Delft University of Technology

MANAGEMENT OF TECHNOLOGY

Can Households Help Balance the Grid?

A Causal Study of Dynamic Electricity Pricing and Demand Flexibility

Author: *Remco Y. Hoen*
Student: *5880785*

Supervisors: *Dr. E. (Enno) Schröder*
Dr. L. (Linda) M. Kamp

To be defended publicly on Thursday August 21, 2025

Summary

The European Union aims to achieve climate neutrality by 2050. Both increased electricity consumption and dependence on renewable, climate-neutral energy systems have placed growing pressure on national power grids, including those of the Netherlands. Moreover, because grid stress is concentrated in peak hours, much of the available capacity remains unused during off-peak hours, which is inefficient. Although investing in grid expansion appears to be the obvious solution, it is very costly and would not help balance the difference between peak and off-peak loads. If, however, consumers shift electricity consumption away from these peak hours, the grid would become more efficient and possibly lower the need for long-term grid infrastructure investments. Dynamic electricity pricing is recognized as a promising tool to incentivize this demand flexibility. By exposing households to dynamic intraday prices, they have a financial incentive to shift electricity consumption away from expensive peak hours to save money.

This thesis studies the impact of dynamic electricity prices on household electricity consumption patterns. We use high-frequency hourly consumption and price data from 813 Norwegian households. Norway, a country further along the energy transition, offers a unique context for Dutch policymakers due to its high adoption rate of dynamic electricity contracts (ca. 75%) and high degree of electrification (ca. 84%). The question central to this thesis is:

How do dynamic electricity prices influence intra-day electricity consumption patterns among residential consumers?

We approach this question by investigating whether and to what extent households alter their electricity consumption in response to price changes, the prevalence of load shifting behavior, and the role of specific household characteristics and technology in price responsiveness. We take advantage of the 'natural experiment' that is present in our data. That is, we capitalize on the price shock that occurred during the winter of 2021. By comparing household consumption in the price-shock winter to the preceding winter, we isolate the effect of the price shock and, by extension, extract household responsiveness to changing electricity prices.

We use two related models to understand how households respond to changing intra-day electricity prices. The first model looks at the impact of dynamic pricing during the price-shock winter of 2021. The second model investigates how households respond to price fluctuations occurring at the same hour on different days. Both models control for the daily habits of each household and events that could impact consumption and affect all households, like the weather. Lastly, we explore how different household-specific characteristics impact the responsiveness to price changes.

The results indicate that households with dynamic electricity contracts reduced overall electricity consumption more than those with fixed contracts in response to the 2021 price shock. Sensitivity to a 1 NOK price increase is also found to be higher during the price shock. Intraday price responsiveness was observed primarily in peak price hours with an average hourly consumption reduction of 3.3%. The subgroup analysis reveals that certain household subgroups exhibit larger effect sizes than the overall average, indicating heterogeneity in responsiveness. Households that own an Electric Vehicle (EV), especially those who charge their EV using smart-charging systems, demonstrate larger absolute peak-hour consumption reductions, suggesting that enabling technology plays a critical role in residential demand flexibility. Furthermore, these two subgroups also exhibit strong evidence of load-shifting behavior, where households directly shift consumption from expensive peak hours to cheaper off-peak hours. This suggests these households are well positioned to contribute to demand-side flexibility.

From a policy perspective, our findings suggests that dynamic electricity contracts incentivize households to adjust consumption during peak price hours. Widening the gap between peak and off-peak prices could amplify the financial incentive for households to shift consumption away from peak hours. Moreover, the robustness results indicate households might generally be better at responding to multi-day price trends rather than monitoring and responding to intra-day price changes. For that reason, Time Of Use (TOU) contracts, where peak price hours are more predictable, may already be a strong enough incentive to adjust consumption for the average household without enabling (smart) technology. The simplicity and predictability of these contracts contribute to this. Theoretically, real-time pricing (RTP) contracts remains the economically superior design, by aligning electricity prices to real-time electricity supply and demand. With increasing renewable energy generation like solar and wind, the need for RTP contracts becomes increasingly important. The effectiveness of RTP contracts, however, partly depends on the adoption of (enabling) technologies that help households to fully benefit from them.

Policymakers can remain focused on increasing adoption of dynamic electricity contracts. Moreover, policy interventions to advance the adoption of such technologies could increase household price responsiveness and flexibility, thereby improving the ability to optimally interact with RTP contracts. That said, while being focused on very short-term responsiveness, our findings indicate it is unlikely for dynamic pricing alone to resolve overloaded power grids. However, encouraging the adoption of dynamic electricity contracts combined with policy support could be a meaningful contribution to a long-term solution.

Table of Contents

List of Figures

List of Tables

Glossary

2SLS Two-Stage Least Squares. 12, 49, 58

CS Capital Stock. 5

DID Difference-in-Difference. vii, 12, 31–34, 36–44, 46, 47, 52

ES Energy Services. v, 5, 6, 9

ETI Energy Transition Index. 3

EU European Union. 1, 2

EV Electric Vehicle. v, vi, 2, 22, 24, 25, 28, 29, 34, 39, 40, 42, 47, 48, 51, 54, 57, 64

FE Fixed Effect. 32, 33, 52

IV Instrumental Variable. 12

OG Other Goods. v, 5, 6, 9

OLS Ordinary Least Squares. 12, 33, 35, 49, 50

RTP Real-Time Pricing. ii, 8, 9, 14, 15, 28, 29, 44, 49, 54, 56–58

SE Standard Error. 32, 53

SMC Social Marginal Cost. v, 7, 8

TFE Time Fixed Effect. 32, 33

TOU Time-Of-Use. 8, 54, 56–58

US United States. 14

V2H Vehicle-to-Home. 2

WLS Weighted Least Squares. 12, 58

1 Introduction

1.1 Overloaded Power Grids: A Persistent Challenge to Dutch Climate Neutrality Goals

In 2020, the Member States of the European Union (EU) presented their plan to become climate neutral by 2050. To support this ambition, the EU plans to cut greenhouse emissions by at least 55% compared to 1990 levels at the end of this decade (Commission, 2020). Thereafter, the Dutch government shared plans to adhere to this agreement in 2021. In the Netherlands, 70% of all electricity should be sustainable by the year 2030 (Rijksoverheid, 2022). In other words, 70% of electricity should be originated from renewable sources. Progress to achieve this ambition is, however, limited. In 2024 PBL Netherlands Environmental Assessment Agency shared a report stating the improbability of the Netherlands matching this EU policy of 55% reduction by 2030 (Planbureau voor de Leefomgeving, 2024). Their independent calculations indicate a disappointing 44-52 percent reduction in greenhouse emissions.

The overloaded power grid is presented as an important issue to resolve in order to advance the energy transition (Rijksoverheid, 2024). Grid operator TenneT names both increased electricity usage and dependence on intermittent meteorological-based renewable sources as potential drivers of the grid issues (NOS, 2023c). The increase in renewable electricity production from intermittent sources like wind turbines and solar panels causes unstable electricity production and potential supply-demand mismatches (Ourahou et al., 2020). In 2023, TenneT issued a warning that the Netherlands might face electricity shortages by 2030 (NOS, 2023c). The overloaded power grid in the Netherlands is already affecting some households. In the Dutch city of Almere, the power grid issues have led to situations where houses could not be connected to the grid (NOS, 2023a). Expanding the power grid seems to be a solution. However, as indicated by power grid operators themselves, expanding the grid will need substantial investments, and is not likely to resolve the issue, if at all, for at least another 10 to 15 years (Rabobank, 2024). The overloaded power grid thus represents a persistent barrier to achieving EU climate goals, while electricity consumers face nuisance from grid congestion. This raises the question of how to resolve the issue of overloaded power grids.

1.2 Incentivizing Demand Flexibility Could Be A Solution

The power grid is not always overloaded. Daily peak demand is testing the limits of current power grid capacity (Bosman, 2024). Consequently, reducing peak demand, meaning reducing peak grid loads, would help relieve pressure on the power grid (Bosman, 2024; Rabobank, 2024; TenneT, 2024). Reducing peak electricity usage has also been suggested by the Dutch government and grid operators as a potential solution (NOS, 2023b, 2023d). Assuming "planned" power outages are not an option for reducing peak demand, the reduction must come from the consumer side. This means consumers need to adjust their consumption patterns to lower peak electricity demand. In other words, achieving peak demand reduction requires greater flexibility in electricity usage, commonly referred to as demand flexibility. Achieving demand flexibility has thus become a key topic of interest in the energy transition, as it reduces the need for grid investments.

Electricity demand arises from multiple sectors of the economy (e.g., Industry, Transport, Residential). Each sector is unique in its electricity consumption patterns, drivers, and characteristics. Demand flexibility is therefore likely to be different across sectors. In the Netherlands, 12.3% of total electricity consumption was attributed to households in 2023 (CBS, 2025). Although aggregate industrial consumption was considerably higher, accounting for 54.4% (when combining the industry and the energy sector), it consists of numerous smaller industrial subsectors, from which each is likely to exhibit a unique consumption pattern. This positions the residential sector as a major and intriguing focus for studying electricity consumption. This thesis focuses on the residential sector, where individual households make electricity consumption decisions.

Household electricity consumption is highly dependent on daily routines and the ownership of appliances. Weekday consumption patterns revolve around business hours, with peaks occurring just before people leave for work and shortly after they return home. These peak consumption levels generally coincide with peak pressure in power grids, posing a challenge, as household routines may limit the ability to refrain from electricity consumption during these typical hours. Typical drivers of household electricity consumption include, but are not limited to, lighting, cooking, climate control, laundry, entertainment, and charging needs.

Smart technology systems have been suggested to contribute to relieving pressure on power grids. Smart-controlled devices increase residential flexibility by allowing consumers to shift electricity consumption to different times of the day without adding effort (e.g., automatically running the dishwasher at 3:00 AM instead of immediately after dinner)[1]. Home battery systems could increase flexibility and help flatten the grid demand curve for households by storing cheap energy during the night and using it to decrease peak consumption during the day (Bosman, 2024). The promising Vehicle-to-Home (V2H) technology leverages Electric Vehicle (EV) batteries to provide electricity to homes (Bosman, 2024; Hyundai Motors, 2022). During the day, EV batteries can be charged with renewable electricity sources. Stored electricity can then be used when demand exceeds (renewable) electricity supply or other peak moments. Using stored electricity instead of electricity supplied by the power grid helps relief peak pressure on the grid. While these technological solutions can contribute, some technologies are expensive and still need consumers to change their behavior. This begs the question: why would consumers adopt them without clear incentives?

Dynamic electricity contracts have been recognized as a means to incentivize demand flexibility through price-responsive behavior by consumers (Rabobank, 2024). Dynamic electricity price contracts are agreements where electricity prices fluctuate in response to variations in the day-ahead spot markets. Energy is traded on spot markets, where prices are set using a clearing principle (supply equals demand) (TenneT, 2025). Households can benefit from these contracts by allowing hourly electricity prices to influence their consumption, enabling their electricity usage to adapt dynamically to price fluctuations. Furthermore, dynamic electricity contracts increase the effectiveness of the aforementioned smart technology systems. For example, when considering V2H, dynamic electricity contracts provide a financial incentive to charge batteries at lower night-time rates and use stored electricity during the day, rather than relying on more expensive grid electricity. The EU emphasized the relevance of these contracts by making dynamic electricity price contracts a right for all customers of the electricity market (European Union, 2019).

Interestingly, Rabobank (2024) indicated that only 3% of Dutch households had such a contract by the end of 2023 (Rabobank, 2024). The same article suggested that the price-demand response in the Netherlands may be limited during the coming years, due to low usage of smart (controlled) devices. The lack of technological adoption of smart technologies suggests the Netherlands may not (yet) be equipped for dynamic electricity contracts to serve as a solution for overloaded power grids.

Dutch policy-makers need more information to steer the country towards the right solution. While investing

[1] Although shifting electricity consumption can also be done manually, it is often more difficult to realize. In the case of the dishwasher example, an individual would have to stay up late to turn on the dishwasher at 3:00 AM. Shifting potential is increased noticeably by smart technology.

in grid expansion may seem straightforward, it is both costly and time-consuming. Incentivizing a price-demand response through the adoption of dynamic electricity contracts might be the more efficient solution. Although the Netherlands may not yet be fully equipped to maximize demand flexibility through dynamic electricity contracts, it could be the best long-term solution. Therefore, studying how effective such a price-demand response is in shifting electricity demand from peak hours to off-peak hours remains highly relevant. The implications of such a study could answer the question of whether Dutch policy and legislation should steer the country towards a system where this price-demand response is (more) prevalent.

1.3 Norwegian Demand Flexibility: A Benchmark for Future Energy Policy?

Whereas the Netherlands is actively involved in the energy transition, it ranks only eleventh in terms of the Energy Transition Index (ETI) (World Economic Forum, 2021). Sweden, Norway, and Denmark rank as the top three European countries based on their ETI scores. Interestingly, unlike Dutch households, ca. 75% of Norwegian households have a dynamic electricity contract tied to hourly spot price (Statistics Norway, 2025a). Furthermore, a notable feature of Norways energy consumption is the high share of electricity in its national energy mix. While only 19-25% in the Netherlands, electricity held a staggering share of almost 84% in Norway in 2021 (Energie Nederland, 2021; Statistics Norway, 2025b). Although country demographics are not fully comparable, this Norwegian situation provides an interesting opportunity to study the effect of a price-demand response in shifting electricity demand from peak hours to off-peak hours. Studying a country that is further along the energy transition could, in this context, yield 'a look into the future', and potentially generate invaluable insight for Dutch policy-makers and managers. Norwegian demographics provide insight into a scenario characterized by high smart meter adoption, widespread dynamic electricity contract usage, high electricity dependence, and a more advanced stage in the energy transition. Analyzing whether Norwegian consumers shift electricity demand, how they shift demand, and which types of consumers are more likely to shift or not shift demand, all provide valuable insights for guiding Dutch policy.

1.4 Research Objective

This study aims to address knowledge gaps concerning incentivized demand flexibility. The specific knowledge gaps and corresponding literature review are presented in Chapter 3. We explore and explain the price responsiveness of residential consumers in electricity demand. We examine Norwegian households to gain insight into the dynamics of demand responses in a leading energy transition country. Norwegian insights could potentially guide Dutch policymakers in addressing key challenges related to overloaded power grids, ultimately supporting the European ambition of climate neutrality. This thesis is guided by the following main research question:

How do dynamic electricity prices influence intra-day electricity consumption patterns among residential consumers?

This study takes a quantitative approach to answer this question. Before discussing the methodology, Section 2 explores the theoretical foundations of energy demand, price responsiveness, and dynamic electricity contracts. Next, it presents the reader with a review of empirical evidence in Chapter 3. The above-mentioned main research question is introduced to contribute to the existing knowledge gaps in the literature.

2 Conceptualizing Residential Electricity Demand

To understand household responsiveness to dynamic electricity prices and their potential to alleviate pressure on power grids, we first examine the theoretical framework that explains why electricity prices matter, how they are determined, and how they influence household behavior. This chapter, together with Chapter 3, is part of a broader review of the literature that examines theoretical foundations (2), methodological approaches (3.1), and empirical evidence (3.2, 3.3) related to the flexibility of household electricity demand.

First, a microeconomic theory on energy demand is introduced. Households are presented as utility-maximizing agents whose demand for electricity is derived from the need for energy services. We then establish a basic understanding of energy markets and the concept of economically efficient pricing. This leads to the introduction of dynamic electricity contracts as a mechanism to expose the end-customer to variable electricity prices. Dynamic electricity contracts are suggested to incentivize a demand response through these variable electricity prices. We propose two key short-run mechanisms by which households can respond to price changes.

2.1 Economics of Electricity Demand and Utility Theory

In their book 'An Introduction to Energy Economics and Policy', Filippini and Srinivansan (2024) introduce a microeconomic theory on energy demand (Filippini & Srinivasan, 2024). Energy consumption and demand is different compared to goods like bread or mobile phones. Energy demand is a *derived* demand, meaning its demand is derived from demand for other products or services that use energy as input (Filippini & Srinivasan, 2024; Sorrell, 2015). For example, using a phone can be viewed as combining labor, capital, and energy. The resulting demand for electricity comes from the demand for mobile phone usage. Another example is the electricity demand resulting from the demand for food. To prepare and conserve food, consumers have a stove and fridge. The energy demand that results from using this fridge is thus *derived* from the demand for food (conservation).

In addition, energy demand can be strongly influenced by energy prices, and both the cost and energy efficiency of the technology chosen by the consumer (Sorrell, 2015). We can use the example of the fridge mentioned above to clarify this. Consumers could first of all choose to purchase the cheapest fridge on the market. It can be reasonably assumed that this fridge is of lower quality and therefore consumes more electricity per hour compared to more energy-efficient, higher-end alternatives. The consumer who buys this fridge, by assumption, chooses not to invest in technologically superior capital (i.e., economic capital), but rather has higher electricity consumption. The consumer could have also chosen to invest in better capital, which would lead to reduced electricity consumption. Standard microeconomic theory assumes consumers optimize the costs of both options. Thus, the consumer choice is based on both their budget, capital costs, and electricity costs. Figure 1a illustrates this behavior graphically. Consumers minimize costs by choosing the combination of capital and energy that maximize output, while minimizing costs. The isoquant curve in Figure 1a shows all combinations between capital and energy that yield the same output, whereas the isocost line represents combinations with the same total cost, taking prices of both capital and energy into account. To minimize costs, consumers choose the combination of capital and energy where the isocost and isoquant lines are tangent (point A).

The idealized neoclassical theory of consumer demand depicts consumers as utility-maximizing rational decision-makers (Himmelweit et al., 2001; Sorrell, 2015). The concept of 'utility' originates from ethical theory, but has been further developed by economists in their aim to understand human behavior[2]. The utility theory known in economics today is a theory of preference (Himmelweit et al., 2001). It assumes consumers always have a preference for a specific act or product and can rank these preferences. These preferences are thus of an ordinal nature. Moreover, these preferences are consistent and sovereign, meaning consumers are consistent in their choice and not influenced in any way. As all preferences of acts are ordinal, a relation exists between them. The mathematical representation of this relation is called the *utility function*, which expresses the total utility (U) of the consumer as a function of consumed goods. The standard microeconomic theory assumes consumers to have a preference between all acts or products, and are assumed to be rational in choosing the act/product that gains them the highest utility (or satisfaction), consumers are utility-maximizing (Himmelweit et al., 2001).

