on the electricity demand.

The general model formulation for step 1 with all explanatory variables, and the electricity demand as response variable transformed with the natural logarithm is:

$$\ln(E_i) = \beta_0 + \beta_1 T_i + \beta_2 T2_i + \beta_3 T3_i + \beta_4 W_i + \beta_5 R_i + \beta_6 S_i + \beta_7 H_i + \beta_8 V_i + \sum_{j=9}^{15} \beta_j D_i + \sum_{j=16}^{27} \beta_j M_i + \varepsilon_i \qquad (2)$$

where

E_i – Either average electricity demand per day or in the 6 peak hours of that day in MW

T_i – Average temperature per day in °C

$T2_i$ – Average temperature of the last 2 days in °C

$T3_i$ – Average temperature of the last 3 days in °C

W_i – Average wind speed per day in m/s

R_i – Average relative humidity per day in %

S_i – Average hourly minutes with sun per day in min/hour

H_i – Dummy variable for holidays

V_i – Dummy variable for vacations

D_i – Dummy variables for each day of the week

M_i – Dummy variables for each month of the year

β_0 – Intercept

$\beta_{1...27}$ – Coefficients of the explanatory variables

ε_i – Error term

Explanatory variables for both the weather and the activity level in society are included in the model. Weather variables should have a large explanatory value for heating needs and therewith for electricity demand. Additionally, lagged temperature variables are included since the building bodies form a thermal storage and changes in outdoor temperature affect indoor temperature with a time lag. The other group of explanatory variables captures daily activity patterns that lead to distinguished differences in electricity demand, such as day of the week, vacations, holidays and month of the year.

B. Quality assessment of the models

The following two metrics were used to assess the quality of different model formulations:

- Mean absolute relative error in % (ME)
- Maximal absolute relative error in % (MAX)

IV. Results and Discussions

A. What explanatory variables are needed to explain electricity demand?

The model with the demand for the peak hours of each day was used to determine relevant explanatory variables since the goal is to estimate the price elasticity for these hours. However, all model formulations were also run for the daily average demand data and the results regarding the importance of different explanatory variables were equal. Table 2 summarizes the quality metrics for different combinations of explanatory variables.

TABLE II. Quality of different models measured with Absolute mean and Absolute maximal relative error

Explanatory variables included in the models												*Model quality*	
T	***T²***	***T³***	***T2***	***T3***	***W***	***R***	***S***	***H***	***V***	***D***	***M***	***ME***	***MAX***
1			x	x	x	x	x	x	x	x	x	3.7	26.7
2				x	x	x	x	x	x	x	x	3.7	26.8
3			x		x	x	x	x	x	x	x	3.8	27.3
4					x	x	x	x	x	x	x	4.1	27.0
5	x			x	x	x	x	x	x	x	x	3.7	26.6
6	x	x		x	x	x	x	x	x	x	x	3.3	26.3
7	x	x		x		x	x	x	x	x	x	3.3	25.5
8	x	x		x	x		x	x	x	x	x	3.3	26.4
9	x	x		x	x	x		x	x	x	x	3.3	26.0
10	**x**	**x**		**x**				**x**	**x**	**x**	**x**	**3.4**	**26.4**
11	x	x		x	x	x	x		x	x	x	3.5	27.0
12	x	x		x	x	x	x	x		x	x	3.5	25.6
13	x	x		x	x	x	x	x	x		x	6.2	39.9
14	x	x		x				x	x	x		4.5	29.7

The results show clearly that temperature is the main explanatory variable of the weather variables. The model formulations without wind speed W, relative humidity R and sun S perform almost equally good as the model with all these variables included. From a theoretical perspective, these weather variables should affect the heating needs, but it seems like the effect is so minor that they can be excluded from the model. Possible explanations are that most of the buildings in the city area are at least partly protected from the wind, and that humidity and sun have no significant effect on cold days and therewith on the need for heating. Temperature is such an important explanatory variable that the model quality increases both by including a lagged term and polynomials.

Several explanatory variables as holidays, vacations, weekend and month of the year seem to describe the activity level in metropolitan areas quite well. However, it is difficult to interpret what effect the month variable captures since the other explanatory variables should cover all effects climate variations and reduced activity level due to weekends and similar days.

The final model should, on the one hand, explain the electricity demand well, and on the other hand, be as simple as possible. Therefore, model formulation 10 was selected since performs almost equally good as the model with all explanatory variables included but does not need weather variables besides the temperature.

