BI

WISEflow
Europe/Oslo(CEST)
27 Jun 2023

Handelshøyskolen BI

GRA 19703 Master Thesis

Thesis Master of Science 100% - W

Predefinert informasjon

Startdato:	09-01-2023 09:00 CET	**Termin:**	202310
Sluttdato:	03-07-2023 12:00 CEST	**Vurderingsform:**	Norsk 6-trinns skala (A-F)
Eksamensform:	T		
Flowkode:	202310||11184||IN00||W||T		
Intern sensor:	(Anonymisert)		

Deltaker

Navn:	Erik Jensen og Milos Uksanovic

Informasjon fra deltaker

Tittel *:	Measuring price elasticities with a difference-in-difference design: Investigating the North-South electricity spot price gap in Norway
Navn på veileder *:	Rune Jørgen Sørensen

Inneholder besvarelsen konfidensielt materiale?:	Nei	**Kan besvarelsen offentliggjøres?:**	Ja

Gruppe

Gruppenavn:	(Anonymisert)
Gruppenummer:	158
Andre medlemmer i gruppen:	

Master Thesis

Measuring price elasticities with a difference-in-difference design: Investigating the North-South electricity spot price gap in Norway

Erik Jensen & Milos Uksanovic

Study program: M.Sc. Applied Economics

Supervisor: Rune Jørgen Sørensen

NORWEGIAN BUSINESS SCHOOL

Acknowledgements

We would like to express our sincere gratitude to our supervisor, Rune Jørgen Sørensen, for his patient and inspiring guidance during the entire year of our thesis work. Furthermore, we thank both Elhub AS and Nord Pool AS for providing us with such excellent consumption and price data so that this topic could become our thesis project in the first place. The last word goes out to our families who have been the biggest support ever since – from literally day one: thank you!

This study has been conducted using coding in STATA. Upon request, the corresponding STATA files can be made accessible to allow for a replication of our study. However, forwarding the data files used in this study falls under the discretion of Elbub AS and Nord Pool AS and will only be done with their approval.

Abstract

This study uses spot price and municipality-level electricity consumption panel data spanning around three years to derive short run estimates of the price elasticity of electricity demand (PEED) for the Norwegian residential electricity market. A difference-in-difference model is applied on an exogenous spot price shock concentrated in the Norwegian South during 2021 and 2022 which has caused a strong deviation in electricity prices between the Norwegian price areas. A sample of municipalities adjacent to both sides of the North-South price border is assigned to a control (North) and treatment group (South). The main identifying assumption relied upon is that electricity demand in both groups would follow parallel trends under the absence of treatment, i.e., the spot price shock. After having validated that assumption, the study estimates daily, weekly, and monthly values for the spot PEED. Given indication for a lagged response when using an extension to the baseline regression model, we infer that our weekly and monthly PEED estimates better capture the response horizon in this study. Our baseline estimates converge to -0.02 for both residential housing and cabins. This implies a purchase price elasticity of demand of -0.12 for residential electricity consumption and -0.05 for cabins. The purchase PEED estimates are derived by an algebraic approximation using mean spot prices before and during the major price shock phase, averages for additional purchase price components, and a government support scheme for residential electricity consumption. The estimated inelastic demand patterns confirm previous research for the Norwegian electricity market and are consistent with the response in aggregate electricity consumption observed in this paper. Our findings are further discussed with regards to potential non-linearity of price elasticities which may depend on households' electricity expenditure-to-income ratio. Our baseline estimates remain robust for rural Norwegian areas while providing some evidence for slightly more elastic electricity demand in urban areas. In the light of the energy transition, an increase in the efficiency of electricity use is the most straightforward answer to more natural variation in renewable power generation. However, inelastic residential electricity demand, as shown in this paper, underlines the urgency for new policy which incentivizes more flexibility in demand without causing distortions in utility and welfare.

Table of Contents

I. List of Tables

II. List of Figures

1. Introduction

The years 2021 and 2022 have seen increasing and more volatile electricity prices in the Southern part of Norway. Amid concerns about resulting financial hardship for affected households, proposals for new policies to regulate wholesale electricity prices have been debated in Norway but also on the European level. However, ideas such as a price cap are controversial since they may disrupt balancing market mechanisms and security in supply (Norwegian Competition Authority, 2022). In the long-term perspective, with the electrification of fossil-fuel based systems seen as a facilitator to meet climate targets (e.g., International Energy Agency, 2019), elevated prices and volatility in electricity markets are a possible scenario as Europe transitions from fossil to renewable energy sources. These policy-related debates underline the urgency to analyze how residential electricity consumption is impacted in the event of higher and more volatile wholesale prices. Insights on demand responses to price shocks can provide guidance for optimal policy in the pursuit of secure, affordable, and sustainable power supply. In academia, the demand response to changes in electricity prices, the *price elasticity of electricity demand* (*PEED*), became subject to major attention in the 1970s and 1980s, when there was yet another energy crisis (Espey & Espey, 2004, p. 65). PEEDs have frequently been estimated in many geographical settings and for different types of data aggregation for the short- and the long run, however, often using purchase prices or expenditure data instead of wholesale prices.

This study analyses the response in Norwegian residential electricity demand with regards to the spot price shock in the South of Norway starting in 2021. As this price shock is directly linked to a lack of precipitation in Southern Norway and price effects from Europe (e.g., rising gas prices in 2022), it is exogenous in nature and thus ideal to investigate the demand response. We test the hypothesis that consumers react to this shock by significantly adapting their electricity off-take in the short run. This we base on an observed deviation from usual seasonal patterns in indexed per-capita electricity consumption in the Southern price areas NO1, NO2, NO5 compared to NO3 in the North. Figure 1 shows that indexed residential electricity use in the South shrinks relative to its equivalent in the North towards the end of our period of investigation. This coincides with the period where spot prices in the South rise significantly compared to spot prices in the North.

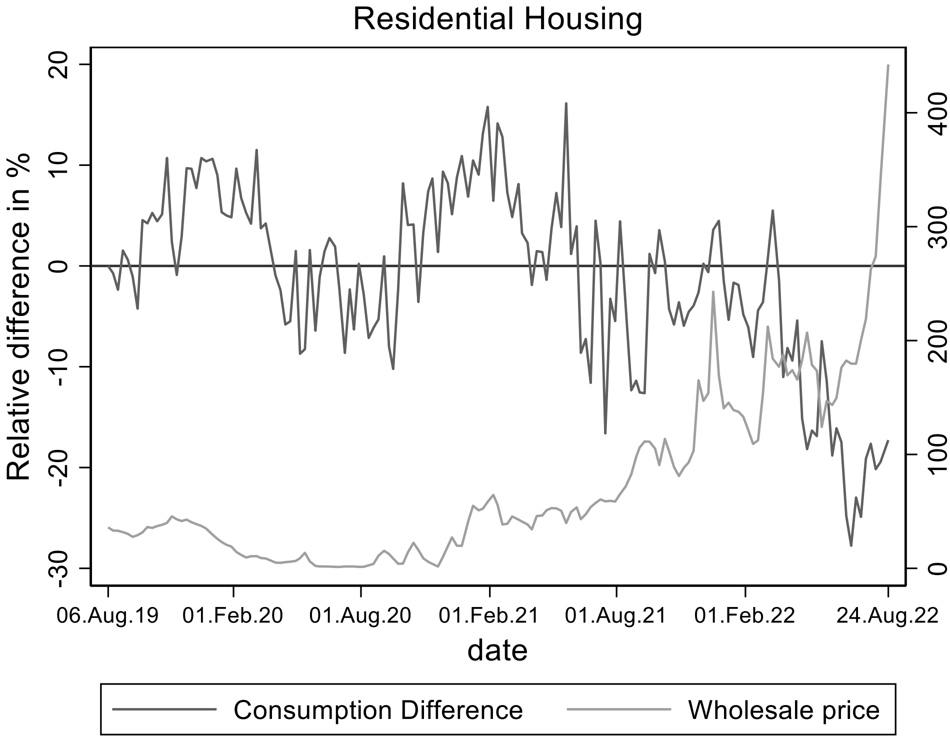


Figure 1: The South-North difference in indexed per-capita residential electricity consumption[1] and Southern wholesale prices[2]

We estimate daily, weekly, and monthly spot PEED values for residential housing and cabins. Thereby, we employ a difference-in-difference design on a sample of municipalities in proximity to the pricing border that separates two Southern price areas experiencing the price shock from one Northern price area with comparably lower and less volatile spot prices. The key identifying assumption used is the so-called *parallel trends assumption,* describing that treatment and control groups follow parallel trends in electricity consumption outcomes in the absence of treatment, or in this case, the price shock. Our baseline estimates are derived from a regression model that utilizes municipality-level consumption panel data for

[1] The mean per-capita consumption for the North and South of Norway (excluding NO4) are normalized to 100 in the first complete week in August 2019. Thereafter, the difference between Southern (NO1, NO2, NO5) minus Northern (NO3) indexed consumption values is divided by the normalized Northern value.
[2] The wholesale price is given as the weekly mean value for the Southern price areas NO1, NO2 and NO5. The first and last week are removed as they are incomplete.

Note on Figure 1: The cyclical pattern indicates higher seasonal demand fluctuation in Southern Norway. The downward path in the relative difference in the third year is hypothesized to originate from the price shock since it coincides with a rise in Southern wholesale prices. Relative to the North, the Southern residential electricity consumption deviates by eyeballed 10 to 15 percentage points more around the summer of 2022 compared to the same season in the two prior years.

residential housing and cabins as well as average daily spot market prices ranging from the beginning of August 2019 until the end of August 2022. Weekly and monthly spot PEED values, which we argue are more informative in this study, are estimated to be around -0.02. Since these baseline estimates are based on wholesale prices, we further approximate the *purchase PEED* for household consumers. Thereby, we add proxies for other purchase price components and consider a government support scheme for electricity use in residential housing introduced in December 2021. According to our findings, the purchase PEED can be approximated by the value of -0.12 for residential housing and -0.05 for cabins. These PEED estimates for the household response comply with the more inelastic spectrum of results from studies on a global perspective and confirm previous research for the Norwegian electricity market. Amongst the aspects discussed in this study are the absence of substitutes for electricity, the time lag in the demand response and low initial electricity prices combined with relatively high financial security in terms of household income and the welfare state. Furthermore, our results remain robust for rural areas in Norway with urban areas indicating a somewhat stronger demand response. We acknowledge that deriving conclusions for the household-level response based on aggregated municipality-level data may be problematic due to aggregation bias. As the use of aggregate data to investigate residential electricity demand is common among other reviewed studies (see Chapter 3) and personal data protection concerns complicate the collection of household-level data, we refer to aggregate municipality-level data, nonetheless.

In the following, we describe the research background by giving an overview on the institutional setting and the research context in Chapter 2. This is followed by a literature review on the underlying theoretical framework and previous research in Chapter 3, a data description in Chapter 4, as well as a presentation of the methodology including descriptive statistics and sample balance checks in Chapter 5. In Chapter 6, we validate the parallel trends assumption and present the results on estimates for short run spot price elasticities of electricity demand from our baseline regression model. Chapter 7 includes the algebraic derivation of the purchase PEED and robustness checks. Besides, it discusses extensions and limitations important for the interpretation of our results. Lastly, we link our results to the previous literature and discuss the external validity of our study as well as implications for policy-making and future research.

2. Research background

In the following chapter, we present the electricity price shock of interest and discuss the use of wholesale (i.e., spot) instead of purchase prices. Therefore, we look at the current structure of the Norwegian electricity market as well as the degree to which households are exposed to spot market prices through their electricity contracts. Additionally, we show how the gap in spot prices between Northern and Southern Norway has evolved during the period of our research.

2.1. Institutional setting

This section focuses on the underlying structure of the Norwegian electricity market, the components of common electricity contracts for Norwegian households, and the exposure of purchase prices given by these contracts to the spot prices on the wholesale market.

2.1.1. The Norwegian electricity market

Following the deregulation of power markets during the 1990s, national electricity markets have become more integrated, leading to the establishment of the interconnected European power network as we know it today. For Norway, the exchange of electricity with neighbouring states has thus grown over time. The intention behind this integration process has been to ensure the stability of national power grids while using power generation capacities more efficiently and balancing supply surpluses and deficits across borders (The Norwegian Government, 2021; Statnett, n.d.).

The Norwegian electricity market is divided into five price areas as depicted in Figure 2. In Norway, there are only limited capacities to transport electricity across the country which impacts how supply and demand for electricity can be balanced. The five price areas reflect these physical limitations, related abundance or scarcity of power supply, and enable an equilibrium response through price signals (Statnett, 2022). In addition to domestic grid connections, there exist several connections to the following neighboring countries and their respective price areas: Sweden, Finland, Denmark, the Netherlands, Germany, and the United Kingdom (Statnett, n.d.).

Figure 2: Map of price areas in the Norwegian electricity market (Statnett, 2022)[3]

Spot prices in the Norwegian wholesale market result from a two-stage settlement process from day-ahead and intraday trading via the power market exchange managed by *Nord Pool*. Wholesale prices for each hour on the following day are determined after the deadline for purchase and sell orders at 12:00 CET when *Nord Pool* matches aggregated demand and supply curves based on these orders (Nord Pool, n.d.). During intraday trading, wholesale prices adjust to updated information on demand and supply (Nord Pool, n.d. b). Daily averages of these final spot rates are implemented in our study. Hence, we use the terms ‘wholesale price’ and ‘spot price’ synonymously.

2.1.2. Purchase price exposure to wholesale prices

Since 2000, electricity expenditures of Norwegian households have become increasingly directly dependent on contemporaneous spot prices (SSB, 2015). According to figures published by Norway’s national bureau for statistics, around 80% of all electricity contracts for households were bound to the spot price as of the third quarter in 2022 with another 14.5% being variable contracts (SSB, 2023). Variable contracts are also bound to the wholesale price but respond to changes less

[3] In this paper, we refer to NO3 & NO4 as the Northern and NO1, NO2 & NO5 as the Southern price areas.

frequently. All in all, this implies that variation in spot prices is contemporaneously reflected in the price that most households need to pay for their respective electricity consumption.

Prior to the Southern price shock in 2021 and 2022, wholesale prices accounted for around a third of the entire purchase price that households needed to pay (SSB, 2023b). Other major components to electricity bills are a grid rent to the local network operator as well as taxes and fees. However, in several municipalities in Northern Norway, consumers are exempted from paying a part of the grid rent and value added taxes. Even though the spot price is not the only component of the purchase price, it is the main source for purchase price variation since the grid rent remains relatively constant (SSB, 2016).

2.2. Research context

Having looked at the institutional setting, we discuss two events that have largely affected Norwegian household electricity prices during 2021 and 2022: the spot price shock which has been particularly concentrated in the South of the country and the introduction of a government support scheme for households.

2.2.1. Elevated wholesale prices and the North-South price gap

With an abundance in hydroelectric power (SSB, 2023c), Norway historically enjoyed low electricity prices, while electricity accounts for a major share of domestic energy use by Norwegian households (Energifakta Norge, 2021). However, the last three years have been characterized by unusually large variation in electricity prices compared to historical records with low spot prices in 2020 and spiking prices in 2021 and 2022 (see also Figure 3).
Several events have been seen as factors contributing to this situation (Statnett, 2022b). The most important contribution to the elevation in electricity prices has come from high gas prices due to the reduced supply from Russia and higher post-pandemic demand. Higher coal and CO2 prices as well as lower hydro storage levels in the South of Norway in 2021 and 2022 have also led to upward pressures on electricity prices. By contrast, the new transmission cables to the UK and Germany are regarded to have only a minor impact on domestic Norwegian spot prices (Statnett, 2022b).

When comparing the evolution of wholesale prices in Norway among the five price areas, it shows that there is a significant difference in the exposure to the price increases depending on the location of the price area. As shown in Figure 3, spot prices become not only more volatile in 2021 and 2022 compared to previous years, but average daily prices for the Southern areas NO1, NO2, and NO5 became multiple times higher than the Northern spot rates in NO3 and NO4. This is what we refer to as the 'price shock'.