When applying the (neoclassical) utility theory to energy demand, households are believed to gain utility from the consumption of goods that serve as input in the production of Energy Services (ES) and Other Goods (OG). Energy Services, like the fridge from the aforementioned example, are created by combining Capital Stock (CS) with Energy (E). This yields the following utility function:

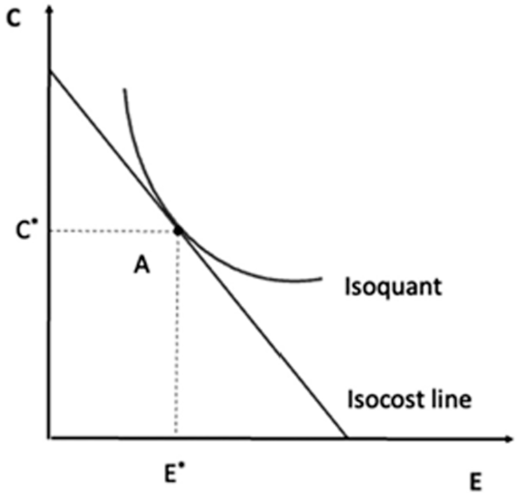
$$U = u(ES(E, CS), OG) \tag{1}$$

Under the constraint of their income, consumers optimize the consumption of both Energy Services and Other Goods in a utility-maximizing manner. A graphical representation of this optimizing behavior is given in Figure 1a (Filippini & Srinivasan, 2024, p. 52). The income constraint of consumers is represented by the budget line in figure 1b. The budget line represents the linear relationship between the two points where the entire budget is spent on one good (ES and OG). The budget line has the following formula:

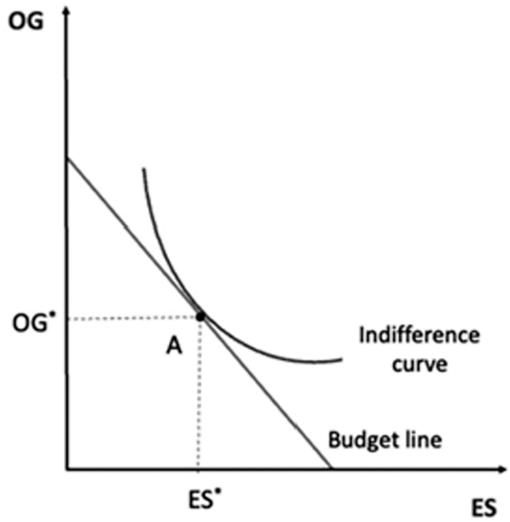
$$Income = Price_{ES} \times Q_{ES} + Price_{OG} \times Q_{OG} \tag{2}$$

Q_{ES} and Q_{OG} represent the consumed quantity of Energy Services and Other Goods.

[2]'Utility' is a term that has known many definitions over the past two centuries. Daniel Bernoulli defines it as 'benefit' or 'advantage', while Jeremy Bentham defined utility as 'pleasure' (Himmelweit et al., 2001)



(a) Consumers choose inputs to minimize production costs of Capital (C) and Energy (E), while maximizing output. Consumers can invest in capital and consume less energy, or consume more energy while investing less in capital.



(b) Consumers choose the optimal combination (utility-maximizing) of goods where the budget line is tangent to the indifference curve. Point A with consumption OG* and ES*.

Figure 1: Consumers optimize consumption of Energy Services (a) and minimize costs of production of Energy Services (b) (Filippini & Srinivasan, 2024, p. 52).

2.2 Energy Markets and Pricing

In microeconomic theory, markets are assumed to work through price-clearing mechanisms that balance supply and demand. Both supply and demand are driven by the respective willingness to produce and consume at a specific price level. When a price level exceeds the willingness to pay of consumers, demand (at price P) will decrease. Suppliers, on the other hand, have a willingness to produce at price P. When suppliers are not willing to produce at price P, supply will decrease. As a response to both behaviors, prices fluctuate. Prices rise when demand exceeds supply, and fall when supply exceeds demand. Eventually, supply and demand will reach an equilibrium state around the 'equilibrium price' (Borenstein et al., 2002). A graphical representation of such a market equilibrium is presented in figure 2. Supply and demand curves intersect at price P and quantity Q.

Many consumers have electricity contracts where the price of electricity is fixed. Based on the market equilibrium principle explained above, we know the market price is the result of the equilibrium between supply and demand. Fixed prices must therefore either assume constant supply and demand over the contract period, or represent the 'expected' average level of supply and demand from which the fixed price is derived. This presents the electricity market with an efficiency problem. Supply and demand are not constant. Electricity consumption fluctuates throughout the day, week, month, and year. Simultaneously, especially with the arrival of renewable electricity sources, supply is also prone to fluctuations. Renewable electricity sources, such as wind turbines and solar panels, are subject to intermittency, meaning their power output is not constant but rather dependent on weather conditions. Wind turbines only generate power when there is sufficient wind while solar panels need sunlight. Problems with intermittent power sources arise whenever electricity production is not correlated with demand patterns (Ourahou et al., 2020). This unstable supply-demand mismatch makes it inherently difficult to derive an accurate fixed price, resulting

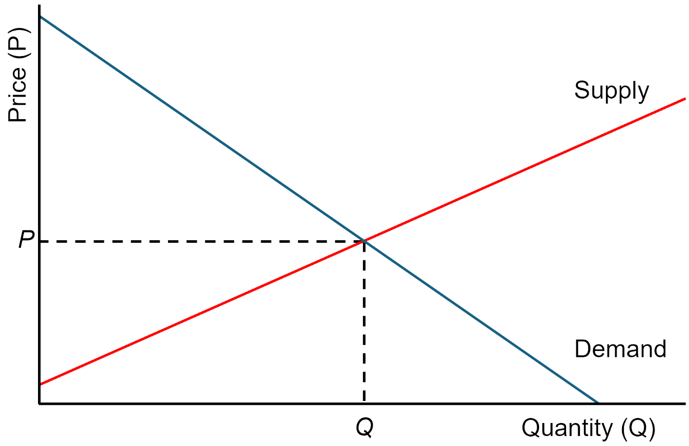


Figure 2: Market equilibrium at the intersection of supply and demand curves. At equilibrium, quantity Q is consumed at price level P.

in either the consumer or the power company generating a profit from the contract, which is inefficient. The next section addresses the inherent inefficiency in fixed pricing that arises when faced with volatile electricity supply and demand.

Microeconomic theory suggests that the pricing of goods and services can be optimized. Pricing at short-run Social Marginal Cost (SMC) is considered to be economically efficient (Borenstein, 2016). To clarify, SMC refers to the total social cost of producing another unit of, in this case, energy. Social cost includes both the marginal cost of production and external factors (e.g., pollution). The closer the price of energy is to the SMC, the greater the incentive for consumption. A difference between SMC and the price point is economically inefficient, and a deadweight loss for society (Borenstein, 2016). Prices higher than SMC result in limited consumption, whereas lower prices create inefficient consumption. Renewable electricity sources introduce an additional layer to efficient pricing, as renewable sources operate at a near-zero marginal cost (Blazquez et al., 2018). Consequently, SMC of renewable sources is much lower compared to fossil sources, indicating that electricity prices should be lower when renewable sources supply power.

Economically efficient pricing means that prices should be equal to SMC at any time of day. Since supply and demand are not constant over time, prices must also fluctuate accordingly. Fixed electricity contracts, where the consumer pays a fixed price per kWh, do not facilitate this pricing flexibility. Switching to dynamic electricity contracts is therefore likely to result in gains in economic efficiency (Borenstein, 2005). Section 2.3 elaborates on these types of contracts.

Figure 3 illustrates a scenario where supply and demand are not constant during the day. For simplicity reasons, we only differentiate between peak and off-peak household demand time intervals. We assume household demand peaks just before and after business hours. Furthermore, on the supply side, we assume solar panels generate considerable power around noon. This scenario can be represented by two demand curves and two supply curves. The off-peak equilibrium price is lower compared to the peak price, as a result of renewable power production and lower demand.

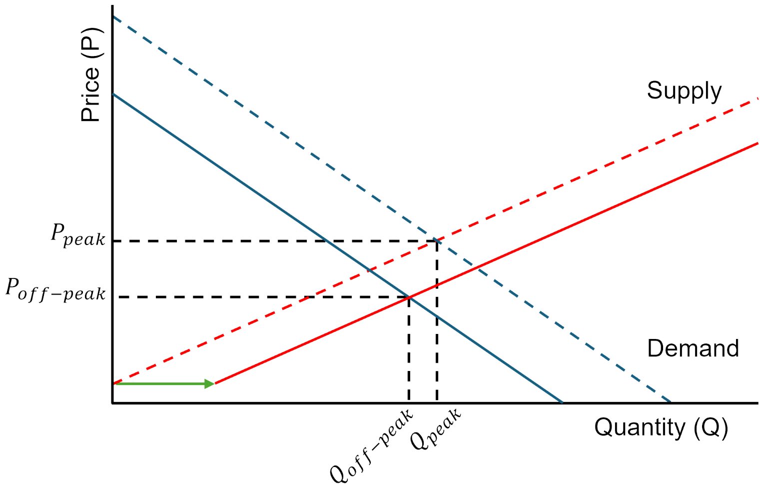


Figure 3: Market equilibrium in a system with two supply and demand curves. Peak periods are represented by the dashed lines. The off-peak demand curve shifts to the left, as demand is lower in off-peak hours. Renewable power generation at near-zero SMC during off-peak hours (noon) causes the supply curve to shift to the right. The renewable power generation shift is shown by the green arrow. Both reduced demand and cheaper supply result in lower quantity consumed and lower off-peak electricity prices.

2.3 Dynamic Electricity Contracts

Section 2.2 introduced the reader to the economics of energy demand and neoclassical rational utility-maximizing model. Section 2.2 provides the foundation for the idea that fluctuating electricity prices are economically efficient. Dynamic electricity contracts are introduced as a mechanism to facilitate increased efficiency by allowing prices to fluctuate based on supply and demand. This section elaborates on two prominent types of dynamic contracts.

Dynamic energy contracts are contracts between electricity suppliers and end customers where the hourly electricity price can vary based on the current (day-ahead) spot price of electricity (European Union, 2019). Suppliers generally charge a small fee for providing the service. While this fee is added to the wholesale electricity price, price variation results from changes in wholesale spot prices. Whereas fixed electricity contracts maintain a constant price per kWh throughout the contract's duration, dynamic contracts directly charge their customers electricity spot prices. We introduce two prominent types of dynamic electricity pricing contracts: Real-Time Pricing (RTP) contracts and Time-Of-Use (TOU) contracts.

RTP contracts are contracts that charge consumers the hourly electricity spot prices (Dutta & Mitra, 2017). These contracts are often based on the day-ahead market, meaning that hourly prices can change every day. TOU contracts are similar, but instead of hourly price fluctuations, they feature peak and off-peak pricing periods (Dutta & Mitra, 2017). In other words, instead of 24 price periods per day, TOU contracts only have two price periods per day. Both types calculate prices based on supply and demand mechanisms. Prices are higher when demand is peaking, and, in general, lower when renewable energy is produced. As a result, dynamic electricity contracts enable market efficiency to reach households. Moreover, dynamic contracts create a financial incentive for utility-maximizing consumers to potentially profit from price changes. By shifting consumption from expensive to cheaper hours, consumers can reduce their electricity bills.

This study predominantly focuses on hourly electricity consumption and prices. RTP contracts are therefore most relevant to this research. More information on the type of electricity contracts and pricing dynamics relevant to the data used in this study can be found in section 4.2.4.

2.4 Consumers Respond to Price Signals

The previous section indicates that dynamic electricity contracts create a financial incentive to change consumption behavior. From a neoclassical microeconomic point of view, it is rational for consumers to respond to this financial incentive (Naastepad & Storm, 2024). A decrease in electricity prices would make consuming Energy Services cheaper than Other Goods. This would lead to a reduction in the slope of the budget line in Figure 1b (eq. 2), allowing consumers the opportunity to rebalance their consumption. Rebalancing consumption in response to a price decrease benefits consumers by increasing total utility without affecting their budget. Figure 4 gives a graphical representation of this scenario. Please note that the consumer is now able to consume more Other Goods and more Energy Services simultaneously.

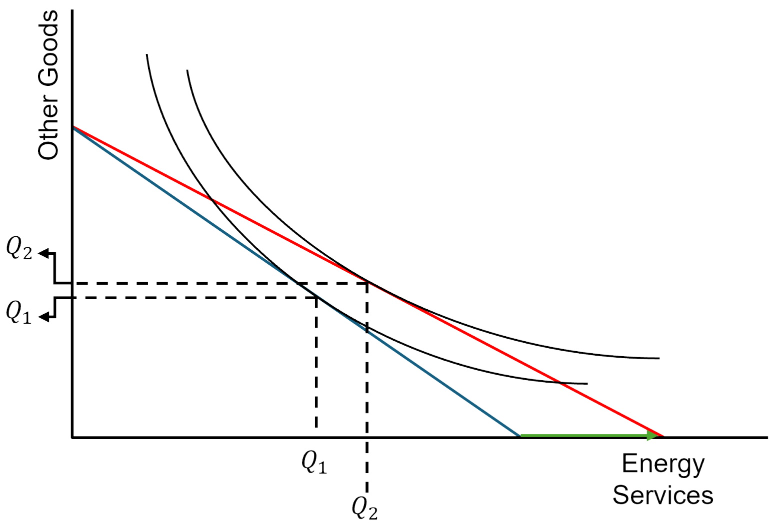
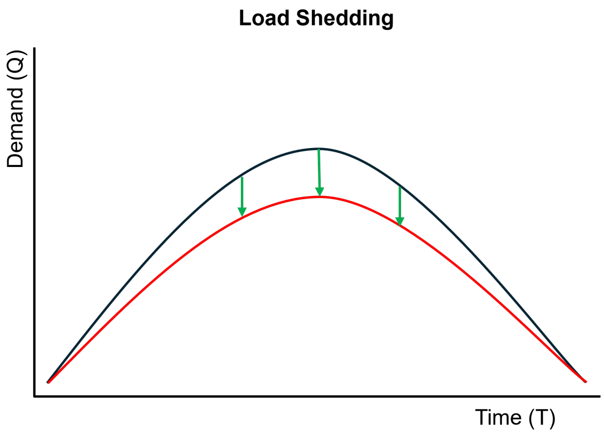


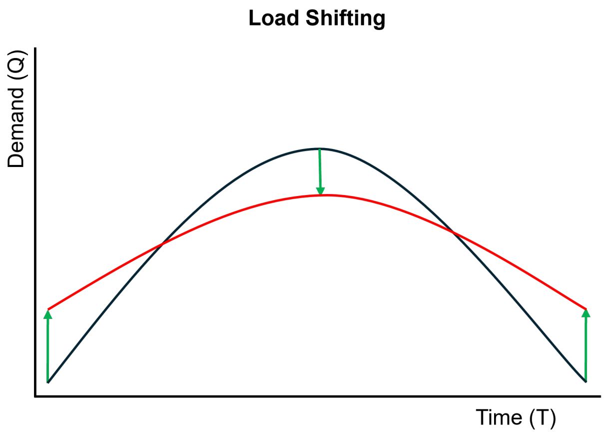
Figure 4: Graphical representation of rational, utility-maximizing consumer. When the price of Energy Services decreases, the substitution effect optimizes consumption distribution: the consumer will buy more ES and less OG. The consumer, however, now also has a higher purchasing power. The income effect carries the consumer to the new highest possible indifference curve, resulting in more consumption for both OG as ES.

It is important to distinguish between the short-term and long-run utility-maximizing behavior of consumers in the context of energy demand. Namely, in the short run, capital (Figure 1a) is thought to be fixed or constant (Filippini & Srinivasan, 2024). This suggests that, in the short run, consumers are unable to replace energy-inefficient capital with energy-efficient alternatives. Returning to the previous example, consumers are not able to purchase a more energy-efficient fridge in response to an increase in electricity prices. It is therefore assumed that, in the short-run, variation of energy demand only depends on variation of demand for Energy Services. In other words, as investing in more energy-efficient capital is not possible, in the short-run, consumers can only engage in behavioral changes in energy consumption to maximize utility. This leads to the idea that a long-term response is likely to be higher compared to a short-term one. But how do households respond to these signals in the short run?

Consumers can generally respond by two key mechanisms: load-shedding and load-shifting behavior. These terms refer to the demand that can be eliminated by the consumer and the demand that can be shifted to different times of the day, respectively. A graphical representation of both behaviors is presented in Figure 5. Shiftable load is reported to have the largest potential for demand response, as it may be easier to shift consumption compared to eliminating it altogether. Furthermore, cost savings are also predominantly linked to load-shifting behavior. Load shedding, however, contributes the most to energy savings (Wang et al., 2018).



(a) Electricity profile of load shedding behavior. The load from the initial electricity consumption pattern (black) is shed, resulting in the load-shedded electricity profile (red). Consumers reduce overall electricity consumption by eliminating specific electricity demand. The consumption pattern is lowered.



(b) Electricity profile of load shifting behavior. The load from the initial electricity consumption pattern (black) is shifted to other times, resulting in the load-shifted electricity profile (red). Consumers reduce peak electricity consumption by shifting specific electricity demand. The consumption pattern is flattened.

Figure 5: Graphical representation of load shedding (5a) and load shifting (5b) consumer behavior. Images are inspired by Wang et al., 2018.

It is important to note that households are likely to have different responses to price changes. Households have different preferences, causing them to behave differently. Load-shifting behavior, for example, has the added risk of backfiring, where the reduction in peak-hour consumption is smaller than the subsequent increase in off-peak consumption, resulting in a net rise in overall demand. Furthermore, as not all electricity consumption has the same shifting or shedding potential, household-specific characteristics may influence the price response sensitivity. To illustrate, it will be difficult for households to eliminate or shift the electricity consumption related to cooking. It is, however, possible to eliminate some consumption linked to heating by wearing warmer clothing. At the same time, charging mobile devices or running laundry appliances has the potential to be moved to other times of day.

3 Literature Review

Chapter 2 introduced the theoretical framework that is used in this study to explain why and how households respond to electricity prices. Chapter 3 builds on this by reviewing empirical evidence that tests these theoretical ideas. This chapter investigates how researchers have studied price responsiveness in practice, the methods and data sources they have used (3.1), and what empirical evidence reveals about the magnitude (3.2) and heterogeneity (3.3) of household responses to electricity price fluctuations. Evidence on the role of enabling technologies in household responsiveness is also reviewed in Section 3.3. This chapter concludes by summarizing existing knowledge gaps and formulating the research questions that guide this study.

The literature was obtained through a Scopus search engine and Google search. A first set of articles was acquired by formulating a Scopus search string that aims to define the scope and boundaries of this review of the literature. This literature search was then supplemented by articles on more specific topics found through both Google search and Scopus.

3.1 Methods used in Literature

To understand the empirical evidence on household price responsiveness, it is important to examine the methodology used in previous research. This section provides an overview of common study designs, data types, analytical methods, and the metrics studied to evaluate electricity demand response. Highlighting these methods helps identify both common practices and sets the stage for the empirical approach adopted in this thesis.

Studies on price responsiveness of household electricity demand are often performed using observational data (Fabra et al., 2021; Hirth et al., 2024; Hofmann & Lindberg, 2019, 2023; Møller Andersen et al., 2024; Zhu et al., 2018), or data from experimental setups (Allcott, 2011a; Buckley, 2020; Hofmann & Lindberg, 2024). Observational data is generally recognized for its generalizable value. In contrast, experimental setups can provide a stronger basis for causal inference studies, as treatment effects can be more effectively isolated. Experimental setups allow researchers to control the setting from which data is gathered. Experimental setups are widely used in medical studies, as they allow researchers to isolate test subjects and ensure consistent exposure to treatments, such as administering a medication under controlled conditions. While causal evidence is strong in these settings, one could question whether the same effect would have been observed outside laboratories. Observational studies obtain data from real-life situations, often featuring a sample that is a more representative measure of the broader population, making a stronger case for generalizable results.

Temporal resolutions for estimating price elasticity range from common intervals such as annual, quarterly, and monthly data (Auray et al., 2019; Krishnamurthy & Kriström, 2015; Schulte & Heindl, 2017; Zhu et al., 2018) to more granular hourly price and consumption data (Allcott, 2011a; Fabra et al., 2021; Hirth et al., 2024; Hofmann & Lindberg, 2019, 2023, 2024; Møller Andersen et al., 2024). The latter often focus on alternative metrics, such as evidence of load shifting, (peak) demand reduction, and consumption profiles.
Cross-sectional, time-series, and panel data are all common dataset types in this field of research. Though, time-series and panel data is used more frequently when analyzing a demand response over time. Meta-analysis showed cross-sectional data to produce less elastic estimates compared to time-series and panel datasets (Zhu et al., 2018).

