SARA MARI DU TOIT (9087) & BENGT MAGNE ESPELI (9096)
SUPERVISOR: DORA ZSUZSANNA SIMON

Limiting peaks in the electricity grid.

Experiences from the Norwegian market.

Master thesis, 2023

Master of Science in Business Administration

University of Stavanger Business School

Specialization: Economics

PREFACE

Firstly, we would like to thank Dora Zsuzsanna Simon, our supervisor, for all her help and guidance during this process.

Secondly, we thank Hammad Shaikh for his assistance and open-door policy.

Thirdly, we are very grateful to the Lnett team, who has given us the opportunity and access to incredible resources to conduct this analysis.

Finally, and most importantly, a special thanks to our families who have supported us through 5 years of studying.

ABSTRACT

Electrification leads to a need for more grid capacity, and at the same time, the grid is underutilized. High demand occurs only during short periods. To reduce these high peaks, utility companies have implemented a new network tariff to incentivize consumers to even out their energy demand throughout the day and shift their demand from peak to off-peak hours. Using hourly meter readings, survey-, weather- and spot price data, we analyze the effect of a new tariff on households' peak demand. We investigate the causal relationship between peak-pricing and each household's peak demand using a two-way fixed effects model. We further explore the effects of Time-of-Use tariffs by doing a descriptive analysis. We find that households have reduced their daily peak demand by ~2% after implementing the new network tariff. The households with more occupants, more electric vehicles, or high income are among the groups that have responded the strongest. Our descriptive analysis of Time-of-Use shows a shift from peak- to off-peak hours due to this policy. While the results show a clear response to both the peak-pricing and Time-of-Use components in the tariff, the tariff is insufficient to reach the policy's goal. We suggest shifting more focus to the Time-of-Use component.

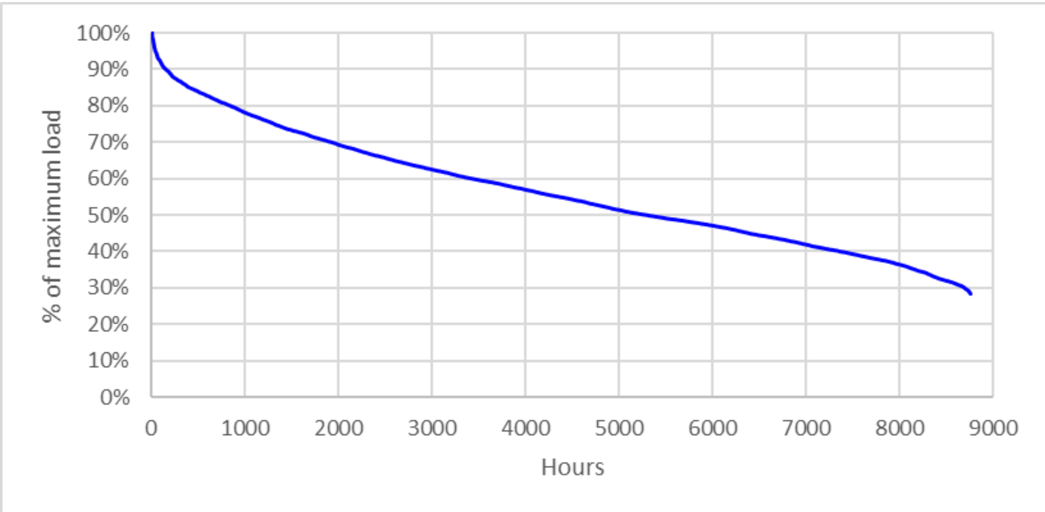
TABLE OF CONTENTS

1 INTRODUCTION

The purpose of the electricity grid is to connect and allow energy to be transported from producers of electrical energy to consumers of electrical energy (from here on referred to as energy). The current global grid has taken 130 years to build, and The International Energy Agency (IEA) estimates that the length of the network will have to increase by 150% to reach net zero by 2050. Average annual global grid investments are estimated to be 800 million USD (2019) from 2030 to 2040 (International Energy Agency, 2021). Increasing the grid's capacity is necessary to reach the climate target. However, utilizing the existing and planned infrastructure is also essential. Due to the nature of the electricity system, the grid must be scaled according to how much electricity is being demanded simultaneously. It is the highest momentarily demand that determines the necessary grid capacity. However, for practical reasons in pricing and policy decisions, peak demand is measured as the sum of energy consumed over one hour.

Data from Lnett AS, a utility provider in southern Norway, shows that the electricity load exceeded 80% of the maximum load for 830 hours in 2022. 830 hours a year translates to 9,5% of the time. The area above the solid blue line and below 100% is non-utilized yearly capacity[1]. See Figure 1.

Figure 1: Load-Duration curve



Notes: Data retrieved from Lnett AS (Lnett AS, 2023).

[1] Assuming that aggregated peak demand equals the full grid capacity. According to Lnett AS this is a fair assumption since grid load is close to the maximum capacity in brief periods during the winter season.

Though demand peaks occur in short periods, limiting the peaks is essential to reduce the necessary grid investment. It has been argued that consumers should pay according to the costs they impose onto the grids by making network tariffs more cost-reflective to deal with challenges related to grid capacity (Passey et al., 2017).

Since the consumption of energy in households is generally based on habits, consumers need to understand that their behavior is relevant. Network tariffs are used to incentivize consumers to change their consumption patterns (Norges Vassdrags- og Energidirektoratet, 2022a). The term *demand-charge* is often used when describing tariffs aiming to limit peak demand. Peak demand is the energy demanded over a short period (usually one hour). A consumer will have to pay a higher fee if the energy needed is consumed over a shorter period and a lower fee if consumption is evened out over a more extended period. We are experiencing that the term *demand-charge* is misleading, and we will use the term *peak-pricing* when referring to tariffs aimed at compressing peak consumption. *Peak-pricing* makes it clear that the peaks drive the relevant price and not the total energy demanded over a billing period. Tariffs aiming at the total energy demanded, independent of the length of the period in which the energy is being consumed, are referred to as energy pricing. The consumer will have to pay according to the energy used, independent of if it is used over one hour or smoothed over a full billing period. Energy pricing is not the subject of this paper. A third common tariff type is Time-of-Use tariffs (ToU), where energy pricing varies between peak and off-peak hours (Bartusch et al., 2011). It is common for tariffs to combine peak-, energy, and ToU pricing components.

Peak-pricing has been used in the commercial and industrial sectors for years but has not been widely utilized in the residential sector due to meter reading challenges (Hledik, 2014). However, peak pricing and ToU have become more popular in recent years, especially in the Nordic countries (Lanot & Vesterberg, 2021). The installation of smart meters in homes has enabled consumers to use electrical energy more efficiently and allows utility companies to offer their consumers better services (Norges Vassdrags- og Energidirektoratet, 2022b).

Peak-pricing and ToU tariffs are used as tools to increase grid utilization by incentivizing consumers to compress peak demand and shift more demand to periods where the grid load is lower (off-peak hours). This has led to the research question in this paper: *How do network tariffs affect households' demand patterns for electrical energy?*

To answer this question, we explore households' behavior change after the introduction of a new network tariff in Norway, consisting of peak-pricing and ToU components. We use meter readings, survey-, weather- and spot price data to investigate changes in *peak demand* due to the network tariff. Our main outcome variable is each household's *peak demand.*

Our analysis consists of four parts. (1) We use a conventional multiple regression to explore the relationship between the households' peak demand and a list of covariates in our dataset. This allows us to interpret how the different covariates are associated with peak demand. (2) We analyze the causal relationship between peak demand and the new network tariff using a canonical 2x2 difference in differences (DD) and a two-way fixed effect (TWFE). In order to use these estimation methods, we need to construct a treatment- and a control group. Faced with the challenge that the new network tariff was introduced to all consumers at the same time, we categorized households based on their peak demands leading up to the policy implementation as well as their knowledge about the new tariff. We inspect the trends between the treatment- and the control group before the new network tariff was implemented to confirm that the common trends assumption holds. We also test for anticipatory effects by studying whether the households' peak demand changes in the lead-up to the policy date. (3) We conduct a heterogeneity analysis using the same TWFE model. We do this to explore how the new network tariff has impacted a household's peak demand based on various household characteristics and socio-economic attributes obtained from the survey. (4) By using a descriptive analysis, we show how the new network tariff has impacted when households have their peak demand during the day.

Many studies we have reviewed find electricity consumers to be price elastic (Deryugina et al., 2020; Taylor & Schwarz, 1990; Yan et al., 2018). Some studies found that peak-pricing leads to an increase in both the own-price elasticity of peak demand and an increase in the cross-price elasticity of peak demand with respect to pricing in peak hours versus off-peak hours. Off-peak energy is also found to be a substitute for peak energy (Filippini, 1995; Taylor & Schwarz, 1990). However, demand is more elastic in the long run than in the short run (Deryugina et al., 2020). Residential consumers also take longer to adjust to price changes since electricity consumption is based on habits. (Buckley & Llerena, 2022; Deryugina et al., 2020; Taylor & Schwarz, 1990).

The literature on electricity and consumption is vast. However, the share of the literature focusing on how peak- and ToU pricing affects demand is not extensive. Most studies investigating demand response to peak- and time-of-use pricing have found that consumers are responsive (Bartusch et al., 2011; Bartusch & Alvehag, 2014; Yan et al., 2018). In Sweden, where distribution is free during off-peak hours, a study has found little to no changes in peak demand due to a combined peak-pricing and ToU tariff in the short run. In the long run, the effect is a reduction of peaks by ~5% and ~10-12% during peak and off-peak hours, respectively (Bartusch et al., 2011). Households respond to these price signals by shifting their consumption from peak to off-peak hours (Bartusch & Alvehag, 2014). Stokke et al. found a reduction of 5% when investigating a voluntary power pricing tariff (2010). Öhrlund et al. found similar results of 7.4% reduction per household during their 2-year study period (2019). A more recent study by Lanot and Vesterberg found that demand in Swedish households is inelastic, and that the implementation of peak-pricing is not likely to lead to significant changes in peak demand (2021). In the US, peak-pricing varies across the country (Proudlove, 2018). Hledik explored previous experiences of residential power pricing in the US (2014). He noted that only a few utility companies offer peak-pricing tariffs for households, but interest in these tariffs is growing (Hledik, 2014).