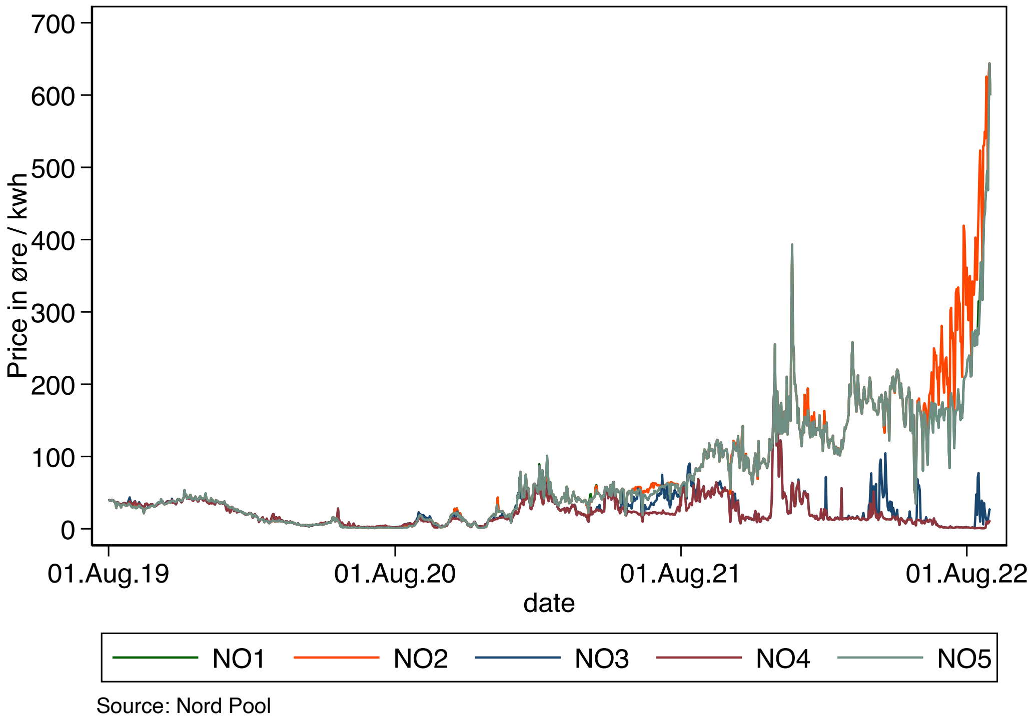


Figure 3: Average daily spot prices for price areas NO1 – NO5 in øre per kwh[4]

2.2.2. Government support policy

As a reaction to the unprecedently high electricity prices, the Norwegian government introduced a policy in December 2021 that temporarily supports households with their electricity expenditures – so-called *Strømstøtteordningen*. Households are compensated for the share of the average monthly spot price paid that is above a cap of 70 øre per kwh for all consumption up to 5000 kwh per month (including VAT). For December 2021, the support covered 55% of that excess-cap

[4] The graph is based on average daily spot price data as provided by the Nord Pool dataset in EUR/MWh for each price area. This data is converted into Norwegian currency using historical exchange rates stated by Norges Bank (Norges Bank, n.d.) and kwh to have a measure in øre per kwh.

expenditure, for January until August 2022 it is increased to a coverage rate of 80% (NVE, 2023).

We can draw two important inferences from this policy. Firstly, we define the 1st of December 2021 as the beginning of the major price shock phase, as the government used this as the start date for its support. Secondly, the government has weakened the direct effect from wholesale price variation on households' electricity expenditures. Average household data for the year 2022 shows that a large part of the spot price shock was absorbed by the support scheme even though average purchase prices were still up by 32 percent compared to the previous five years (SSB, 2023b). However, this number does not account for the regional price differences between the North and the South. Further implications are discussed in Section 7.1, when estimating the purchase PEED.

2.3. Main take-aways for our research

Summing up all institutional elements described above, we see a high share of spot price contracts, an exogenous shock to wholesale prices which disproportionately affects the South of Norway, and a partially muted pass-through to purchase prices due to the government support policy. This combination provides us with an interesting case to investigate the response in residential electricity demand to the spot price shock as well as to approximate the effect of corresponding changes in the purchase price.

3. Literature review

The literature review starts with a short introduction of the interaction between supply and demand as well as the relevance of the price elasticity of demand in the context of liberalized electricity markets. This is followed by a reflection on results from previous research on price elasticities for residential electricity demand from a global perspective and with a particular focus on findings from Norway. Besides, we contemplate a paper by Feehan (2018) which serves as inspiration for our own research as it uses a difference-in-difference design for PEED estimation. Lastly, we briefly refer to the implications of aggregation bias on studies of this kind.

3.1. Price elasticities in the wholesale market

In public policy analysis, the short-term economic efficiency is about finding productive and allocative efficiency given a set of assets (Biggar & Hesamzadeh, 2014, p. 4f.). This is illustrated in the power market where electricity is not consumed directly but by means of a stock of appliances which is built up in the past (Biggar & Hesamzadeh, 2014, p. 7).

For establishing a balance between demand and supply, it is crucial to understand that the amount of electricity that can be supplied and will be demanded real-time is uncertain (IEA, 2003, p. 43f). Thus, the settlement occurs in two stages. First, there is the day-ahead market where optimal dispatch of electricity is calculated based on forecasts for, e.g., the next 24 hours. Second, there is the spot market which rules the optimal actual dispatch based on updated information from the supply and demand side (Biggar & Hesamzadeh, 2014, p. 126). The supply side usually comprises generators. On the demand side, only consumers of high amounts of electricity act individually in the spot market while most consumers have contracts with retailers. Prices are determined by the marginal offer of the generator (hence, the ‘marginal generator’) where supply and demand cross (Biggar & Hesamzadeh, 2014, p. 291; IEA, 2003, p. 44).

Like for any other market, to design policies that lead to an efficient outcome, it is crucial to understand the response in demand resulting from price changes, also known as the price elasticity of demand (PED). The price elasticity can generally be defined as a one-percent change in demand for a particular good due to a one-percent change in the price of the same good:

$$\text{PED} = \frac{\Delta\%Q}{\Delta\%P}$$

The PED in the electricity market (i.e., the PEED) provides useful information for measuring and forecasting demand responses which is generally assumed and found to be very low in absolute terms in the short run (Biggar & Hesamzadeh, 2014, p. 282f.; IEA, 2003, p. 21). Nonetheless, the size of price elasticity estimates depends on the model and data used with aggregation yielding larger PEED values (Bohi, 2011, p.78). Low short run PEED estimates are being related to the fixed stock of appliances (IEA, 2003, p. 21), limitations in the ability to substitute consumption intertemporally (Biggar & Hesamzadeh, 2014, p. 283) and the need for a real-time balance between supply and demand since electricity is primarily consumed when being produced (IEA, 2003, p. 143). However low or high its estimate, it is important to note that the PEED may not necessarily be symmetrical (Bohi, 2011, p. 78; IEA, 2003, p. 21), meaning that the demand response may vary in size depending on the sign of the price change. Besides, it may be non-linear in a sense that a larger price change triggers a more than proportional response (IEA, 2003, p. 21f.). Figure 4 depicts a simplified model of demand and supply in the wholesale market and shows why the degree of elasticity can be of such high relevance. Curve D2 shows a demand curve with moderately elastic demand compared to an entirely inelastic demand curve (D1). The resulting difference in real-time clearing prices in the wholesale market may be large. Whether the true demand resembles D1 or D2 can affect at which price level electricity markets settle and thus impacts the average prices consumers will face in the long run (IEA, 2003, p. 44f.).

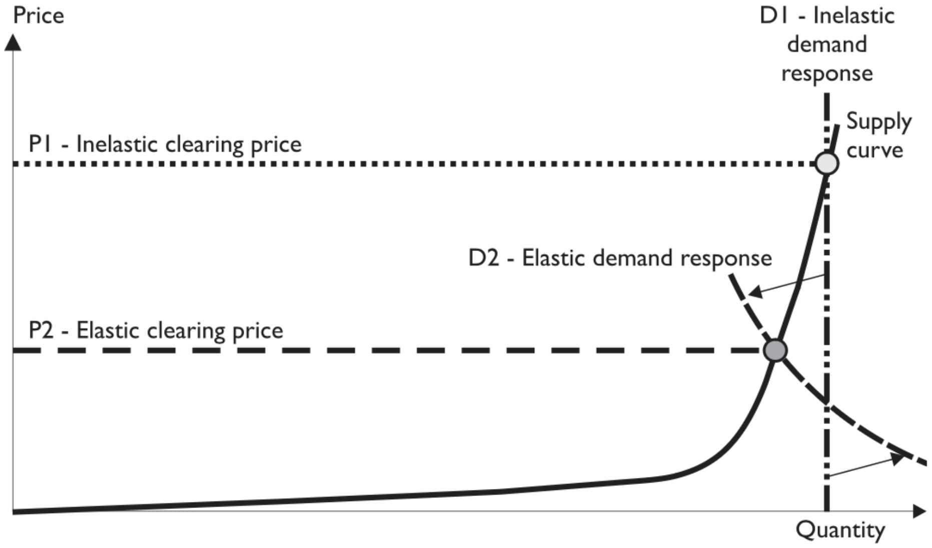


Figure 4: Impacts of demand elasticity on the wholesale price (IEA, 2003, p. 45)

3.2. International research on residential electricity demand

Our empirical analysis focuses on estimates for the short run price elasticity of electricity demand which typically looks at responses in demand when the capital stock is fixed (IEA, 2003, p. 21). In several of the reviewed studies, the short run is regarded to be in the context of the same year or one year or less (e.g., Lijesen, 2007; Burke & Abayasekara, 2018; Csereklyei, 2020). However, to provide a better understanding of the research context and since many studies provide both short- and long run elasticity estimates, we include a few insights on long run elasticities in this literature review, too. An overview of short- and long run PEED estimates from a selected number of reviewed studies using different statistical methods in a variety of time dimensions and structural settings is provided in Appendix 1.

Research on estimates of price elasticities for residential electricity demand has been conducted over several decades. Espey and Espey (2004) provide an often-cited meta-analysis of 36 studies published between 1971 and 2000. They identify previously estimated price elasticities to range from -2.01 to -0.004 in the short run and -2.25 to -0.04 in the long run (Espey & Espey, 2004, p. 66).
According to this paper, residential demand for electricity tends to be more inelastic in the short run than in the long run but estimates may also vary substantially in magnitudes between studies. This finding is supported by reviews included in e.g., Alberini et al. (2011) and Filippini et al. (2018). Espey and Espey (2004) explain that variation in elasticity estimates may arise from differences in demand specifications, data characteristics as well as the time and location of the research. In his review, Bohi (2011) adds that "income, appliance stocks, competing fuel prices, and climate variables are important determinants of demand and will influence price responses" (p. 77).

One controversy refers to the choice of the demand specification. Here, researchers have chosen different approaches from static models to dynamic models for electricity demand. In contrast to dynamic models, static models of demand do not consider the interdependence of consumption decisions over time (Filippini et al., 2018, p. 138). Espey and Espey (2004) find dynamic models to estimate smaller values for price elasticities than static models (p.71). One concern in dynamic models is that lagged dependent variables might be correlated with the error term (Alberini & Filippini, 2011, p. 892; Blazquez et al., 2013, p. 653). Several studies aim to make dynamic partial adjustment models more robust against this dynamic panel bias (Blazquez et al., 2013; Csereklyei, 2020) and measurement errors (Fell et al., 2014) by introducing methods such as the generalized method of moments (GMM). Filippini et al. (2018) argue that dynamic partial adjustment models do not account for forward-looking behaviour of consumers but estimate relatively similar short run elasticities for both the traditional and forward-looking dynamic model (p. 148).

Many of the frequently cited studies on short- and long run price elasticities investigate the US electricity market. Kamerschen and Porter (2004) estimate elasticities between -0.94 and -0.85 (p. 97) – hence almost unit elastic demand. However, other US studies which use aggregate state-level (Alberini & Filippini, 2011; Burke & Abayasekara, 2018; Filippini et al., 2018) and community-level panel data (Deryngina et al., 2020) give rather differentiated and largely more inelastic results in short and long run estimates (see also Appendix 1). For the European continent, Csereklyei (2020) uses aggregate panel data on EU-member states to confirm the notion from US-studies that residential demand tends to be more inelastic in the short run (p. 9). Furthermore, we find similar conclusions for Boogen et al. (2017, p. 90) and Blazquez et al. (2013, p. 655) who investigate the Swiss and Spanish electricity market using utility-level and province-level panel data. In the Nordic context, for the Swedish electricity market, Lanot and Vesterberg (2021) show an inelastic response in the short run (-0.037 to -0.002). The use of cross-sectional data is relatively rare compared to panel data but can be found in Krishnamurthy and Kriström (2015) and Vaage (2000) that estimate (long run) price elasticities for the electricity market in 11 OECD countries and Norway, respectively. Bernard et al. (2011) apply a pseudo panel technique for several independent cross-sections to overcome missing energy price variability and the disregard of the dynamic relationship between energy use and technical appliances (p. 316).

Another controversy in previous literature is whether consumers respond to marginal or average prices. This discussion reflects that economic theory suggests the marginal price to be the decisive benchmark. From a review of studies, Bohi (2011) concludes that marginal prices may be the better choice over average prices given the mixed results on whether average prices yield an acceptable alternative

(p. 77). However, the average price is often the only available price (Espey & Espey, 2004, p.73; Alberini et al., 2011, p. 872; Krishnamurthy & Kirström, 2015, p. 73). Short run elasticity estimates based on marginal prices are found to be smaller than those that considered average prices (Espey & Espey, 2004, p. 73). A concern raised when using the average instead of the marginal price is that this could lead to measurement error (Alberini & Filippini, 2011, p. 893; Alberini et al., 2011, p. 873). A view in favour of the average price as the price variable consumers react to is initially brought into academic debate by Shin (1985). Some recent studies refer to consumers' limitation in understanding (Ito, 2014, p. 560) or perceiving (Shaffer, 2020) pricing structures and the need for appliances to monitor consumption such that one could respond to marginal price changes (Ito, 2014, p. 561). However, we also find research that points to missing validation of the average price response assumption due to the lack of household-specific electricity expenditure data (Fell et al., 2014, p. 47).

An argument in favour of average prices is that the investigated consumers may not possess the right monitoring means (Ito, 2014, p. 561). Further research on effects of real-time information could provide insights on the validity of this reasoning. After reviewing studies showing a low response to real-time pricing (Lijesen, 2007) and no substantial effect of up-to-date information on the response to prices (Lanot & Vesterberg, 2021), but also an increasing effect of real-time feedback on the demand response (Jessoe & Rapson, 2014), we conclude that there is still further research needed to draw more certain conclusions on that matter.

3.3. Studies on residential electricity demand in Norway

Previous research conducted on price elasticities of residential electricity (or, energy) demand for Norway is often built on an exploration via the relationship to the stock of heating or household appliances (Halvorsen and Larsen, 2001; Nesbakken, 1999; Vaage, 2000). Norwegian residential electricity (or, energy) consumption is found to respond relatively inelastically in the short run, with Nesbakken (1999) reporting a short run energy price elasticity of around -0.50 (p. 509) and Halvorsen and Larsen (2001) reporting a short run electricity price elasticity of -0.433 (p. 15). However, since the mentioned studies rely on data from between 1975 to 1995, these results must be regarded with caution.

Many previous studies in- and outside of Norway use purchase prices or consumer expenditure survey data for estimating elasticities. Bye and Hansen (2008) are one of the few that base their research on spot prices. They find small differences in their results depending on the time of day, weekdays, and seasons with real-time estimates being -0.02 in the winter and 0.00 in summer (Bye & Hansen, 2008, p. 13ff.). These estimates also remain fairly robust when considering demand responses to different lags (Bye & Hansen, 2008, p. 23f.). Thereby, Bye and Hansen also noted that one should consider that elasticity estimates from analyses based on wholesale prices would need to be multiplied by the purchase/spot price ratio to account for the true impact of spot price changes as they make up only a share of the purchase price (Bye & Hansen, 2008, p. 27). Our paper follows up on this thought in Section 7.1.

Holstad and Pettersen (2011) show similarly low findings when using monthly consumption data and modelling a one-percent change in the spot price. They find the average PEED to be -0.05 with most of this response happening in the same month of the price change (Holstad & Pettersen, 2011, p. 28f.). It is also evidence presented that price elasticities have been converging closer to zero in recent years (Holstad & Pettersen, 2011, p. 30). Hofmann and Lindberg (2019) which contemplate electricity consumption in the metropolitan area of Oslo find almost no significant PEED results and, in addition, reject the hypothesis that higher price levels combined with elevated public awareness led to a larger demand response. It needs to be mentioned that the later studies (Bye & Hansen, 2008; Holstad & Pettersen, 2011; Hofmann & Lindberg, 2019) also include non-residential demand. However, it is fair to assume that in all the three studies, household consumers are an essential part of the data aggregates used.