Data analysis methods generally include an Ordinary Least Squares (OLS) regression (Allcott, 2011a; Zhu et al., 2018). Several studies also use a Two-Stage Least Squares (2SLS) model, arguing electricity price is not exogenous (Fabra et al., 2021; Hirth et al., 2024). When price is assumed to be endogenous, OLS is not fit to handle the simultaneity of both the price and demand equation (Hirth et al., 2024)[3]. In this context, 2SLS models often utilize an Instrumental Variable (IV) for price to prevent the error term of price from being correlated with the error term of demand. Weighted Least Squares (WLS) is also mentioned as analytical method in the literature (Zhu et al., 2018). WLS can be used when data is heteroskedastic, meaning the variance of the error term is not constant across observations. Log-log models are occasionally used to interpret regression results in percentages directly. Nonetheless, Hirth et al. (2024) noted that this becomes difficult when electricity prices reach zero or fall below zero (Hirth et al., 2024).

Difference-in-Difference (DID) models are also used in prior literature (Hofmann & Lindberg, 2023). DID models can be used to, for example, evaluate the effect of a policy intervention by comparing two otherwise similar groups, only one of which is exposed to a new policy (Wooldridge, 2020). These types of models generally compare outcomes across two periods: before and after the policy intervention. By ensuring the two groups are similar before policy implementation, the model assumes that any change in outcome can be attributed to the policy. In statistical terms, this is often referred to as the *average treatment effect* of such a policy.

Several studies use Fixed Effects in their modeling approach (Allcott, 2011a; Azarova et al., 2020; Hofmann & Lindberg, 2024). Fixed Effects control for (heterogeneous) omitted variable bias. These models control for unobserved heterogeneity in observations by assuming heterogeneity is constant over time (Wooldridge, 2020). In the context of household electricity consumption, for example, including household-level Fixed Effects controls for differences in baseline consumption across households. Additionally, hourly variation in electricity use could also be the result of household-specific routines rather than baseline consumption or price variation. Assuming these routines are constant over time, fixed-effects models can control for this variation by demeaning household-specific hourly consumption data. This isolates consumption variation that is 'abnormal' for a given household and hour. This household-hour combination of Fixed Effects has previously been implemented by Hofmann and Lindberg, 2024. In contrast, time-fixed effects controls for unobserved shocks that occur at a specific point in time, but affect all households uniformly (Wooldridge, 2020). For example, if all households increase electricity consumption in response to abnormally low outdoor temperatures on a given day, this common shock will be accounted for through time fixed effects.

These methodological choices found in the literature shape the types of insights studies can provide. The following section reviews what the empirical evidence has found using these different approaches.

3.2 Price-Demand Response: Empirical Evidence

The topic of demand response to variable electricity prices is a topic that has often risen and vanished from the (academic) stage. Analysis by Faruqui et a. (2017) discussed that the topic first came into the interest of researchers in the 1970's and 1980's (Faruqui et al., 2017). Technological barriers, specifically the lack of smart meters, led to a weakened interest in the subject. During the California energy crisis of 2000, researchers theorized about incentivizing consumers to reduce electricity usage at peak hours. Later, with the support of enabling technologies, pilots testing this effect became more frequent.

[3] Price endogeneity assumes price affects demand and demand affects price. This feedback loop would work through the market mechanism where price is set through the equilibrium between supply and demand.

This section provides a review of empirical evidence on consumer responsiveness to fluctuating electricity prices. The review progresses from long-term demand response to a narrow focus on short-term intra-day responses observed through hourly consumption data.

Many studies on the long-term price elasticity of electricity leverage annual or semi-annual consumption data and average electricity prices. A cross-country analysis of residential electricity demand in eleven OECD countries found strong price responsiveness in the long run (Krishnamurthy & Kriström, 2015). The study reported a long-term weighted price elasticity of -0.62 for the full sample. Sweden, a neighboring country to Norway, had a price elasticity of -0.71. Germany was found to have a price elasticity of electricity of -0.431 (Schulte & Heindl, 2017). Based on semi-annual data, a French study on the price elasticity of electricity demand estimated a long-term elasticity of -0.8 (Auray et al., 2019). These results indicate the existence of large differences in long-term responsiveness between countries and households.

As discussed in Section 2.4, short- and long-term price responses differ in the tools households have available to respond to price changes. Households are assumed to rely on behavioral change in the short run, whereas the long run allows for technology changes as well. The meta-analysis by Zhu et al., 2018 on the price elasticity of residential electricity demand highlights the clear difference in the magnitude of responsiveness between the short and long term. Based on 175 and 196 studies, respectively, the mean short-term price elasticity was found to be -0.228, while it was -0.577 in the long term. Although both elasticities were negative, residential responsiveness is higher in the long term. This aligns with the theory introduced in Section 2.4. The meta-analysis covered the period from 1950 to 2014 and was based on (among others) annual, quarterly, and monthly consumption data. Interestingly, monthly data were found to be a better measure for short-term price responses by households compared to their annual counterparts. This finding suggests that a shorter time interval in consumption data is capable of detecting price responsiveness in higher detail.

Increased smart meter adoption enables researchers to study the price-demand response at shorter time intervals, including hourly intervals. Surprisingly, however, relatively few studies have taken advantage of this opportunity to gain a deeper understanding of hourly or even daily household responsiveness to fluctuating prices. Among the studies that do leverage hourly data, consumer responses are often reported using alternative indicators rather than (short-term) price elasticity estimates. Common metrics include peak-hour consumption reductions, changes in total electricity use (load shedding), shifts in hourly consumption patterns, and evidence of load-shifting behavior.

In Germany aggregate electricity demand response to fluctuating wholesale prices was studied (Hirth et al., 2024). A short-term price elasticity of -0.05 was reported based on hourly consumption data. This study did, however, only look at aggregate electricity consumption, and did not exclude industrial consumers. Although the study provides evidence of demand flexibility, our focus concentrates specifically on residential consumers. Another study reported the short-term price elasticity of electricity demand in Oslo. Based on aggregate hourly consumption data, the found elasticity ranged between -0.011 and -0.075 (Hofmann & Lindberg, 2019). This study also failed to separate households from office buildings in its analysis.

A recent Norwegian study shared evidence of demand flexibility in response to hourly price signals (Hofmann & Lindberg, 2024). The researchers conducted a large-scale experiment involving 3,746 Norwegian households. Households were found to reduce electricity consumption by an average of 2.92% in peak hours. Households were also revealed to be sensitive to the type of price signal (i.e., duration and frequency), and the magnitude of price increase. (Hofmann & Lindberg, 2024). This aligns with both economic theory introduced in Section 2.4, and a United States (US) based RTP experiment (Allcott, 2011a). Higher electricity price differences increase the financial incentive (for rational consumers) to be more price responsive. This finding is also consistent with a Danish study that found the short-term price elasticity for total electricity consumption to increase when prices were high and unstable in 2022. Furthermore, electricity consumption profiles in 2021 and 2022 were showing more consumption during the night compared to 2019. This 'flattening' of the consumption profile is evidence of load shifting behavior (Møller Andersen et al., 2024)[4]. In contrast, based on observational data, Spanish households did not show differences in behavior between households with dynamic (RTP) contracts compared to non-RTP contracted households (Fabra et al., 2021). These counterintuitive findings are attributed to the absence of enabling technologies, low awareness, and low price variation. The latter corresponds to the findings of the two above-mentioned studies (Allcott, 2011a; Hofmann & Lindberg, 2024).

Another Norwegian study, conducted during the 2021/2022 energy crisis, found demand flexibility among households during periods of extreme electricity prices (Hofmann & Lindberg, 2023). Immediately after prices increase, consumers reduced their energy consumption, achieving total savings of 11.4% during winter. Interestingly, this study did not find the existence of hourly intra-day price responsiveness for the average household. The study suggests that consumers primarily react to awareness of high electricity prices rather than daily price variations, which corresponds with other studies (Fabra et al., 2021; Møller Andersen et al., 2024). The average household may have limited capacity to shift demand away from peak hours. However, some household subgroups did demonstrate reduced consumption during peak hours as a result of higher electricity prices. This indicates household specific characteristics could be of interest in understanding demand flexibility. Section 3.3 reviews empirical evidence on the importance of household characteristics, and the heterogeneity of residential price responsiveness.

A meta-analysis conducted in 2020 showed that incentivizing consumers to reduce electricity demand will result in a demand reduction of 3.91% (Buckley, 2020). The authors also named a more conservative estimate of 1.87%. Interestingly, while the article confirms that dynamic pricing strategies are effective during periods of high demand, the authors also suggest dynamic pricing is less effective in reducing overall demand (Allcott, 2011b). This, potentially counterintuitive, result is theorized to be the consequence of a so-called rebound effect, introduced in Section 2.4. Households may reduce peak hour consumption, but elevate off-peak consumption by a greater factor (Buckley, 2020; Torriti, 2012). While the recent Norwegian experiment mentioned earlier did not observe a rebound effect in their results (Hofmann & Lindberg, 2024), other studies have reported the effect (Azarova et al., 2020; Schofield et al., 2015).

In conclusion, this section presents various studies that investigate the price elasticity of electricity demand, short-term demand flexibility, and the type of consumption responses. Households are generally seen to reduce electricity consumption in response to increasing electricity prices (Buckley, 2020; Hirth et al., 2024; Hofmann & Lindberg, 2019). Hofmann and Lindberg, 2024 reported an average 2.92% peak hour consumption reduction in their Norwegian field experiment. Literature suggests households are sensitive to the magnitude

[4]Households represented 25% of this sample

of price increase (Allcott, 2011a; Hofmann & Lindberg, 2024), and can exhibit signs of load-shifting (Møller Andersen et al., 2024). Load-shifting is sometimes linked to a rebound effect in the literature (Azarova et al., 2020; Buckley, 2020; Schofield et al., 2015; Torriti, 2012). Hofmann and Lindberg, 2023 reported an 11.4% decrease in electricity consumption during winter in response to a price shock. However, literature is not conclusive about the effect as Fabra et al., 2021 did not find a behavioral difference between RTP and non-RTP contracted households.

3.3 Residential Characteristics Moderating the Demand Response

The theoretical framework presented in Chapter 2 provides an economic theory on energy demand (2.1), and introduces theory on price responsiveness (2.4). These sections state that demand is the result of consumer preferences (2.1). Consumer preferences are specific to every household. Therefore, households might respond differently to price signals (2.4). This section expands on these insights by exploring determinants that have been empirically identified in literature to explain variations in residential energy consumption, and factors that moderate the relationship between price and demand.

Numerous researchers have emphasized appliance-related factors[5] as a key driver of electricity demand. In general, appliance factors are positively correlated with price responsiveness (Faruqui & George, 2005). This observation can be logically explained by differences in household motivation and the availability of tools or technologies that enable price-responsive behavior. Since higher appliance ownership is associated with higher electricity consumption (Chen et al., 2022; Wiesmann et al., 2011), it could also increase the financial incentive for households to respond to price changes, which would explain the aforementioned correlation. Additionally, EVs in particular have been identified as a technology that can potentially moderate the price-demand response of residential consumers (Hofmann & Lindberg, 2023; Møller Andersen et al., 2024; Wang et al., 2018). Subsequently, EVs are identified to have a major influence on load shifting potential by households, as they belong to the major electricity-consuming devices, and charging is not bound by time (Wang et al., 2018). Meanwhile, demand related to electric cooking harms price responsiveness (Faruqui & George, 2005). This suggests appliance-specific demand flexibility, as consumers respond to price changes with specific appliances, as theorized in Section 2.4.

Related to household appliances and electricity consumption by consumers are technologies that allow consumers to be more price-responsive. These smart technologies facilitate greater control over appliances. Greater control, automation, and reduced cognitive costs suggest smart technology could moderate the relation between electricity price and consumption (Allcott, 2011a; Bedir et al., 2013; Bobbio, 2021; Fabra et al., 2021; Faruqui & Sergici, 2013; Özkan, 2016; Parrish et al., 2019). Parrish et al. (2019) reported a 15% higher demand response in trials where participants have access to automation technology (Parrish et al., 2019). Furthermore, the lack of enabling technologies was also suggested as a cause of the non-response found in the Spanish study mention in Section 3.2 (Fabra et al., 2021)

Socio-structural factors also influence the price responsiveness of residential consumers. High-income household are reported to be more price responsive compared to low-income households (Frondel et al., 2019). Preference for and accessibility to energy-efficient appliances could be a contributing factor in this relationship (Alberini et al., 2011). Households with high electricity consumption, homeowners (as opposed to tenants), and individuals with higher levels of education have also been found to demonstrate greater response (Fron-

[5] Appliance-related factors refer to the presence, efficiency, and usage of electrical devices

del et al., 2019). On the other hand, people per household is discovered to reduce price sensitivity (Faruqui & George, 2005). These variables are assumed to be correlated to some extent. Income and education level are likely to be positively correlated. The link between socioeconomic status and appliance ownership also deserves attention. Socio-economic factors, such as income and education, influence both the size of the dwelling and the number of appliances owned, which in turn contribute to higher electricity consumption, and more potential for a demand response (Karatasou & Santamouris, 2019).

3.4 Knowledge Gaps & Research Questions

After reviewing the methods, empirical findings, and moderating factors explored in the literature, this section identifies the key gaps that motivate this thesis.

The literature on the price elasticity of household electricity (3.2) reveals several important gaps. The first major limitation is the minimal usage of high-frequency data. Although hourly electricity consumption data is increasingly available through increased smart meter adoption, many studies on price elasticity and demand responsiveness continue to rely on monthly or annual datasets. While these studies are valuable, they risk overlooking the dynamic nature of household behavior. Moreover, while existing research often investigates *whether* electricity consumption changes as a result of price, it often disregards the *mechanism* through which these changes occur. Hourly consumption data allows for a deeper understanding of behavioral dynamics by capturing very short-term responsiveness. Hourly data enables us to distinguish between peak and off-peak hours, helping to identify when and where consumption changes occur.

Another area where further investigation is needed concerns the moderating role of household characteristics. As discussed in Section 3.3, some factors (e.g., income, household size) have been studied, but often at a broad level. The availability of hourly data offers new opportunities to examine how these characteristics influence short-term or even intra-day responsiveness to price signals.

Finally, existing studies mainly focus on countries with low adoption rates of dynamic electricity contracts and limited electrification of energy end-uses. This contextual focus brings external validity into question, specifically whether the findings would be representative in the context of higher adoption in that country. For example, households that live in carbon-intensive countries and choose to purchase an EV could be more conscious about the climate, and, therefore, be more inclined to be flexible in electricity consumption. The observed price responsiveness of such studies may not reflect the behavior of the average household. Studying these knowledge gaps in a highly electrified country with widespread adoption of dynamic electricity contracts would offer more representative insights into household demand flexibility in response to price signals.

This study aims to shed light on knowledge gaps surrounding the heterogeneity of responses to electricity price fluctuations. Specifically, we investigate whether and to what extent households alter their electricity consumption in response to price changes, the prevalence of load shifting behavior, and the role of household characteristics and technology in moderating price responsiveness. This research is guided by the following main research question:

How do dynamic electricity prices influence intra-day electricity consumption patterns among residential consumers?

Three sub-questions are defined in support of answering the main question.

1. *What is the effect of intra-day electricity price fluctuations on hourly household electricity consumption?*
2. *To what degree do higher intra-day electricity prices lead to a shift in consumption from peak to off-peak hours?*
3. *To what extent do household characteristics moderate the effect of price changes on electricity consumption and load shifting?*

The 2021-2022 electricity price crisis presents a unique opportunity to study these questions. This period saw a sharp rise in the overall electricity price level and price volatility. Although households with fixed-price contracts are generally not exposed to these short-term changes, households with dynamic contracts were directly exposed. This setting allows us to observe the effects of more pronounced real-time price signals on households' electricity consumption. Through this 'natural experiment', we can investigate how exposure to this price shock affects household consumption and the extent to which dynamic contract households change their consumption behavior. This scenario presents an ideal opportunity to address all three sub-questions. Further details and characteristics of this price shock are shown in section 4.2.4.

The first sub-question aims to establish the baseline effect for understanding the responsiveness of households to price changes. The aim is to identify the pure treatment effect of price fluctuations on consumption. Next we investigate by what mechanism consumers respond. Do consumers engage in load-shifting, load-shedding, or another type of behavior? The third question aims to dismantle consumer responsiveness, and uncover the heterogeneity of consumer demand flexibility. We aspire to generate a more nuanced understanding of residential electricity consumption responsiveness to prices. Together, these sub-questions build the answer to the main research question, and could provide valuable insights with meaningful implications for policymakers and technology managers.

4 Data

This chapter explores the dataset that was obtained for this study. After some general remarks, we first explore all available data in Section 4.2. We then explain a sampling strategy based on our research questions. Finally, Section 4.2.3 gives a detailed description of the sample and subgroups of interest.

4.1 Data Collection & General Remarks

Data is collected from already available online sources. We have found a recent dataset that fits our objective[6]. The dataset was collected by the Department of Electric Power Engineering of the Norwegian University of Science and Technology (Hofmann et al., 2023). Hofmann et al. (2023) first shared the dataset. This Norwegian panel dataset contains rich data on individual (hourly) electricity consumption, aggregated (hourly) electricity consumption, (hourly) electricity prices, and a rich set of survey answers on household electricity consumption behavior and awareness, electricity price contracts, household characteristics, and socio-demographic information (Hofmann et al., 2023). Hofmann et al. (2023) combined the collected consumption data by local grid companies and the National Electricity Consumption Data Platform (Elhub). Smart meters allowed the collection of household consumption data.

The dataset is a balanced panel, meaning all units are observed in every period, without missing values. In addition, we acquired hourly temperature data to enrich the existing dataset. The data figures and calculations that we developed are run in RStudio (Posit team, 2025). This section explores and presents the data and discusses its usefulness.

4.2 Consumption and Price Dynamics (Full Period)

4.2.1 Regions

The Norwegian power grid is divided into five so-called *bidding zones*. These five bidding zones have their own electricity price. This is the result of high dependence on meteorologically based electricity sources, and insufficient grid capacity to balance these effects countrywide. To illustrate, the northern part of Norway has many hydroelectric power plants that take advantage of the elevated geography of the region. However, the connection of the grid to the southern regions does not allow the transfer of generated electricity at all times. Southern regions, therefore, feature separate supply-demand patterns compared to their northern counterpart, meaning electricity prices can be different. These differences can be observed by looking at the electricity price data in Section 4.2.4.

[6]Please note that this dataset was obtained early in the research process, prior to finalizing the specific methodological approach.

Figure 6: Electricity bidding areas in Norway. Image taken from Statnett (Statnett, 2025).

4.2.2 Aggregate Electricity Consumption

Hofmann et al. (2023) collected and shared aggregated consumption data per Norwegian bidding area (Hofmann et al., 2023). Data is collected for the period July 2019 to July 2022 on an hourly basis. Aggregate demand data is classified by both total MWh demand. Figure 7 presents aggregate demand per bidding area over time. We present the descriptive statistics for this aggregate hourly demand dataset in Table 1. The table was created based on our own calculations in R.