A meta-study done by Hayn et al. looks at how different household characteristics impact energy demand. They found the main socio-demographic attributes contributing to the increase in energy demand to be household size, net income, and employment status. The age of the reference person is ambiguous, while education has little or no impact on the energy demanded (Hayn et al., 2014).

Our research contributes to the literature in three ways. (1) We analyze the causal relationship between the peak-pricing and households' peak demand. According to Öhrlund et al., they are the only study performing a causal analysis of a mandatory peak-price's effect on demand. In their analysis, they create the outcome variable by aggregating hourly consumption to a daily level and dividing it by 24 to get an hourly average (Öhrlund et al., 2019). By creating the outcome variable this way, they do not capture the effect of consumers moving consumption to other periods within the same day. This effect is an essential part of network tariffs, which we capture in our analysis. (2) While many studies have small sample sizes (Bartusch et al., 2011; Bartusch & Alvehag, 2014; Stokke et al., 2010), our larger sample size enables us to construct well-sized treatment- and control groups. The large sample size also allows us to analyze heterogeneity in subgroups based on household- and socio-economic characteristics obtained from our survey. (3) We analyze the effects of a new network tariff implemented in Norway on July 1, 2022. We concluded our study twelve months after the new policy was implemented, and to our knowledge, we are the first to do so.

The rest of this paper is structured as follows: Section 2 provides a brief background on tariff structures in Norway and Lnett AS, a utility provider for the southern part of Rogaland, Norway. The data is described in section 3. Section 4 presents the models, estimations, and results, and we conclude in Section 5.

2 THE NORWEGIAN ELECTRICITY MARKET AND LNETT

Over the past few decades, there have been two major changes in the Norwegian network tariff structure. Since the 1930s, Norwegian consumers have been charged a tariff referred to as H3. The H3 tariff was based on consumers paying a lower price per kWh under a subscribed level and a higher price per kWh when consumption exceeded this prescribed level. This tariff structure was put into place to limit peak loads. In the 1970s, consumers gradually transitioned to the H4 network tariff. Under the H4 tariff, a much simpler model, consumers paid a fixed monthly price and a fixed price per kWh demanded. The H4 tariff, however, did not incentivize consumers to limit their peaks (Westskog & Winther, 2014).

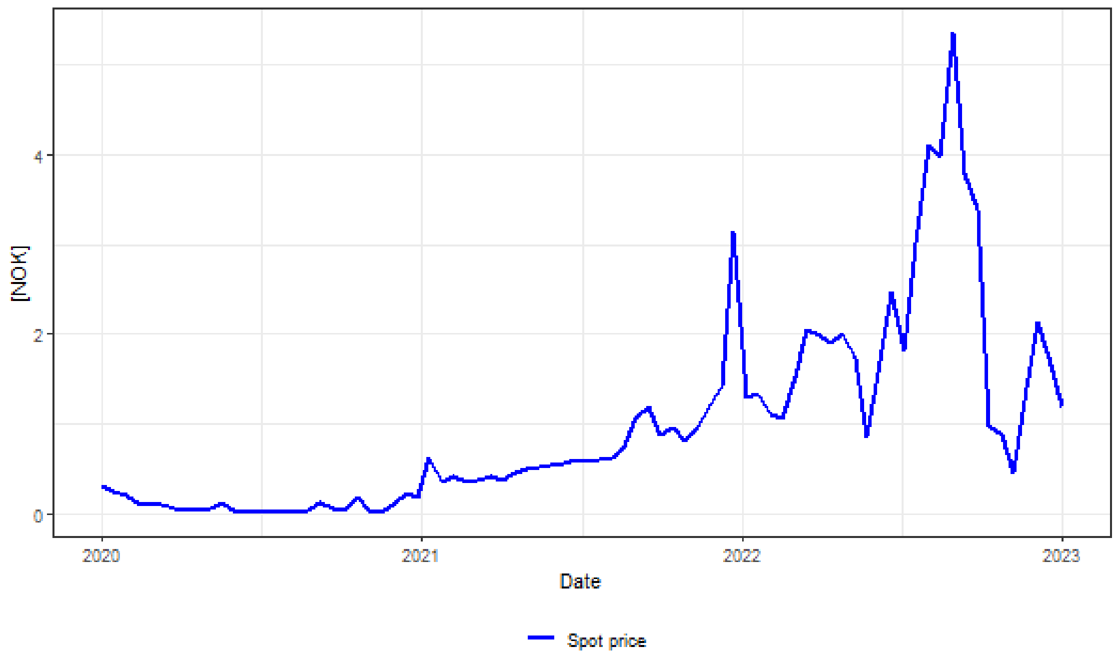
On July 1, 2022, a new network tariff was introduced in Norway. The government instructed all utility companies to implement a new network tariff model for their residential consumers. This new tariff aimed to "facilitate the most effective use of the transmission network as well as a fair distribution of costs between their consumers" (Olje- og energidepartementet, 2022)[2]. The utility providers are free to choose how this tariff should be structured. However, since the utility providers are strictly regulated in Norway, the general principle behind the design of these network tariffs is that they must be in line with their income cap according to the tariff structure regulations (Norges Vassdrags- og Energidirektoratet, 2021). Lnett AS is a utility provider for the southern part of Rogaland, a municipality in Norway, and has approximately 135 000 consumers affected by the new network tariff. The new tariff was implemented for all consumers with an annual consumption of less than 100 000kWh and consists of two elements, much like the previous H3 tariff. First is a peak-pricing element based on the averages of a household's three highest demand peaks within a month (from here on referred to as monthly

[2] Own translation.

peak average)[3]. These monthly peak averages determine to which price category or tier the household belongs. Tier 1 includes households with monthly peak averages of 0kWh/h to 5kWh/h. Tiers 2 and 3 are monthly peak averages ranging from 5kWh/h to 10kWh/h and 10kWh/h to 15kWh/h, respectively (Lnett AS, 2021). Second, the new network tariff also includes a ToU element. What is new with the demand element is that energy demand is more expensive during peak hours (06:00 – 22:00 weekdays) than during off-peak hours. This tariff was implemented to reduce high peaks and spread demand more evenly throughout the day. Doing so will reduce grid congestion and minimize future investments in grid expansion (Lnett AS, 2021).

The new network tariff was not the only major event in the Norwegian electricity market during 2022. The country also faced historically high spot prices, as shown in Figure 2. Facing increasing spot prices, the government of Norway implemented an energy support program to subsidize households' electricity costs by refunding households a percentage of the average cost of electricity (Olje- og energidepartementet, 2023).

Figure 2: Spot price from 2020 to 2023



Notes: Data retrieved from Nordpool Group (Nordpool Group, 2023). The plot shows spot prices for the NO2 area in Norway. It is smoothed using LOESS smoothing. The spot price peaked on 2022.08.29. at 8.44 NOK

[3] The maximum peaks are taken from different days. No maximum peaks should be from the same day.

3 DATA

We have created the dataset used for this analysis, and it can be classified as “non-standard” data as it has not been used by other researchers. The data is observational and consists of a combination of (1) consumption- (2) survey- (3) spot prices- and 4) weather data.

In cooperation with Lnett AS, all private customers (no industrial consumers) classified as primary residences (no holiday homes), without any local power generation (e.g., solar panels), which have been customers throughout the entire year of 2022, were identified (a total of 116 000 households). All households have power meters that automatically record and report hourly consumption.

A survey, designed and created by us, was sent out to the 116 000 households. The survey was short and took about 3 minutes for the respondent to complete. It was self-completable and consisted of factual and demographic questions to which the answers were readily available to the respondent and, thereby, likely to be accurate. The survey started with a question asking the participants whether they had either heard about the new network tariff, knew the details of it, or had never heard about it. It continued with questions relating to household characteristics such as the size and age of the house, how many people live in the house, and the number of electric vehicles (EVs). The survey also included questions related to socio-economic attributes such as income- and education levels as well as the age of the reference person. 3907 respondents consented to their meter readings being extracted and matched with their survey answers (Lnett AS, 2023). 3609 respondents answered at least one question. See Appendix 7.2 for a breakdown of questions and answer distributions. The raw dataset of hourly meter readings and survey answers consists of 92 440 514 data points.

We removed all participants who had changed their primary residence during our analysis period (2020.01.01 – 2022.12.31) since a new living situation can impact energy consumption[4]. This reduced the number of households in the dataset to 2831. Using this dataset, we then identified each household’s daily hour where their demand was at its highest from January 1, 2020, to December 31, 2022. The demand in this hour, referred to as peak-demand, serves as our main outcome variable. By doing so, we converted our dataset from hourly- to daily observations.

[4] Households that have moved during this period reduced the sample size by 778 households.

The dataset was cleaned by removing all observations where the peak demand was negative and all observations where peak demand was outside average peak demand +/- two times the standard deviation. A wider range will include observations where peak demand is implausibly high.

We collected daily average wind and temperature data from the Norwegian Centre for Climate Services (Norsk klima service senter, 2023)[5]. We also collected hourly spot prices from the NO2 price area, as shown in Figure 2 (Nordpool Group, 2023)[6]. See Table 1 for summary statistics. We combined and matched the weather- and spot price data to the dataset containing the daily peak demand and survey answers. This final dataset includes 2 392 422 points, consisting of daily observations from January 1, 2020, to December 31, 2022, for the remaining 2831 households and their survey answers.

Table 1: Summary statistics

	Peak demand [kWh]	**Spot prices [NOK/100]**	**Air temperature (daily average) [°C]**	**Wind speed (daily average) [m/s]**
Min.	0.029	-1.97	-9.8	1.0
1st qu.	2.653	12.54	5.3	3.1
Median	3.941	57.53	8.8	4.7
Mean	4.217	98.48	9.0	5.0
3rd qu.	5.488	143.44	13.4	6.5
Max.	19.984	844.00	23.7	15.0

Notes: Summary of observations from January 1, 2020, to December 31, 2022.

[5] The weather station used: #SN44560.
[6] NO2 covers Lnett's distribution area.