3.4. Previous research using a difference-in-difference design

For estimating price elasticities of residential electricity demand, a difference-in-difference design has not been used many times. A paper by Feehan (2018) provides insights on how a difference-in-difference analysis can be applied to estimate the PEED. The underlying idea of this paper has served us as inspiration for conducting our own research. Feehan's (2018) paper is built on a natural experiment caused by a price shock in one out of two regions in the Canadian provinces of Newfoundland and Labrador. The study exploits the removal of a block pricing scheme in one of the two regions which historically recorded the same pricing schemes for electricity. The price shock was sudden in nature, economically significant (e.g., a 55% pricing difference for consumption in excess of 1000 kwh in 2015) and sustained in the long-term (Feehan, 2018). An important assumption made is that both regions are either similar in their characteristics, such having identical weather conditions, or follow common trends (for instance, in family income) where differentials remain relatively unchanged throughout the more than 20 years investigated (Feehan, 2018, p. 14). This main identifying assumption follows a classical difference-in-difference set-up and serves us as guidance for our own methodology. However, we acknowledge that Feehan (2018) conducted his research in another time and geographical context and focuses on an estimation of the long run price elasticity. Furthermore, instead of using a regression model, the price elasticity is calculated by using the arc formula and building a counterfactual based on the pre-shock difference in consumption (Feehan, 2018, p. 15). This is possible as Feehan (2018) compares only two geographical entities – the L'Anse au Loup and Isolated Southern Labrador region. Thus, parallels between Feehan (2018) and our study can only be drawn to a limited degree.

3.5. Aggregation bias in the analysis of electricity demand

As reviewed in the prior sections of this chapter, many previous studies use electricity consumption data that is aggregated either over different end-uses or higher-level measurement levels. Bohi (2011) describes the resulting dilemma from aggregation the following way: "Often the only available consumption data combine the activities of different consumers, where each may have different uses for the same fuel as well as different propensities for consumption in each application." (p. 28). This means that estimation results likely run into aggregation bias. The question is how our paper should account for this type of bias. According to Bohi (2011, p. 30), there is not much one can do despite ensuring the least aggregation and highest degree of homogeneity possible in a sample. Focusing on residential demand can be seen as a minimum level of disaggregation (Bohi, 2011, p. 30). Our thesis is limited in the type of municipality-level data available and for reasons of data protection it was not possible to obtain equivalent consumption data aggregated on the household-level. Hence, the best we can do in this paper is to run robustness checks with a different sample size and compare our results to other studies that, in part, used different data aggregation levels.

4. Data

In the following chapter, the main datasets in use for our research and initial adjustments to the data are described. Secondly, a summary is provided on socioeconomic variables that are used for descriptive purposes and balance checks in our sample. Lastly, we present summary statistics on all data.

4.1. Description of the main dataset

We use municipality-level panel data on electricity consumption aggregated for metering points. The data is provided by *Elhub* which is an entity of *Statnett*, a state-owned company responsible for operating and constructing the power grid. This consumption data has been categorized per municipality, price area and consumer groups in accordance with the Standard Industrial Classification (SIC 2007). For our study, we focus on the two categories *Husholdning* (= residential housing) and *Fritidsbolig* (= cabin). Consumption volumes are measured in MWh and given for each day. The data corresponds to the time from 01.08.2019 until and including 31.08.2022. For the same period, we obtained data on average daily electricity spot prices measured in Euro per MWh for each of the five Norwegian pricing areas from the power exchange *Nord Pool*. These average daily rates are derived from the hourly spot prices that are established as explained in Section 2.1.1. All spot prices are converted into Norwegian currency using historical exchange rate data as published by *Norges Bank* (Norges Bank, n.d.).

Table 1 summarizes information on average daily spot prices (in øre per kwh) and their standard deviations for three different periods: a *pre-shock phase* (01.08.2019 – 31.07.2021), an *initial shock phase* (01.08.2021 – 30.11.2021) and a *second shock phase* (01.12.2021 – 31.08.2022). That differentiation between the two shock phases is done since prices in the South began to deviate from the Northern prices around the beginning of August (see also Figure 3). However, as the price shock became stronger over time, the government imposed a support mechanism for residential electricity consumption as discussed in Section 2.2.2. We assume that the government is targeting what it regards as the major phase of the shock. Hence, we take the 1st of December 2021 as the beginning of the second – major – shock phase.

	NO1	NO2	NO3	NO4	NO5
Average daily spot prices in øre/ kwh (Standard deviation)					
Pre-Shock	26.81	26.96	23.57	20.96	26.72
01.08.2019 – 31.07.2021	(19.70)	(19.74)	(16.23)	(14.34)	(19.65)
Initial shock phase	96.17	96.49	44.89	39.75	96.18
01.08.2021 - 30.11.2021	(26.04)	(26.15)	(34.26)	(32.92)	(25.79)
Second shock phase	181.29	206.32	24.00	17.87	180.55
01.12.2021 - 31.08.2022	(79.60)	(105.19)	(24.93)	(21.46)	(79.20)

Table 1: Average daily spot prices in NO1-NO5 in øre pr kwh[5]

Table 1 shows that daily average spot prices in the Southern price areas NO1, NO2 and NO5 have indeed become higher and more volatile over the two respective shock phases compared to spot prices in the Northern price areas NO3 and NO4. During the second shock phase, NO2's spot prices deviate from NO1 and NO5 and increase even more on average.

To account for differences between municipalities in terms of population size and the number of cabins, we obtained municipality population data for 2019 until 2022 (SSB, 2023d) as well as data on the number of registered cabins in each municipality for 2020 until 2022 (SSB, 2023e). Figures 5 and 6 depict scatter plots for aggregate per-municipality electricity consumption in residential housing and cabins excluding the highly populated municipality Oslo. They relate each municipality's residential electricity demand to the size of its population (Figure 5), and electricity consumption at cabins to the number of cabins (Figure 6).

Figure 5 shows a very pronounced linear fit. Thus, we continue the analysis of residential housing using a consumption-per-municipality-capita proxy (in kwh per municipality-capita) instead of aggregate data only. This also allows us to account for people changing their residence within Norway during the period of our investigation. Given the decent linear fit in Figure 6, we apply the same logic for the cabin category and continue with a consumption-per-cabin proxy (in kwh per cabin) to account for the build-up of new cabins in each municipality over time. Since the cabin counts are not available for 2019, they are approximated by the 2020 value.

[5] The data is based on average daily spot price data in EUR/MWh for each price area which is converted into Norwegian currency using historical exchange rates provided by Norges Bank (Norges Bank, n.d.) and per kwh to obtain a measure in øre per kwh.

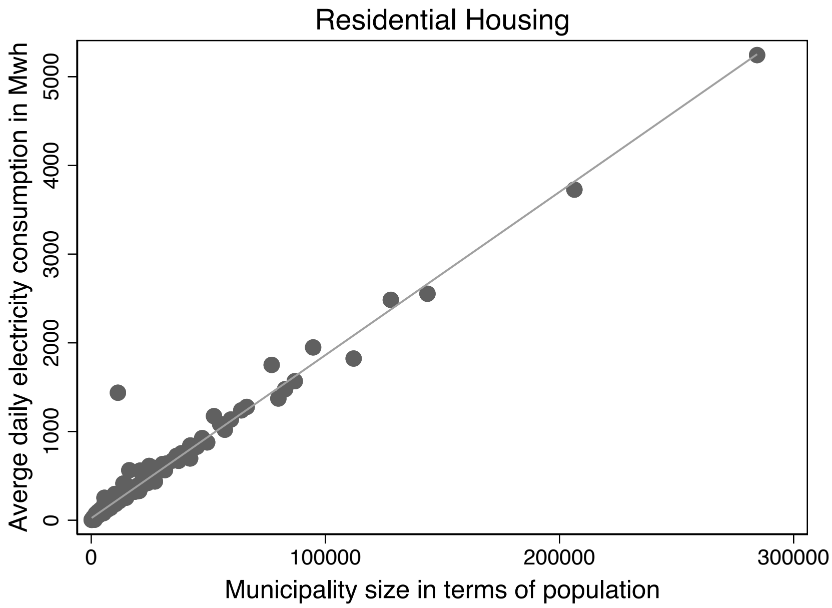


Figure 5: Average daily consumption per municipality relative to population size[6]

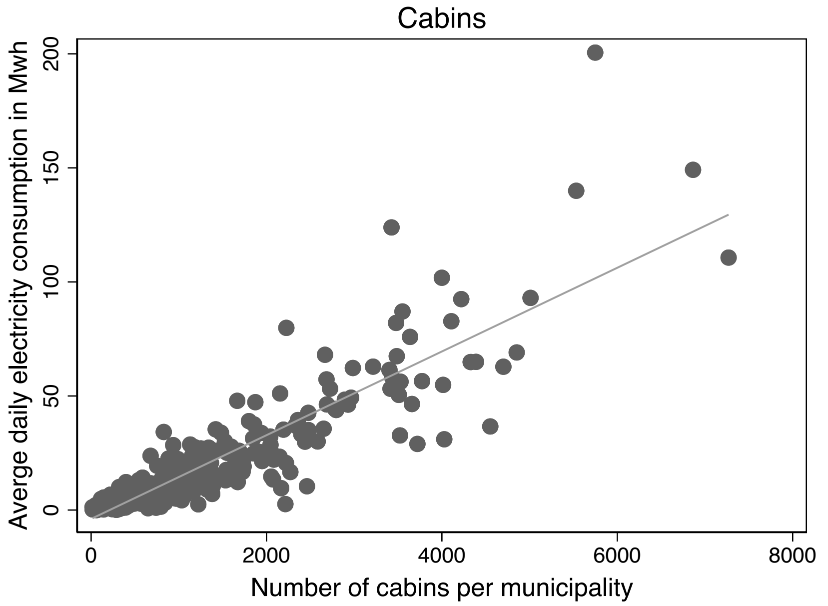


Figure 6: Average daily consumption per municipality relative to the cabin count[7]

[6] Municipality Oslo (Nr. 301) is excluded. Municipality size in terms of population is derived by the average of population counts for the years 2019 – 2022 as provided by SSB. Average daily electricity consumption in MWh is based on per-municipality mean consumption in electricity for the period 01.08.2019 until 31.08.2022 for the category 'Husholdning'. 345 municipalities are included after an initial round of data cleaning.

[7] Municipality Oslo (Nr. 301) is excluded. The number of cabins per municipality is derived by the average of cabins registered in each municipality between 2020 and 2022 as provided by SSB. Average daily electricity consumption in MWh is based on per-municipality mean consumption in electricity for the period 01.08.2019 until 31.08.2022 for the category 'Fritidsbolig'. 345 municipalities are included after an initial round of data cleaning.

4.2. Socioeconomic variables

The main dataset is extended by a range of municipality-level socioeconomic variables. Among those, one can find demographic variables such as inhabitants' mean age or the number of people living in one household. Besides, we obtain variables referring to the financial situation of households, i.e., on median household income or the share of households in particular wealth cohorts. Another selection of variables provides more information on the living situation of households such as the shares of single buildings, the ownership rate of housing or the share of registered electric vehicles. These variables are primarily used for balance checks presented in Section 5.4 but also serve as references for the discussion chapter. More details on specifications of the socioeconomic variables and the corresponding data sources can be found in Appendix 2.

4.3. Summary statistics

In Table 1, we already provide summary statistics on spot prices that show the size of the price shock on NO1, NO2 and NO5 as presented in Chapter 2. Table 2 provides summary statistics on the consumption data from our main dataset and the socioeconomic variables. The socioeconomic variables are weighted by population sizes of the municipalities within each price area except for the number of cabins.

Average per-capita and per-cabin electricity consumption are each comparably alike across price areas, though the highest values are found in the Northern price area NO4 most likely due to its climatic conditions. An interesting point to note is the shift in the share of people from the lower net-wealth cohorts to the upper three cohorts between 2020 and 2021. This indicates higher savings of households during that period and coincides with a comparable increase in median household incomes in all price areas but also the time of pandemic-related restrictions which may have induced higher saving rates. The share of housing ownership – which includes sole and shared ownership – is overall very high in Norway. However, it tends to be slightly lower in NO1 and NO5 which comprise the two metropolitan areas Oslo and Bergen, respectively. While the number of people living in one household is comparable among all five price areas, single buildings are especially common in the North as well as in NO2. The ratio of registered electric vehicles to capita is especially high in NO1 and NO5 compared to the remaining three price areas. Besides, most cabins are registered in the two Southern price areas NO1 and NO2.

	NO1	NO2	NO3	NO4	NO5
Number of municipalities	82	79	74	83	28
Mean population (2020-2022)	2,149,837	1,278,903	812,075	485,615	475,113
Mean age	40.4	40.6	41.1	42.2	40.0
Average daily electricity consumption in kWh (Standard deviation) – entire period					
Residential housing	20.68	20.01	20.23	27.20	22.09
Per capita	(8.86)	(8.25)	(7.54)	(15.45)	(8.53)
Cabins	11.39	14.82	13.46	17.65	17.42
Per cabin	(9.61)	(11.19)	(9.44)	(14.30)	(11.56)
Pers. p. HH	2.12	2.20	2.15	2.09	2.14
Median HH income	570,548	581,310	571,182	554,573	578,277
2021 (2020) in NOK	(547,873)	(558,262)	(549,938)	(536,583)	(556,712)
HH net-wealth 2021 (2020) in %					
Cat. 1	27.2	26.5	28.2	29.4	27.0
< 250k NOK	(28.6)	(29.0)	(30.5)	(31.2)	(28.6)
Cat. 2	3.6	4.4	5.1	5.2	4.3
250k – 499,999 NOK	(3.8)	(5.0)	(5.4)	(5.5)	(4.8)
Cat. 3	5.5	8.1	8.6	8.7	7.5
500k – 999,999 NOK	(6.2)	(9.0)	(9.3)	(9.4)	(8.1)
Cat. 4	10.7	15.1	15.3	16.1	13.5
1m – 1,999,999 NOK	(11.8)	(15.6)	(15.7)	(16.9)	(13.9)
Cat. 5	10.3	12.4	12.4	12.7	11.6
2m – 2,999,999 NOK	(10.9)	(12.3)	(12.3)	(12.6)	(11.8)
Cat. 6	9.0	9.5	9.3	8.8	9.5
3m – 3,999,999 NOK	(9.0)	(9.0)	(8.7)	(8.3)	(9.4)
Cat. 7	33.7	23.9	21.1	19.0	26.7
> 4m NOK	(29.7)	(20.0)	(18.0)	(16.2)	(23.4)
Housing ownership in %	75.7	79.7	76.4	75.9	74.3
Share of single houses in %	39.1	58.3	55.2	62.1	44.0
EV-to-capita ratio in % (2021)	10.4	8.0	6.2	3.5	11.4
No. Cabins (3-year mean)	141,097	109,658	74,552	54,957	44,640

Table 2: Summary statistics for the population data[8]

[8] Consumption values are given p. capita / p. cabin based on municipality population / cabin count and their standard deviation are calculated per price area. Due to municipality mergers, variables based on 3-year means (2020-2022) weighted by within-price-area municipality populations are: mean age, pers. p. HH, housing ownership (self- and share owning), share of single houses. The table includes all municipalities after initial data cleaning (Residential: 10 municipalities dropped, Cabins: 11 dropped - thus 81 municipalities in NO1).

5. Methodology and research design

This chapter presents the difference-in-difference design used in this study, the specifications of the baseline regression model and related identifying assumptions. Furthermore, an explanation of the sampling process as well as descriptive statistics and balance checks for the main sample are provided.

5.1. The difference-in-difference design

Previous research discussed in Chapter 3 often uses models with municipality-level temperature data as controls. Due to the absence of this type of data in our dataset, we implement a difference-in-difference design with a linear regression as our baseline model as presented in Section 5.2.

The main assumption relied upon in a difference-in-difference analysis is the so-called *parallel trends assumption.* It says that, in the absence of treatment, control and treatment groups follow similar paths, i.e., that differences in outcomes do not vary over time (Angrist & Pischke, 2015, p. 178ff.). For this assumption to hold, the analysis focuses on municipalities that experience the spot price shock to a different extent but are geographically adjacent to another. Choosing proximate municipalities ensures relatively similar climatic conditions as well as common geographical characteristics on both sides of the border. Furthermore, the comparatively short period of investigation (37 months) makes the occurrence of significant sociodemographic shifts between municipalities unlikely. By conducting balance checks for the sociodemographic variables (Section 5.4) and validating the parallel trends in electricity consumption before the spot price shock (Section 6.1), we ensure that the Southern spot prices and – in the case of a response – Southern electricity consumption during the period of elevated prices are the only observable parameters that significantly diverge.