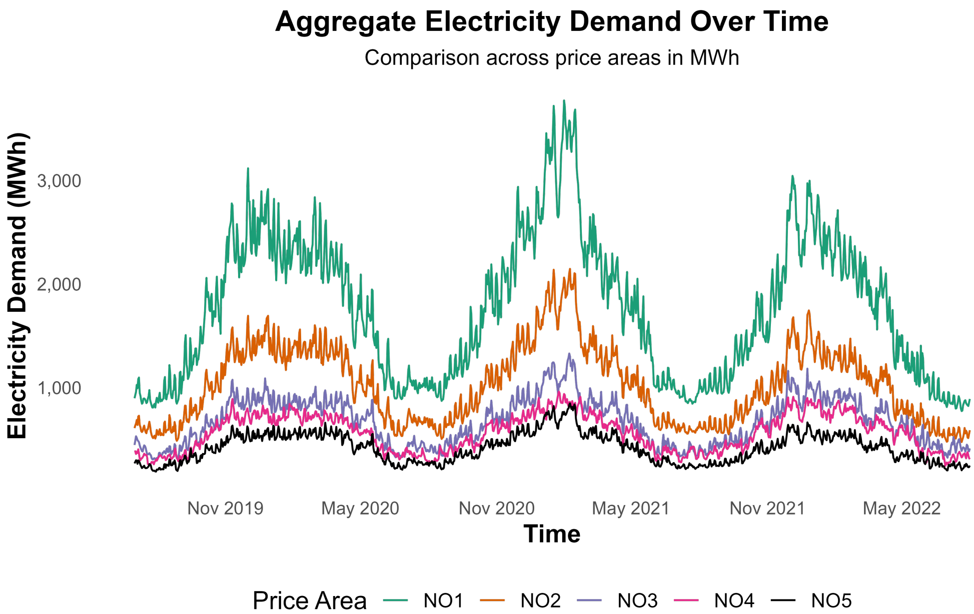


Figure 7: Aggregate demand in MWh over time. Note that regional and seasonal differences can be spotted. We visualized the data by showing hourly consumption at noon. Region NO1 consumes the most electricity, followed by NO2, NO3, and NO4. Winter months represent the peaks in aggregate electricity demand. The figure was created specifically for this thesis using the dataset provided by Hofmann et al. (2023).

Table 1: Descriptive Statistics per bidding area for Aggregate Demand Data (kWh)

Data	N	Mean	SD	Median	Min	Max	Range
NO1 Demand Avg (kWh)	27,048	1.634	0.670	1.590	0.520	3.750	3.230
NO2 Demand Avg (kWh)	27,048	1.703	0.645	1.670	0.580	3.780	3.200
NO3 Demand Avg (kWh)	27,048	1.728	0.607	1.720	0.550	3.650	3.100
NO4 Demand Avg (kWh)	27,048	2.338	0.763	2.410	0.770	4.160	3.390
NO5 Demand Avg (kWh)	27,048	1.672	0.603	1.650	0.550	3.620	3.070

Our research is focused specifically on household responsiveness to changing electricity prices. Therefore, we will not leverage this aggregate consumption data. Descriptive statistics on aggregate data can, however, be valuable in establishing whether the selected household data is representative of the whole country. Table 1 and Figure 7 show NO4 to be the highest consuming region in Norway. NO4 is also the northernmost region, which could explain this pattern due to a greater need for heating. Both mean and median consumption in the other regions look rather similar. While there are some minor differences in consumption, comparing the consumption ranges between regions does not suggest underlying patterns of interest. Figure 7 highlights the seasonal variation in consumption. Winter months represent peak consumption periods.

4.2.3 Household Level Data

The Household data, collected by Hofmann et al., 2023, consists of both a survey, and electricity consumption data. Survey answers were gathered through willing individuals online. The survey was conducted by a market research company called Ipsos. The household sample was pre-recruited. Region NO2 was not represented in the household survey. Hofmann et al. (2023) matched household consumption to survey data whenever households permitted data sharing. Not all households that authorized data sharing were included in the final dataset. Some households could not be matched to consumption data by name, and were consequently excluded from the consumption dataset. As a result, individual consumption data from our dataset is limited to the regions of Oslo (NO1) and Bergen (NO5) by default. The creation of the final household sample used by Hofmann et al. (2023) is explained in the next paragraph. Please note that these cleaning steps were performed before the dataset was acquired for this study.

A total of 4,446 households were surveyed. Of these 4,446 households, 3,011 consented to share their electricity consumption data from the period October 2020 to March 2022. Individual electricity consumption data could only be acquired from the regions of Bergen and Oslo, further reducing the number of households to 1,609. If households had missing (hourly) consumption data, these households were excluded from the dataset. This resulted in a total of 1,161 observations. Outliers were identified and excluded based on three criteria: the share of zero values, maximum consumption, and average consumption. Subsequently, a total of 25 households were excluded, resulting in a total of 1,136 households. This section describes consumption and survey data for the full 1,136 household dataset.

Figure 8 presents the distribution of electricity contract types in the dataset. As shown, not all households that met the criteria mentioned in the previous paragraph have dynamic electricity contracts. Interestingly, 13.6% of the households have a *variable* contract. The full definition of such a variable contract and the differences with hourly spot contracts are left undefined in the original dataset. According to Strømtest, one of Norway's most popular electricity price comparison websites, a variable contract is essentially an intermediate between fixed and hourly spot contracts (Strømtest.no, 2025). Electricity suppliers need to inform households with variable contracts of a price change two weeks in advance. Hourly electricity prices, therefore, fluctuate periodically instead of daily.

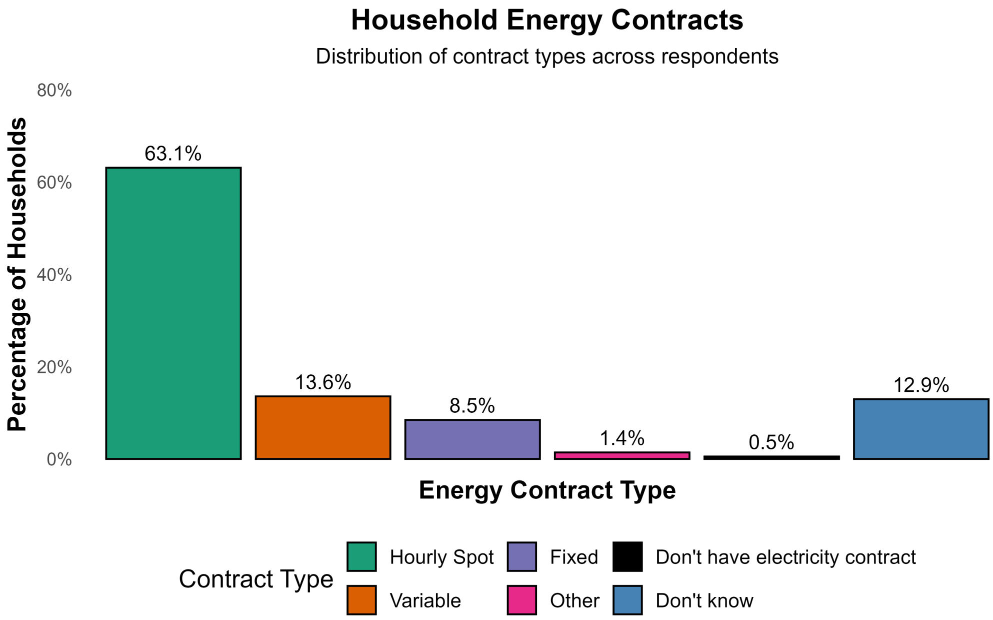


Figure 8: Distribution of electricity contract types in household dataset. The figure was created for this thesis using the dataset provided by Hofmann et al. (2023). (N = 1,136)

As mentioned before, individual consumption data was acquired through home-installed smart meters. Households authorized the use of their data. Descriptive statistics, split per region, are shown in Table 2. This table was produced based on our own calculations. The number of observations is based on hourly consumption data from October 2020 until March 2022 for each household. This explains the high number of observations. The majority of households appear to reside in the NO1 region, where the mean hourly consumption is slightly lower. Though, the difference falls well within the standard deviation and is therefore not considered a concern. Mean consumption is higher than median consumption for both regions, which is a sign of positive skew in our data.

Table 2: Descriptive Statistics for Household Consumption Data (kWh)

Data[7]	N[8]	**Mean**	**SD**	**Median**	**Min**	**Max**	**Range**
NO1 Household Consumption	10,344,864	1.496	1.616	0.942	0	19.638	19.638
NO5 Household Consumption	4,568,544	1.778	1.554	1.356	0	18.396	18.396

When analyzing our household consumption data further, we focus on daily consumption patterns. We visualize the consumption pattern of three random households in Figure 9. The figure shows the average daily consumption pattern, meaning the average consumption per hour of the day. The baseline consumption seems to be different for all three households. Furthermore, evenings seem to be high consumption hours for these households.

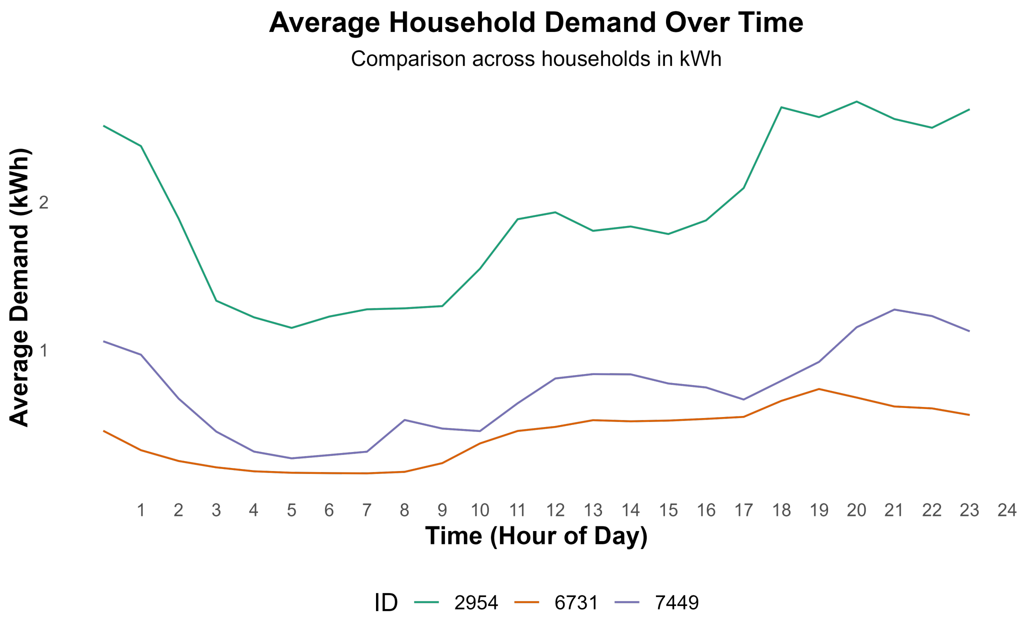


Figure 9: Hourly average household consumption over time (hour of day). Three households were sampled at random to create this figure. Average consumption per hour of day reveals interesting consumption dynamics and differences. Average electricity consumption for household 6731 peaks at around 19:00. Though, household 2954 has its peak at around midnight. The figures were created exclusively for this thesis using the dataset provided by Hofmann et al. (2023).

The consumption pattern of household *2954* is particularly interesting. Instead of peaking during dinner, consumption seems to peak in the middle of the night, whereas the other households reduce consumption just before midnight. This could be a trace of household heterogeneity. The midnight peak could potentially be attributed to household-specific factors (e.g., EV charging), or different routines. This topic is later revisited.

4.2.4 Electricity Prices

Norway is split into five separate bidding zones. In theory, all bidding zones can feature different electricity prices. Table 3 gives an insight into these differences. The table was constructed for this thesis and is based on data shared by Hofmann et al. (2023). We reiterate that the number of observations is high because the dataset is structured as a panel. Mean and median prices are lower in the northern regions NO3 and NO4, when compared to their southern counterparts. When interpreting the range across all five areas, it becomes apparent that prices tend to reach lower maximum levels in regions NO3 and NO4. In addition, southern regions (NO1, NO2, NO5) do not exhibit price differences of interest.

Table 3: Descriptive Statistics for Electricity Price (NOK)

	N	Mean	SD	Median	Min	Max	Range
NO1	27,048	0.635	0.625	0.400	-0.020	6.540	6.560
NO2	27,048	0.672	0.715	0.400	-0.020	6.540	6.560
NO3	27,048	0.264	0.238	0.210	0	3.690	3.690
NO4	27,048	0.231	0.210	0.190	0	3.690	3.690
NO5	27,048	0.633	0.622	0.400	0	6.540	6.540

Figure 10 presents the average price levels per region of interest for each time of day. As shown in the figure, the average hourly electricity prices in NO1 and NO5 follow each other closely. Furthermore, time-specific trends also become visible. Prices seem to peak (on average) both around 9 and 19 O Clock.

Figure 10: Average hourly electricity price in regions NO1 and NO5. These averages were calculated using the full period that is available in the data. The figure was created specifically for this thesis using the dataset provided by Hofmann et al. (2023).

Figure 11 presents the development of average daily electricity prices per region of interest over time. Prices rose sharply toward the end of 2021 and the beginning of 2022, which is a sign of the electricity crisis in the corresponding period. The two gray areas show winter seasons. The winter season of 2021-2022 seems to coincide with the peak of the electricity price crisis.

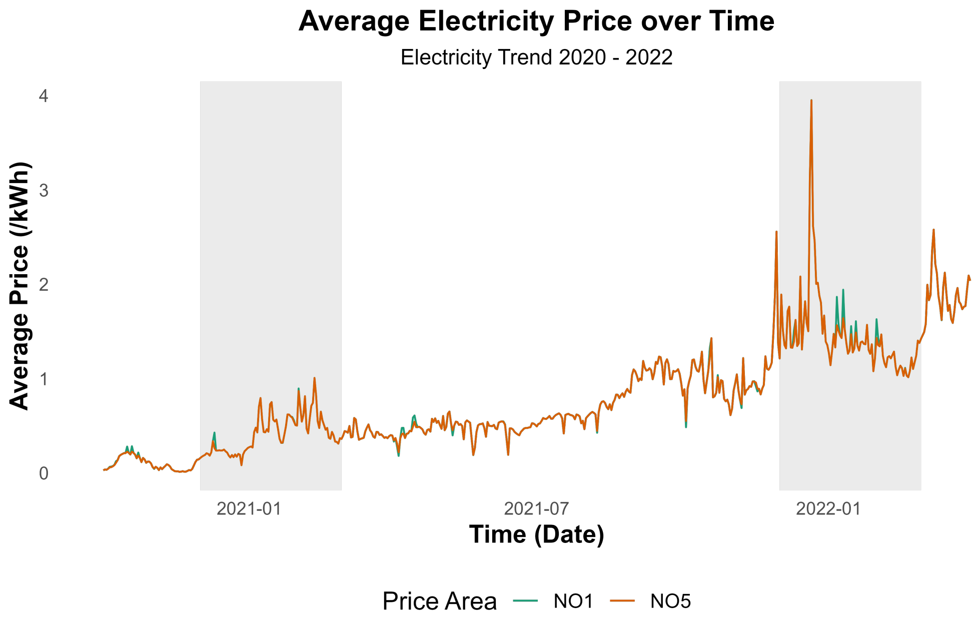


Figure 11: Average daily electricity price over time. Prices increased rapidly at the end of 2021. The figure was created for this thesis using the dataset provided by Hofmann et al. (2023).

4.3 Sample Construction

The dataset presented in the previous section enables a broad range of sampling possibilities. Not all available data is relevant to our research questions. We therefore construct a preliminary household sample and identify several subgroups of interest. The reasoning behind this sample is linked to the methodological approach in Section 5.4. The sample used in this study should contribute to answering the research questions that were defined in Section 3.4. Our research questions are focusing on three areas of interest: the baseline effect of price fluctuations on electricity consumption, the mechanism (e.g., occurrence of load shifting) by which households respond to these price fluctuations, and whether specific household subgroups are more responsive to price fluctuations.

The analysis in this thesis draws on household-level electricity consumption data from both available regions NO1 and NO5. We take advantage of the occurrence of the electricity price shock by limiting our analysis to the two winter seasons in our dataset. Households are categorized based on their electricity contract type. We include households with hourly spot (dynamic) contracts, and fixed contracts. Households that do not have knowledge of their electricity contract, do not have an electricity contract, or have a variable contract are excluded from consideration[9]. Thus, our final sample contains 813 households.

Combining the survey with household-level consumption data allows for the identification of specific household subgroups[10]. The reasoning for the household subgroups considered in this thesis is based on prior literature and is consistent with the theory presented in previous chapters. The included subgroups are *EV ownership*, *Smart-charging behavior*, *Home ownership*, and *Active monitoring of electricity prices*. These household characteristics connect to previous literature from Section 3.3 by focusing on appliance factors, enabling technology, a combination of socio-economic factors and dwelling factors, and awareness, respectively. The *Home*

[9] Inclusion could weaken the validity of causal inference regarding the impact of dynamic prices on consumption.
[10] The full list of survey questions can be found in Appendix A.

ownership characteristic combines multiple factors of interest worth explaining in more detail. First of all, owning a home reflects a household's economic and social standing (SES), as it often correlates with income and wealth. Second, it determines the degree of control household have over the dwelling. Finally, the distinction between owning and renting is policy-relevant, as it could help focus policy interventions.

The next section describes the transformation of the data in preparation for analysis, the creation of the aforementioned household subgroups, and the final distinction central to our analysis: peak and off-peak hours.

4.4 Key Variables Used in Analysis

To facilitate our focus on households with fixed or hourly contracts, we constructed two binary indicator variables: *DynamicContract* and *FixedContract*. The household-level consumption data is then filtered to include only these two contract types, resulting in a final sample of 813 households. The temporal restriction is realized by creating a *Winter* dummy[11], and filtering out all observations that are made on non-winter days. The final sample consequently covers a total of 180 days, spanning two consecutive winter seasons.

We construct a binary EV ownership dummy based on survey questions 29 and 30. The dummy is equal to one for households that own an EV, charge it (at least sometimes) at home, and is charged on the same smart meter as the rest of the house. The final distinction is made to be sure EV charging consumption is captured by the data available to us.

We construct a binary dummy representing smart charging of electric vehicles. The dummy is based on survey question 31. Charging behavior is classified as smart charging when it is automated based on hourly electricity prices. Households that avoid high-price hours by manual or time-scheduled intervention, are not captured by the smart charging dummy.

We formulate a binary ActiveMonitoring dummy based on survey questions 1 and 4. This dummy identifies households that both monitored their power consumption and checked electricity prices on a daily basis. Home ownership is derived from survey question 24, with households classified as renters if they reported not owning the house they live in.

Finally, we introduce both a Peak and Off-Peak dummy variable. Peak hours are defined as hours during which the electricity price is at least 20% higher than the daily average. In contrast, off-peak hours are hours where price is at least 20% below the daily average. These definitions allow these hours to vary for each day based on price. It is important to understand the price-focused approach in this variable. Although theory suggests that price peaks coincide with demand peaks, this it not always the case. Finally, it is important to understand that, under this definition, not every day features a peak or off-peak hour.

[11]Winter is defined by official season: December-February.

Figures 12 and 13 show the distribution of peak and off-peak hours in the winters of 2020 and 2021.