4 EFFECTS OF POWER PRICING ON PEAK CONSUMPTION

Using conventional multiple regression analysis, we explore the relationship between our main outcome variable, peak demand, and a list of covariates using the model described by equation (1).

$$\begin{aligned} Peak\ demand_{it} &= \beta_0 + \beta_1 Temperature_t + \beta_2 Wind_t + \beta_3 Spot\ price_{it} \\ &\quad + \beta_4 Age_i + X_i + \nu_{it} \end{aligned} \tag{1}$$

where i indexes households (i = 2831) and t indexes days[7]. In addition to the variables temperature, wind, and spot prices, the model contains a vector of other covariates, denoted X_i. The covariates consist of household-specific characteristics such as house size, number of occupants, age of reference person, building year of the house, number of electric vehicles owned, and socio-economic characteristics such as income and education levels. These variables have all been treated as categorical (bar for the age of the reference person). The outcome reflects the relationship between the covariates and the daily peak demand. An excerpt of the results, including spot price, average wind, and temperature, is shown in Table 1. We have included the detailed results in Appendix 7.1.

[7] Spot price is subscripted with both i and t since it has variation across units within the same day. Each household's hour of peak demand occurs in different hours of the day, and our dataset contain spot price information on an hourly level.

Table 1: Results from model 1.

	Peak demand [kWh]
Temperature	-0.037
	(0.00004)***
Wind	0.012
	(0.0001)***
Spot price	-0.0005
	(0.00000)***
Constant	0.801
	(0.278)***
Control Variables	YES
Observations	2,802,918
R2	0.237
Adjusted R2	0.237
Standard errors	Robust
Notes	**p<0.1; **p<0.05; ***p<0.01*

The covariates mostly enter with the expected signs. An increase in temperature leads to a decrease in peak demand, while an increase in wind leads to an increase. Spot prices show to have little effect on peak demand. A higher spot price will limit the demand in the respective hour, possibly leading to a lower peak. On the other hand, a lower price in other hours will lead to the opposite shift and possibly incentivize higher demand peaks.

The household- and socio-economic attributes associated with higher peak demand are high income levels, an increase in the number of occupants in the house, the size of the living space, and an increase in the number of EVs owned. Attributes associated with a lower peak demand are houses built from 2000 and onwards, the age of the reference person, and higher education levels.

The remainder of this section is structured as follows: We use a difference-in-differences analysis to study the causal relationship between the new network tariff and peak demand at both aggregate- and consumer group levels. We then do a descriptive analysis to study the Time-of-Use effect of the new tariff.

The analyses are done using R (R-Core-Team, 2023), with the following packages: Tidyverse, Stargazer, dplyr, ggplot2, rdd, plm, and openxlsx (Croissant & Millo, 2008; Dimmery, 2016; Hlavac, 2022; Schauberger et al., 2023; Wickham, 2016; Wickham, Averick, et al., 2023;

Wickham, François, et al., 2023). Code is written using R-Studio and Microsoft Visual Code (Microsoft, 2023; RStudio Team, 2022).

4.1 POLICY EFFECT ON CHANGES IN POWER DEMAND

To analyze the causal relationship between the network tariff and the daily peak demand, we use the canonical 2x2 difference-in-differences (DD) model (2) and a two-way fixed effects (TWFE) model (3). In both models *i* indexes households, and *t* indexes days.

$$
\begin{aligned}
log(Peak\ demand_{it}) = \beta_0 + \beta_1 treated + \beta_2 postPolicy \\
+\ \beta_3 treated \times postPolicy + u_{it}
\end{aligned}
\tag{2}
$$

$$
\begin{aligned}
log(Peak\ demand_{it}) = \beta_0 + \beta_1 Treated \times Postpolicy \\
+ \beta_2 Spot\ price_{it} + \ \alpha_i + \delta_t + u_{it}
\end{aligned}
\tag{3}
$$

Due to how we constructed our outcome variable by extracting the one hour with maximum consumption from each day for each household (not the same hour for every household), there are variations in the spot price across units within the same day and across days for the same unit. We have added spot price as a time-varying confounder to the TWFE model (3). Since we are interested in studying the changes in the outcome variable, we have opted for a log-linear model.

Our main challenge related to describing the causal relationship between the new network tariff and the peak demand is that the policy was introduced to all consumers in our dataset at the same time. To construct control- and treatment groups, we asked the participants to rate their own knowledge about the new network tariff. We gave the respondents three options. (1) Have not heard about the new network tariff, (2) have heard about it but do not know the details, (3) know the details. The information on the participants' knowledge about the policy enables us to create two specifications of different control- and treatment groups. The participants who have heard about the tariff but do not know the details (option 2) have been dropped. We dropped this group because it is uncertain whether they have had enough knowledge about the tariff to react to it[8].

[8] People who have heard about the new network tariff but do not know the details were dropped, reducing the sample size by 974 households.

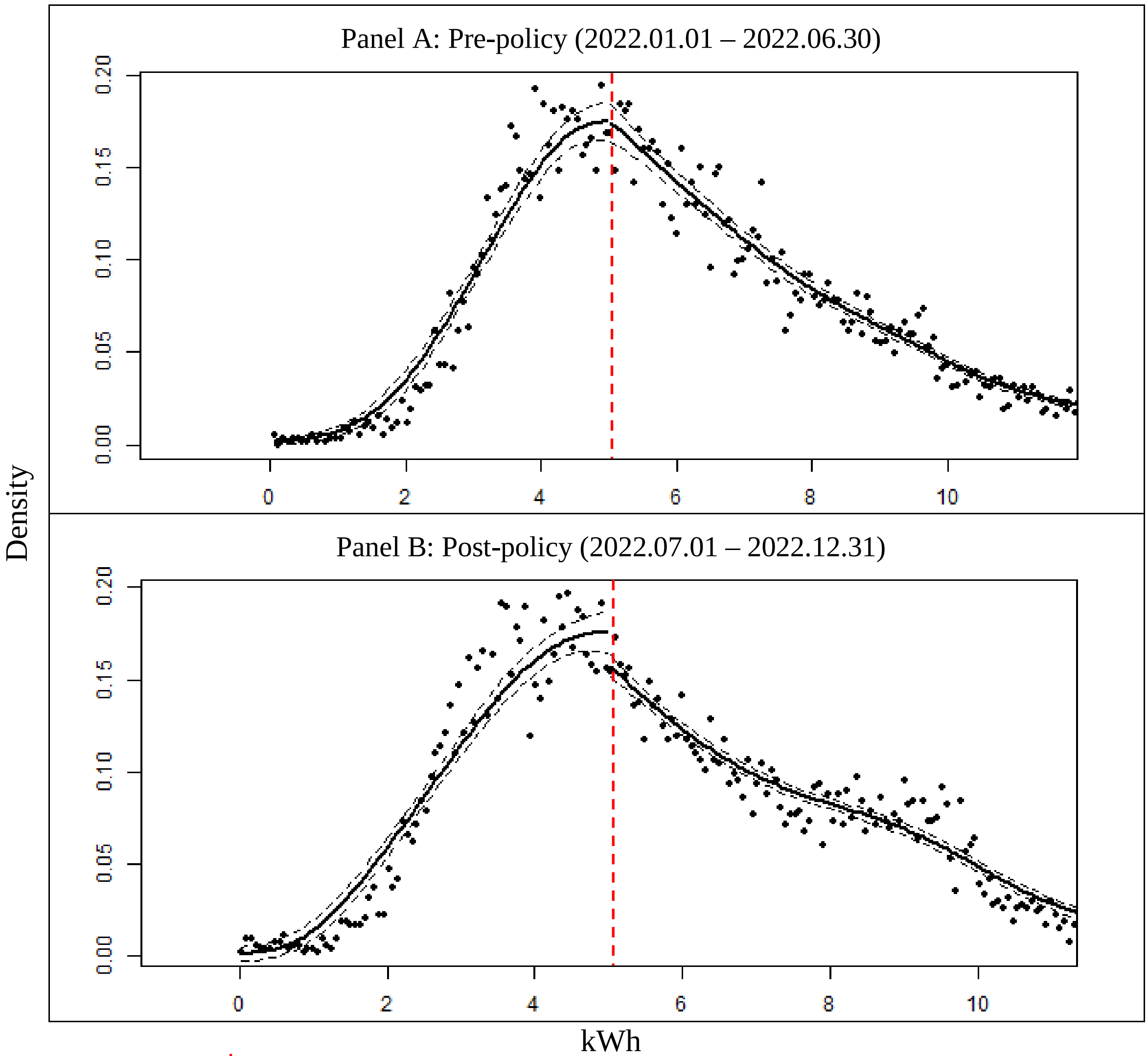
In the first specification, two criteria must be met for a household to be in the treatment group. (1) Know the details of the new network tariff. We assume that a consumer needs knowledge about the new tariff to respond to it. (2) Have had at least one month in the pre-policy period corresponding to the new network tariff's tier 2 or above. If the consumer has never had a peak above tier 1, the consumer has no incentive to limit peaks since prices did not change for tier 1. The treatment group consists of 1402 households. The control group consists of the 455 households who have not heard about the new tariff or never had a monthly average corresponding to tier 2 and above.

In the second specification, we only study the consumers who claim to know the details of the new network tariff. In this specification, the treatment group consists of the same 1402 households as in the first specification. The 219 households who know the details but have not had a month before July 1, 2022, corresponding to tier 2 or above, make up the control group.

To get an initial overview of the possible impact of the new network tariff, we use the McCrary's density test to see if there are discontinuities in the distribution of the monthly three peaks average. The cutoff was set to 5kWh/h, which is between tier 1 and tier 2 in the new tariff. The test was run only on the treatment group, as the control group by design only has monthly peak averages below 5kWh/h. We ran a test for the six months before the network tariff was introduced (2022.01.01 – 2022.06.30) and for the six months after the introduction of the new tariff (2022.07.01 – 2022.12.31). P-values are respectively 0.986 and 0.0513[9]. The distribution is plotted in Figure 2. The McCrary's density test indicates that the density is continuous over the 5kWh/h cutoff before the policy was introduced (Panel A) and discontinuous after the introduction (Panel B).

[9] H0: There is no manipulation or density discontinuity at the threshold. HA: There is manipulation or density discontinuity at the threshold.

Figure 2: McCrary's density test



Cutoff between tier 1 and tier 2 in the new network tariff.