5.2. The baseline regression model

Equation (1) shows the baseline model used for this research where electricity consumption data is regressed on contemporaneous spot market prices. There are three different time specifications used as given by *t*: daily average values (given by the dataset), as well as average weekly and monthly data based on aggregation of the dataset on the time dimension. Separate regressions are applied for residential housing and cabins as denoted by *i*. Since the analysis is conducted on the municipality-level, *m* indicates the respective municipality:

$$(1)\ \log(Cons_{mt}^{i}) = \beta_0^i + \beta_1^i * \log(Priceinørekwh_{mt}^{i}) + \theta_t + \omega_m^i + \varepsilon_{mt}^i$$

The term ε_{mt}^i captures statistical noise. Besides, we introduce time fixed effects θ_t and municipality fixed effects ω_m^i to control for time-invariant higher-level variances and thus avoid that our estimates suffer from heterogeneity bias (Bell & Jones, 2015, p. 138). Our parameter of interest, β_1^i, represents the variation in electricity consumption ($Cons_{mt}^i$) that is explained by a change in the spot price variable $Priceinørekwh_{mt}^i$. The consumption variable $Cons_{mt}^i$ is measured in kwh per municipality-capita or per cabin in each municipality, respectively.

As consumption and spot prices are converted into log-log form, the estimates for β_1^i represent the percentage change in electricity consumption following a one percentage change in the spot price. This is in accordance with the general definition of the price elasticity of demand as discussed in Section 3.1. The natural logarithm is only defined for values larger than zero. For spot market price data in the electricity market, this is a relevant concern since hourly spot prices can temporarily undershoot the zero-value. However, due to the aggregate nature of our price data, all average daily spot price values are positive.

5.3. Sampling strategy and sample descriptive statistics

A balanced sample is needed to ensure that deviations in electricity consumption from assumed similar trends are due to price differences and not based on deviations in other observable variables. The sampled municipalities that are located in the Southern price areas and experience the price shock are assigned to the treatment group. Municipalities from the sample that are in the Northern price area, where the price shock did not occur, are assigned to the control group.

Our sampling strategy focuses on municipalities lying in proximity to the price borders between NO3 and NO1 as well as NO3 and NO5 which together represent the frontier between the North and South in the Norwegian electricity market. This we call our *border criterium*. Municipalities sampled from NO3 are thus included in the control group while sampled municipalities from NO1 and NO5 are assigned to the treatment group. When selecting municipalities on both sides of the border, we build a geographically rectangular sample to account for locational differences between the East and the West of Norway. However, there is no fixed requirement on the maximum distance of a sample municipality to the pricing border. This is due to differences in the sizes of municipalities, the non-verticality of the pricing border and the partial disconnect between the pricing border and municipality borders.

Secondly, applying the *price area criterium*, sampled municipalities located in two price areas are excluded from the sample unless demand observations in one price area are found to be economically insignificant.

Thirdly, we use an *observations criterium* to ensure that for each analysis of residential housing and cabins, respectively, we have a complete set of observations in each municipality. Sampled municipalities with an incomplete set of observations are excluded. Figure 7 shows the selected sample (as listed in Appendix 3) after all criteria are applied.

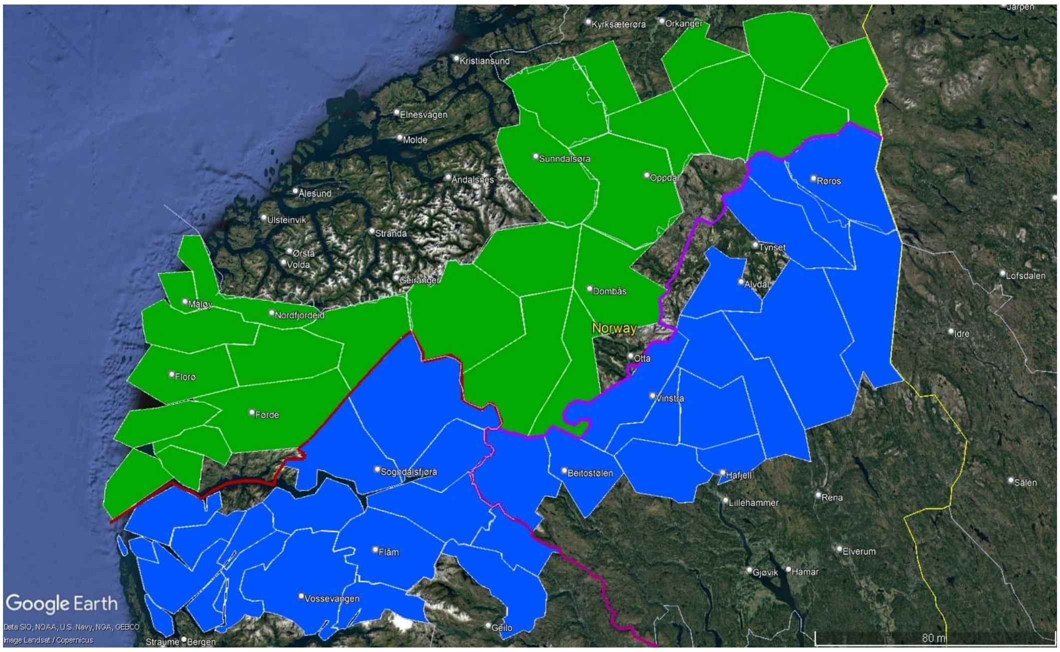


Figure 7: Main sample municipalities along the North-South border[9]

Based on the above-mentioned criteria, the main sample comprises 58 municipalities of which are 14 in NO1, 25 in NO3, and 19 in NO5. Given the time horizon of the analysis, the per-municipality count of observations reads 1127, 161, and 37 for the daily, weekly, and monthly regressions.

Table 3 provides summary statistics only with regards to our main sample. The sample is on average older for all three price areas, with sampled municipalities

[9] North (NO3): green; South (NO1 and NO5): blue. The map is created using Google Earth. The gaps along the border which are not filled by color show municipalities that are removed from our sample as they contain economically significant data points in two price areas.

from NO1 showing the highest mean age while they also have fewer people sharing one household. Average daily per-capita electricity consumption is higher for the Southern sample municipalities while the overall picture in consumption resembles the data presented in the population summary statistics.

With regards to the trends in income and net-wealth distribution, similar inferences can be made compared to the population data set. Between 2020 and 2021, median household income growth is about 20,000 NOK in each price area and net-wealth shifts slightly towards the upper cohorts. Compared to the population data, housing ownership rates in the sample are higher in all price areas and the share of single buildings in NO1 is double the size.

Besides, the EV-to-capita ratio is far lower for NO1 in the sample compared to the population. A major reason for this difference is that NO1 in the sample is dominated by rural municipalities while the metropolitan area Oslo – which is included in the population statistics – is absent. In contrast, the sampled municipalities in NO5 are relatively close to the city of Bergen.

	NO1	NO3	NO5
Number of municipalities	14	25	19
Population (2020-2022)	45,944	139,989	131,691
Mean age	45.0	42.4	40.9
Average daily spot prices in øre/ kwh (Standard deviation)			
Pre-Shock	26.81	23.57	26.72
01.08.2019 - 31.07.2021	(19.70)	(16.23)	(19.65)
Initial shock period	96.17	44.89	96.18
01.08.2021 - 30.11.2021	(26.04)	(34.26)	(25.79)
Second shock period	181.29	24.00	180.55
01.12.2021 - 31.08.2022	(79.60)	(24.93)	(79.20)
Average daily electricity consumption in kWh (Standard deviation) – entire period			
Residential housing	23.03	20.38	21.94
Per capita	(9.93)	(7.63)	(8.14)
Cabins	16.21	13.42	16.44
Per cabin	(13.46)	(8.68)	(10.92)
Pers. p. HH	2.08	2.24	2.30
Median HH income	522,479	580,614	615,936
2021 (2020) in NOK	(502,725)	(558,527)	(594,822)
HH net-wealth 2021 (2020) in %			
Cat. 1	28.5	27.3	25.1
< 250k NOK	(30.3)	(29.6)	(27.0)
Cat. 2	6.0	5.5	4.8
250k – 499,999 NOK	(6.3)	(5.6)	(5.2)
Cat. 3	10.5	8.9	8.5
500k – 999,999 NOK	(10.7)	(9.7)	(9.1)
Cat. 4	17.7	16.1	15.1
1m – 1,999,999 NOK	(18.6)	(16.6)	(15.6)
Cat. 5	13.4	13.2	12.7
2m – 2,999,999 NOK	(13.1)	(13.3)	(13.1)
Cat. 6	8.5	9.5	10.4
3m – 3,999,999 NOK	(7.9)	(9.0)	(10.0)
Cat. 7	15.3	19.7	23.4
> 4m NOK	(13.1)	(16.4)	(20.0)
Housing ownership in %	77.4	78.6	79.5
Share of single houses in %	83.1	72.6	71.4
EV-to-capita ratio in % (2021)	2.7	4.4	9.1
No. Cabins	32,286	28,308	20,258

Table 3: Summary statistics for the main sample[10]

[10] This table is made using the same calculation methods as for the population statistics (Table 2) described in footnote 8.

5.4. Sample balance checks

As depicted in Table 4, when applying t-tests to check our main sample of 58 municipalities for statistical balance according to the set of socioeconomic variables, there are a few, however no systematic, statistically significant differences in means between the treatment group in the Southern price areas NO1 and NO5 and the control group from the Northern price area NO3.

There are only two prevailing differences in means between the treatment and control group in the shares of people in the fourth category in 2021 (at the 10 %-significance level) and the fifth wealth category in 2020 (at the 5 %-significance level). We argue that these wealth differences in the composition of the middle class are of minor importance, provided that the overall wealth distribution is quite balanced. Nonetheless, we acknowledge that we need to check for the robustness of our balance checks by introducing per-municipality population weights to account for the relative differences in municipality sizes.

Thus, the balance checks are repeated after weighting our socioeconomic variables with the per-municipality average population data. Overall, the resulting p-values from these balance checks shown in Table 5 confirm our inference on the balance of the sample from Table 4. The only exceptions that can be found relate to the composition of the wealth distribution for cohorts 2 – 4 for which we find statistically significant differences. However, in line with the logic applied in Feehan (2018), these statistically significant differences stay relatively unchanged when comparing the respective values from 2020 to 2021. Even though the wealth difference between the second and the fourth cohort is considerable in economic terms, we reemphasize that the statistical differences seem to primarily reflect differences in the composition within the middle class instead of systematic imbalances between the shares of low-wealth, middle-class and high-wealth households.

Furthermore, we find statistically significant differences in means for the share of single buildings which also stay constant over the time of the investigation. For instance, the weighted difference in means for the share of single buildings remains at around -1.78 to -1.77 for all three years tested.

Unweighted t-tests	North – South			
	2019	2020	2021	2022
Income				
Levels in NOK		-797.58	1329.70	
		(11,337.89)	(11,536.12)	
Change rate			0.0041	
(2020 to 2021)			(0.0042)	
Persons per HH		0.0222	0.0284	0.0314
		(0.0318)	(0.0313)	(0.0313)
HH net-wealth 2021 (2020) in %				
Cat. 1		-0.4366	-0.9378	
< 250k NOK		(0.9802)	(1.0076)	
Cat. 2		-0.1896	0.1788	
250k – 499,999 NOK		(0.3127)	(0.3228)	
Cat. 3		0.2753	-0.3359	
500k – 999,999 NOK		(0.5109)	(0.5095)	
Cat. 4		0.6276	1.2903*	
1m – 1,999,999 NOK		(0.6929)	(0.7062)	
Cat. 5		0.9422**	0.6421	
2m – 2,999,999 NOK		(0.4512)	(0.4084)	
Cat. 6		-0.1257	-0.0246	
3m – 3,999,999 NOK		(0.4518)	(0.4271)	
Cat. 7		-1.0672	-0.8248	
> 4m NOK		(1.2488)	(1.4725)	
Housing ownership in %				
(only) Self-owned		0.2385	0.7246	0.6869
		(1.2943)	(1.3465)	(1.3268)
Building type				
Single building		-1.2635	-1.1116	-0.9373
		(2.4528)	(2.4859)	(2.5059)
EV-to-capita ratio	-0.0076	-0.0083	-0.0108	
	(0.0052)	(0.0060)	(0.0073)	

* Significance at the 10%-level. ** Significance at the 5%-level. *** Significance at the 1%-level.

Table 4: Differences in means and standard errors from unweighted t-tests[11]

[11] The t-test included the 58 main sample municipalities North and South of the price border between NO3 and NO1 & NO5. The table states the differences in means and (in parentheses) in the related standard errors.

P-values for weighted t-tests	**North – South**			
	2019	2020	2021	2022
Income				
Levels in NOK		0.1773	0.1810	
Change rate (2020 to 2021)			0.2230	
Persons per HH		0.1662	0.1683	0.1709
HH net-wealth 2021 (2020) in %				
Cat. 1 *< 250k NOK*		0.1286	0.1138	
Cat. 2 *250k – 499,999 NOK*		0.0559*	0.0794*	
Cat. 3 *500k – 999,999 NOK*		0.0752*	0.0472**	
Cat. 4 *1m – 1,999,999 NOK*		0.0796*	0.0937*	
Cat. 5 *2m – 2,999,999 NOK*		0.1494	0.1330	
Cat. 6 *3m – 3,999,999 NOK*		0.1852	0.1730	
Cat. 7 *> 4m NOK*		0.2212	0.2473	
Housing ownership in %				
(only) Self-owned		0.1067	0.1118	0.1134
Building type				
Single building		0.0597*	0.0600*	0.0591*
EV-to-capita ratio	0.2733	0.2887	0.2721	

* Significance at the 10%-level. ** Significance at the 5%-level. *** Significance at the 1%-level.

Table 5: P-values resulting from the weighted t-test[12]

[12] The t-test included the 58 main sample municipalities North and South of the price border between NO3 and NO1 & NO5. Averages for the North and the South were derived as weighted averages according to the relative population sizes of the municipalities they comprise.

Furthermore, as shown in Table 6, checking for a balance in differences in means with regards to the number of cabins, we only see statistically significant differences at the 10%-level for the number of cabins when taking a closer look at the Eastern cohort of the sample. Despite this significant difference in levels, one can observe that the difference in means stays relatively constant over time. Thus, the results do not provide us with a strong signal that this observed difference interferes with our parallel trends assumption in electricity consumption outcomes.

Unweighted t-test	**2020**	**2021**	**2022**
Number of cabins		**North - South**	
Per municipality	-447.17	-458.65	-473.91
	(283.42)	(288.12)	(296.20)
Number of cabins		**NO3.East – NO1**	
Per municipality	-690.28*	-711.16*	-740.76*
	(371.93)	(382.36)	(396.81)
Number of cabins		**NO3.West – NO5**	
Per municipality	-424.59	-431.71	-439.50
	(331.23)	(331.63)	(337.39)

* Significance at the 10%-level. ** Significance at the 5%-level. *** Significance at the 1%-level.

Table 6: Differences in means and standard errors resulting from the unweighted t-test for the number of cabins[13]

[13] The t-test included the 58 main sample municipalities North and South of the price border between NO3 and NO1 & NO5. The number of cabins is formed as a 3-year average between 2020 and 2022. The table states the differences in means and (in parentheses) in the related standard errors.

6. Results

In the following chapter, we first present evidence for the validity of our *parallel trends assumption* by using indexed per-capita electricity consumption values for residential housing and cabins. In the second part, we provide the short run spot PEED estimates from our baseline regression.

6.1. Verifying the parallel trends assumption

Figures 8 and 9 show consumption indexes for the Northern control group and the Southern treatment group of the main sample. Demand is normalized to the value of 100 for the initial full week in August 2019. Following relative changes compared to the normalized values are plotted for the entire period of our investigation. Figure 8 depicts the trends in electricity consumption for residential housing while Figure 9 shows the equivalent for cabins. Parallel trends can be clearly identified for both categories. Seasonal swings in consumption shown in both figures mainly seem to originate from higher electricity demand for heating and lighting in the winter season.