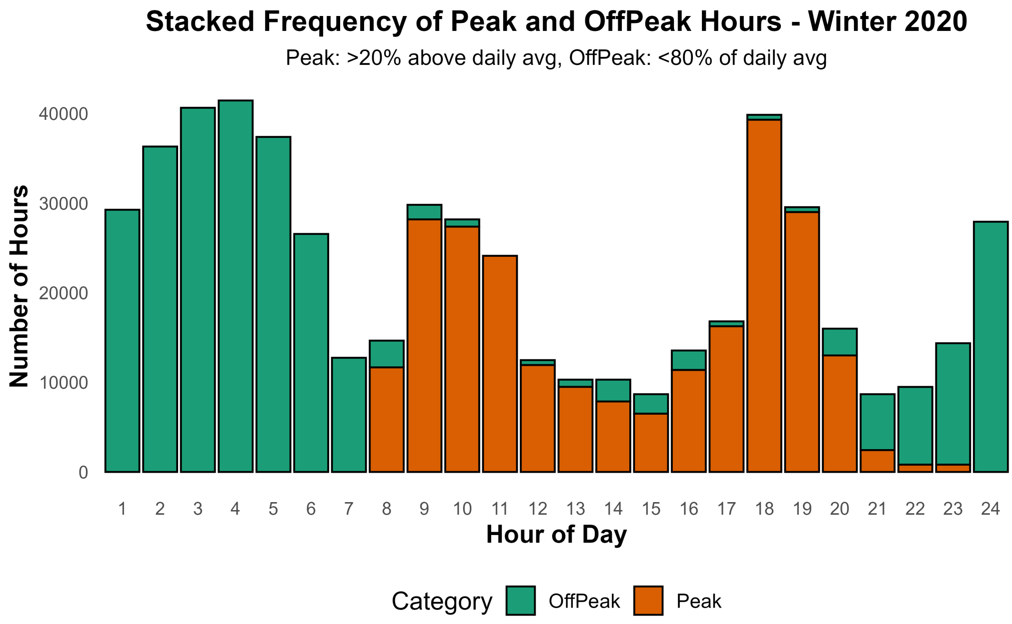


Figure 12: Peak / off-peak distribution throughout the day during the pre-shock winter. Off-peak hours are predominantly night hours. Peak hours are concentrated around the beginning and end of business days. The figure was created for this thesis using the dataset provided by Hofmann et al. (2023).

The peak/Off-Peak patterns displayed in Figures 12 and 13 correspond to the average hourly price pattern presented earlier (Fig. 10). Prices tend to peak both in the morning and later afternoon. Interestingly, the amount of hours classified by either dummy are lower during the price shock winter in 2021.

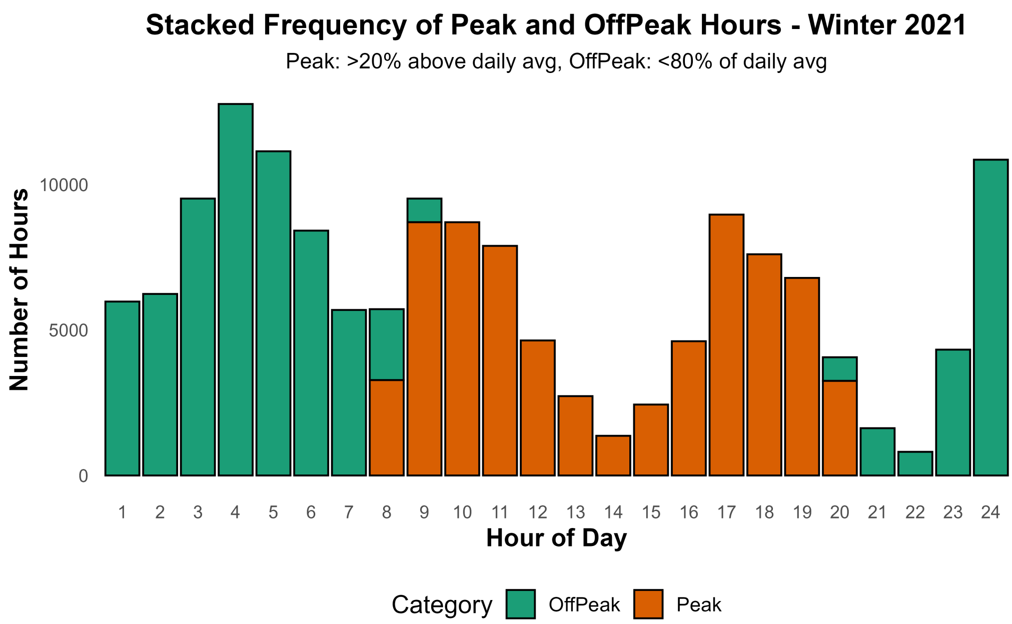


Figure 13: Peak / off-peak distribution throughout the day during the price shock winter. Off-peak hours are predominantly night hours. Peak hours are concentrated around the beginning and end of business days. The figure was created for this thesis using the dataset provided by Hofmann et al. (2023).

4.5 Descriptive Statistics

This section presents descriptive statistics on the final analytical sample defined in Section 4.3. For most descriptions, we either make a distinction between contract types or household characteristics. Electricity consumption characteristics of the included households during winter are explored first.

The hourly consumption range across households is large, which suggests that there exist considerable hourly consumption differences between households. We therefore compute the mean daily electricity consumption for each household. Figure 14 presents these mean consumption levels in a density plot. Average consumption levels can be seen to be positively skewed, meaning the distribution is not normal but clustered around the left tail.

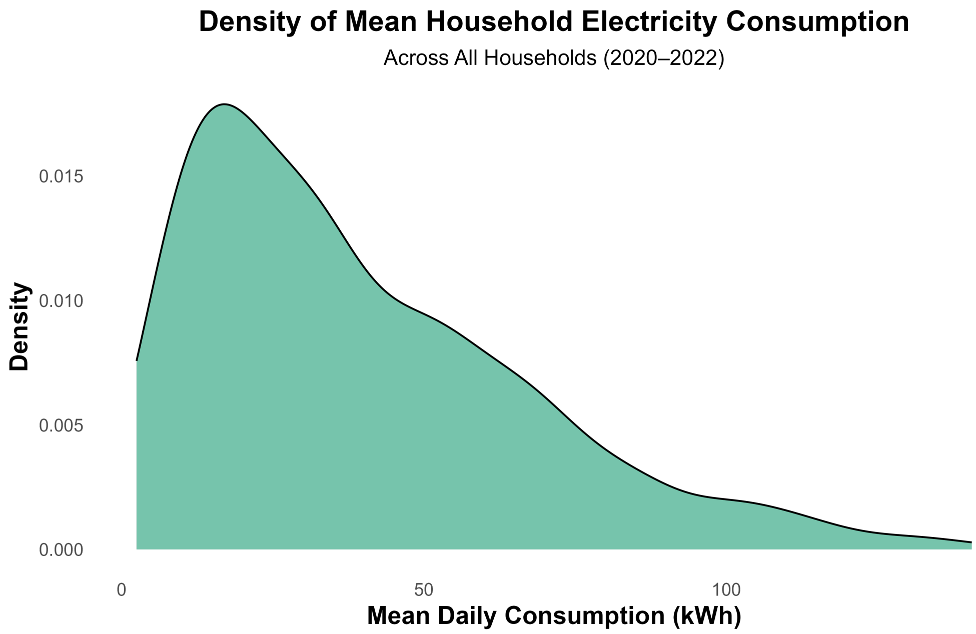


Figure 14: Mean (daily) household electricity consumption. Electricity consumption is positively skewed. This figure is produced for this thesis and is based on data provided by Hofmann et al. (2023). The figure is created with R.

Table 4 displays descriptive statistics by contract type for both the pre-shock winter and during the price shock. Both dynamic and fixed contract households show lower average hourly consumption levels.

Table 4: Descriptive Statistics for Hourly Demand (kWh) by Contract Type

Group	N	mean	sd	median	min	max	range
Dynamic - Winter 2020	1,548,720	2.400	2.061	1.856	0	18.922	18.922
Fixed - Winter 2020	207,360	2.364	2.006	1.903	0	18.396	18.396
Dynamic - Winter 2021	1,548,720	2.007	1.787	1.545	0	18.859	18.859
Fixed - Winter 2021	207,360	2.056	1.768	1.648	0	18.908	18.908

To further examine household heterogeneity, Figure 15 presents the distribution of education levels across dynamic and fixed electricity contracts. Education level is defined as the highest level of education within the household, meaning not all household members necessarily have this level of education. The distribution differences between the contract types are visibly negligible. However, in this dataset, higher university education is more prevalent in households with hourly spot contracts (RTP contracts).

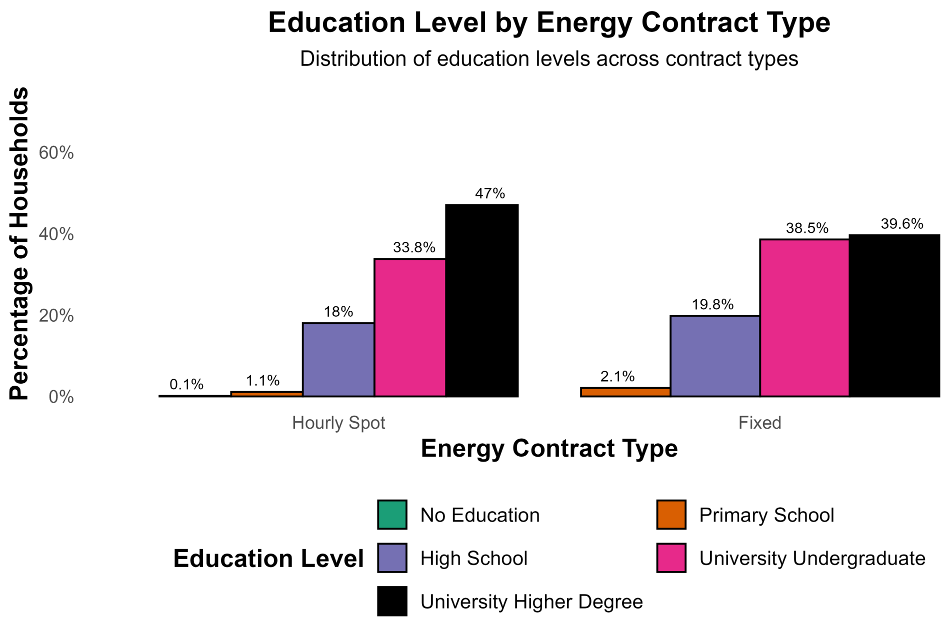


Figure 15: Distribution of education level grouped by electricity contract types. The figure was created for this thesis using the dataset provided by Hofmann et al. (2023). (N = 813)

Figure 16 explores EV ownership across households grouped by their type of electricity contract. Although households generally do not own EVs, household EV ownership is highest for households with hourly spot RTP contracts.

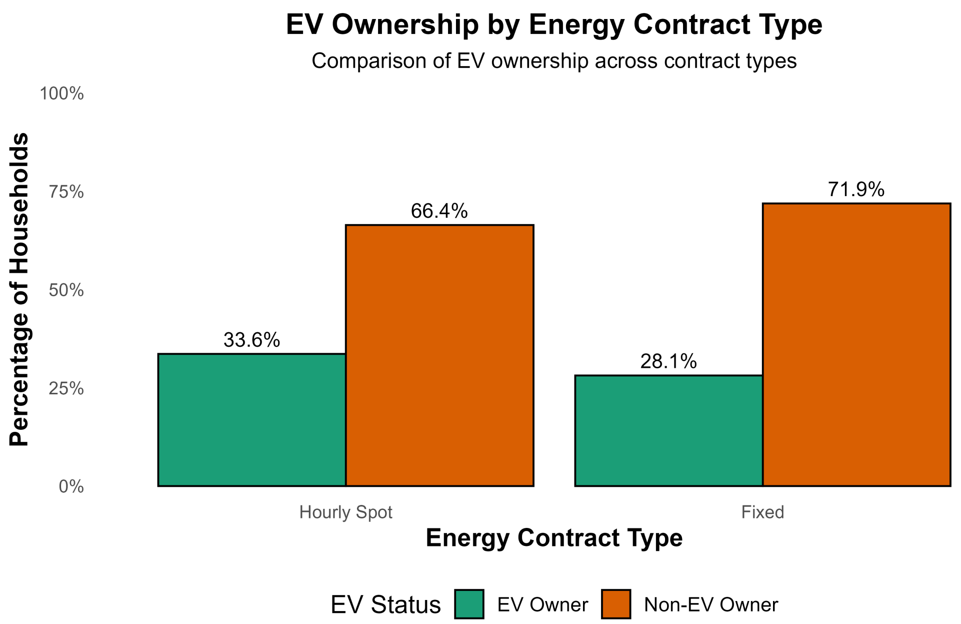


Figure 16: Distribution of EV ownership grouped by types of electricity contract. The figure was created for this thesis using the dataset provided by Hofmann et al. (2023). (N = 813)

Expanding on this, the charging behavior of EV owning households has been mapped in Figure 17. Interestingly, smart charging behavior seems to be quite different when comparing fixed and RTP contracted households. Households with dynamic electricity contracts exhibit more effort in trying to avoid charging in high-priced hours. More than 50% of these households respond manually, but about 15% rely on smart charging technology. We must note that not all EV owning households have provided an answer to this survey question (N = 183).

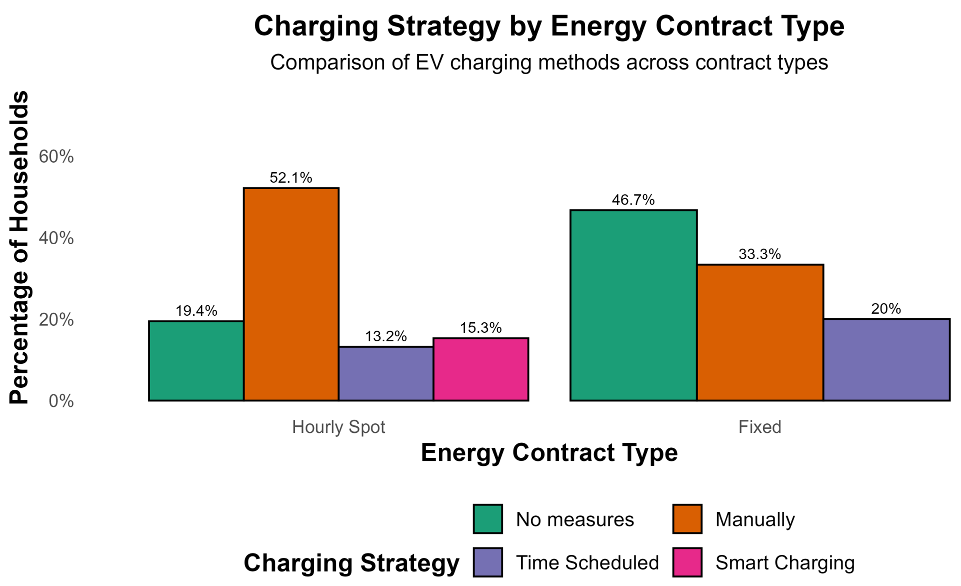


Figure 17: Distribution of EV (smart) charging behavior in response to avoiding high-priced hours. Household answers are grouped by type of electricity contract. The figure was created exclusively for this thesis using the dataset provided by Hofmann et al. (2023). (N = 183)

Our final sample contains households with dynamic and fixed contracts. Average hourly electricity consumption patterns are explored for both contracts during the pre-shock winter. Figure 18 presents these consumption profiles. Without additional restrictions or focus, both curves appear very similar. Table 5 presents the descriptive statistics for all subgroups used in our final sample during the pre-shock winter. Average hourly consumption levels are different across subgroups. Renters consumed considerably less electricity compared to both levels reported in Table 4 and other subgroups. Households that own an EV consume most electricity.

Table 5: Descriptive Statistics for Hourly Demand (kWh) by Subgroup

Group	N	mean	sd	median	min	max	range
Dynamic EV - Winter 2020	311,040	3.893	2.373	3.527	0	18.409	18.409
Dynamic SmartCharge - Winter 2020	47,520	4.252	2.504	3.726	0.200	18.032	17.832
Dynamic HomeOwner - Winter 2020	1,416,960	2.486	2.099	1.948	0	18.922	18.922
Dynamic Renter - Winter 2020	131,760	1.472	1.271	1.195	0.008	10.499	10.491
Dynamic ActiveMonitoring - Winter 2020	397,440	2.634	2.036	2.168	0	17.768	17.768

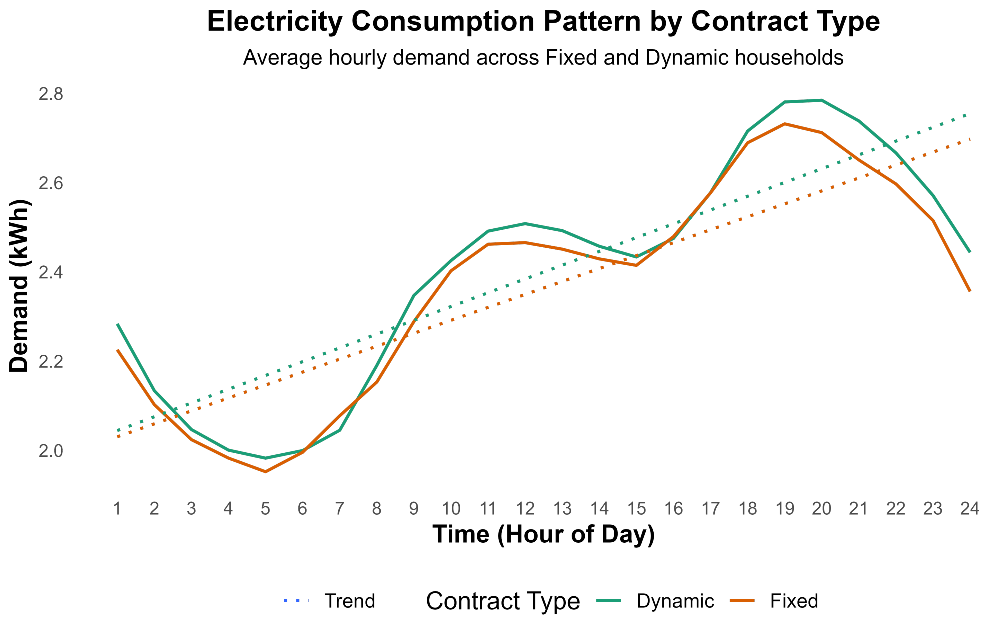


Figure 18: The electricity consumption pattern of households grouped by electricity contract type. The average is taken for the pre-shock winter of 2020. Both weekdays and weekends are included. The differences between patterns are negligible. We created this figure for this thesis. The figure is created with R.

Figure 19 compares average hourly electricity consumption patterns between weekdays and weekends during both winter seasons. Households can be seen to have a different (average) consumption pattern during weekends. Increased home occupancy on weekends could contribute to this. This figure does not distinguish between contract types.