The estimated results from models (2) and (3) using both specifications are shown in Table 2. All four results show that the new network tariff, on average, compresses the daily peak demand among the treated compared to their counterfactual. The first specification yields a lower reduction compared to the second specification. However, as shown later in this section, the first specification violates the no-anticipation assumption. Therefore, we believe the average treatment effect among the treated (ATT) is closer to the ~2% change estimated using the second specification. Our results are lower than previous studies (Öhrlund et al., 2019; Stokke et al., 2010). Some of the previous studies were based on pilot programs and other studies were based on areas where network tariffs have already been implemented, but the consumers could choose whether to have the peak demand pricing plan. (Bartusch et al., 2011; Stokke et al., 2010). We assume that participation in pilot programs and tariff models with peak-pricing as an option gives consumers stronger incentives to change their behavior than our mandatory policy setup.

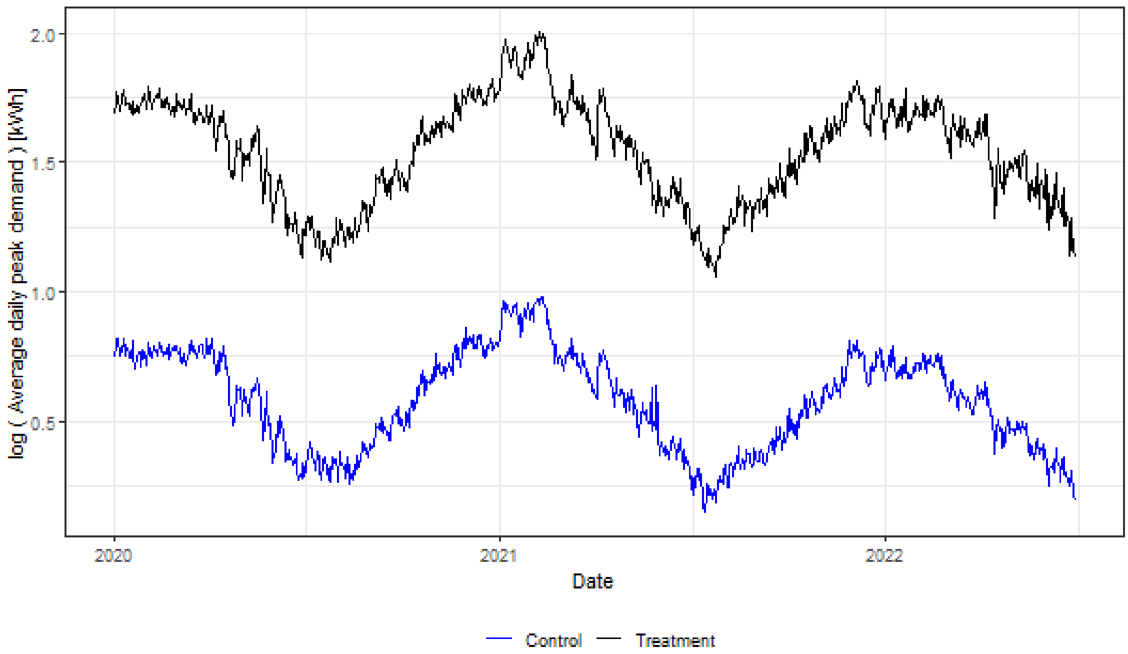
Table 2: Causal inference results. Estimation of models 2 and 3.

	log (Peak demand)			
Specification	First specification		Second specification	
Model	(2)	(3)	(2)	(3)
Treatment group	0.712		1.018	
	(0.024)***		(0.027)***	
Post policy	-0.219		-0.207	
	(0.002)***		(0.003)***	
Spot price		-0.001		-0.001
		(0.00001)***		(0.00001)***
Treatment group : Post policy	-0.007	-0.010	-0.019	-0.022
	(0.002)***	(0.002)***	(0.003)***	(0.002)***
Constant	0.709		0.403	
	(0.021)***		(0.026)***	
Observations	1,925,106	1,925,073	1,682,001	1,681,974
Num. of households	1 857	1 857	1 621	1 621
R^2	0.031	0.002	0.031	0.002
Adjusted R^2	0.031	0.0001	0.031	0.001
Standard errors	Robust	Robust	Robust	Robust
Notes:	**p<0.1; **p<0.05; ***p<0.01*			

Two key assumptions must be in place to overcome the challenge of identifying the ATT (Roth et al., 2023). First, the common trends assumption, which states that the average outcome for the treated and control groups would have evolved in parallel if no treatment was implemented, and second, the no-anticipation assumption, which assumes “that the treatment has no causal effect prior to its implementation” (Roth et al., 2023, p. 5).

For the second specification, we plotted the logarithm of daily peak demand averaged across the households in both the treatment and control groups. This plot allows us to see how the treatment and control group’s trends compare. These trends are shown in Figure 3.

Figure 3: Control- and treatment groups' average daily peak demand.



To better see whether the control- and treatment groups have a common trend before introducing the policy, we subtract the changes in the control group from the changes in the treatment group (Equation (4)).

$$Difference = log(mean(Peak\ demand_{Treatment}) - log(mean(Peak\ demand_{Control})) \tag{4}$$

We then regress the difference in changes between the groups on the date in the 2.5 years leading up to the introduction of the new network tariff. The results will tell us whether the difference is changing over time. Table 3 shows that while the estimated coefficient from this regression is highly statistically significant, it is very close to zero and not economically significant. On average, the difference between these two trends is increasing by one hundredth of a percentage every day. This analysis shows strong evidence for a common trend.

Table 2: Results from parallel trend analysis.

	Difference in log (Peak demand)
Date	0.0001
	(0.00000)***
Constant	-0.722
	(0.070)***
Observations	1,820
R2	0.243
Adjusted R2	0.243
Notes:	**p<0.1; **p<0.05; ***p<0.01*

To test for anticipatory effects, we assume that the treatment period started on June 1, 2022, one month before the new network tariff was implemented. We also drop all observations after June 31, 2022. This setup allows us to analyze whether the treatment group's peak demand changed in the month leading up to the introduction of the new tariff. Both models, (2) and (3), are estimated using these changes for each of the two specifications. Results are shown in Table 3. For the first specification, there are changes in the power demand before introducing the tariff. However, for the second specification, the estimated coefficients are low and insignificant. The latter result indicates that daily peak demand did not change between June 1 and July 1, 2022; thus, there are no anticipatory effects. Therefore, we believe the estimates from the second specification are closer to the true ATT than those from the first specification.

Table 3: Result from anticipation analysis

	log (Peak demand)			
Specification	First specification		Second specification	
Model	(2)	(3)	(2)	(3)
Treatment group	0.709		1.011	
	(0.024)***		(0.027)***	
Post June 1, 2022	-0.323		-0.315	
	(0.004)***		(0.006)***	
Spot price		-0.001		-0.001
		(0.00002)***		(0.00002)***
Treatment : Post June 1, 2022	0.014	0.014	0.006	0.007
	(0.005)***	(0.004)***	(0.006)	(0.005)
Constant	0.723		0.421	
	(0.021)***		(0.025)***	
Observations	1598650	1598617	1396841	1396814
Number of households	1857	1857	1621	1621
R^2	0.016	0.0004	0.016	0.001
Adjusted R^2	0.016	-0.001	0.016	-0.001
Standard errors	Robust	Robust	Robust	Robust
Notes	**p<0.1; **p<0.05; ***p<0.01*			

4.1.1 Policy implications

It would not be fair to assume that our treatment group is a random selection from the population. It is plausible that people who know the details of the new network tariff, despite modest information, would respond differently than the rest of the population, who would need more information about the new tariff to be viewed as treated. Consumers who are informed about prices tend to be more sensitive to price changes than uninformed households who are price-inelastic (Frondel & Kussel, 2019). Therefore, we are careful with inferring our results onto the entire population.

Nevertheless, to understand the new network tariff's impact on the power grid, we estimate the counterfactual power demand on a day when the overall load on the grid is high. The highest load in Lnett's grid in the post-policy period occurred on December 15, 2022[10], between 09:00

[10] Maximum post policy load in our period of analysis, ending on December 31, 2022

and 10:00. In this hour, the total demand was 756 000 kWh[11]. 6493 of Lnett's 135 042 households had their daily peak demand at this time. Of the 756 000kWh, 22 000kWh were demanded by the 6493 households. 313 000kWh came from the remaining 128 549 households, which did not have their daily peak during the relevant hour but had their peak during other times on the same day. Non-residential consumers contributed the remaining 421 000kWh (Lnett AS, 2023).

The 6493 consumers with their daily peak demand in the relevant hour account for 2.9% of the total load in that hour. Our analysis shows that peaks are reduced by 2% compared to the counterfactual scenario. Therefore, the 6493 households with peak consumption between 09:00 and 10:00 reduced their demand on average by 2%. This means that on December 15, between 09:00 and 10:00, there was a 2% decrease in 2.9% of the aggregated grid load, equaling 0.06%, as a response to the new network tariff. In levels, the total load decreased from 756 453 kWh to 756 000 kWh based on our estimates.

The modest reduction in aggregate grid load is due to the households' low response to the new tariff and the fact that peaks occur at different hours throughout the day. While the tariff has led to a decrease in demand in all hours through December 15, not just from 09:00 to 10:00, the total reduction over a day does not lead to lower demand for grid expansion since the grid has to be expanded based on the highest peak.

4.1.2 Heterogeneity analysis

In our dataset, we have information on various household specifics. Thereby allowing us to analyze how different household segments reacted to the new network tariff. We estimate the effect using the TWFE model (3) and data subsets filtered on the different household characteristics. The results are shown in Table 4, Table 5, Table 6, Table 7, Table 9, and Table 10. Results with a grey background have too few households in the control group and should not be given any weight.

The results indicate that households with lower education, more EVs, higher income, higher education levels, newer houses, and more occupants all reduced their peak demand post-policy compared to their counterparts.

[11] All time high in Lnett is approximately 1 000 000 kWh.

One of the strongest effects of the policy is found among households who own EVs. Households with one EV reduced peak demand by 6.2% on average. These results are as expected since EV charging is flexible, and limiting the energy demanded by the charge is relatively easy.

Households with income from NOK 450 000 and upwards have reduced their peaks by 4.0 - 6.7% post-policy. Among the low-income households, with income below NOK 450 000, the new tariff has had no effect. Higher income levels allow for investments in technologies which in turn lowers the demand by acquiring more efficient appliances (Spees & Lave, 2007). Households with reference persons with different education levels all show reductions in their peak demand, though no clear trend.