B. Can a significant short-term price elasticity be observed?

Based on the results the final log-log model for estimating the price elasticity is formulated as:

$$\ln(\mathrm{E}_i) = \beta_0 + \beta_1 \ln(P_i) + \beta_2 \mathrm{T}_i + \beta_3 T_i^2 + \beta_4 T_i^3 + \beta_5 \mathrm{T3}_i + \beta_6 \mathrm{H}_i + \beta_7 \mathrm{V}_i + \sum_{j=8}^{14} \beta_j \mathrm{D}_i + \sum_{j=15}^{26} \beta_j \mathrm{M}_i + \varepsilon_i \quad (3)$$

The main variable of interest in this formulation is the coefficient β_1 of the average electricity price P_i in the peak hours, represented by the spot price. This coefficient is a direct estimate of the daily short-term price elasticity in the log-log model. This model was also used for estimating the price elasticity based on average daily values. In both cases, the full data could be used since sunshine is part of the formulation.

The results in Table III show the price elasticity over the complete time span. Price elasticities were calculated both on a daily level and for the six peak hours with the highest demand in a day. In addition, it was also tested if the response in electricity demand is maybe not related to the electricity price on the same day but to the price level of the last week or weeks. It may exist an informatory time-lag so that end-users are first aware of high electricity prices after a given time span. However, the results show clearly that the price elasticity is not significantly different from zero since the p-value is over 0.05 for all cases. A check of the assumptions for the general linear model, that is normally distributed residuals, variance homogeneity and linear effects of continuous explanatory variables, show that these are satisfied, and the model is applicable.

TABLE III. PRICE-ELASTICITIES WITH THE AVERAGE PRICE OF THE DAY AND AVERAGE PRICE OF THE LAST 1, 2, 3 AND 4 WEEKS.

	Estimate for price elasticity	*p-value*
6 peak hours	-0.005	0.272
Daily	-0.004	0.159
1 week lag	0.002	0.541
2 weeks lag	0.002	0.421
3 weeks lag	0.002	0.629
4 weeks lag	0.001	0.756

When using the whole data set for estimating the price elasticity, it gives one average value over the whole time series. However, the price elasticity could be significantly different from zero in specific sub-datasets. Therefore, it was checked if significant price elasticity is present in the six peak hours dependent on different months, weekdays, and intervals of temperature, price level, and electricity demand levels.

1) Temperature, electricity demand and months

Colder temperatures could lead to higher price elasticities since it directly affects the ability of electricity consumers to react to price signals. Electricity is widely used for space heating in the Oslo region and consumers could have a substitute available by switching to other heating sources, namely wood or oil. On the other hand, the price elasticity could be lower on cold days, since all heating sources are needed to keep a comfortable indoor temperature.

The following figures summarize the results for different temperature intervals, for different ranges of electricity demand, and for each month of the year. All figures show the estimates of the price elasticity for the peak hours of each day together with the 95 % confidence interval. The price elasticity is not significant if the confidence interval includes zero. The number of observations in the dataset for each group is shown as bars in the figures.

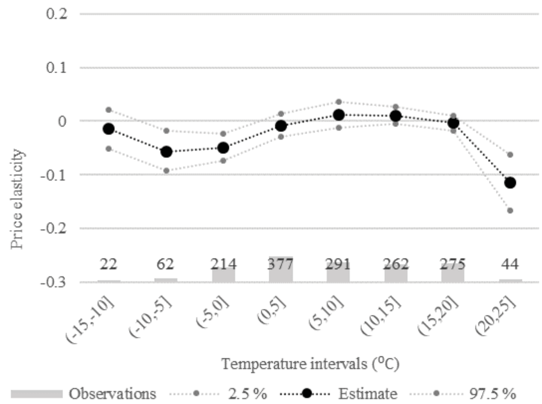

Figure 3. Short-term price elasticity of the six peak hours in each day with a 95 % confidence interval for different temperature intervals.

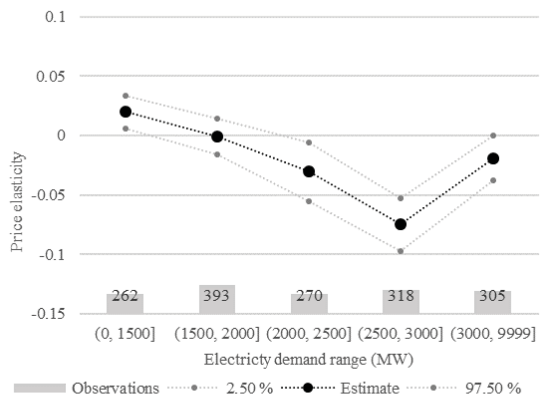

Figure 4. Short-term price elasticity of the six peak hours in each day with a 95 % confidence interval for different electricity demand ranges.