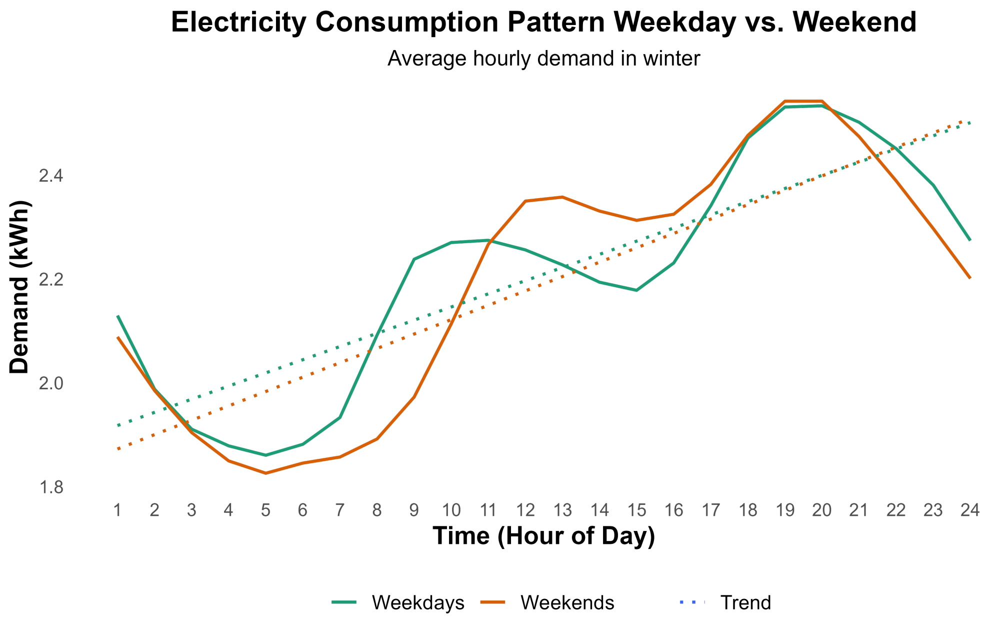


Figure 19: Average electricity consumption per hour in winter season, grouped by weekdays and weekends. Note that households have different average consumption profiles, indicating different routines. We created this figure for this thesis. The figure is created with R.

5 Method

To investigate the effect mentioned in both the main and sub-questions, we take a quantitative approach and construct an econometric model (5.2) based on the theory and empirical evidence presented before. Statistical estimation techniques used for analysis are explained in Section 5.3. Section 5.4 elaborates on the household subgroups that we investigate. Finally, modeling assumptions and limitations are discussed in Section 5.5.

5.1 Model Overview

The objective of this quantitative model is to generate accurate and meaningful insights into the main research question:

How do dynamic electricity prices influence intra-day electricity consumption patterns among residential consumers?

To support answering this question, three sub-questions are defined in support of answering the main question.

1. *What is the effect of intra-day electricity price fluctuations on hourly household electricity consumption?*
2. *To what degree do higher intra-day electricity prices lead to a shift in consumption from peak to off-peak hours?*
3. *To what extent do household characteristics moderate the effect of price changes on electricity consumption and load shifting?*

Several key topics can be identified that should be addressed by this model. The model should first help to establish the baseline effect of electricity price on household electricity consumption. The relation between price and consumption is of central interest. Next, the model should distinguish between peak and off-peak consumption to reveal whether households engage in load-shifting behavior. Finally, the moderating effect of several household-specific characteristics is investigated.

A linear regression model is formulated based on the theory and evidence presented in Chapters 2 and 3, respectively. The dependent variable of interest is household electricity consumption. Electricity price serves as the main independent variable in this study. The exact definition and explanation of the linear regression model is presented in Section 5.2.

5.2 Econometric Model

Our method comprises two linear regression models that complement each other, allowing for a more comprehensive analysis of the effect of electricity prices on consumption. First, a DID model is formulated. This model is used to investigate whether households with dynamic contracts respond differently to price shocks compared to fixed-contracted households. Next, we estimate a complementary regression model that directly includes electricity price as an independent variable. Both models are inspired to some extent by previous studies in Norway (Hofmann & Lindberg, 2023, 2024) and Germany (Ruhnau et al., 2023).

5.2.1 Difference-in-Differences (DiD) Treatment Effect Model

We first built a two-way fixed-effects DID regression model to analyze the available data and generate insightful results. Chapter 4 describes the panel dataset used in combination with this model. We use a DID model to calculate the causal impact of the electricity (price) crisis in the winter of 2021 on electricity consumption. The treatment group consists of consumers with dynamic electricity contracts, whereas the price shock is our treatment period. Consumers with fixed-price contracts are taken as the control group, as the nature of fixed contracts shields them from real-time price shocks during the contract period. This is justified by reviewing the exploratory figure 18, which shows the consumption profiles of both groups during the pre-shock period. Under normal conditions, average consumption patterns between the two groups are similar, supporting the validity of the parallel trends assumption[12].

The DID model is defined by regressing consumption ($C_{i,t}$) on the interaction between the treatment group dummy (D_i^D) and the treatment period dummy (D_t^{PS}). Both Fixed Effects (FEs) (α_i) and Time Fixed Effects (TFEs) (γ_t) are added to control for unobserved heterogeneity. Standard Errors (SEs) are clustered on the household (ID) level to allow for heteroskedasticity and autocorrelation. A second equation adds the comparison between Peak (D_t^{Peak}) and Off-Peak ($D_t^{OffPeak}$) hours. Furthermore, household subgroups are investigated by adding a fourth dummy (D_i^x) to the interaction. The exact subgroups investigated with this model are defined in Section 5.4. The model equations with and without the subgroup dummy are presented below.

$$\mathrm{C}_{i,t} = \beta_0 + \beta_1(\mathrm{D}_i^D \times \mathrm{D}_t^{PS}) + \alpha_i + \gamma_t + \epsilon_{i,t} \tag{3}$$

$$\mathrm{C}_{i,t} = \beta_0 + \beta_1(\mathrm{D}_i^D \times \mathrm{D}_t^{PS} \times \mathrm{D}_t^{Peak} \times \mathrm{D}_i^x) + \beta_2(\mathrm{D}_i^D \times \mathrm{D}_t^{PS} \times \mathrm{D}_t^{OffPeak} \times \mathrm{D}_i^x) + \alpha_i + \gamma_t + \epsilon_{i,t} \tag{4}$$

5.2.2 Complementary Price Responsiveness Model

In addition to the DID model, we define a second model. This complementary model also investigates the difference between the pre-shock winter of 2020 and the crisis winter of 2021. In contrast, this model includes price directly as a key independent variable. We compose the model in equations 5 and 6 by regressing consumption ($C_{i,t}$) on price ($P_{i,t}$). We again add FEs (α_i) and TFEs (γ_t) to control for unobserved heterogeneity. Price is interacted with the contract group dummy (D_i^D) and the price shock period dummy (D_t^{PS}). We again add the comparison between Peak (D_t^{Peak}) and Off-Peak ($D_t^{OffPeak}$) hours to the second equation. Finally, a fifth dummy (D_i^x) is introduced that again specifies household subgroups. By interacting price with this household subgroup dummy, we investigate whether price responsiveness of dynamic contract households is different between these subgroups. Section 5.4 details these household subgroups and other sampling efforts in further detail. SEs are clustered on the household (ID) level to allow for heteroskedasticity and autocorrelation. The statistical method used to estimate equations 5 and 6 is explained in Section 5.3.

$$\mathrm{C}_{i,t} = \beta_0 + \beta_1(\mathrm{P}_{i,t} \times \mathrm{D}_i^D \times \mathrm{D}_t^{PS}) + \alpha_i + \gamma_t + \epsilon_{i,t} \tag{5}$$

$$\mathrm{C}_{i,t} = \beta_0 + \beta_1(\mathrm{P}_{i,t} \times \mathrm{D}_i^D \times \mathrm{D}_t^{PS} \times \mathrm{D}_t^{Peak} \times \mathrm{D}_i^x) + \beta_2(\mathrm{P}_{i,t} \times \mathrm{D}_i^D \times \mathrm{D}_t^{PS} \times \mathrm{D}_t^{OffPeak} \times \mathrm{D}_i^x) + \alpha_i + \gamma_t + \epsilon_{i,t} \tag{6}$$

It is important to understand the nuance between our two models. The DID model calculates the treatment effect of the 2021 price shock on electricity consumption, meaning we compare average hourly consumption across two periods rather than including price as the independent variable. The complementary model, on

[12] The parallel trends assumption states that the control group and treatment group should trend the same in the absence of any treatment

the other hand, directly estimates the effect of price changes on electricity consumption while comparing two periods. The subtle nuance between our models allows us to analyze results under different modeling assumptions. If both models yield similar results, this could strengthen the robustness of our findings, as they were obtained under different conditions. Meanwhile, a difference in results could be just as interesting, as it could reveal additional details about consumer responsiveness to electricity price.

5.2.3 Two-Way Fixed Effects

Our two-way fixed effects, captured through α_i and γ_t, are defined similarly to the classification used by Hofmann and Lindberg, 2024

Our Fixed Effects term needs to control for unobserved household-specific heterogeneity. We essentially want to control for the unique hourly consumption profile of each household. This allows households to have different baseline consumption levels, as well as different consumption routines. This FE term is realized by interacting the household ID with the 24 hours in a day.

In addition to the comprehensive FE term explained above, we should also introduce a sophisticated TFE term. The TFE term should control for time-specific variation that is constant across all households. Energy shocks and weather extremes are examples of important events that TFE are meant to control for. As mentioned in Section 4.2.3, our household data originates from the two Norwegian bidding areas NO1 and NO5, which lie about 300 kilometers apart (Oslo - Bergen). Weather events in NO1 do not have to coincide with those in region NO5. Households, therefore, do not experience the same event at the same time. To control for these TFE, we interact our time index (DateTime) with these two Norwegian regions. By doing so, we control for region-specific effects that are constant for all households within the region but vary across regions over time.

5.3 Estimation Technique and Interpretation

We run all calculations and regressions in RStudio (Posit team, 2025). The econometric model introduced in Section 5.2 is estimated by applying the well-established two-way Fixed Effects OLS technique. The FIXEST package for R is used to facilitate running the regressions (Bergé, 2018). As mentioned before, two-way fixed effects regression implicitly controls for omitted heterogeneous variables. We run regressions using absolute units from the dataset. The unit of price is the Norwegian Krone (NOK). As of May 2025, one Norwegian Krone (NOK) is equivalent to approximately 0.087 Euros. Electricity consumption is measured in kilowatt-hours (kWh). Since the two models estimate a different type of effect, interpretation of the estimates depends on which model was used to calculate it.

The DID model estimates a treatment effect, meaning the estimate represents the response of the treatment group in comparison with the control group. Since electricity consumption is our dependent variable, the model calculates how much more (or less) the dynamic contract group changed consumption during the price shock, compared to the control group. The estimate is calculated in the unit of electricity consumption, which is kWh. If the DID regression from equation 3 or 4 yields $\beta_1 = -0.5$, it would suggest that, on average, households with dynamic contracts reduced hourly electricity consumption during the price shock by 0.5 kWh more than households with fixed contracts.

In contrast, the estimate (β_1) that follows from our complementary model equation 6 should be interpreted as the hourly change in the amount of kWh consumption as a result of an increase in price of 1 NOK. This estimate is specific for the group assigned to the interaction term D_i^x. Suppose D_i^x is a binary indicator equal to 1 for dynamic contract households with an EV, and 0 for those without an EV. If the regression from equation 6 yields $\beta_1 = -0.5$, it would suggest that, in response to a 1 NOK increase in (hourly) price, households with dynamic contracts consume 0.5 kWh less than comparable households without EV.

Using absolute units (e.g., kWh and NOK) can limit direct interpretability and the ability to compare results to other studies. Specifically, one might, for example, ask about the practical relevance of results: *How large is a 0.5 kWh decrease of hourly consumption in relative terms?*. Although we considered the well-established log-log regression, which allows for interpretation on relative percentage scales, it introduces certain drawbacks. Logarithmic transformation cannot handle zeros and negative values. Since both our consumption data and price data contain these types of values, log-log implementation would require additional operations. To maintain a balanced dataset, we would need to remove these days from consideration or adjust these values by adding small constant values, making them nonzero. While these adjustments are not uncommon, they introduce additional assumptions and potential distortions. Moreover, a rough percentage effect can still be calculated by comparing the estimate to the mean hourly consumption of households in the dataset.

5.4 Sample Alignment with Methodology

Section 5.2 explains the model used in the regression analysis. It introduces the dummy variable D_i^x that facilitates the analysis of price responsiveness across several household subgroups. This section elaborates on how the sample construction in Section 4.3 aligns with our methodological approach, and reiterates the subgroups under investigation.

As explained in Section 5.2, the difference between dynamic and fixed contract households is captured by our DID approach. By only including winter data in our sample, we can compare pre-shock consumption patterns to electricity consumption during the price shock. Weekdays and weekends are both included in our sample. We calculate the equations in Section 5.2 separately for weekdays and weekends, allowing for a comparison of price responsiveness on both types of days. Household characteristics of interest, as introduced in Section 4.3, are captured by the subgroup dummy D_i^x. The peak and off-peak hours, as defined in Section 4.4, are captured by their corresponding dummies D_t^{Peak}) and $D_t^{OffPeak}$.

5.5 Assumptions and Limitations

To be fully transparent about potential issues that could arise from adopting the approach introduced in this chapter, we outline several key assumptions underlying the models.

1. **Parallel Trends Assumption**
   A DID model estimates the causal effect of a treatment by comparing the change in outcome between the treatment and control group. This methodological approach assumes that, in the absence of any treatment, the control group and treatment group would trend at the same rate and direction (Wooldridge, 2020). This assumption is called the parallel trends assumption. In our case, it assumes consumption trends between dynamic and fixed-contract households are similar in the absence of the price shock.

2. **Fixed Contracts as Control Group**
   The methodological approach in this thesis assumes that fixed contract households were not exposed

to the price shock during the 2021-2022 winter season. This assumption is supported by the nature of fixed contracts, where the price per kWh is constant over the contract period. We also assume that the fixed contract has not been renewed during, or just before, the price shock.

3. **Price is exogenous**
   Our current model assumes that price is exogenous. In other words, we assume prices are set outside of our model considerations, and are not influenced by variables within our model.

4. **Price-Demand Response is linear**
   The choice for the OLS estimation technique, by definition, assumes linearity in the relationship between price and demand. By using OLS we assume the marginal effect of price increase is constant across the price distribution. It suggests that, for example, there is no difference in response between a price increase in the lower and upper quartiles.

We reflect on these assumptions in Section 7.5.

6 Results

This chapter reports results of both models, highlights trends, and compares estimates across models. Before diving into model results, we explore the electricity price shock that is central to our DID model. We then present the baseline model results (Eq. 3 & Eq. 5), after which effects across subgroups (Eq. 4 & Eq. 6) are discussed. Finally, the main results are summarized.

6.1 The Price Shock: Magnitude and Characteristics

The electricity price crisis of 2021 is of major importance to both our models defined in Section 5.2. Until now, the only indication of price shocks has come from Figure 11 in Section 4.2.4. The figure presents a timeline of average daily price levels in both price areas. Visual inspection shows that the higher price levels coincide with the winter of 2021. Though, the magnitude of price shocks remains unclear. Furthermore, as we are focused on the effect of hourly electricity price changes on consumption, price volatility is also of interest. Quantifying both the magnitude of increase in average price levels and the change in price volatility relative to the reference period provides insight into the conditions that households were exposed to.

First the difference in overall price level is outlined in Figure 20. The figure displays price level distributions in a density plot. Price level distributions of the winter of 2021 are fully shifted to the right. Hourly price levels in 2021 were, on average, 1.047 NOK higher compared to 2020 (p-value = 0.0007346).

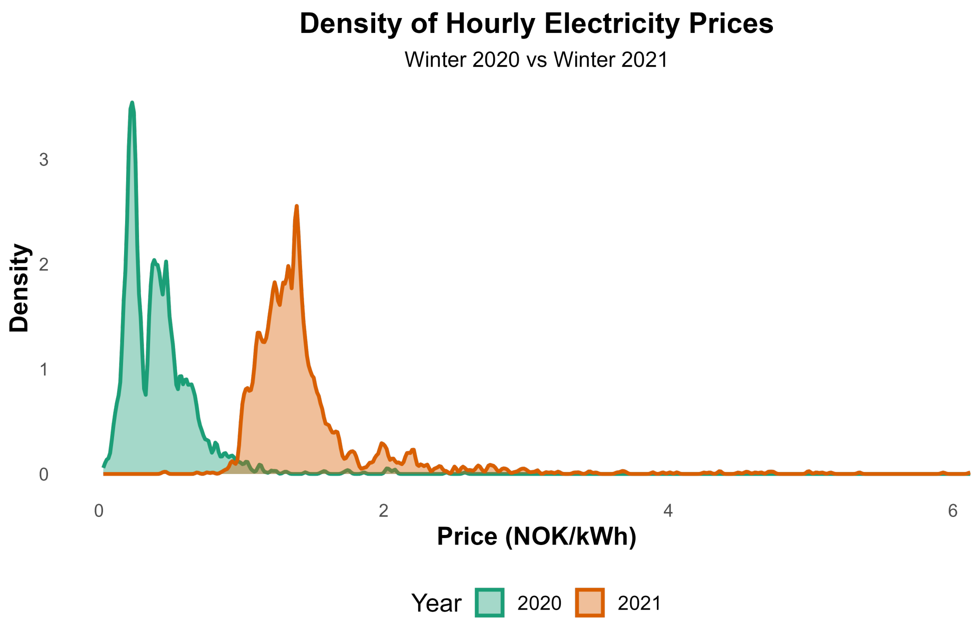


Figure 20: Mean hourly price in the winter of 2020 was 0.415 NOK, whereas the winter of 2021 saw an average of 1.462 NOK. We created this figure for this thesis. The figure is created with R.

The increase in average price levels already provides additional insight into the magnitude of the price shock. However, in this study, we are mostly focused on responsiveness to intra-day price fluctuations. For this reason, intra-day price volatility is also of key importance in understanding the price shock (treatment) that households are exposed to. Figure 21 plots the average standard deviation for all winter days in 2020 and 2021. Standard deviation and volatility are interchangeable terms. The daily average represents the average intra-day price volatility. Intra-day price volatility is observed to be mostly higher during the first half of the

2021 winter. Overall, mean intra-day volatility levels almost doubled during the price shock, increasing from 0.1003 to 0.1855.

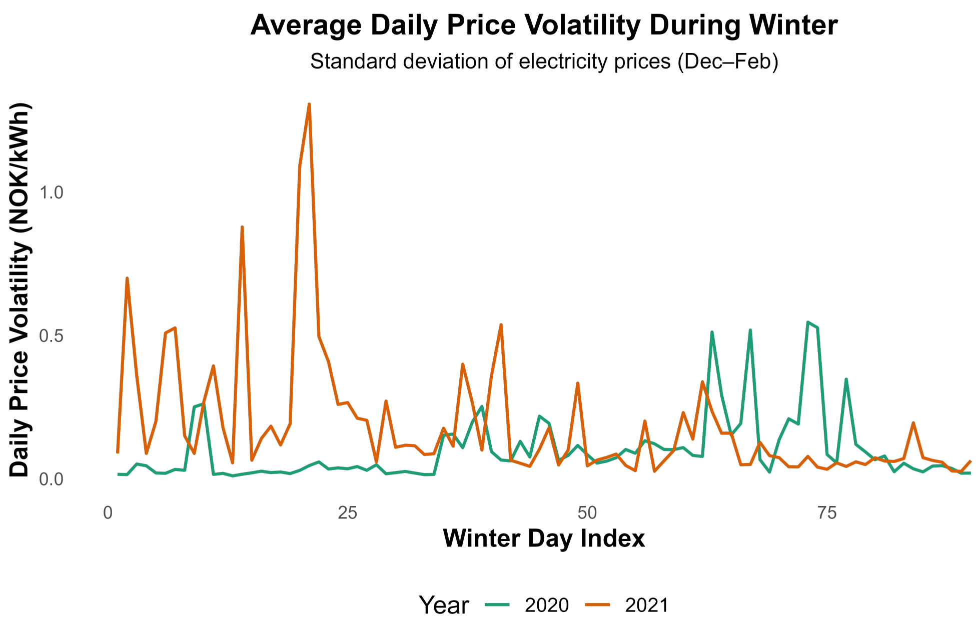


Figure 21: Mean intra-day standard deviation was 0.1003 during the winter of 2020. The price shock winter of 2021 saw mean intra-day volatility levels climb to 0.1855. We created this figure for this thesis. The figure is created with R.