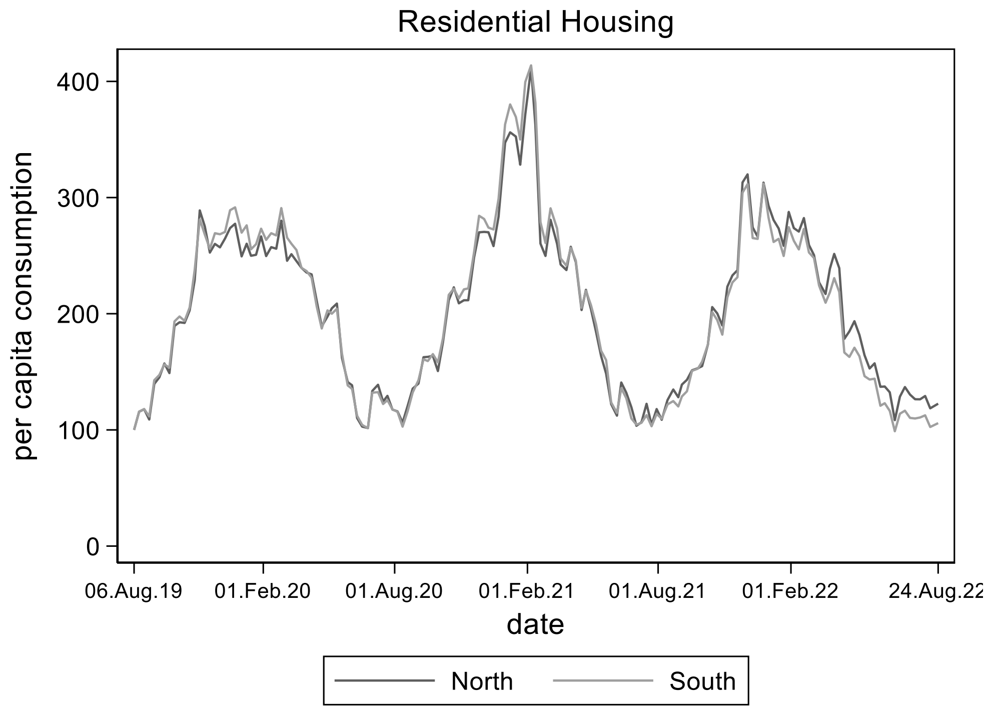


Figure 8: Consumption indexes for residential housing[14]

[14] The mean per-capita consumption for the Northern and Southern group of municipalities in our sample is normalized to 100 for the first full week in August 2019, respectively. Thereafter changes are accounted for as an index relative to the initial normalized value.

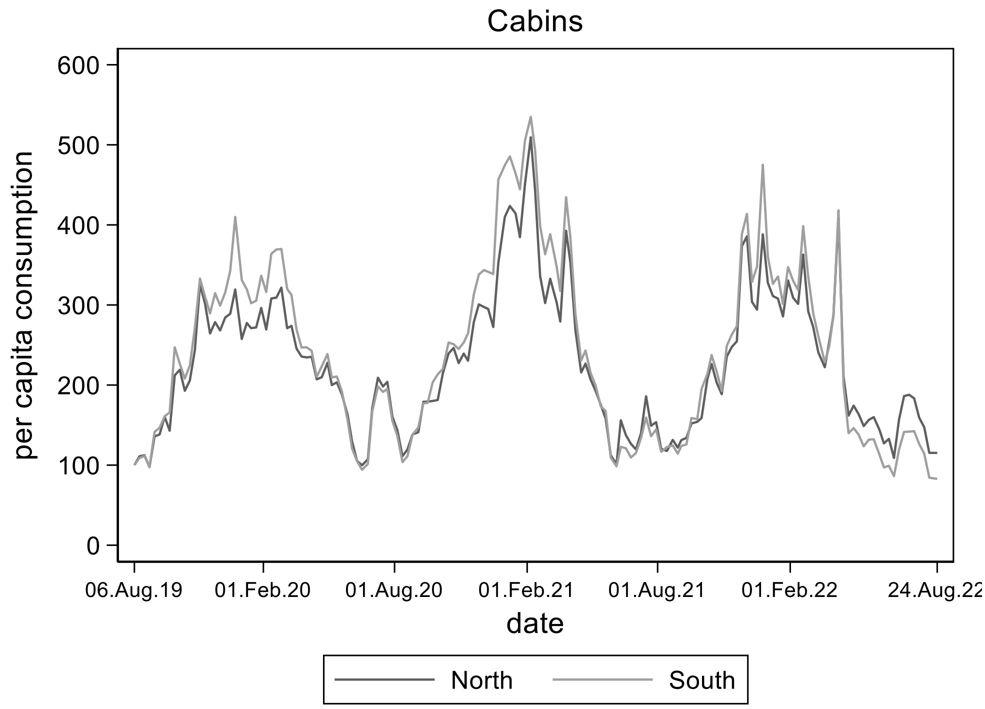


Figure 9: Consumption indexes for cabins[15]

The most striking observation can be made in the last episode of the investigation from around December 2021 until the end of August 2022. This corresponds to the period with the largest observed spot price differences between the Northern and Southern price areas. In this episode, indexed Southern electricity consumption is initially not as much larger than its Northern counterpart as opposed to similar periods in the two years prior, while it eventually undershoots the Northern index.

This change in the relative differences between both sample groups becomes even more visible when looking at Figures 10 and 11. These figures depict the relative differences in percent between the indexed trends for the sampled Southern and Northern municipalities. Towards the year 2022, indexed Southern electricity consumption decreases by around ten to fifteen percentage points more relative to the Northern part of the sample as compared to similar times in prior years where the consumption indexes show very similar paths and swings in the relative difference are of seasonal character.

[15] The mean per-cabin consumption for the Northern and Southern group of municipalities in our sample is normalized to 100 for the first full week in August 2019, respectively. Thereafter changes are accounted for as an index relative to the initial normalized value.

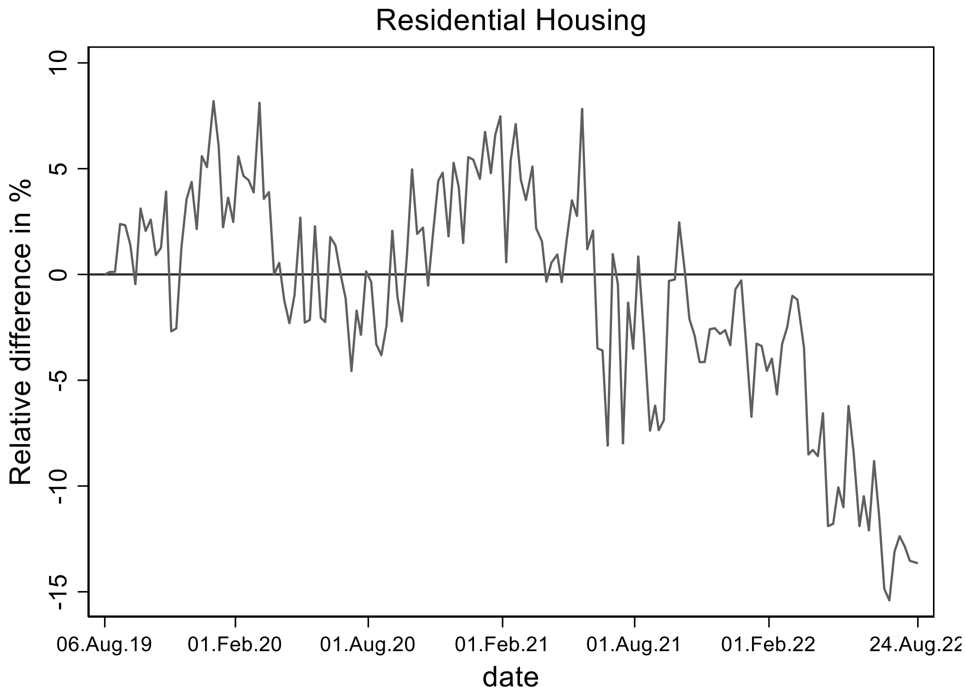


Figure 10: Relative South-North difference in indexed per-capita residential electricity consumption for the main sample[16]

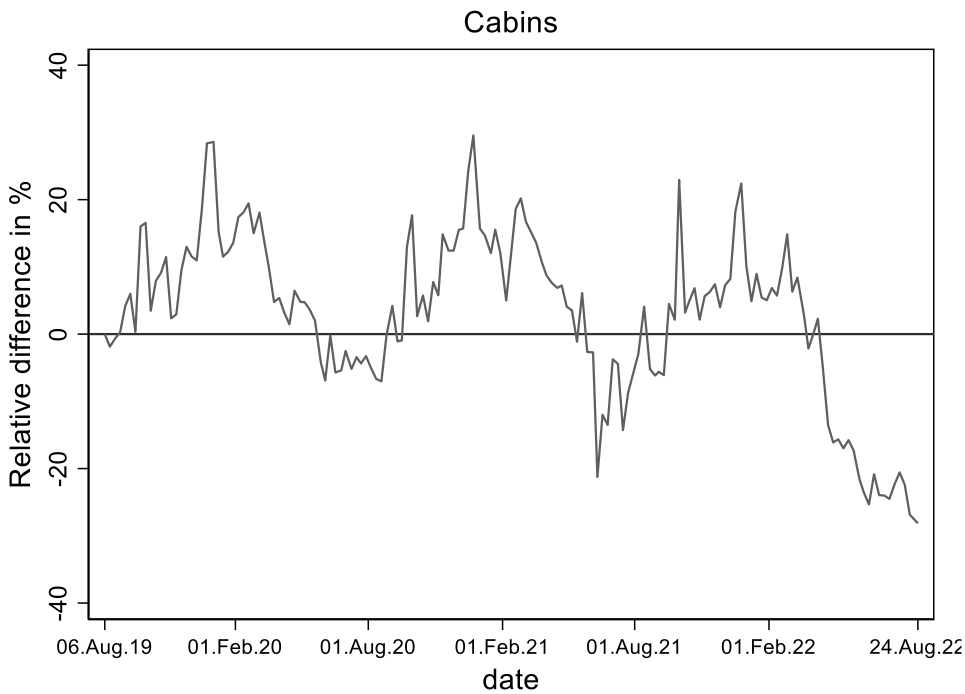


Figure 11: Relative South-North difference in indexed per-cabin electricity consumption at cabins for the main sample[17]

[16] The relative difference is derived by the difference between the Southern and Northern group of the sample in indexed electricity consumption as depicted by Figure 8 and divided by the normalized Northern value.

[17] The relative difference is derived as in Figure 10 using the indexed consumption from Figure 9.

6.2. PEED estimates for the baseline regression model

As shown in Table 7, the baseline regression spot PEED estimates for residential housing are all negative and highly statistically significant. The estimated coefficients for contemporaneous residential demand responses amount to -0.013 for daily, -0.018 for weekly and -0.02 for monthly specifications.

For cabins, the daily, weekly, and monthly PEED estimates from the baseline model are -0.023, -0.022, and -0.02. All baseline estimates show very inelastic electricity demand, that is slightly higher in absolute terms at cabins. However, both estimates converge for the monthly specification showing that in a longer time specification, households' demand response is similar for both electricity consumption at home and at cabins.

	Residential housing	**Cabins**
	Daily PEED estimates	
$log(Priceinørekwh^{i}_{mt})$	-0.0133***	-0.0230***
	(0.0027)	(0.0036)
	Weekly PEED estimates	
$log(Priceinørekwh^{i}_{mt})$	-0.0179***	-0.0217***
	(0.0025)	(0.0039)
	Monthly PEED estimates	
$log(Priceinørekwh^{i}_{mt})$	-0.0198***	-0.0195***
	(0.0026)	(0.0042)

The main values are the PEED estimates. The corresponding robust standard errors are given in parentheses. * Significance at the 10%-level. ** Significance at the 5%-level. *** Significance at the 1%-level.

Table 7: Spot PEED estimates from the baseline regression model

7. Discussion

In the following, we discuss our baseline findings and use them to derive an approximation for the *purchase price elasticity of electricity demand (= purchase PEED)*. Secondly, the regression exercise is repeated with an increased sample size to check for the robustness of our results. Furthermore, we discuss extensions and limitations in the interpretation of our PEED estimates. Additionally, we link our findings to those from previous literature, discuss the external validity of our study and highlight aspects requiring further research and policy implications.

7.1. Deriving the purchase PEED

To facilitate the comparison of our PEED estimates to most of the previous research, we need to consider that other results are often based on consumption expenditure data or purchase prices. As previously explained, variation in spot prices is highly relevant for but not reflected one-to-one in the purchase price for Norwegian households. For our approximation of the purchase PEED, we use a simplified version of the total purchase price for a variable contract, given by the following equation:

$$\begin{aligned} &Purchase\ price\ per\ kwh \\ &\qquad = (grid\ rent + spot\ price + Enova\ levy + el.levy)^{18} * 1.25 \end{aligned}$$

In addition to the spot price, consumers pay for the grid rent, the Enova levy, and an electricity levy, with 25% VAT on the sum. The levies and rents are charged per kwh consumed. Based on the close similarity of spot price contracts and variable contracts, and given that they together account for approximately 95% of all household contracts (SSB, 2023), we use this simplified formula from above for our discussion. We account for household averages of the grid fee (28.3 øre/ kwh), the electricity levy (15.6 øre/ kwh) and the Enova levy (1 øre/ kwh) for the period between Q3/2019 and Q3/2022 (SSB, 2023f).
The mean spot price south of the border for our main sample is 27 øre/ kwh before the first shock phase (before 01.08.2021) and 181 øre/ kwh during the second (major) shock phase (after 01.12.2021). During the second shock phase, the Northern spot price remains close to the initial mean pre-shock spot price which is in line with our counterfactual assumption (= the absence of treatment).

To estimate the purchase PEED, we need to consider the government support (*Strømstøtte*) introduced exclusively for residential electricity consumption as of December 2021. Apart from December 2021 (55%), it has covered 80% of excess expenditure if the average monthly spot price has been above 70 øre/ kwh for up to 5000 kwh household consumption per month. Households have then been paid back 80% of the difference between the actual spot price and the cap including VAT. For reasons of mathematical simplicity, we assume an 80%-level from December 2021

[18] Grid rent = *nettleie eksl. avgifter*; El. levy = *forbruksavgift*

and that no household exceeds 5000 kwh in monthly electricity consumption. This reasoning is supported by our dataset providing average values for monthly household-level consumption of 1391 kwh based on a monthly average of 656 kwh per capita and an average household size of 2.12 persons (SSB, 2023g). The purchase price formula including the government support is then represented the following way:

$$Purchase\ price\ per\ kwh =$$
$$(grid\ rent + spot\ price + Enova\ levy + el.levy) * 1.25 - \ Gov.support$$

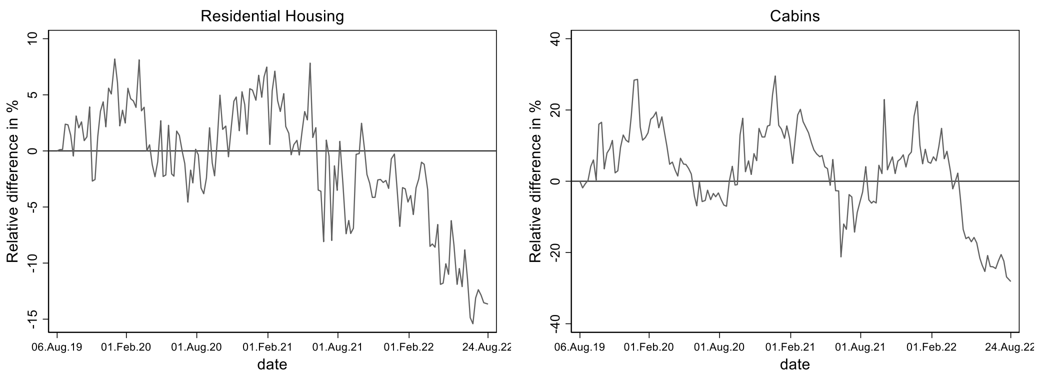
With the government support given by:

$$Gov.support =$$
$$0.8 * 1.25 * (average\ monthly\ spot\ price\ in\ øre\ per\ kwh\ -$$
$$70\ øre\ per\ kwh)\ if\ average\ monthly\ spot\ price > 70\ øre/\ kwh$$

Provided the assumptions above and using our monthly baseline regression estimate which converges to -0.02 for both residential housing and cabins, we approximate the average purchase price and the purchase PEED.
Given an increase in the mean spot price from 27 øre/ kwh to 181 øre/ kwh and an estimated spot PEED of -0.02, we predict a reduction in average electricity consumption of -11.4% that would be purely induced from this spot price increase. For residential demand, however, using the purchase price equation derived above, the mean purchase price before the first shock phase equals about 89.9 øre/ kwh compared to 171.4 øre/ kwh during the second shock phase. Hence, the approximate average purchase price increases by just 90.6%. A 90.6% increase in the purchase price leading to an 11.4% reduction in household-level electricity consumption then corresponds to a purchase PEED of about -0.12 (see also Appendix 4).

For cabins, the purchase PEED is higher (or lower in absolute terms) than for residential housing as this consumption category is not subject to government support. Our simplified algebraic exercise approximates the mean purchase price to increase from 89.9 øre/ kwh to 282.4 øre/ kwh. This is equal to an increase in the approximate average purchase price of 214.1%. Such an increase, considering a spot-PEED-predicted 11.4% decline in electricity demand, corresponds to a purchase PEED approximation of -0.05 (see also Appendix 5)

Visually, these results align with the deviation in indexed Southern per-capita electricity consumption relative to the Northern counterfactual as illustrated by Figures 10 and 11 in Chapter 6. For residential demand, an eyeballed deviation of negative ten to fifteen percent relative to the 90.6% mean purchase price increase matches the purchase PEED estimate of -0.12 reasonably well. The relative reduction in electricity demand at Southern cabins as depicted in Figure 11 in response to a 214.1% purchase price increase provides us with some confidence on the estimated purchase PEED of -0.05 for cabins, too.