When looking at the building year of the house, we have grouped houses into three categories. (1) Built before 1980, (2) built between 1980 and 2010, and (3) built after 2010. These categories are based on two major changes in building regulations in 1985 and 2014 (Kommunal- og distriktsdepartementet, 2018). For the category with houses built before the 1980s, the estimated coefficient is positive. It seems unreasonable that households would increase their demand peaks as the price increases. We cannot provide any explanation as to why we got this result. However, peak demand among houses built after the 1980s has slightly decreased, and the newest houses have been shown to have decreased their peaks the most by 3.8%. This can be due to newer houses using a lower share of energy on heating. Heating is less flexible than other types of consumption, especially in old, less insulated houses.

The size of the living space for each household has also been grouped into three categories. We had to group the answers because many of the survey options[12] had too few respondents to be analyzed separately. These categories can be seen in Table 9. In general, the results show no clear trend. Smaller houses have the highest reduction compared to the other categories and have reduced their peaks by 3%.

Table 10 shows the changes in peak demand with regards to the number of occupants. The results show reductions in peak demand across all categories, and the coefficient is trending downwards to -8.2% for households with more than two people. The more people in the house, the larger the reductions in peak demand.

[12] The survey had answer options for each 25m^2 interval.

Table 4: Policy response grouped by EVs owned.

	log (Peak demand)			
EVs	0	1	2	> 2
Spot price	0.00004**	-0.001***	-0.001***	-0.001***
	(0.00002)	(0.00002)	(0.00003)	(0.0002)
Treatment group: Post policy	-0.040***	-0.062***	-0.182***	
	(0.005)	(0.005)	(0.018)	
Observations	704029	725036	242485	10,24
Control Group	149	66	4	0
Treatment Group	531	632	229	10
R^2	0.0003	0.004	0.009	0.007
Adjusted R^2	-0.002	0.002	0.003	-0.110
Standard errors	Robust	Robust	Robust	Robust
Notes:	**p<0.1; **p<0.05; ***p<0.01*			

Table 5: Policy response grouped by income level.

	log (Peak demand)			
Income level [kNOK]	0 - 450	450 - 700	700 - 1400	>1400
Spot price	-0.0002***	-0.0004***	-0.001***	-0.001***
	(0.00004)	(0.00003)	(0.00002)	(0.00002)
Treatment group : Post policy	0.009	-0.048***	-0.040***	-0.067***
	(0.006)	(0.005)	(0.004)	(0.008)
Observations	101529	271442	771054	537949
Control Group	50	65	85	20
Treatment Group	49	197	695	497
R^2	0.0002	0.001	0.002	0.004
Adjusted R^2	-0.012	-0.004	-0.0003	0.001
Standard errors	Robust	Robust	Robust	Robust
Notes:	**p<0.1; **p<0.05; ***p<0.01*			

Table 6: Policy response grouped by education level.

	log (Peak demand)			
Education	(Low)	(Low - Mid)	(Mid - High)	(High)
Spot price	-0.0004***	-0.001***	-0.001***	-0.001***
	(0.0001)	(0.00002)	(0.00002)	(0.00002)
Treatment group : Post policy	0.052***	-0.025***	-0.038***	-0.012**
	(0.010)	(0.005)	(0.004)	(0.005)
Observations	55216	383434	622806	620518
Control Group	11	57	80	71
Treatment Group	42	313	521	526
R^2	0.001	0.003	0.002	0.002
Adjusted R^2	-0.020	-0.001	-0.001	-0.0005
Standard errors	Robust	Robust	Robust	Robust
Notes:	**p<0.1; **p<0.05; ***p<0.01*			

Table 7: Policy response grouped by house age.

	log (Peak demand)		
Building year	(Before 1980)	(1980 - 2010)	(2010 - 2023)
Spot price	-0.001***	-0.001***	-0.001***
	(0.00002)	(0.00002)	(0.00004)
Treatment group : Post policy	0.015***	-0.011***	-0.039***
	(0.004)	(0.004)	(0.006)
Observations	685654	727266	269054
Control Group	55	98	66
Treatment Group	605	603	194
R^2	0.002	0.002	0.005
Adjusted R^2	-0.001	-0.001	0.0002
Standard errors	Robust	Robust	Robust
Notes:	**p<0.1; **p<0.05; ***p<0.01*		

Table 9: Policy response grouped by house size.

	log (Peak demand)		
House size [m^2]	(0 - 100)	(100 - 150)	(150 - 250)
Spot price	-0.0002^{**}	-0.001^{***}	-0.001^{***}
	(0.00004)	(0.00002)	(0.00002)
Treatment group : Post policy	-0.030^{***}	-0.008^{*}	-0.026^{***}
	(0.005)	(0.005)	(0.007)
Observations	235048	428145	782534
Control Group	122	68	22
Treatment Group	107	344	730
R^2	0.0002	0.002	0.003
Adjusted R^2	-0.005	-0.001	0.001
Standard errors	Robust	Robust	Robust
Notes:	**p<0.1; **p<0.05; ***p<0.01*		

Table 10: Policy response grouped by occupants in the household.

	log (Peak demand)		
Occupants in the household	1	2	>2
Spot price	-0.0002^{***}	-0.001^{***}	-0.001^{***}
	(0.00004)	(0.00002)	(0.00002)
Treatment group : Post policy	-0.061^{***}	-0.063^{***}	-0.082^{***}
	(0.005)	(0.004)	(0.006)
Observations	223497	653098	805379
Control Group	104	83	32
Treatment Group	113	545	744
R^2	0.001	0.002	0.005
Adjusted R^2	-0.005	-0.001	0.003
Standard errors	Robust	Robust	Robust
Notes:	**p<0.1; **p<0.05; ***p<0.01*		

4.2 POLICY EFFECT ON TIME OF USE

We conducted a descriptive analysis to study whether the new network tariff affected the ToU. Figure 3 shows the distribution when peak demand occurs over a day[13]. The grey bars show the distribution for 2021, while 2022 is shown by the blue bars. The distribution is shown for the treatment- and control group, for the first and the last six months of each year. Since the new network tariff was introduced on July 1, 2022, the blue bars in panels C and D will show the post-policy period.

First, we examine the treatment group from July to December (Panel D). There is a clear shift in the distribution of peak demand from 2021 (pre-policy) to the same months in 2022 (post-policy). From 2021 to 2022, there is a reduction in the share of peaks in the peak period (16 – 21), while there is an increase in the off-peak period (22 – 05). When comparing the same periods for the control group (Panel C), we see that the shift is lower than for the treatment group.

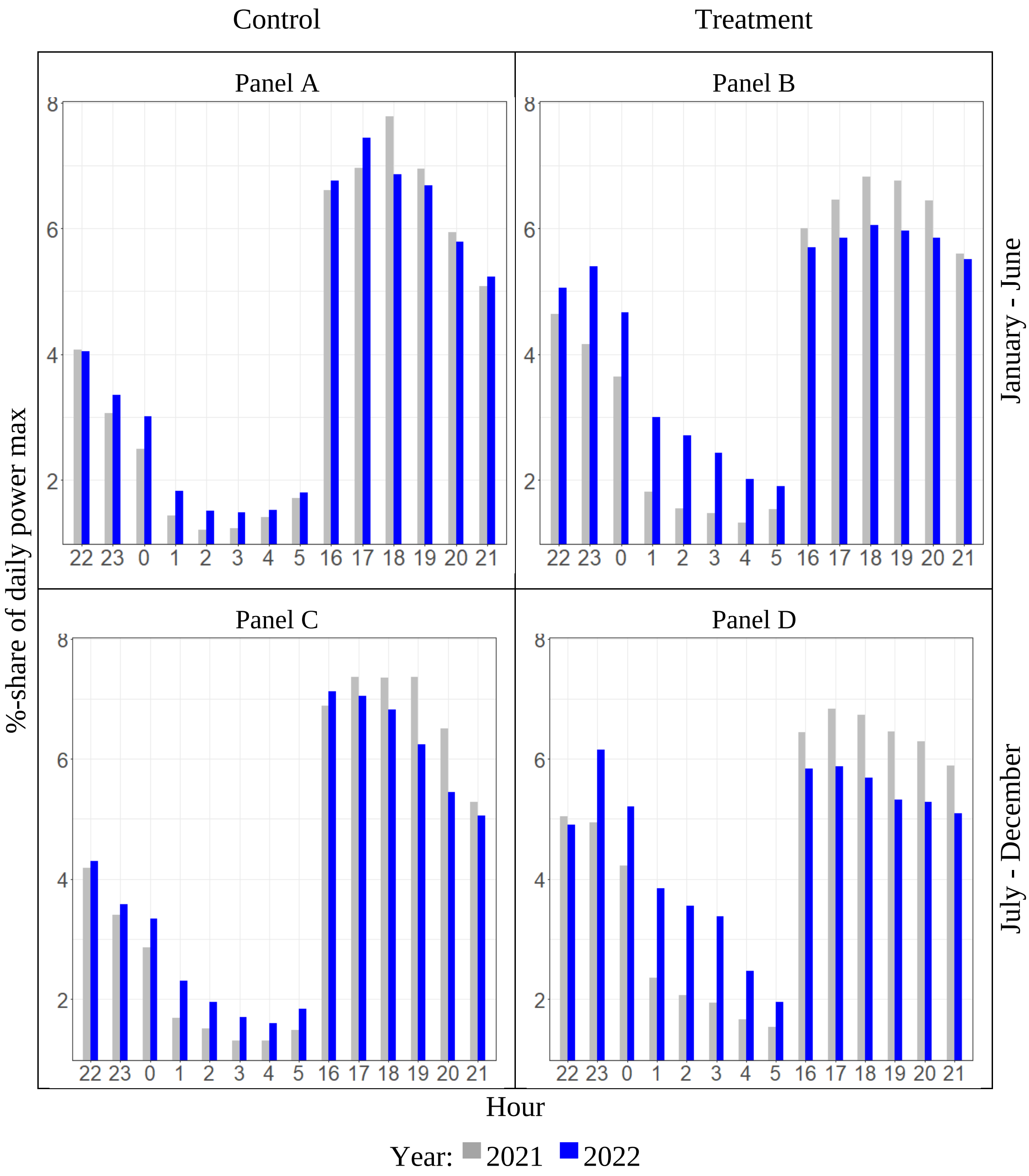
Second, we compare the two groups from January to June (Panel A and B). This comparison shows a similar pattern to the first comparison. There is a stronger shift in the distribution of peak demand in the treatment group than in the control group. Since the policy was introduced on July 1, 2022, neither the control- nor the treatment group are treated in these panels. Hence, the shift we see in panels A and B has to be driven by some other factors than the new network tariff.