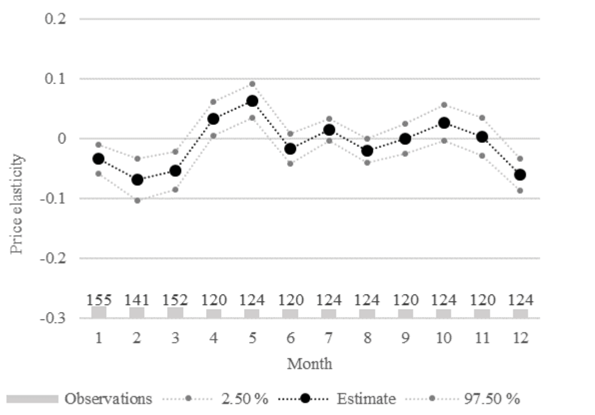

Figure 5. Short-term price elasticity of the six peak hours in each day with a 95 % confidence interval for different months.

No significant price elasticity is existent on the coldest days when the average temperature is below -10 ºC. However, a significant price elasticity between -0.049 and -0.056 can be observed when the daily average temperature is above -10 ºC and below 0 ºC. Similar results appear for different electricity demand levels since these are closely related to the temperature. On the days with the highest peak hours consumption, the price elasticity is not significant, whereas significant estimates of -0.075 are given on days with average electricity demand between 2500 and 3000 MW in the peak hours. In addition, a significant daily price elasticity between -0.011 and -0.033 can be observed in the winter months of December to March.

In addition, the price elasticity for the whole day was estimated, and the results are quite similar. In general, the significant price elasticity estimates are less negative than in the peak hours, but the same periods have a significant elasticity.

These results seem to support both the theory that the electricity consumers in Oslo have a better possibility to react to price signals when there is a high electricity demand due to cold temperatures and that the elasticity is not available on days with very cold weather and therewith very high peak electricity demand. A possible explanation could indeed be that substitution possibilities for heating are limited on very cold days, since both electrical heating and the substitutes may be needed to keep comfortable indoor temperatures.

2) Price levels

A hypothesis could be that the general price level affects the price elasticity. Periods with high prices attract more attention from media and therewith the general population and could, in consequence, lead to a greater response in electrify demand. However, the results do not support this hypothesis. Significant price elasticity can only be observed when the average spot price in the peak hours is between 200 and 300 NOK/MWh. The elasticity estimate is -0.029, but the confidence interval includes almost zero. In all other price ranges including periods with high prices have no price elasticity.

3) Weekdays

Weekdays could have an influence on the price elasticity since the activity level and therewith the electricity demand is higher in the week. In addition, office buildings may have automated control of heating and ventilation that can react to price signals, and office buildings would have a higher electricity demand in their opening hours. The results seem to support this at least partly since significant price elasticity of -0.024 and -0.053 respectively is observed on Tuesday and Wednesday. However, it is difficult to interpret why there is no price elasticity on other weekdays.

V. CONCLUSIONS

The results based on data from the Oslo region show that temperature is by far the most important explanatory variables when estimating the short-term price elasticity of electricity demand in metropolitan areas with electricity-based heating. Other weather variables as wind speed, humidity and sun are not needed to get an adequate model for the electricity demand and therewith for estimating price elasticity. In addition, other explanatory variables which describe the activity level in society are needed.

Another conclusion is that a general price elasticity over the whole data set cannot be observed in the historical data of Oslo. Also, no price elasticity is present on the days with the highest peak consumption, which is the focus of this study. The only significant elasticity estimates for the daily peak hours can be found generally in the winter months, on days with an average temperature between -10 and 0 ºC, and with an average electricity demand between 2500 and 3000 MW in the peak hours. Price elasticities estimates are for these periods between -0.011 and -0.075. These results are in line with previous Norwegian studies, but lower than estimates from experimental pricing studies.

Based on these results, it can be concluded that the electricity demand in metropolitan areas, here the case of Oslo, responds to variable electricity prices in some periods, but do not contribute to lower peak demand for electricity. The end-users in Oslo are not price sensitive on the days with the highest electricity demand. Therefore, an impact on the need for transmission grid capacity cannot be expected. However, the results should still be included in long term demand forecast studies to improve them in general.

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