Recap of Figures 10 and 11 (p. 39): Relative South-North differences in indexed electricity consumption for the main sample

If cabin-owning households who are affected by an electricity price shock were to initially forgo electricity consumption of lower priority, one might expect that the willingness to defer electricity use at cabins is higher since it can arguably be regarded as luxury expenditure rather than essential cost of living. If this notion was true, one should expect a more negative PEED for cabins compared to residential housing. Our findings show the opposite. For a discussion on why the purchase PEED for cabins is not as small as that of residential housing, we refer to the discussion provided on the non-linearity of the price elasticity in Section 7.3.2.

7.2. Robustness checks

In our baseline regression, we use municipalities close to the North-South price border that, due to their geographic proximity, are assumed to follow parallel electricity demand trends in the absence of the price shock. To evaluate the robustness of our PEED estimates from Chapter 6, we repeat the baseline regression exercise for all municipalities with full observations except the most Northern price area NO4 with results presented in Appendix 6.

The estimates for both residential electricity consumption and the equivalent at cabins are relatively close to another. This points to a comparable (un)willingness for Norwegian households to forgo electricity consumption at homes and cabins. For cabins, estimates move to a monthly value of -0.027, showing a minor negative bias compared to results from our main sample. Overall, consumption patterns for cabins closely follow that of households, and the estimated PEEDs of our main sample. Thus, we focus our robustness analysis on residential housing and assume that inferences apply equally to cabins.

In the case of residential demand, weekly and monthly baseline estimates converge to -0.03 at high statistical significance. This is a 50% larger estimate in absolute terms compared to the estimate of our main sample, though continues to show an inelastic demand response. Explanations for the observed deviation from the main sample analysis are not straightforward and should be considered with caution.

One explanation may be that spot prices in NO2 have begun to diverge from NO1 and NO5 spot prices as of 15.06.22 (see also Figure 3) at an average of 323 øre/ kwh. This is 87 øre/ kwh higher than the equivalent mean for NO5. The additional price shock may have induced behavioural changes for household consumers in NO2 which are not accounted for in our main sample as it does not consider municipalities from NO2. However, this explanation cannot be verified in our data. An adjusted parallel trend index with NO1 and NO5 treated as "North" and NO2 treated as "South" shows no evidence of changes in consumption patterns towards the end of the period of investigation as we have previously seen in our main sample (comparing Figure 12 vs. Figure 10).

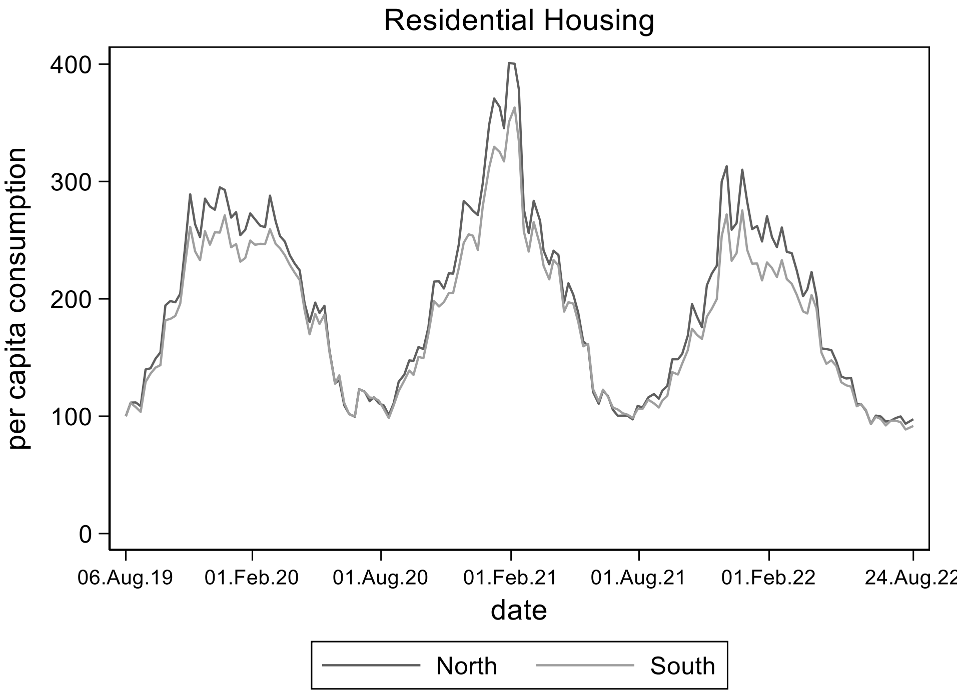


Figure 12: Adjusted indexes for residential electricity consumption comparing NO1 & NO5 to NO2[19]

Another reason for why the extension to our sample provides us with higher baseline PEED estimates may be found in the higher share of electric vehicles used in urban areas. By including major Norwegian metropolitan areas, such as Oslo, Bergen, Stavanger, Trondheim, and Kristiansand, we relatively expand the share of EV users compared to our main sample. This is best illustrated when comparing the EV-per-capita ratio in NO1 in the population summary statistics with its equivalent for the main sample (10.4% vs 2.7%). As most urban areas are in the South and thus exposed to elevated spot prices, we now include more households in the treatment group that may be more sensitive to electricity price changes as one major item of electricity demand (an EV) is more common there. Sudden price shocks may induce urban households owning EVs to substitute their use which is facilitated by the availability of alternatives in cities in form of, for instance, public transportation. This argument is supported when eliminating the population size weights which reduces the importance of populated municipalities with high EV rates. In this case, PEED estimates increase to -0.0247 for weekly and -0.027 for monthly specifications, respectively. A similar change can also be seen for our main

[19] Figure 12 is created like Figures 8 and 9 but including all municipalities (after initial data cleaning) in the Southern population data and treating NO1 & NO5 as “North” and NO2 as “South”.

sample, thus indicating a difference in the consumption response of people who live in urban compared to rural areas.

Other unobserved demand patterns of those who live in more densely populated areas may also explain the difference in estimates between our main sample and the extended sample. PEED estimates when keeping the main sample municipalities in NO3 and municipalities with high population density such as Bergen, Oslo, Asker and Bærum, are -0.0372 (weekly) and -0.0398 (monthly) – at high statistical significance (1%-level). However, when including all municipalities in the population-weighted baseline regression, apart from those in NO4 and the municipalities Oslo, Bergen, Asker, Bærum, Kristiansand and Stavanger, we obtain PEED estimates of -0.0247 (weekly) and -0.027 (monthly) – again at a significance level of 1%.

Overall, the robustness checks show that our baseline PEED estimates for residential housing seem representative for the Norwegian residential electricity demand response outside populated urban areas. This aligns with the parallel trends assumption applied to our main sample that comprises mainly rural municipalities.

7.3. Extensions and limitations to the baseline PEED estimates

In the following, we extend our regression model by lagged price variables to analyse the mechanism behind the residential demand response to spot price changes. Furthermore, we discuss the implications of the price elasticity being non-linear instead of linear as implied by the specification in our regression model.

7.3.1. Lagged response of the average household consumer

The regression exercise is repeated after extending the main regression by lagged spot price variables as shown in Equation (2):

$$(2)\ \log\left(Cons_{mt}^{i}\right) = \beta_0^i + \beta_1^i * \log\left(Priceinørekwh_{mt}^{i}\right) + \sum_{k=1}^{T}\left(\beta_{1+k}^{i} * \log\left(Priceinørekwh_{mt-k}^{i}\right)\right) + \theta_t + \omega_m^i + \varepsilon_{mt}^{i}$$

Thereby, we aim to analyze in how far electricity demand may respond to changes in spot prices in previous periods. For the daily PEED estimation, lagged spot prices up to seven days prior are included ($T = N\{1, \dots, 7\}$). The weekly regression includes lagged mean weekly spot prices up to eight weeks prior (T = $\mathrm{N}\{1, \dots, 8\}$) and the monthly specification up to six lags (T = $\mathrm{N}\{1, \dots, 6\}$). As the inclusion of lags requires, among other things, to drop observations where not all lags can be defined, we need to determine the optimal number of lags to include. Therefore, we conduct AIC tests for all numbers of lags based on Equation (2) and choose the regression modification with the lowest AIC value (Appendix 7). For both categories, residential and cabin-located electricity consumption, this test justifies including 7 lags for the daily and 2 lags for the monthly specification. For the weekly specification, it is 5 lags for residential housing and 8 lags for cabins.

Given this choice of lags for both categories, we accumulate the statistically significant estimates from the weekly and monthly specification of the extended regression model. We find that the resulting summed responses are slightly larger in absolute terms though very close compared to the baseline estimates. For residential housing, PEED estimates accounting for a lagged response accumulate to -0.027 (weekly) and -0.035 (monthly) while being at -0.044 and -0.042 for cabins (see Appendices 8 and 9). Nonetheless, due to the (counterintuitively) positive contemporaneous coefficients, we should not place too much interpretation on the estimates themselves. Instead, the number of chosen lags may give us more insight on the horizon of the demand response to spot price changes.

For residential housing, we find it to be optimal to include lagged variables of average spot prices for the five weeks prior and two months prior, respectively, instead of higher orders. Hence, the lagged response seems to be captured best when considering spot prices changes up to the previous two months. We showcase this interpretation through a hypothetical example, on how the average household receives information about and responds to monthly electricity expenditures:

Historically stable and low electricity prices have given little incentive for Norwegian households to worry about day-to-day fluctuations in spot prices. As provided in the literature review, households may neither be in possession of the technical means nor have enough of an understanding for marginal pricing to respond in real time (e.g., Ito, 2014), i.e., in our case day-to-day. Imagine a typical household that regards the monthly electricity bill as one of many bills due to pay in the middle of the month. If we assume that a permanent price shock occurs in the last week of the November month, it does not significantly affect the bill to pay in December. Therefore, if the household is not fully informed about the dynamics of supply and demand in the electricity market and the permanence of the shock, it does not adjust its behaviour upon receiving the bill in December. However, in the months to come, the household will feel the price shock in its pocket which alters expectations about future bills and may imply adjustments in electricity consumption. In this scenario, consumption responds to price changes with a delay of nearly two months – just as described in our results from the regression model with lagged price variables.

To conclude, while our baseline estimates are reasonably in line with accumulated lagged responses, we infer that behavioral changes due to the recent shock do not seem to occur instantly in full, but over 1 – 2 months, as above-expectations expenditures from electricity bills may be paid more attention to by household consumers as they are reoccurring. For the scope of this study, this makes us believe that our weekly and monthly baseline PEED estimates are more informative about the true residential electricity demand response than the daily baseline specification.

7.3.2. The non-linearity of price elasticities

In Section 7.1, the purchase PEED estimate (-0.12) is approximated based on the log-log baseline regression estimate of our entire sample period. This would imply a 0.12% reduction in electricity use following a 1% increase in the purchase price. This calculation is based on an approximated purchase price increase from around 90 øre/ kwh to 171 øre/ kwh (90.6%). But would the same estimate hold true if there was a 90.6% increase in the purchase price when 171 øre/ kwh was the mean baseline level?

We use an illustrative example with data for households in NO1 and take a closer look at the ratio of electricity expenditure relative to (constant) household income. We denote c as the average monthly electricity bill for NO1 where the average monthly consumption for households reads 1315 kwh, and the median monthly household income for 2021 is 47.546 NOK.[20] Besides, we assume three consecutive periods where the purchase price increases by 90.6% for each period.

$m = 47546$	*Monthly household income*
$c_1 = 0.90 * 1315$	*Electricity bill in period 1*
$c_2 = c_1 * (1 + 0.906) = c_1 * 1.906$	*Electricity bill in period 2*
$c_3 = c_2 * (1 + 0.906) = c_1 * 1.906^2$	*Electricity bill in period 3*
$\frac{c_1}{m} = 2.49\% \quad \frac{c_2}{m} = 4.74\% \quad \frac{c_3}{m} = 9.04\%$	*Expenditure-to-income ratio*

Assuming average consumption and income to remain constant, the share of the income in period 1 dedicated to paying the electricity bill is 2.49%. The first 90.6% increase in the final cost of electricity leads to an increase in this share to 4.74%. This means that the average household would pay 2.25 percentage points more of its monthly income to cover electricity costs. Thus, the willingness to consume the same amount of electricity may fall due to a combination of income and substitution effects.

Imagine another price increase at 90.6% when period 2 is the baseline. The share of income that goes to paying the bill jumps from 4.74% to 9.04%. This time, it follows that the same increase in percentage terms leads to 4.72 percentage points more of total income dedicated to paying the electricity bill. Income and substitution effects following this price change may thus be larger. Household consumers need to forego more than double the additional share of their income and give up more on other goods to cover for the same percentage-size increase in the price. Thus, we can assume that households are more likely to reduce their electricity consumption for the hypothetical price shock happening from period 2 to period 3.

Purchase PEED estimates might thus have been larger in absolute terms if we had conducted the analysis on a sample which experienced a 90.6% increase in the total average purchase price from 171 øre/ kwh to 326 øre/ kwh. This corresponds to attributing residential electricity demand a non-linearly increasing response to price changes. Hence, the demand response would not only depend on the size of the price shock, but also on the initial level of the price – assuming no large variation

[20] Data from Table 2: 1315 kwh = (30 days*20.68 kwh)*2.12 persons; 47.546 NOK per month = 570.548 NOK / 12 months

in income. This argumentation aligns with the general notion about the non-linearity of price elasticities presented in the literature (IEA, 2003, p. 21f.).
The example from above may also provide further insight into why the PEED for cabins is estimated to be more inelastic than the one for residential housing. In 2022, the Norwegian median gross salary was 572,000 NOK (SSB, 2023h). This is presumably representative for the average consumer in our residential housing category. *Prognosesenteret*, a Norwegian market analytics enterprise that works with European housing markets, estimates the median gross income of Norwegian cabin owners to be 646,000 NOK for 2020 (Prognosesenteret, 2021), which is most likely even higher in 2022. Besides, they estimate that Norwegians who bought cabins in 2020 had relatively large financial resources compared to the group which has already owned cabins prior to 2020. This illustrates that consumers who own cabins belong to a group with higher average income compared to the average consumer. Cabin-owners would thus have a lower expenditure-to-income ratio for the same amount of electricity consumed. Under the assumption that our argument of non-linearity holds true, this may explain why the purchase PEED estimate is lower in absolute terms for cabins than for residential housing, at -0.05 compared to -0.12.

7.4. Comparison with previous research

Compared to previous global research findings on the price elasticity of residential electricity demand, our baseline PEED estimate of -0.02 based on spot prices and the derived corresponding proxy for the purchase PEED of -0.12 are relatively low in absolute terms. In perspective to estimates collected in often cited meta-analyses (Espey & Espey, 2004; Alberini et al., 2011; Filippini et al., 2018), our findings are at the rather inelastic end of the spectrum of results. However, when considering late research from Norway (Bye & Hansen, 2008; Holstad & Petersen, 2011; Hofman & Lindberg, 2019), the PEED estimates of this study are much in line and confirm previous conclusions that electricity demand in Norway is comparably inelastic. This difference in Norwegian and global findings confirms the notion put forward by Espey and Espey (2004), that estimates depend on demand specifications, data characteristics as well as the time and location of the respective research. Even though we have not explicitly investigated the circumstances of the real time response of consumers (e.g., effects of digital appliances to receive up-to-date information on spot prices) the results after introducing lagged price variables to our regression model provide us with at least some indication that households do not fully adjust to spot price changes instantly but rather over one or two months which is relatively close to findings from Holstad and Pettersen (2011, p. 28f.) who attribute most of the response to the month of the price change but also a smaller part to the following month.

7.5. External validity

The external validity of our findings depends on the extent to which institutional, geographical and time settings differ in future studies that analyse demand responses. Besides acknowledging that this study estimates the PEED based on spot prices instead of purchase prices, our external validity discussion focuses on two aspects: the expenditure-to-income ratio combined with the presence of a strong welfare state and differences in heating systems between Norway and other states.

We have already discussed the possible implications of expenditure-to-income ratios of consumers and the non-linearity of price elasticities. Let us assume that we had investigated another country with lower median household income where the initial expenditure-to-income ratio was, for instance, at 8%. If households in this country experienced an electricity purchase price increase of 90.6%, the larger relative effect on total available income may induce households to save more on electricity consumption, thus yielding a more elastic PEED estimate than for our study with Norwegian households.
One may also take into consideration that Norway has a comparatively strong welfare state. This may provide people with higher confidence in the government's ability and willingness to provide financial support in the event of negative economic shocks, as it indeed happened with the so-called *strømstøtte* in 2021. These policies may contribute to a smaller response in electricity demand to negative price shocks. In contrast, for countries where households have comparably smaller confidence in their government to help them through negative economic shocks, a similar price increase may induce more risk aversive behaviour and higher precautionary energy savings, hence, a larger demand response.