If we compare the two differences, how the two groups' distribution is shifting from 2021 to 2022, we see that the shift appears to be stronger for the treatment group in the post-policy period (panel D) than for the treatment group in the pre-policy period (panel B).

The differences in the distribution of peak hours indicate that the policy has led to households moving more of their consumption to the off-peak period. An explanation for this shift we see in our data can be due to the rapid evolution in systems that automatically move consumption to off-peak periods. For example, systems like smart EV chargers and water heaters.

[13] Hours 6 to 15 have been removed since there was little to no shift in the distribution during these hours.

Figure 3: Distribution of peak demand.



Notes: Hour 0 describes the period from 00:00-01:00, while hour 23 describes the period from 23:00-00:00)

5 CONCLUSION

Our analysis shows that the new network tariff has led to a statistically significant behavior change for the households in our treatment group. On average, these households have reduced their daily peak demand by ~2%. The low response combined with peaks occurring in different hours across the day leads to a modest reduction in the aggregate peak load on the power grid. Consequently, the new tariff contributes little to the government's goal of reducing costs by smoothing consumption, at least in the short run. Our data was limited to six months after the new tariff was introduced. Previous literature has found consumers to be more elastic in the long run. We have also shown that households shift their consumption to other times of the day if there is a price difference. The ToU component seems to be the preferred tariff to achieve this goal. A ToU tariff with a higher price during peak hours will target all households' demand in the relevant period, regardless of whether the demand is the household's daily peak demand, thereby leading to a higher reduction in aggregate peak demand. Our study and previous studies have shown that consumers' peak- and energy demand is price elastic. The effect of the tariff could be further strengthened by increasing the difference between peak and off-peak periods. There are real-world examples where the energy-based element has been set to zero in off-peak periods.

Further, we found that the number of occupants, EVs, and income-levels are positively correlated with peak demand. These are also the three attributes associated with the highest peak reduction due to the new network tariff. Our suggested expansion of the ToU tariff will incentivize households with more occupants, more EVs, and higher income levels, as well as all other households, to reduce demand in peak hours.

As discussed in paragraph 4.1.1, how we constructed the treatment groups is a limitation in our analysis. Additional data from grid providers who did not introduce the new network model on July 1, 2022, could be used in future research. This would enable the researchers to create treatment- and control groups consisting of consumers with a broad range of knowledge about the tariff. Future research could also use the dataset we collected to expand our descriptive TOU analysis with an empirical analysis.

6 REFERENCES

Bartusch, C., & Alvehag, K. (2014). Further exploring the potential of residential demand response programs in electricity distribution. Applied Energy, 125, 39–59. https://doi.org/10.1016/j.apenergy.2014.03.054

Bartusch, C., Wallin, F., Odlare, M., Vassileva, I., & Wester, L. (2011). Introducing a demand-based electricity distribution tariff in the residential sector: Demand response and customer perception. *Energy Policy, 39*(9), 5008–5025. https://doi.org/10.1016/j.enpol.2011.06.013

Buckley, P., & Llerena, D. (2022). Nudges and peak pricing: A common pool resource energy conservation experiment. *Journal of Behavioral and Experimental Economics, 101*, 101928.

Croissant, Y., & Millo, G. (2008). *Panel Data Econometrics in R: The plm Package*. 10.18637/jss.v027.i02.

Deryugina, T., MacKay, A., & Reif, J. (2020). The long-run dynamics of electricity demand: Evidence from municipal aggregation. *American Economic Journal: Applied Economics*, *12*(1), 86–114. https://doi.org/10.1257/app.20180256

Dimmery, D. (2016). rdd: Regression Discontinuity Estimation (0.57).

Filippini, M. (1995). Swiss residential demand for electricity by time-of-use: An application of the almost ideal demand system. *The Energy Journal*, *16*(1). https://doi.org/10.5547/ISSN0195-6574-EJ-Vol16-No1-2

Hayn, M., Bertsch, V., & Fichtner, W. (2014). Electricity load profiles in Europe: The importance of household segmentation. *Energy Research & Social Science*, *3*, 30–45. https://doi.org/10.5547/ISSN0195-6574-EJ-Vol16-No1-2

Hlavac, M. (2022). stargazer: Well-Formatted Regression and Summary Statistics Tables (5.2.3).

Hledik, R. (2014). Rediscovering residential demand charges. *The Electricity Journal*, *27*(7), 82–96. https://doi.org/10.1016/j.tej.2014.07.003

International Energy Agency. (2021). *Net Zero by 2050 – Analysis*. IEA. https://www.iea.org/reports/net-zero-by-2050

Kommunal- og distriktsdepartementet. (2018, May 22). *Bygningsregelverket fra 1965 – 2017* [Innhold]. Regjeringen; regjeringen.no. https://www.regjeringen.no/no/tema/plan-bygg-og-eiendom/bygningsregelverket-fra-1965--20172/id2590706/

Lanot, G., & Vesterberg, M. (2021). The price elasticity of electricity demand when marginal incentives are very large. *Energy Economics*, *104*, 105604. https://doi.org/10.1016/j.eneco.2021.105604

Lnett AS. (2023). *Customer data* [Data set].

Lnett AS. (2021, November 8). *New tariffs 1. July 2022*. Lnett. https://www.l-nett.no/nynettleie/new-tariffs-1-july-2022

Microsoft. (2023). *Visual Studio Code* (1.78.2). Microsoft. https://code.visualstudio.com/

Nordpool Group. (2023). *Data portal* [Data set]. https://www.nordpoolgroup.com/en/services/power-market-data-services/data-portal/

Norges Vassdrags- og Energidirektoratet. (2021, August 12). *Network tariffs*. NVE. https://www.nve.no/norwegian-energy-regulatory-authority/network-regulation/network-tariffs/

Norges Vassdrags- og Energidirektoratet. (2022a, January 7). *Ny nettleie (fra 1. Juli 2022)*. NVE. https://www.nve.no/reguleringsmyndigheten/kunde/nett/ny-nettleie-fra-1-juli-2022/

Norges Vassdrags- og Energidirektoratet. (2022b, January 12). *Smart metering (AMS)—NVE*. NVE. https://www.nve.no/norwegian-energy-regulatory-authority/retail-market/smart-metering-ams/

Norsk klima service senter. (2023). *Observations and weather statistics—Seklima* [Data set]. https://seklima.met.no/

Öhrlund, I., Schultzberg, M., & Bartusch, C. (2019). Identifying and estimating the effects of a mandatory billing demand charge. *Applied Energy*, *237*, 885–895. https://doi.org/10.1016/j.apenergy.2019.01.028

Olje- og energidepartementet. (2023). *Regjeringens strømtiltak* (Redaksjonellartikkel No. 168/21). Olje- og energidepartementet. https://www.regjeringen.no/no/tema/energi/regjeringens-stromtiltak/id2900232/

Olje- og energidepartementet. (2022, May 6). *Justerer innføringen av ny nettleiemodell* [Nyhet]. Regjeringen; regjeringen.no. https://www.regjeringen.no/no/aktuelt/justerer-innforingen-av-ny-nettleiemodell/id2911788/

Passey, R., Haghdadi, N., Bruce, A., & MacGill, I. (2017). Designing more cost reflective electricity network tariffs with demand charges. *Energy Policy*, *109*, 642–649. https://doi.org/10.1016/j.enpol.2017.07.045

Proudlove, A. (2018). Residential Demand-Charge Proposals Vary Across the United States. *Natural Gas & Electricity*, *34*(10), 13–17. https://doi.org/10.1002/gas.22052

R-Core-Team. (2023). *R: A Language and Environment for Statistical Computing* (4.3.0). https://www.R-project.org/

Roth, J., Sant'Anna, P. H., Bilinski, A., & Poe, J. (2023). What's trending in difference-in-differences? A synthesis of the recent econometrics literature. *Journal of Econometrics*. https://doi.org/10.1016/j.jeconom.2023.03.008

RStudio Team. (2022). *RStudio* (2022.12.0 Build 353). Integrated Development for R. RStudio, PBC, Boston, MA. http://www.rstudio.com/

Schauberger, P., Walker, A., Luca, B., Joshua, S., Garbuszus, J. M., & Barbone, J. M. (2023). *openxlsx: Read, Write and Edit xlsx Files* (4.2.5.2).

Spees, K., & Lave, L. B. (2007). Demand Response and Electricity Market Efficiency. *The Electricity Journal*, *20*(3), 69–85. https://doi.org/10.1016/j.tej.2007.01.006

Stokke, A. V., Doorman, G. L., & Ericson, T. (2010). An analysis of a demand charge electricity grid tariff in the residential sector. *Energy Efficiency*, *3*(3), 267–282. https://doi.org/10.1007/s12053-009-9071-9

Taylor, T. N., & Schwarz, P. M. (1990). The Long-Run Effects of a Time-of-Use Demand Charge. *The RAND Journal of Economics*, *21*(3), 431. https://doi.org/10.2307/2555618

Westskog, H., & Winther, T. (2014). Electricity consumption: Should there be a limit? Implications of people's attitudes for the forming of sustainable energy policies. *Consilience*, *11*, 97–114. https://www.jstor.org/stable/26188731

Wickham, H. (2016). *ggplot2: Elegant Graphics for Data Analysis* (3.4.2). Springer-Verlag New York. https://ggplot2.tidyverse.org

Wickham, H., Averick, M., Bryan, J., Chang, W., McGowan, L. D., François, R., Grolemund, G., Hayes, A., Henry, L., Hester, J., Kuhn, M., Pedersen, T. L., Miller, E., Bache, S. M., Müller, K., Ooms, J., Robinson, D., Seidel, D. P., Spinu, V., … Yutani, H. (2023). *Welcome to the tidyverse* (2.0.0).