6.2 Average Treatment Effect on Consumption

6.2.1 Baseline DiD Results

This section presents the results of estimating equation 3. By interacting the treatment group dummy with the treatment period dummy, we investigate whether the treatment group (dynamic contract household) responds to the treatment (price shock) differently compared to our control group (fixed contract household). Please note that this baseline model does not distinguish between peak and off-peak hours. Temporal resolutions are specified in the column title. This analysis provides a foundation for interpreting the results from other data subsets examined in subsequent specifications.

First, Figure 22 presents the consumption profile of both dynamic contract households and fixed contract households during the price shock. The figure highlights the lower hourly consumption of dynamic contract households during the treatment period compared to the control group. Looking at the trend line of both groups, dynamic contract households consume less electricity on average. This trend corresponds with descriptive statistics presented in Table 4. Figure 22 only allows for a qualitative comparison of consumption patterns. The regression model in equation 3 enables quantitative analysis of a potential treatment response by dynamic contract households. The key regression estimates from equation 3 are presented in Table 6. The first two columns apply our DID approach, whereas the final two columns reveals the results from our complementary model, as defined in Section 5.2. Temporal resolution (weekday vs. weekend) is specified per column.

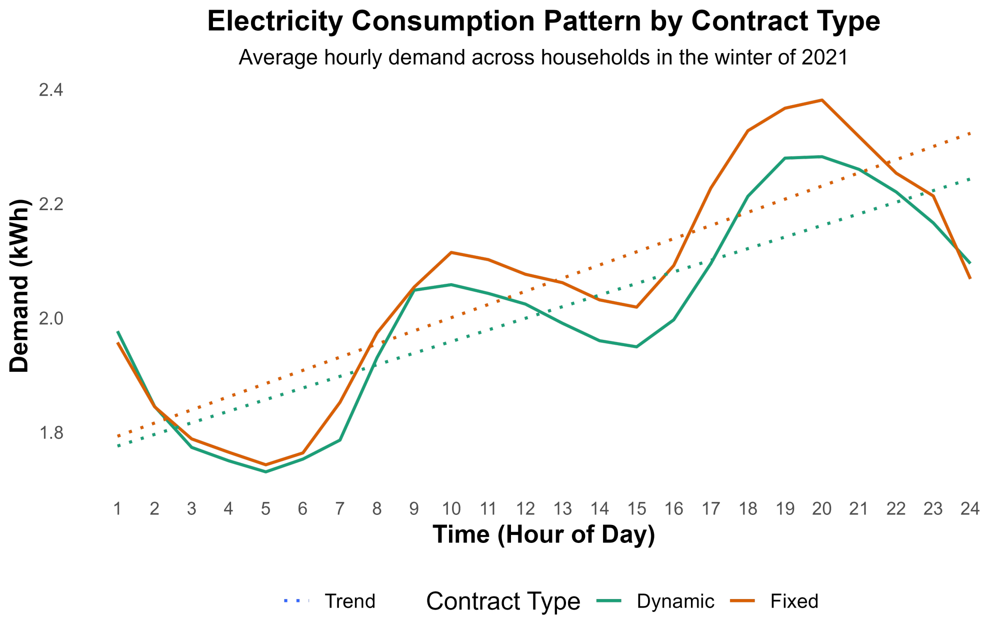


Figure 22: Consumption profiles of both dynamic contract households (treatment group) and fixed contract households (control group). On average, households with dynamic contracts consume less electricity during daytime hours. Night-time profiles seem rather comparable across groups. I created this figure for this thesis.

Table 6: Estimates of the Average Treatment Effect of dynamic contracts during the Electricity Price Shock (kWh)

Dependent Variable:	Demand (kWh)			
Model:	(DID - Weekday)	(DID - Weekend)	(Comp - Weekday)	(Comp - Weekend)
Variables				
$D_i^{DynamicContract} \times D_t^{\text{PriceShock}}$	-0.0830*	-0.0945**	-0.0523**	-0.0694**
	(0.0475)	(0.0459)	(0.0234)	(0.0301)
Fixed-effects				
ID-Hour	Yes	Yes	Yes	Yes
PriceArea-DateTime	Yes	Yes	Yes	Yes
Fit statistics				
Observations	2,497,536	1,014,624	2,497,536	1,014,624
R^2	0.77715	0.76913	0.77716	0.76913
Within R^2	0.00021	0.00027	0.00025	0.00029

Clustered (ID) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

The regression focused on the interaction $D_i^{DynamicContract} \times D_t^{\text{PriceShock}}$ reveals negative coefficients for both models. Both models are consistent with a higher weekend estimate. DID results show that, in response to the price shock, households with dynamic contracts reduced their hourly electricity consumption by 0.0830 kWh more than fixed-contract households on weekdays. During weekends, hourly consumption reduced, on average by 0.0945. The visually observed reduction in electricity consumption among dynamic contract households during price shock (Fig. 22) is consistent with the estimated treatment effect presented in Table 6. Weekday estimates in Table 6 are statistically significantly different from zero at the 10% level, while weekend estimates achieve significance at the 5% level.

To support the findings from the DID model, the complementary model explicitly tests how variations in electricity prices influence consumption across two winter seasons. During the price shock period, dynamic contract households reduced hourly consumption by 0.0523 kWh on weekdays and 0.0694 kWh on weekends in response to a 1 NOK increase in electricity price. These results of the complementary model align with the regression results of DID based on the estimate sign (Table 6). All estimates are statistically significant at the 5% level. The complementary model, which includes price directly, has a slightly higher R^2. The Within R^2 seems to be very small for all four regressions in Table 6.

6.3 Heterogeneous Effects Across Subgroups

6.3.1 Peak vs Off-Peak and Other Subgroups (DID Extension)

In addition to the baseline models, from which the results are presented in the previous section, equations 4 and 6 distinguish between peak and off-peak hour responsiveness within several subgroups. As defined in Section 4.4, Peak hours are hours during which the electricity price is at least 20% higher than the daily average. In contrast, off-peak hours are hours where price is at least 20% below the daily average. This section presents the results of the subgroup analysis. The results for the Home Ownership subgroup[13] are provided separately in Appendix B.

Subgroup regression results for both models are displayed in Table 13. By estimating the average treatment effect across subgroups, we investigate the importance of household characteristics and peak / off-peak hours. As before, both model type and temporal resolution are specified per column.

Dynamic contract households respond differently during peak and off-peak price hours. Hourly electricity consumption of dynamic contract households during peak hours decreased, on average, by 0.0886 kWh on weekdays and 0.1068 kWh during weekends. These estimates are statistically significant at the 1% and 5% level, respectively. Off-peak hour estimates were not statistically different from zero.

Next, peak/off-peak differences in consumption response are examined for dynamic contract households that own an EV. The regression results in Table 13 show a stronger reduction in peak hour consumption for both time resolutions compared to the average dynamic contract household estimate presented in the paragraph above. Dynamic contract households that own an EV decrease hourly consumption in peak hours by an average 0.1502 kWh on weekdays and 0.1610 kWh in weekends. In contrast, dynamic contract households that own an EV are revealed to increase electricity consumption in off-peak hours. However, this estimate is only significantly different from zero on weekdays, where the average hourly increase in off-peak consumption is 0.1440 kWh. These results highlight the difference in sign between peak and off-peak hours.

Dynamic contract households with EVs can have a so called *smart* charging strategy. As explained in Section 4.2.3, households can avoid high-priced hours by smart technology automatically responding to hourly spot prices. Consumption response for this subgroup is reported in Table 13. Regression results are similar to the EV subgroup, but larger in magnitude. Peak consumption for this subgroup is reduced by an hourly average of 0.1899 on weekdays an 0.2910 in weekends. The sign flips for off-peak consumption response, where hourly consumption is increased by an average of 0.3249 kWh and 0.3944 kWh for weekdays and weekends respectively.

[13] Introduced and defined in Sections 4.3 and 4.4 respectively.

Finally, dynamic contract households that actively monitor hourly spot prices are shown to decrease hourly consumption in peak hours by an average of 0.1628 kWh on weekdays, and 0.1582 kWh during weekends. Similar to the baseline peak/off-peak response, no statistically significant off-peak consumption response is revealed for this group.

6.3.2 Subgroup Price Responsiveness (Complementary Model)

The complementary model directly includes the effect of price fluctuations on consumption. These results are broadly consistent in sign and significance with the effects found in the DID model (Table 13). Effect magnitudes however, tend to be smaller.

Dynamic contract households exhibit a more pronounced peak-hour response to price fluctuations during the electricity crisis compared to fixed contract households. The price response is larger during weekends, which aligns with DID model results from Table 13. No statistically significant response is observed for off-peak hours.

Subgroup patterns found in Table 13 are also mostly consistent with DID model results. EV-owning households display stronger reductions in peak consumption and an increase in off-peak consumption. The observed off-peak effect is only significant on weekdays. Even though the effect size is smaller than the DID model, the complementary model reveals a comparable flip in sign between peak and off-peak consumption for EV-owning households. In line with the DID model, smart charging technology displays even greater responsiveness to price change. Weekday results again feature a change in the estimate sign when moving from peak to off-peak response. Lastly, households actively monitoring prices remain more price-responsive than the average household. Off-peak responsiveness, however, remains statistically insignificant for this group.

Table 7: Heterogeneous Treatment Effects Across Household Subgroups (DID Model)

Dependent Variable:	Demand (kWh)			
Model:	(DID - Weekday)	(DID - Weekend)	(Comp - Weekday)	(Comp - Weekend)
Variables				
Peak Hour	-0.0886***	-0.1068**	-0.0279***	-0.0489**
	(0.0300)	(0.0477)	(0.0091)	(0.0233)
OffPeak Hour	-0.0231	0.0214	-0.0231	0.0121
	(0.0306)	(0.0335)	(0.0193)	(0.0295)
Appliance Subgroups				
EV - Peak	-0.1502***	-0.1610**	-0.0497***	-0.0781**
	(0.0466)	(0.0672)	(0.0136)	(0.0330)
EV - OffPeak	0.1440***	0.0936	0.0683**	0.0850
	(0.0543)	(0.0605)	(0.0326)	(0.0523)
SmartCharge - Peak	-0.1899*	-0.2910*	-0.0651**	-0.1465*
	(0.1052)	(0.1633)	(0.0296)	(0.0807)
SmartCharge - OffPeak	0.3249**	0.3944*	0.1487*	0.2349
	(0.1335)	(0.2087)	(0.0779)	(0.1647)
Awareness Subgroup				
ActiveMonitoring - Peak	-0.1628***	-0.1582***	-0.0486***	-0.0770***
	(0.0330)	(0.0387)	(0.0098)	(0.0190)
ActiveMonitoring - OffPeak	-0.0014	0.0388	-0.0054	0.0347
	(0.0366)	(0.0391)	(0.0222)	(0.0326)
Fixed-effects				
ID-Hour	Yes	Yes	Yes	Yes
PriceArea-DateTime	Yes	Yes	Yes	Yes
Fit statistics				
Observations	2,497,536	1,014,624	2,497,536	1,014,624

Clustered (ID) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

6.4 Summary of Key Results of Findings

We investigated the price effect on consumption using two models (Eq. 3-6). The DID model estimates, under the parallel trends assumption, represent the causal effect of the price shock on electricity consumption. In contrast, our complementary model captures the marginal effect of price during the price shock period (winter 2021).

Regression results are divided into two parts: the average treatment effect of the price shock on consumption, and the heterogeneity in consumption responsiveness. First, our DID model revealed that dynamic contract households decreased average hourly consumption in response to the price shock. The magnitude of reduction is observed to be slightly higher during weekends. Households mainly reduced consumption during peak price hours, while off-peak consumption is not decreased on average. Households that actively monitor hourly spot prices showed more substantial consumption reductions compared to the average household. Regression estimates for dynamic contract households that own an EV are approximately twice as negative during peak hours compared to the average response, suggesting a stronger reduction in consumption for this subgroup. Furthermore, the EV ownership subgroup shows signs of load shifting during weekdays, as this subgroup increased consumption during off-peak hours. Finally, households that charge their EV with smart technology saw both the highest peak hour consumption decrease and off-peak hour consumption increase. Please note that all regression estimates are stated in absolute units, restricting direct comparability of estimates. The complementary model results are largely consistent with the DID model.

7 Discussion

This chapter presents a comprehensive discussion about the regression results introduced in Chapter 6. This discussion follows the structure of the three sub-questions that guide this research. We first discuss the average hourly consumption response in Section 7.2, drawing on results introduced in Section 6.2. Section 7.3 explores how households respond to price fluctuations. The moderating effect of household characteristics is discussed in Section 7.4. The analyses in Sections 7.3 and 7.4 are based on the results from Section 6.3. Next, we discuss the validity of our results, robustness, and sensitivity. Before recommending future research steps, we delineate the policy implications of this study.

7.1 Interpreting Results Across Both Models

To fully understand household electricity consumption responses to dynamic pricing, this study employed two complementary regression approaches: a Difference-in-Differences (DiD) model and a price interaction model. This section interprets and contrasts the results of both models, highlighting where they align and where they diverge. Finally, we explain what these differences reveal about household behavior under dynamic pricing conditions.

Both models align with the direction of the estimated effect. However, as highlighted before, the DID model consistently yields larger effect sizes. In other words, it suggests a greater reduction in electricity consumption in response to the treatment than the complementary model does. The nature of both models is likely to explain this difference. In contrast to the DID model, the complementary model interacts hourly electricity prices with both the contract type and the treatment period. The inclusion of price changes the model setup from estimating the treatment effect of the price shock (the DID model) to calculating the difference in price sensitivity during the price shock. The consistent difference in estimated effect size indicates that price variation captured by the complementary model is not the only variable of interest during the price shock.

We can make sense of this observation by incorporating the results in Section 6.1. Analysis of the price shock revealed that it was characterized not only by higher average price levels but also by increased intra-day price volatility. As the DID model compares two periods in time, it does not distinguish between these price effects, and treats consumers with both. The price variable in the complementary model specifically captures hourly price variation during the price shock. As a result, this model is primarily sensitive to intra-day price volatility and does not account for elevated average price levels. The consistently higher estimates produced by the DID model may therefore suggest that households respond not only to increased price volatility but also to the higher average price levels observed during the shock period. Furthermore, the DID model could also capture non-price effects that contribute to a higher consumption response to higher average price levels. Awareness campaigns, for example, could make dynamic contract households more sensitive to higher average prices, potentially contributing to the larger observed decrease in consumption.

7.2 Hourly Consumption Response to Dynamic Pricing

This section interprets the results presented in Chapter 6 while addressing our first research question:

What is the effect of intra-day electricity price fluctuations on hourly household electricity consumption?

7.2.1 Key Findings Related To RQ1

Regression results presented in Section 6.2 indicate that, in response to the price shock, the dynamic contract household reduced their average hourly electricity consumption by 3.45% more on weekdays and 3.97% more on weekends compared to fixed contract households. As opposed to our DID model, the complementary model isolates intra-day price fluctuations more directly. Complementary model regression results indicate that dynamic contract households reduced their average hourly electricity consumption by 2.17% on weekdays and 2.9% during weekends compared to households with fixed contracts. These results corroborate our DID findings, demonstrating that households reduce electricity consumption in response to intra-day changes in hourly prices. As explained in Section 7.1, the difference between both models highlights that households do not only respond to intra-day price fluctuations, but also to (awareness of) higher overall price levels. Contrary to Hofmann and Lindberg, 2023, who did not find evidence for intra-day price responsiveness, our complementary model results do highlight the existence of this type of short-term responsiveness.

Crucially, while statistically significant, the estimates represent an average effect over a group of households with diverse mean consumption. As a result, the absolute kWh reductions are likely to vary substantially, being more pronounced for high-consuming households and relatively small for low-consuming ones. Although the approximation in percentage terms improves interpretability, the average percentage change might still not be representative of every household during every hour as a result of the positive skew in average hourly consumption data.

That said, the observed differential reductions[14] in consumption among dynamic contract households point to increased responsiveness to the 2021 price shock, which was characterized by both higher electricity prices and intra-day price volatility. This negative relationship aligns with the standard microeconomic theory in which consumers are expected to be sensitive to price fluctuations in their effort to optimize utility (Sec: 2.4). Moreover, our findings support the conclusion drawn by Buckley, 2020, who report a 3.91% reduction in consumption and argue that incentivizing demand reduction during high price periods is effective. In contrast, our findings contradict the absent differential effect between RTP and non-RTP contracts found in Spain by Fabra et al., 2021. This contradiction may be explained by the significant price variation in our dataset, which was not present in the Spanish study.

The magnitude of the observed reduction suggests households are slightly more responsive during weekends compared to weekdays. This finding highlights the variation between weekend and weekday consumption flexibility, and could be related to a difference in routine (Fig. 19). However, given that average price levels were approximately 250% higher and intra-day price volatility about 85% higher during the price shock, the observed effect size is relatively modest.

To summarize, the results indicate that dynamic contract households respond to increased intra-day electricity price fluctuations by decreasing electricity consumption. Their response is statistically significantly different from fixed contract households, while the effect size appears to be modest.

[14] *Differential reduction*: Reduction in our treatment group relative to our control group.

7.2.2 Modest Effect Size

Although the estimated hourly reductions appear modest compared to the price shock, they reflect the unweighted average effect across all 24 hours a day. This means that hours with high consumption response are potentially diluted by unresponsive hours. Consequently, the average hourly estimate levels out heterogeneity of household consumption patterns throughout the day, which provides a conservative (or realistic) bottom-line estimate rather than an overestimate. In contrast, estimates that focus specifically on peak reduction periods or daily, weekly, or monthly totals capture concentrated consumption reductions without this dilution, making them appear larger even if the total amount of saved electricity is comparable.

Our estimates, particularly the complementary model, capture very short-term consumption changes, which could help explain the lower-than-expected magnitudes. Since electricity prices for dynamic contract households are set only one day in advance, any hourly consumption response to price changes must occur with only one day's notice, which is a very short-term response. Strict model specifications may contribute to low effect sizes. The inclusion of our two-way fixed effects (defined in Section 5.2.3) absorbs a large amount of variation. Our Fixed Effects (IDxHour) effectively restricts consumption variation to differences within a household for the same hour of day during different days. In addition, our Time Fixed Effects (DateTimexPriceArea) only leaves the relative difference between dynamic and fixed contract households within the same hour and price area unabsorbed. While this approach may yield more conservative estimates, its strength lies in the stricter definitions that improve causal interpretability, thereby providing more robust insights into the direct impact of price changes.