Another very important aspect that may impact the size of the PEED estimate is the type of heating used and the sources of heating fuel. In Figures 8 and 9, we index the evolution of consumption per capita over approximately three years based on

August-level demand. August is one of the warmest months in Norway, and thus the demand for heating is at the lowest level during the year. The cyclical variations in electricity demand peak during winter months where per-capita consumption increases to between 3-fold and 4-fold for residential housing, and to between 4-fold and 6-fold for cabins.

The main driver of this cyclical component is the demand for electric heating. *Elvia*, Norway's largest grid operator, reports that 60% of household electricity consumption results from heating, with an additional 15-20% from water heating (Elvia, n.d.). According to a report prepared in 2017 for the UK's *Department of Business, Energy and Industrial Strategy*, electricity accounts for 85% of energy used for heating in buildings in Norway, with a low share of households connected to gas grids (Vivid Economics & Imperial College, 2017). This reliance on electricity – with no relevant substitutes – makes Norway somewhat unique. In the UK, 78% of energy used from heating in buildings is sourced from gas, and 85% of households are connected to gas grids. In the Netherlands, 83% of heating energy is based on gas, with 94% of households being connected to the gas grid (Vivid Economics & Imperial College, 2017). It is thus not unreasonable to expect that conducting a similar study on a comparable price shock in countries which use less electricity for heating and have means of substitution may yield different PEED estimates, even though electricity and gas prices are to a certain extent correlated.

Even if another region of interest was similarly dependent on electric heating as Norway, possible geographical (altitude, proximity to sea currents, latitudes etc.) and temperature differences may alter demand profiles for heating.

7.6. Future research and policy relevance

Our estimates show a relatively inelastic response in Norwegian residential electricity demand to the spot price shock that occurred in 2021 and 2022. The PEED based on an approximation of the purchase price is only somewhat higher in absolute terms and thus confirms the notion that Norwegian households' electricity demand is relatively rigid despite sizable price changes. Some of the reasons mentioned are the absence of broad-scale substitutes for heating (thus high switching costs), initially low and stable historical electricity prices (hence 'learned' consumption patterns), remaining 'buffers' in available income and the response of the welfare state. An idea for future research in the Norwegian electricity market would be to conduct the same analysis on a dataset with a longer or different time horizon, including purchase prices for electricity, as well as accounting for changes in available income. Thus, one may estimate the purchase price elasticity of electricity demand in Norway more precisely, not only in the short-run, but also the long-run. To meet concerns regarding aggregation bias and to measure its impact on resulting PEED estimates, we propose that future studies additionally use household-level consumption data and compare resulting estimates to their equivalents based on aggregate data. Besides, one can add income elasticities to the analysis to provide a more differentiated picture on the drivers in households' electricity demand response. We also suggest that future research in Norway should investigate the differences in responses between rural and urban areas which we have spotted in the robustness checks of our analysis.

As for the inclusion of lagged spot price variables, we recommend further analysis on that matter since our interpretation of the resulting estimates referred more to the horizon of the response than the estimates themselves. Furthermore, in a difference-in-difference analysis, it is common practise to add event studies. However, this has not been possible in our study, as the main shock in electricity prices coincided with two other events, namely the beginning of the winter season and the introduction of the government support. With a dataset where the price shock happened within a season, we would suggest including an event study. Alternatively, one may test our estimates through other methodologies than a difference-in-difference model.

From a market perspective, future electricity supply will increasingly originate from renewable energy sources which are more volatile in their output. Apart from more efficient use of energy (referring to the common wisdom that 'the best energy used in the energy saved'), price signals indicating excesses or shortages in supply may thus become more relevant. However, our findings indicate that the price signals need to be of significant size for Norwegian households to adjust their demand. In the interest of maintaining stability in the electricity grid, the question remains if households are willing and even able to make substantial flexible adjustments to their electricity demand. As discussed in Section 7.3, households' available income and time for adjustments may be relevant factors here.

Through the social lens, with growing renewable capacities, power production may become more asymmetric relative to (inelastic) electricity demand patterns in households' everyday lives. This may cause concerns among policy makers about the social ramifications following larger and more volatile electricity prices which would reflect these asymmetries to balance supply and demand. Hence, the dilemma on how to induce more flexible electricity demand without causing distortions in households' utility and societal welfare is one that academia and policy makers need to further investigate.

8. Conclusion

Using municipality-level electricity consumption panel data spanning from 01. August 2019 to 31. August 2022, we have performed a difference-in-difference analysis regressing average spot prices on per-municipality-capita demand at residences and cabins. Thereby, we make use of the large exposure of Norwegian residential and cabin-located electricity use to spot prices.

The assignment to the control and treatment group has been conducted in line with the proximity to the North-South price border. Sampled municipalities from the Southern price areas NO1 and NO5 experienced the treatment in form of a shock to spot prices, while sampled municipalities from the Northern price area NO3 have been regarded as the counterfactual where this kind of treatment remained absent. Based on the validated assumption of parallel trends in electricity consumption in the absence of the spot price shock, we have been able to estimate daily, weekly, and monthly values for the spot PEED.

Combined with some initial indication for a lagged response mechanism in demand from an extension to the regression model, we infer that our weekly and monthly baseline PEED estimates are more informative for the scope of this study. These estimates converge to -0.02 for both categories and are highly statistically significant. We further use these results to derive an algebraic estimate of the PEED, not for the wholesale, but the purchase price. By considering mean purchase prices before and during the major price shock phase, additional price components, and the government support for residential electricity consumption, our estimates decrease to an approximate value of -0.12 for residences and -0.05 for cabins. A relatively inelastic response of residential electricity demand to price changes confirms previous research for the Norwegian electricity market. Comparisons on a global level are rather difficult since, as for instance described by Espey and Espey

(2004), PEED estimates are dependent on where, when, and how the individual research is conducted.

Residential electricity consumption is found to be more elastic (though low on absolute levels) than demand at cabins. The study links this finding to higher average gross average income of cabin owners and the non-linearity of price elasticities which may depend on households' electricity expenditure-to-income ratio. Our robustness checks provide us with confidence that these estimates can be used for average rural residential electricity demand in Norway while there is some evidence that the demand response to price shocks is higher in more densely populated urban areas.

Even though Norway produces the largest share of its electricity from its hydro reserves, the build-up of new renewable power sources and the connection to the European neighbors may create more urgency to incentivize flexibility in how supply and demand of electricity are balanced. As this study confirms the notion of previously shown inelastic electricity demand, academia and policy makers in Norway need to conduct further research on efforts to incentivize that flexibility without causing distortions in utility and welfare.

III. References

[01] Alberini, A., & Filippini, M. (2011). Response of residential electricity demand to price: The effect of measurement error. *Energy Economics*, *33*(5), 889–895. https://doi.org/10.1016/j.eneco.2011.03.009

[02] Alberini, A., Gans, W., & Velez-Lopez, D. (2011). Residential consumption of gas and electricity in the U.S.: The role of prices and income. *Energy Economics*, *33*(5), 870–881. https://doi.org/10.1016/j.eneco.2011.01.015

[03] Angrist, J. D., & Pischke, J.-S. (2015). *Mastering 'metrics: the path from cause to effect*. Princeton University Press.

[04] Bell, A., & Jones, K. (2015). Explaining Fixed Effects: Random Effects Modeling of Time-Series Cross-Sectional and Panel Data. *Political Science Research and Methods*, *3*(1), 133–153. https://doi.org/10.1017/psrm.2014.7

[05] Bernard, J.-T., Bolduc, D., & Yameogo, N.-D. (2011). A pseudo-panel data model of household electricity demand. *Resource and Energy Economics*, *33*(1), 315–325. https://doi.org/10.1016/j.reseneeco.2010.07.002

[06] Biggar, D. R., & Hesamzadeh, M. R. (2014). *The Economics of Electricity Markets* (1st ed.). Wiley. https://doi.org/10.1002/9781118775745

[07] Blázquez, L., Boogen, N., & Filippini, M. (2013). Residential electricity demand in Spain: New empirical evidence using aggregate data. *Energy Economics*, *36*, 648–657. https://doi.org/10.1016/j.eneco.2012.11.010

[08] Bohi, D. R. (2011). *Analyzing demand behavior: a study of energy elasticities*. RFF Press.
https://ebookcentral-proquest-com.ezproxy.library.bi.no/lib/bilibrary/reader.action?docID=1569716&ppg=74

[09] Boogen, N., Datta, S., & Filippini, M. (2017). Dynamic models of residential electricity demand: Evidence from Switzerland. *Energy Strategy Reviews*, *18*, 85–92.
https://doi.org/10.1016/j.esr.2017.09.010

[10] Burke, P. J., & Abayasekara, A. (2018). The Price Elasticity of Electricity Demand in the United States: A Three-Dimensional Analysis. *The Energy Journal*, *39*(2), 123–145.
https://doi.org/10.5547/01956574.39.2.pbur

[11] Bye, T., & Hansen, P. V. (2008). How do Spot prices affect aggregate electricity demand?. *Discussion papers, No. 527, Statistics Norway, Research Department, Oslo,* 1–82.
http://hdl.handle.net/10419/192509

[12] Csereklyei, Z. (2020). Price and income elasticities of residential and industrial electricity demand in the European Union. *Energy Policy*, *137*, 1–12.
https://doi.org/10.1016/j.enpol.2019.111079

[13] Deryugina, T., MacKay, A., & Reif, J. (2020). The Long-Run Dynamics of Electricity Demand: Evidence from Municipal Aggregation. *The American Economic Journal*, *12*(1), 86–114.
https://doi.org/10.1257/app.20180256

[14] Elvia. (n.d.). *Hva bruker mest strøm?*.
https://www.elvia.no/nettleie/alt-du-ma-vite-om-ny-nettleie-for-2022/hva-bruker-mest-strom/

[15] Energifakta Norge. (2021). *Energibruken i ulike sektorer.*
https://energifaktanorge.no/norsk-energibruk/energibruken-i-ulike-sektorer/

[16] Espey, J. A., & Espey, M. (2004). Turning on the Lights: A Meta-Analysis of Residential Electricity Demand Elasticities. *Journal of Agricultural and Applied Economics*, *36*(1), 65–81.
https://doi.org/10.1017/S1074070800021866

[17] Feehan, J. P. (2018). The long-run price elasticity of residential demand for electricity: Results from a natural experiment. *Utilities Policy*, *51*, 12–17. https://doi.org/10.1016/j.jup.2018.02.003

[18] Fell, H., Li, S., & Paul, A. (2014). A new look at residential electricity demand using household expenditure data. *International Journal of Industrial Organization*, *33*, 37–47.
https://doi.org/10.1016/j.ijindorg.2014.02.001

[19] Filippini, M., Hirl, B., & Masiero, G. (2018). Habits and rational behaviour in residential electricity demand. *Resource and Energy Economics*, *52*, 137–152. https://doi.org/10.1016/j.reseneeco.2018.01.002

[20] Halvorsen, B., & Larsen, B. M. (2001). The flexibility of household electricity demand over time. *Resource and Energy Economics*, *23*(1), 1–18. https://doi.org/10.1016/S0928-7655(00)00035-X

[21] Hofmann, M., & Lindberg, K. B. (2019). Price elasticity of electricity demand in metropolitan areas – Case of Oslo. In *2019 16th International Conference on the European Energy Market (EEM),* 1–6.
https://doi.org/10.1109/EEM.2019.8916561

[22] Holstad, M., & Pettersen, F. E. L. (2011). Hvordan reagerer strømforbruket i alminnelig forsyning på endringer i spotpris?. *Økonomiske analyser 2/2011*, 27–31.
https://ssb.brage.unit.no/ssb-xmlui/bitstream/handle/11250/178884/holstad_pettersen_2011.pdf?sequence=1

[23] IEA. (2003). *The Power to Choose: Demand Response in Liberalised Electricity Markets*. OECD Publishing.
https://doi-org.ezproxy.library.bi.no/10.1787/9789264105041-en

[24] International Energy Agency. (2019). *Perspectives for the Clean Energy Transition: The Critical Role of Buildings.* https://iea.blob.core.windows.net/assets/026bff1b-821d-48bc-8a0e-7c10280c62bc/Perspectives_for_the_Clean_Energy_Transition_2019.pdf

[25] Ito, K. (2014). Do Consumers Respond to Marginal or Average Price? Evidence from Nonlinear Electricity Pricing. *The American Economic Review*, *104*(2), 537–563. https://doi.org/10.1257/aer.104.2.537

[26] Jessoe, K., & Rapson, D. (2014). Knowledge is (Less) Power: Experimental Evidence from Residential Energy Use. *The American Economic Review*, *104*(4), 1417–1438. https://doi.org/10.1257/aer.104.4.1417

[27] Kamerschen, D. R., & Porter, D. V. (2004). The demand for residential, industrial and total electricity, 1973–1998. *Energy Economics*, *26*(1), 87–100. https://doi.org/10.1016/S0140-9883(03)00033-1

[28] Krishnamurthy, C. K. B., & Kriström, B. (2015). A cross-country analysis of residential electricity demand in 11 OECD-countries. *Resource and Energy Economics*, *39*, 68–88. https://doi.org/10.1016/j.reseneeco.2014.12.002

[29] Lanot, G., & Vesterberg, M. (2021). The price elasticity of electricity demand when marginal incentives are very large. *Energy Economics*, *104*, 1–22. https://doi.org/10.1016/j.eneco.2021.105604

[30] Lijesen, M. G. (2007). The real-time price elasticity of electricity. *Energy Economics*, *29*(2), 249–258. https://doi.org/10.1016/j.eneco.2006.08.008

[31] Nesbakken, R. (1999). Price sensitivity of residential energy consumption in Norway. *Energy Economics*, *21*(6), 493–515. https://doi.org/10.1016/S0140-9883(99)00022-5

[32] Nord Pool. (n.d.). *Day-ahead market*.
https://www.nordpoolgroup.com/en/the-power-market/Day-ahead-market/

[33] Nord Pool. (n.d. b). *Intraday market*.
https://www.nordpoolgroup.com/en/the-power-market/Intraday-market/

[34] Norges Bank. (n.d.). *Exchange Rates*.
https://www.norges-bank.no/en/topics/Statistics/exchange_rates/?tab=currency&id=EUR

[35] Norwegian Competition Authority. (2022). *Kronikk: Fraråder makspris på strøm*.
https://konkurransetilsynet.no/kronikk-frarader-makspris-pa-strom/

[36] NVE. (2023). *Kompensasjonsordning for høye strømpriser*.
https://www.nve.no/reguleringsmyndigheten/nytt-fra-rme/nyheter-reguleringsmyndigheten-for-energi/kompensasjonsordning-for-hoeye-stroempriser/

[37] Prognosesenteret. (2021). *Hyttekjøperne med høyest inntekt.*
https://blogg.prognosesenteret.no/hyttekjoeperne-med-hoeyest-inntekt

[38] Shaffer, B. (2020). Misunderstanding Nonlinear Prices: Evidence from a Natural Experiment on Residential Electricity Demand. *American Economic Journal: Economic Policy*, *12*(3), 433–461.
https://doi.org/10.1257/pol.20180061

[39] Shin, J.-S. (1985). Perception of Price When Price Information Is Costly: Evidence from Residential Electricity Demand. *The Review of Economics and Statistics*, *67*(4), 591–598.
https://doi.org/10.2307/1924803

[40] SSB. (2015). *Strømprisen avhengig av hvor man bor*.
https://www.ssb.no/energi-og-industri/artikler-og-publikasjoner/stromprisen-avhengig-av-hvor-man-bor

[41] SSB. (2016). *Hva viser de ulike elektrisitetsstatistikkene?*. https://www.ssb.no/energi-og-industri/energi/artikler/hva-viser-de-ulike-elektrisitetsstatistikkene

[42] SSB. (2022). *Gjennomsnittsalder og medianalder i kommuner, fylker og hele landets befolkning (K) 2000 – 2022.* https://www.ssb.no/statbank/table/13536

[43] SSB. (2022b). *10320: Hushald (prosent), etter region, nettoformue, statistikkvariabel og år.* https://www.ssb.no/statbank/table/10320/

[44] SSB. (2022c). *09747: Privathusholdninger, personer i privathusholdninger og personer per privathusholdning (K) (B) 2005 – 2022.* https://www.ssb.no/statbank/table/09747

[45] SSB. (2023). *09364: Kraftpriser i sluttbrukermarkedet, etter kontraktstype 2012K1 – 2023K1.* https://www.ssb.no/statbank/table/09364/