Wickham, H., François, R., Henry, L., & Müller, K. (2023). *dplyr: A Grammar of Data Manipulation* (1.1.2). https://github.com/tidyverse/dplyr

Yan, X., Ozturk, Y., Hu, Z., & Song, Y. (2018). A review on price-driven residential demand response. *Renewable and Sustainable Energy Reviews*, *96*, 411–419. https://doi.org/10.1016/j.rser.2018.08.003

7 APPENDIX

7.1 APPENDIX 1: MULTIPLE REGRESSION RESULTS

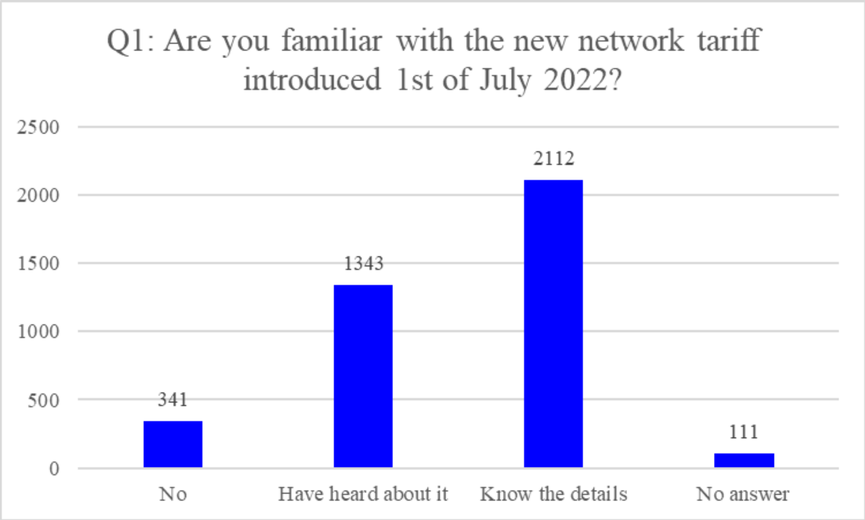
	log (Peak demand)
Average daily temperature	-0.034***
	(0.00004)
Average daily wind speed	0.015***
	(0.0001)
Spot price	-0.001***
	(0.00000)
Age	-0.002***
	(0.001)
factor(Occupants): 2	0.201***
	(0.024)
factor(Occupants): 3	0.343***
	(0.029)
factor(Occupants): 4	0.382***
	(0.030)
factor(Occupants): 5	0.377***
	(0.036)
factor(Occupants): 6	0.482***
	(0.059)
factor(Occupants): More than 6	0.414***
	(0.106)
factor(Residence building ear): 1900 - 1909	0.092
	(0.107)
factor(Residence building year): 1910 - 1919	0.078
	(0.079)
factor(residence building year): 1920 - 1929	-0.048
	(0.093)
factor(Residence building year): 1930 - 1939	0.043
	(0.081)
factor(Residence building year): 1940 - 1949	-0.039
	(0.088)
factor(Residence building year): 1950 - 1959	-0.009
	(0.068)

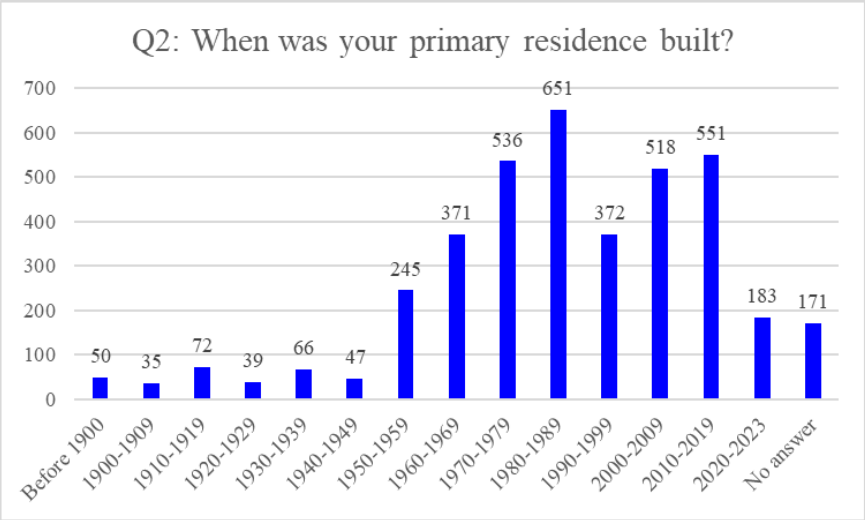
factor(Residence building year): 1960 - 1969	-0.023
	(0.066)
factor(Residence building year): 1970 - 1979	-0.047
	(0.065)
factor(Residence building year): 1980 - 1989	-0.049
	(0.064)
factor(Residence building year): 1990 - 1999	0.010
	(0.066)
factor(Residence building year): 2000 - 2009	-0.164**
	(0.065)
factor(Residence building year): 2010 - 2019	-0.366***
	(0.065)
factor(Residence building year): 2020 - 2023	-0.312***
	(0.104)
factor(Residence size): 100 - 124	0.521*
	(0.269)
factor(Residence size): 125 - 149	0.611**
	(0.270)
factor(Residence size): 150 - 174	0.702***
	(0.270)
factor(Residence size): 175 - 199	0.737***
	(0.270)
factor(Residence size): 200 - 224	0.795***
	(0.270)
factor(Residence size): 225 - 249	0.805***
	(0.271)
factor(Residence size): 25 - 49	0.033
	(0.275)
factor(Residence size): 250 - 274	0.819***
	(0.271)
factor(Residence size): 275 - 299	0.972***
	(0.273)
factor(Residence size): 300 - 324	0.846***
	(0.274)
factor(Residence size): 325 - 349	0.951***
	(0.280)
factor(Residence size): 350 - 374	1.182***
	(0.290)

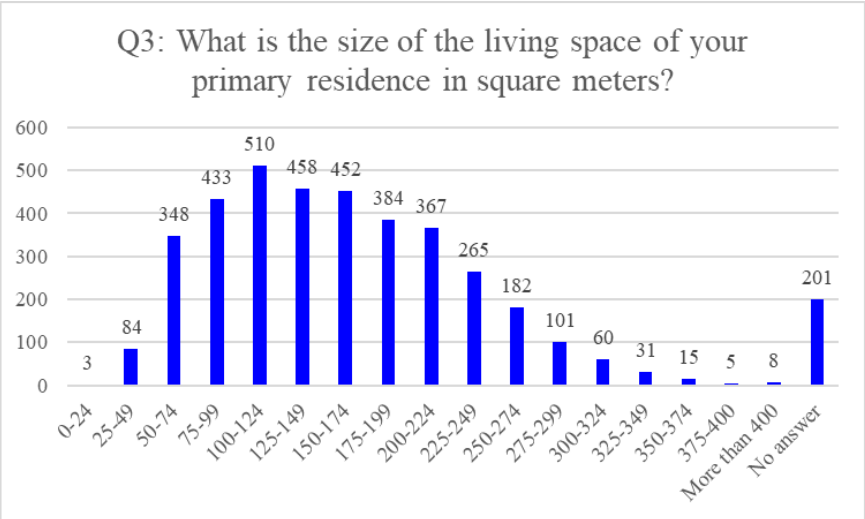
factor(Residence size): 375 - 400	1.123***
	(0.330)
factor(Residence size): 50 - 74	0.235
	(0.269)
factor(Residence size): 75 - 99	0.324
	(0.269)
factor(Residence size)More than 400	1.040***
	(0.312)
factor(Number of EVs): 1	0.121***
	(0.016)
factor(Number of EVs): 2	0.276***
	(0.025)
factor(Number of EVs): More than 2	0.358***
	(0.107)
factor(Household income): 450 000 - 700 000	0.002
	(0.030)
factor(Household income): 700 000 - 1 400 000	0.027
	(0.031)
factor(Household income): More than 1 400 000	0.078**
	(0.035)
factor(Education level): Higher, more than 4 years	-0.092**
	(0.037)
factor(Education level): Higher, up to 4 years	-0.060*
	(0.036)
factor(Education level): Upper secondary	-0.011
	(0.036)
Constant	0.754***
	(0.277)
Observations	2932371
R^2	0.217
Adjusted R^2	0.217