[46] SSB. (2023b). *Record high electricity price in 2022 – curbed by Electricity support for households.* https://www.ssb.no/en/energi-og-industri/energi/statistikk/elektrisitetspriser/article-for-electricity-prices/record-high-electricity-price-in-2022--curbed-by-electricity-support-for-households#:~:text=Price%20records,kWh%20higher%20than%20in%202021

[47] SSB. (2023c). *Elektrisitet.* https://www.ssb.no/energi-og-industri/energi/statistikk/elektrisitet

[48] SSB. (2023d). *06913: Endringer i kommuner, fylker og hele landets befolkning (K) 1951 – 2023.* https://www.ssb.no/statbank/table/06913/

[49] SSB. (2023e). *05467: Eksisterende bygningsmasse. Antall fritidsbygninger og fritidsbygninger per kvadratkilometer (K) 1998 – 2023.*
https://www.ssb.no/statbank/table/05467/

[50] SSB. (2023f). *09387: Kraftpris, nettleie og avgifter for husholdninger 2012K1 – 2023K1.*
https://www.ssb.no/statbank/table/09387/

[51] SSB. (2023g). *Familier og husholdninger.*
https://www.ssb.no/befolkning/barn-familier-og-husholdninger/statistikk/familier-og-husholdninger

[52] SSB. (2023h). *Hva er vanlig lønn i Norge?.*
https://www.ssb.no/arbeid-og-lonn/lonn-og-arbeidskraftkostnader/artikler/hva-er-vanlig-lonn-i-norge

[53] SSB. (2023i). *06944: Inntekt for husholdninger, etter husholdningstype. Antall og median. Delområder (K) (B) 2005 – 2021.*
https://www.ssb.no/statbank/table/06944

[54] SSB. (2023j). *11084: Eierstatus. Husholdninger (K) (B) 2015 – 2022.*
https://www.ssb.no/statbank/table/11084

[55] SSB. (2023k). *11508: Bygningstype. Husholdninger (K) (B) 2015 – 2022.*
https://www.ssb.no/statbank/table/11508

[56] SSB. (2023l). *11823: Euroklasser, drivstofftyper og kjøretøygrupper (K) 2016 – 2022.*
https://www.ssb.no/statbank/table/11823

[57] Statnett. (n.d.). *Om strømpriser.*
https://www.statnett.no/om-statnett/bli-bedre-kjent-med-statnett/om-strompriser/

[58] Statnett. (2022). *Derfor har vi prisområder*. https://www.statnett.no/om-statnett/bli-bedre-kjent-med-statnett/om-strompriser/fakta-om-prisomrader/

[59] Statnett. (2022b). *Nye kabler utgjør kun rundt 105 av de høye strømprisene*. https://www.statnett.no/om-statnett/nyheter-og-pressemeldinger/nyhetsarkiv-2022/nye-kabler-star-for-rundt-10-av-de-hoye-stromprisene/

[60] The Norwegian Government. (2021). *Kraftmarkedet og strømpris.* https://www.regjeringen.no/no/tema/energi/stromnettet/kraftmarkedet-og-strompris/id2076000/

[61] Vaage, K. (2000). Heating technology and energy use: a discrete/continuous choice approach to Norwegian household energy demand. *Energy Economics*, *22*(6), 649–666. https://doi.org/10.1016/S0140-9883(00)00053-0

[62] Vivid Economics & Imperial College. (2017). *International Comparisons of Heating, Cooling and Heat Decarbonisation Policies: Report prepared for the Department for Business, Energy and Industrial Strategy (BEIS).* https://www.gov.uk/government/publications/international-comparisons-of-heating-cooling-and-heat-decarbonisation-policies

IV. Appendix

Study	Time period	Country / Region	Short description	Price elasticity estimates
Alberini and Filippini (2011)	1995-2007	USA	Static and dynamic models of demand, using aggregate state-level panel data for 48 US states and testing elasticity estimates for robustness to endogeneity in dynamic settings (lagged demand and error term) and measurement errors of the energy price	Short run: between -0.08 and -0.15 Long run: between -0.45 and -0.75
Alberini et al. (2011)	1997-2007	USA	Static and dynamic models of demand, using household-level panel data for 50 metropolitan areas accounting for unobserved heterogeneity by controlling for city-specific, dwelling-specific, and dwelling-household-specific fixed effects	Dynamic model: Short run: -0.736; Long run: -0.814
Bernard et al. (2011)	1989-2002	Canada	Utilization of pseudo-panel data from four cross-sections from the province of Quebec, forming a dynamic demand model around cohorts of homogenous households	Short run: -0.51 Long run: -1.32
Blazquez et al. (2013)	2000-2008	Spain	Dynamic model for electricity demand, using aggregate panel province-level data for 47 Spanish provinces and a form of IV estimation called GMM estimation	Short run: -0.07 Long run: -0.19
Boogen et al. (2017)	2006-2012	Switzerland	Dynamic model of demand, using utility-level aggregate consumption data and three estimation techniques: ordinary least squares, (utility-specific) fixed effects to account for unobserved heterogeneity in the panel data and fixed effects with the Kiviet correction (LSDV method)	Short run (with LSDV): -0.3 Long run (with LSDV): -0.58
Burke and Abayasekara (2018)	2003-2015	USA	IV estimation on three-dimensional panel data for 48 US states, the IV approach on three-dimensional panel data is supposed to address potential endogeneity issues	Short run ("headline result"): -0.1 Long run: -1.0
Csereklyei (2020)	1996-2016	European Union	Utilization of IV estimates (between estimator) and dynamic panel (GMM) estimates to receive estimates for long run elasticities and a first difference approach to obtain short run elasticity estimates based on EU-member-state panel data	Short run: between -0.07 and -0.08 Long run: between -0.53 and -0.56
Deryugina et al. (2020)	2007-2014	USA	Difference-in-difference matching approach and a dynamic model based on a natural experiment in terms of significant and persistent price changes in around 250 communities in the US state of Illinois	Short run: between -0.08 and -0.09 Long run: between -0.21 and -0.27
Feehan (2018)	1994-2014	Canada	Difference-in-difference design based on a natural experiment (price shock in one region due to removal of block pricing) in the Canadian provinces of Newfoundland and Labrador to estimate a 20-year long run price elasticity of electricity demand	Long run: -1.20
Fell et al. (2014)	2006-2008	USA	Estimation of household-level demand based on consumer expenditure survey data from areas across the US thourgh introducing a strategy with GMM estimation assuming that households respond to the average price	Short run: -0.50
Filippini et al. (2018)	1995-2011	USA	A traditional dynamic partial adjustment model is compared to a lead consumption model which addresses forward looking behaviour, applied on panel data from 48 US states using 2SLS fixed effects to account for unobserved time-invariant heterogeneity and endogeneity issues	Short run: between -0.086 and -0.179 Long run: between -0.214 and -0.306
Halvorsen and Larsen (2000)	1976-1993	Norway	Expenditure survey data and a two-step discrete-continuous model, accounting for dynamics in electricity demand household investment's in new appliances	Short run: -0.433 Long run: -0.442
Lanot and Vesterberg (2021)	2015-2018	Sweden	Estimating short run price elasticities for consumers facing non-linear tariffs based on panel data using 2SLS that accounts for endogeneity issues and the bunching approach that accounts for tariff chracteristics	Short run (bunching approach): between -0.002 and -0.037
Nesbakken (1999)	1993-1995	Norway	Estimating short run energy price elasticties based on cross-sectional consumer expenditure data by exploiting the relationship between heating technology choice and energy consumption	Short run: -0.50
Vaage (2000)	1980	Norway	Cross-sectional expenditure survey data and a two-step discrete-continuous choice model, exploiting the relationship between appliance choice and energy demand	Long-run: between -1.24 and -1.29

Appendix 1: Selected studies and elasticity estimates for residential electricity demand

Variable	Description and reference
Mean age	Annual data on the mean age of the population in each municipality (2020 – 2022) (SSB, 2022).
Income	Median annual income after tax in NOK for all types of households per municipality (2020 – 2021) (SSB, 2023i).
HH net-wealth	Annual per-municipality shares of household net-wealth in NOK for category 1 (below 250k), category 2 (250k – 499,999), category 3 (500k – 999,999), category 4 (1m – 1,999,999), category 5 (2m – 2,999,999), category 6 (3m – 3,999,999), and category 7 (4m and above) (SSB, 2022b).
Persons p. household	Annual per-municipality data on number of persons living in one private household (2020 – 2022) (SSB, 2022c).
Ownership status	Annual per-municipality data on shares of households in % that own their real estate or own shares of their real estate (2020 – 2022) (SSB, 2023j).
Building type	Annual per-municipality data on shares for housing in single buildings in % (2020 – 2022) (SSB, 2023k).
Registered cars	Per-municipality data on the number of registered electric vehicles (2019 – 2021) which is then (by the authors) weighted by the size of the population in each municipality (SSB, 2023l).
Number of cabins	Per municipality data on the number of cabins (2020 – 2022) (SSB, 2023e).

Appendix 2: Description of supporting variables

Grouping strategies	**Included municipalities**
North (NO3) – South (NO1 and NO5)	3423, 3424, 3425, 3426, 3428, 3430, 3435, 3436, 3438, 3439, 3440, 3441, 3454, 5025, 1563, 1566, 3431, 3432, 3453, 5021, 5022, 5026, 5027, 5028, 5032, 5033, 5061, 3042, 3043, 4620, 4621, 4627, 4628, 4629, 4630, 4631, 4632, 4633, 4634, 4635, 4639, 4640, 4641, 4642, 4643, 4644, 3433, 3434, 4602, 4636, 4637, 4645, 4648, 4649, 4650, 4651, 4646, 4647

Appendix 3: List of sample municipalities

Before the price shock (All values in øre per kwh)		During the period of the price shock (All values in øre per kwh)	
Mean spot	27	Mean spot	181
Grid rent	28.3	Grid rent	28.3
Enova levy	1	Enova levy	1
El. levy	15.6	El. levy	15.6
Inkl. 25% VAT	**89.9**	Inkl. 25% VAT	**282.4**
		Gov. support	0.8*1.25*(181-70) = **111**
Purchase price	**89.9**	**Purchase price**	**171.4**

Appendix 4: Purchase price calculations for residential housing

Before the price shock (All values in øre per kwh)		During the period of the price shock (All values in øre per kwh)	
Mean spot	27	Mean spot	181
Grid rent	28.3	Grid rent	28.3
Enova levy	1	Enova levy	1
El. levy	15.6	El. levy	15.6
Inkl. 25% VAT	**89.9**	Inkl. 25% VAT	**282.4**
		No gov. support	
Purchase price	**89.9**	**Purchase price**	**282.4**

Appendix 5: Purchase price calculations for cabins

	Residential housing	**Cabins**
	Daily PEED estimates	
$log(Priceinørekwh^{i}_{mt})$	-0.0245*** (0.0032)	-0.0278*** (0.0016)
	Weekly PEED estimates	
$log(Priceinørekwh^{i}_{mt})$	-0.0293*** (0.0033)	-0.0276*** (0.0017)
	Monthly PEED estimates	
$log(Priceinørekwh^{i}_{mt})$	-0.0317*** (0.0035)	-0.0267*** (0.0019)

The main values are the PEED estimates. The corresponding robust standard errors are given in parentheses. * Significance at the 10%-level. ** Significance at the 5%-level. *** Significance at the 1%-level.

Appendix 6: Spot PEED estimates from baseline regression model with extended sample[21]

[21] The extended sample includes all municipalities from NO1, NO2, NO3 and NO5 apart from those that have been dropped in the initial data cleaning process (10 municipalities dropped for residential housing and 11 municipalities dropped for the cabin category).

	Residential housing	**Cabins**
Number of lags	*AIC-values: Daily PEED specification*	
0	-74,176.56	5,440.45
1	-74,212.91	5,351.21
2	-74,274.93	5,318.19
3	-74,360.03	5,338.83
4	-74,487.67	5,283.76
5	-74,688.71	4,664.43
6	-74,971.85	3,842.00
7	**-75,122.96**	**3,778.33**
	AIC-values: Weekly PEED specification	
0	-15,654.80	-5,097.01
1	-15,740.76	-5,250.33
2	-15,908.37	-5,461.67
3	-16,154.26	-5,744.94
4	-16,250.21	-5,865.96
5	**-16,268.49**	-5,929.05
6	-16,212.13	-5,929.65
7	-16,208.93	-5,949.62
8	-16,129.44	**-5,998.37**
	AIC-values: Monthly PEED specification	
0	-4,427.58	-1,848.19
1	-4,568.32	-2,063.77
2	**-4,585.14**	**-2,118.06**
3	-4,484.19	-2,105.94
4	-4,439.25	-2,053.04
5	-4,423.67	-2,031.24
6	-4,347.15	-1,988.91

Appendix 7: AIC values from the extended regression model

	Residential housing
	Daily PEED estimates
$log(Priceinørekwh_{mt}^{i})$	0.0082*** (0.0020)
$log(Priceinørekwh_{mt-1}^{i})$	-0.0008 (0.0020)
$log(Priceinørekwh_{mt-2}^{i})$	0.0072*** (0.0012)
$log(Priceinørekwh_{mt-3}^{i})$	0.0081*** (0.0017)
$log(Priceinørekwh_{mt-4}^{i})$	0.0028*** (0.0009)
$log(Priceinørekwh_{mt-5}^{i})$	0.0021 (0.0013)
$log(Priceinørekwh_{mt-6}^{i})$	-0.0128*** (0.0023)
$log(Priceinørekwh_{mt-7}^{i})$	-0.0305*** (0.0024)
	Weekly PEED estimates
$log(Priceinørekwh_{mt}^{i})$	0.0350*** (0.0018)
$log(Priceinørekwh_{mt-1}^{i})$	0.0004 (0.0033)
$log(Priceinørekwh_{mt-2}^{i})$	-0.0012 (0.0019)
$log(Priceinørekwh_{mt-3}^{i})$	-0.0134*** (0.0042)
$log(Priceinørekwh_{mt-4}^{i})$	-0.0079* (0.0047)
$log(Priceinørekwh_{mt-5}^{i})$	-0.0411*** (0.0050)
	Monthly PEED estimates
$log(Priceinørekwh_{mt}^{i})$	0.0384*** (0.0026)
$log(Priceinørekwh_{mt-1}^{i})$	-0.0226*** (0.0022)
$log(Priceinørekwh_{mt-2}^{i})$	-0.0504*** (0.0034)

The main values are the PEED estimates. The corresponding robust standard errors are given in parentheses. * Significance at the 10%-level. ** Significance at the 5%-level. *** Significance at the 1%-level.

Appendix 8: Spot PEED estimates from the extended regression model for residential housing

	Cabins
	Daily PEED estimates
$log(Priceinørekwh_{mt}^{i})$	-0.0599*** (0.0061)
$log(Priceinørekwh_{mt-1}^{i})$	0.0189*** (0.0032)
$log(Priceinørekwh_{mt-2}^{i})$	0.0360*** (0.0028)
$log(Priceinørekwh_{mt-3}^{i})$	0.0512*** (0.0028)
$log(Priceinørekwh_{mt-4}^{i})$	0.0551*** (0.0023)
$log(Priceinørekwh_{mt-5}^{i})$	0.0011 (0.0023)
$log(Priceinørekwh_{mt-6}^{i})$	-0.0932*** (0.0053)
$log(Priceinørekwh_{mt-7}^{i})$	-0.0346*** (0.0051)
	Weekly PEED estimates
$log(Priceinørekwh_{mt}^{i})$	0.0524*** (0.0036)
$log(Priceinørekwh_{mt-1}^{i})$	0.0348*** (0.0034)
$log(Priceinørekwh_{mt-2}^{i})$	-0.0019 (0.0048)
$log(Priceinørekwh_{mt-3}^{i})$	-0.0252*** (0.0065)
$log(Priceinørekwh_{mt-4}^{i})$	-0.0152*** (0.0047)
$log(Priceinørekwh_{mt-5}^{i})$	-0.0280*** (0.0030)
$log(Priceinørekwh_{mt-6}^{i})$	-0.0075*** (0.0025)
$log(Priceinørekwh_{mt-7}^{i})$	0.0133*** (0.0043)
$log(Priceinørekwh_{mt-8}^{i})$	-0.0661*** (0.0025)
	Monthly PEED estimates
$log(Priceinørekwh_{mt}^{i})$	0.0810*** (0.0034)
$log(Priceinørekwh_{mt-1}^{i})$	-0.0400*** (0.0020)
$log(Priceinørekwh_{mt-2}^{i})$	-0.0846*** (0.0028)

The main values are the PEED estimates. The corresponding robust standard errors are given in parentheses. * Significance at the 10%-level. ** Significance at the 5%-level. *** Significance at the 1%-level.

Appendix 9: Spot PEED estimates from the extended regression model for cabins