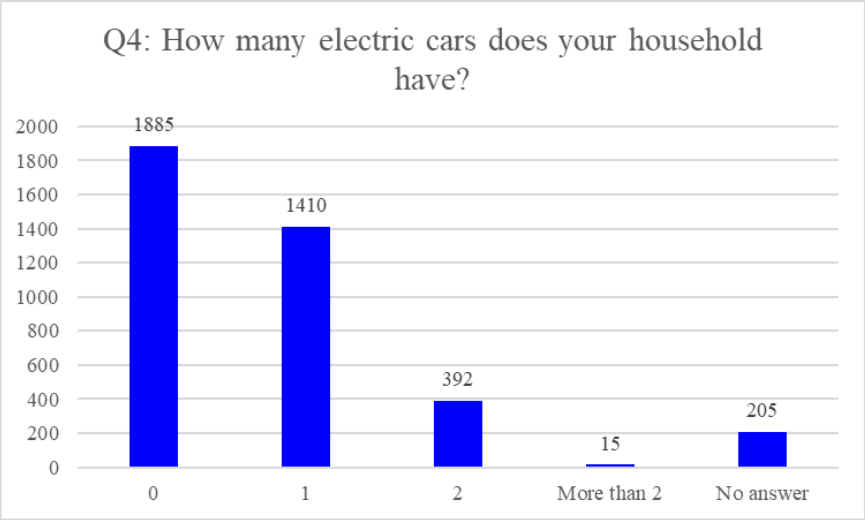
*Notes: *p<0.1; **p<0.05;***p<0.01*

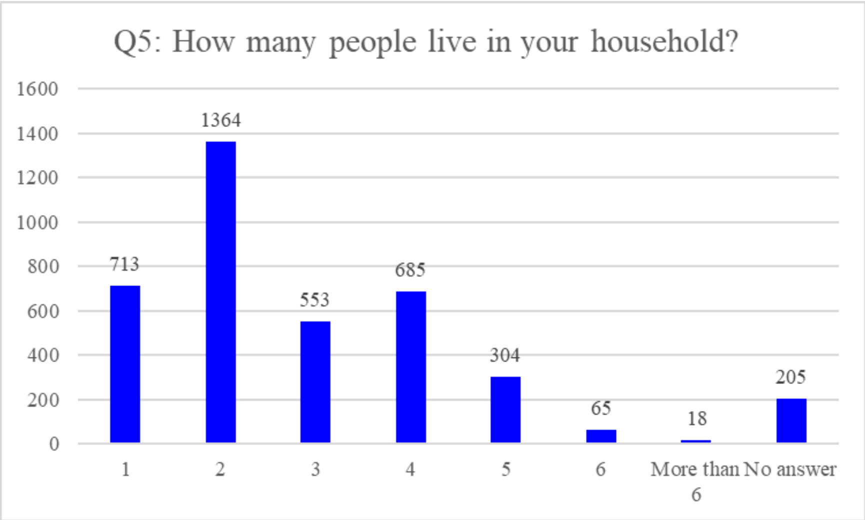
7.2 APPENDIX 2: SURVEY QUESTIONS AND ANSWER DISTRIBUTION

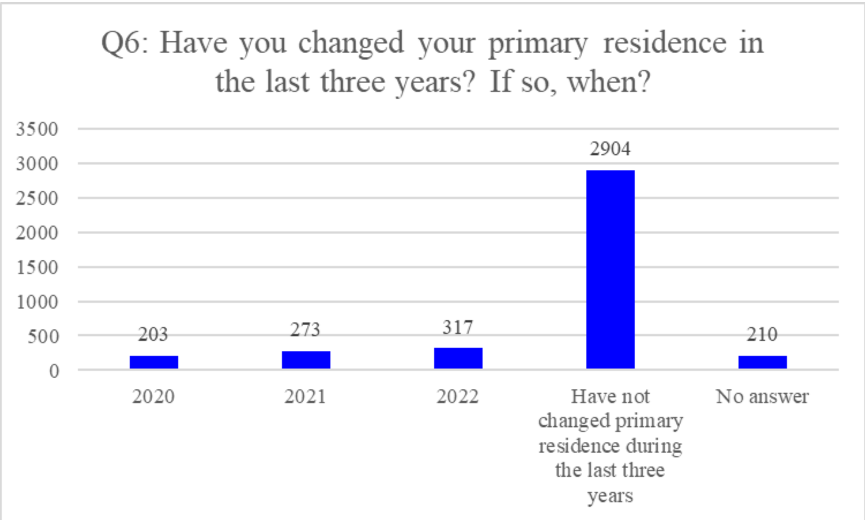


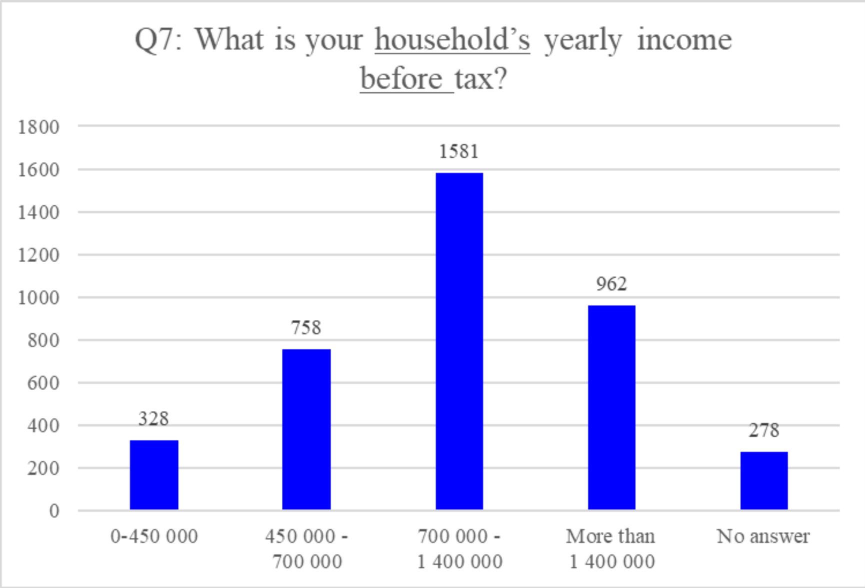


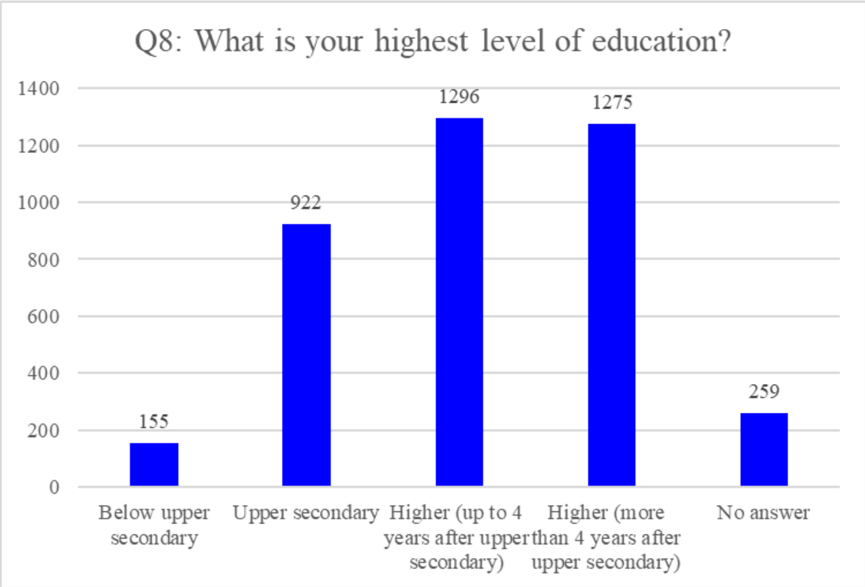


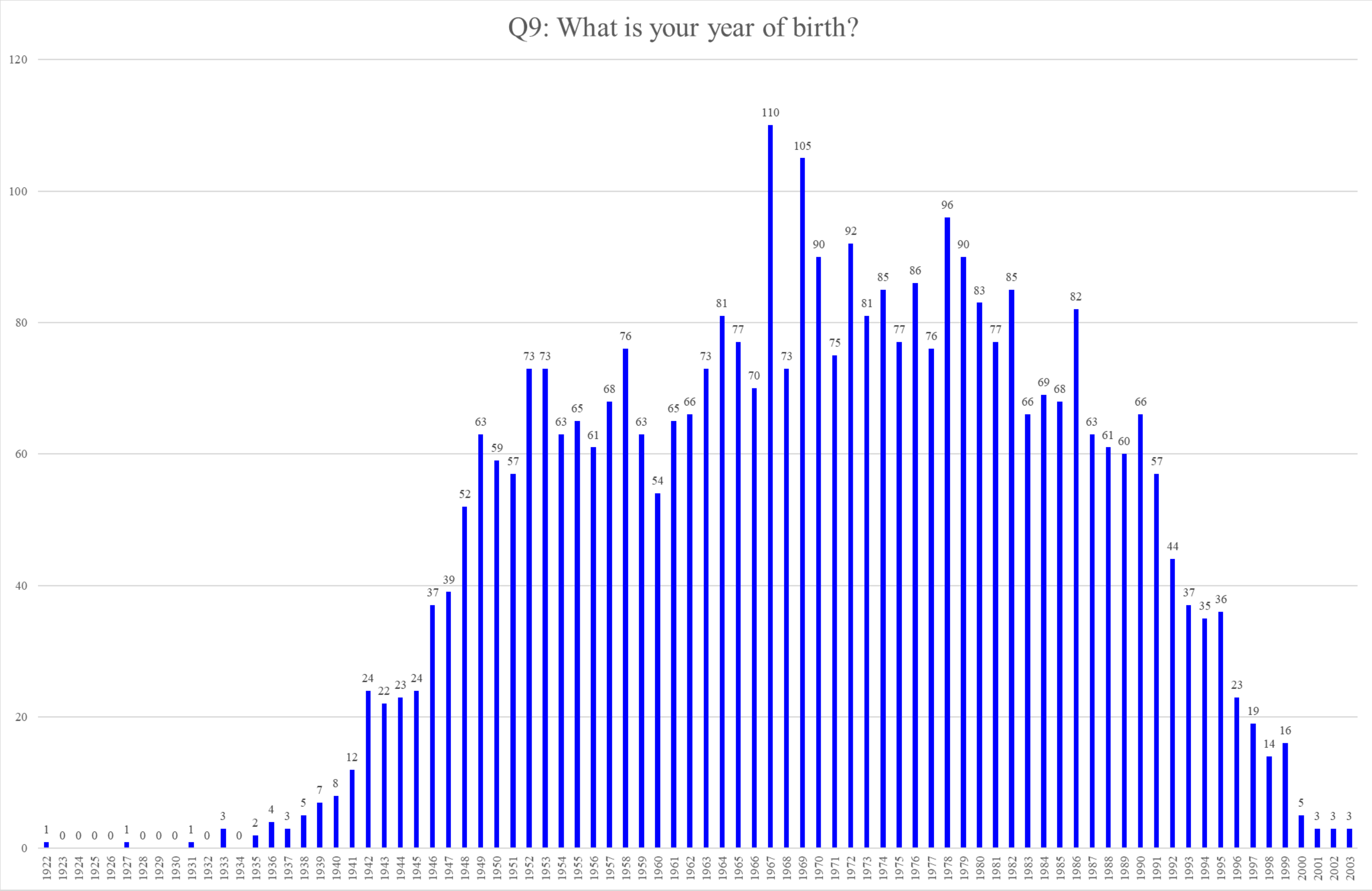

Q4: How many electric cars does your household have?
2000
1800
1600
1400
1200
1000
800
600
400
200
0
1885
1410
392
15
205
0
1
2
More than 2
No answer


Q5: How many people live in your household?
1600
1400
1200
1000
800
600
400
200
0
713
1364
553
685
304
65
18
205
1
2
3
4
5
6
More than 6
No answer


Q6: Have you changed your primary residence in the last three years? If so, when?
3500
3000
2500
2000
1500
1000
500
0
203
273
317
2904
210
2020
2021
2022
Have not changed primary residence during the last three years
No answer


Q7: What is your household's yearly income before tax?
1800
1600
1400
1200
1000
800
600
400
200
0
328
758
1581
962
278
0-450 000
450 000 - 700 000
700 000 - 1 400 000
More than 1 400 000
No answer


Q8: What is your highest level of education?
1400
1200
1000
800
600
400
200
0
155
922
1296
1275
259
Below upper secondary
Upper secondary
Higher (up to 4 years after upper secondary)
Higher (more than 4 years after upper secondary)
No answer



Notes: 221 people did not answer this question. The "No answer" bar is not included in the figure to avoid rescaling the y-axis.