7.2.3 Comparison to the original study

Surprisingly, the Norwegian study using the same consumption dataset found a higher average consumption reduction of 11.4% (Hofmann & Lindberg, 2023). This divergence could be attributed to both methodological differences and the defined focus period of the price shock. Although not explicitly mentioned, Hofmann & Lindberg (2023) seem to have treated the dynamic contract group and fixed contract group as the same in their analysis. Their reported 11.4% reduction thereby reflects an overall drop in consumption, whereas our estimate represents the decrease in consumption relative to households with fixed electricity contracts. If households with fixed contracts also reduced consumption during the price shock, this could help explain the smaller effect size observed in our study. Furthermore, unlike our more rigorous two-way fixed effects approach, Hofmann & Lindberg (2023) mostly focused on time fixed effects, which could potentially lead to overestimation of effects attributed to the price shock. Finally, Hofmann & Lindberg (2023) used a broader time frame than our study. While we focused exclusively on the official winter months, their analysis spans from November to March. Data exploration (Fig. 11) revealed these additional months featured price peaks, which could induce greater consumption reductions and thus contribute to their larger estimate. However, it is unlikely that the inclusion of just two additional months fully accounts for the magnitude of the difference.

7.3 Understanding the Price Response Mechanism

This section interprets the results presented in Chapter 6 while addressing our second research question:

To what degree do higher intra-day electricity prices lead to a shift in consumption from peak to off-peak hours?

7.3.1 Key Findings Related To RQ2

Our second research question focuses on the mechanism by which households respond to fluctuating intra-day electricity prices. Section 7.2 discussed that dynamic contract households decrease average hourly electricity consumption in response to higher price levels and more intra-day volatility. While these results did not specify the type of response behavior, the increase in consumption reduction in response to higher prices suggests, in itself, a potential load-shifting capability of households. In other words, if households respond to higher hourly prices by reducing consumption, they are also likely to increase consumption in hours where the price is low. Regression results from Section 6.3 shed additional light on the mechanism by which households respond.

DID results indicate an absolute 0.0886 kWh (≈3.3%) reduction during weekday peak hours, while a 0.1068 kWh (≈4.0%) reduction is attributed to weekend peak hours. These absolute reductions are slightly larger in magnitude than the average hourly reductions presented in Section 6.2, supporting the idea that the differential reduction of dynamic contract electricity consumption is more prominent during hours where price is peaking. While inconclusive, our findings show close similarity with the average peak hour consumption reduction of 2.92% found by Hofmann and Lindberg, 2024.

Interestingly, the complementary model does not yield higher estimates when peak and off-peak hours are included as separate regressors, producing estimates of -0.0279 kWh for weekdays and -0.0489 kWh for weekends. While households are still price sensitive during peak hours[15], price sensitivity is lower in magnitude than the average hourly response presented in Section 7.2. Although this sounds contradictory to the DID results from the preceding paragraph, which indicate household kWh reductions are larger on average during peak hours, the observed difference can be explained by the way peak hours are defined and by the specific structure of the complementary model. Whereas our DID model captures overall consumption reductions during peak hours, the complementary model estimates marginal price responsiveness to within-peak-hour price variation. The lower estimate, therefore, reveals that households are less price sensitive to within (already expensive) peak hours, meaning that a 1 NOK increase in price leads to a smaller decrease in consumption. Households may, however, anticipate high peak-hour prices and shift their consumption beforehand. Such anticipatory behavior is not captured by the complementary model, and would both explain the low regression estimates, as the difference with the results of the DID model.

In contrast to our expectations, off-peak hours, where prices were at least 20% lower than average for that day, did not yield statistically significant results in either model, leaving the null hypothesis unrejected. Nonetheless, the statistically insignificant results still yield meaningful insights. The difference between peak and off-peak consumption response suggests households did not engage in pure load-shedding behavior, as this would mean off-peak hours would also see consumption reductions in response to the price shock. The observed response is insignificantly different from zero, which indicates that the data do not provide strong enough evidence to distinguish an effect from zero, suggesting that the effect could be zero, positive, or negative. While inconclusive, a potential zero effect does not necessarily rule out load shifting behavior. Many

[15] E.g., a 1 NOK increase in price decreases consumption during weekday peak hours by an average 0.0279 kWh

off-peak hours are nighttime hours, making it more difficult for the average household to shift its consumption. Hours with a likely consumption response may be diluted by unresponsive hours, lowering the overall estimate and potentially explaining an insignificant result. In addition, our complementary model is likely to have a close-to-zero effect during off-peak hours, as price sensitivity within off-peak hours is expected to be low. Consumers tend to increase consumption during off-peak hours due to the relatively lower prices compared to peak hours. This substantial price difference reduces the incentive for further price responsiveness within off-peak periods.

7.4 Moderating Role of Household Characteristics

This section interprets the results presented in Chapter 6 while addressing our third research question:

To what extent do household characteristics moderate the effect of price changes on electricity consumption and load shifting?

Regression results presented in Section 6.3 split Peak and Off-Peak effects for three different household characteristics branches, five characteristics in total. Absolute DID results indicate that EV households displayed a higher average hourly reduction in consumption in peak hours compared to the average household. Furthermore, EV households do exhibit considerable signs of load-shifting behavior, as they subsequently increase off-peak consumption by a statistically significant amount. Complementary model results confirm a similar relationship. Peak hour price sensitivity is higher in absolute magnitude for EV households relative to the average households. These findings provide strong support to prior literature indicating the same positive influence EV ownership can have on price responsiveness and load shifting behavior (Hofmann & Lindberg, 2023; Møller Andersen et al., 2024; Wang et al., 2018). Surprisingly, for both models, the estimate is not significant for weekends, highlighting EV household data that could feature more variation within the sample and more heterogeneity in this period. EV household consumption responses may be more heterogeneous on weekends, as the absence of work-related time limitations allows for greater flexibility in when and how they respond to price signals. Both the higher absolute reduction (DID) and higher sensitivity (Complementary) during peak hours, compared to average households, indicate households that own an EV have a more pronounced consumption response. However, since EV households also have a higher baseline consumption, their relative response in percentage terms is similar to average households (approximately 3.4% on weekdays, and about 3.7% during weekends).

Interestingly, households that own an EV and choose to smart charge their vehicle, demonstrate an even higher absolute consumption response for both weekdays and weekends. Smart charging households again display considerable load-shifting behavior. The complementary model results also indicate a greater reduction in consumption during peak hours in response to a 1 NOK increase in price. This finding adds to existing literature that suggests enabling technology has the potential to improve household responsiveness to price changes (Allcott, 2011a; Bedir et al., 2013; Bobbio, 2021; Fabra et al., 2021; Faruqui & Sergici, 2013; Özkan, 2016; Parrish et al., 2019). That said, as baseline consumption for EV households and smart charging households is not fully comparable, these results are not entirely conclusive on increasing price flexibility. They do, however, indicate that higher-consuming households also exhibit higher electricity consumption reductions, suggesting they could play a more pronounced role in resolving the issue of peak loads on power grids. In addition, regression estimates indicate that the average peak hour consumption reduction is smaller than the average off-peak hour consumption increase, suggesting there is evidence of a potential rebound effect for this household subgroup. Notably, this rebound effect is only observed among smart charging households, highlighting the role of EV charging flexibility in shaping load-shifting behavior. As shown in Figure 23, daily consumption patterns reveal smart charging household consumption peaks during the night, while these typically represent low-demand hours for other households. This pattern, combined with the regression estimates, suggests that smart charging households are significantly more effective at shifting EV charging to off-peak hours.

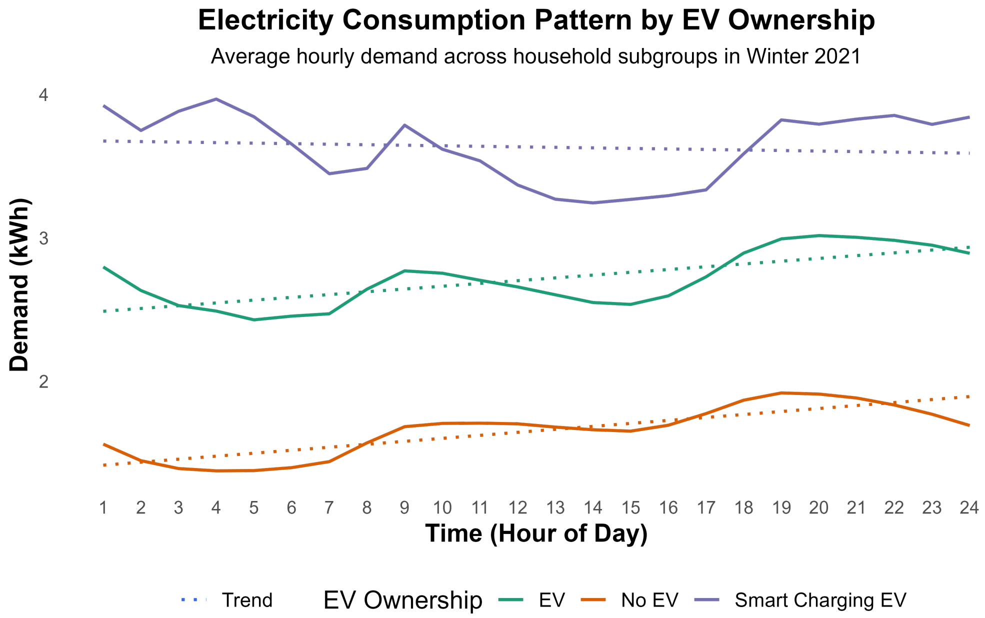


Figure 23: Daily average electricity consumption patterns for three different EV subgroups during weekdays. The average electricity consumption is calculated on an hourly basis per subgroup. A linear trend line is added. The plot shows differences in the average consumption level per household subgroup during the winter of 2021. Households without EV consume the least electricity on an hourly basis, whereas households that smart charge their EV consume the most. The consumption pattern of smart charging households features a third consumption peak during the night. We created this figure for this thesis. The figure is created with R.

The active daily monitoring of electricity prices does seem to moderate the effect of price changes on electricity consumption. Both the absolute reduction in peak hour consumption and the sensitivity to price during peak hours are greater than those observed for the average household. This finding demonstrates the importance of awareness in household responsiveness to price changes. It is important, however, to recognize that awareness may itself be influenced by other underlying characteristics, making it a proxy for the true driver of the effect. For example, if households are only checking electricity prices because they own an EV, then the observed effect should be attributed to EV ownership instead of awareness.

7.5 Internal Validity

In this section, we critically examine the internal validity of this study. We assess the internal validity of key assumptions that underpin our analytical approach and the use of Norwegian data. We discuss the extent to which the results presented in this thesis serve as empirical evidence for a causal relationship between dynamic electricity pricing and consumption flexibility. First, the key assumptions of our approach[16] are reiterated.

[16]First introduced in Section 5.5

7.5.1 Parallel Trends Assumption

Our models rely on the Parallel Trends Assumption that states the treatment and control groups should have similar pre-treatment trends. Although it is reasonable to assume that households with fixed-price contracts do not respond to a price shock, variation in prices during the pre-treatment period could still induce some price-responsive behavior in dynamic contract households. This would imply that even under normal conditions, there may be minor differences in consumption patterns between households with fixed and dynamic contracts. These potential (mild) violations of the parallel trends assumption challenge the internal validity of our models. However, even if the parallel trends assumption is not perfectly satisfied, our approach is still highly informative. The goal of this study is to assess the influence of dynamic pricing on hourly consumption. As we compare price responsiveness to the electricity price shock with and without exposure to real-time prices, the current method remains appropriate.

7.5.2 Fixed-Contract Households as Control Group

When taking fixed-contract households as a control group, we assume these households are not exposed to the price shock. If, however, a fixed contract was renewed during the price shock, the household is exposed to the elevated average price levels associated with the price shock. This exposure could then also induce a consumption response among fixed contract households, which would violate the models assumption of no reaction in the control group. It is, however, important to consider the implications of such a violation. A price (shock) induced consumption response among fixed contract households would reduce the difference in consumption response with our treatment group. As a result, the estimated treatment effect would be biased toward zero. In other words, both models are more likely to underestimate the effect than to overstate the difference between groups. The severity of such a violation would, therefore, depend on whether or not we find a statistically significant effect. If no treatment effect is found, a potential violation of this assumption could cast doubt on the validity of our results. In contrast, for any nonzero result, we know that a potential violation would bias the estimate towards zero, meaning that our results represent a conservative estimate of the true effect. This does not hurt our efforts to present evidence for a causal relationship.

7.5.3 Price Exogeneity

The exogeneity of price is an important assumption in our model. As mentioned in Section 3.1, some other studies specifically use 2SLS instead of OLS to account for possible endogeneity problems with the price variable (Fabra et al., 2021; Hirth et al., 2024). These studies argue that price of electricity is the result of the supply-demand clearing mechanism, and that a demand response will consequently result in a change in price. Although we acknowledge this price mechanism in Section 2.2, we assume that our strategy is justified because of the day-ahead price setting feature in RTP contracts. Consumer prices are ’set’ one day in advance, interrupting the (short-term) feedback loop to price. Therefore, the household response to these prices will not affect the previously communicated day-ahead prices, making price exogenous in the short term. Naturally, when considering the hypothesized price-demand response, price could still be endogenous in longer time frames. We assume, however, that electricity procurement is based on longer time frames than our dataset, discounting potential price endogeneity.

7.5.4 Linear Relation Between Price and Consumption

Our adoption of the OLS estimation technique assumes the relation between price and consumption is linear. While OLS is a common technique, there exists empirical evidence suggesting the effect of price on demand might not be linear. For example, a recent Norwegian experiment suggested households increase their consumption response when prices are higher than 15 NOK/kWh (Hofmann & Lindberg, 2024). That said, even if the underlying relationship is not fully linear, OLS can still be highly informative in detecting whether a relationship exists. However, incorrectly assuming linearity can misestimate the true effect. The models average the effect, which, in the case of a nonlinear relation, could understate the response during price spikes and overstate it in others. The models are also not equipped for recognizing response saturation or potential price thresholds.

7.5.5 Peak / Off-Peak Definition

In addition to the assumptions above, the implications of our peak/off-peak hour definition also deserve attention. We included these types of hours to investigate the mechanism by which households respond to price changes (i.e., if households shift consumption from peak to off-peak hours). Our current definition is price-driven, meaning we define peak and off-peak hours by looking at relative daily price differences. As illustrated in Figures 12 and 13, this definition predominantly identifies peak hours during the daytime hours between 8 AM and 8 PM. Off-peak hours mostly coincide with nighttime hours (11 PM - 7 AM). While this definition is well-suited for understanding price responsiveness, it also comes with certain caveats. Our relative approach results in fewer hours identified during the treatment period compared to the pre-treatment period. Moreover, not every day has to feature a peak or off-peak hour with our current approach. This approach could hurt internal validity if the peak/off-peak classification correlates with unobserved factors that also affect consumption. We expect the severity of this threat to be minimal, as our two-way fixed effects are very comprehensive and should control for most confounding factors. Furthermore, the alternative where we define peak/off-peak hours by fixed daily periods also has limitations. It could, for instance, classify certain hours as 'peak' even though prices are not actually elevated during those times, potentially leading to misinterpretation. In Section 7.7.4, we assess the robustness of our results by re-estimating the model using several alternative definitions for peak and off-peak hours.

Last but not least, some model estimates are only moderately significant at the 10% level, just above the conventional 5% level. These moderately significant estimates indicate weaker statistical evidence against the null hypothesis. Although this is not ideal, we argue that the findings remain informative because the estimates with marginal significance typically stem from small subsamples, limiting the statistical power. These estimates should be interpreted as suggestive or tentative.

7.6 External Validity

The generalizability of our findings to any broader population mostly depends on the representativeness of the sample. This section assesses the external validity of this thesis by examining how well the sample reflects the characteristics of the target population and the extent to which the results may apply beyond the Norwegian context.

7.6.1 Sample Representativeness

The representativeness of our households consumption data can be investigated by comparing electricity consumption from our sample to the aggregated electricity consumption data presented in Section 4.2.2. Aggregate consumption data presented in Table 1 appears to be normally distributed, as indicated by the small difference between the mean and median hourly consumption. In contrast, our sample features lower medians for both price areas, while the mean consumption for region NO5 is larger. This observation demonstrates that our consumption data is positively skewed, where high-consuming households are potentially overrepresented. Over-representation could harm generalizability if we do not acknowledge the existing household heterogeneity in our effect estimates. Although a potential overrepresented group directly impacts the effect size, the effect direction is less likely to be affected, unless high-consuming households respond fundamentally differently from low-consuming households. Moreover, this issue is less likely to distort results within household subgroups that already exhibit higher baseline consumption. For instance, households that own an EV tend to consume more electricity on average than non-EV households. As a result, the potential over-representation of high-consuming households has a smaller impact on estimates within this subgroup, since the sample more accurately reflects the underlying distribution of consumption in the relevant (sub)population.

7.6.2 Sampling Bias

Two notable sources of bias may undermine the external validity of this study. Unfortunately, while we acknowledge their potential presence, our usage of pre-existing data limits our ability to assess the extent to which these biases are present in our sample. First, selection bias in contract types could weaken external validity. The current context allows households to choose their type of electricity contract. If households opt into dynamic contracts, it could mean they are also more energy-conscious or price-aware. This raises the question about the generalization of our findings to all households. Suppose dynamic pricing were adopted more broadly or made the default. In that case, households that would not have chosen it voluntarily may be less responsive to price signals, either due to lower flexibility or lower awareness. That said, while our results provide evidence of behavioral responses under voluntary exposure to dynamic pricing, they may overestimate household sensitivity to price variation if fixed contracts were to disappear from the electricity market.

Second, self-selection bias could exist in the original data collection process. Households that participated in the survey and were willing to share consumption data could be more socially engaged, educated, or climate-aware than the general population. Since our findings rely on pre-existing data, we are unable to evaluate the presence of this bias or correct for it directly.

That said, the data's origin outside an experimental setting could also strengthen generalizability. The potentially lower threshold for sharing data compared to participating in an experiment may also reduce self-selection bias. Households do not need to be strongly committed to the study's underlying cause to consent to data sharing, which could broaden the participant pool beyond those highly engaged with the topic, thereby reducing self-selection bias.

7.7 Robustness Checks and Sensitivity Analyses

7.7.1 Parallel Trends Assumption

As suggested while discussing the internal validity of our study, our models rely on the Parallel Trends Assumption. To assess the robustness of this assumption, we conduct a placebo test by estimating an alternative regression where households are treated with a placebo instead of the original price shock. We define the placebo by splitting the original pre-treatment period (pre-shock winter) in half, and classifying the second half as treatment. This regression, therefore, calculates the differential response to a placebo treatment. If the Parallel Trends Assumption holds, we expect this regression to return insignificant or zero effects.

Regression estimates of the placebo test are shown in Appendix C.1. The average hourly differential response is never significant for both the DID and complementary model, revealing that dynamic contract households did not change behavior relative to fixed contract households in response to the placebo. This demonstrates the robustness of our Parallel Trends Assumption and indicates it holds.

7.7.2 Fixed Effects

As explained in Section 5.2.3, our methodological approach applies two-way fixed effects that control for unobserved heterogeneity. Our Fixed Effects control for unobserved heterogeneity in household-specific consumption patterns, interacting ID with all daily hours. Our Time Fixed Effects specification controls for unobserved heterogeneity in region-specific effects that are constant for all households within the region, but vary across regions and over time. In this section, we discuss the importance of such strict controls by investigating whether our findings remain valid under a more lenient two-way fixed effects definition. We recalculate both models under more straightforward two-way fixed effects terms: Household ID and a time index. This assumes that all households have similar consumption profiles and that the region is of little importance. Regression results are reported in Appendix C.2.

Although the average hourly differential response is similar across classifications, subgroup analysis reveals a different story. Effect sizes are often either larger or insignificant when comparing the simple fixed effects to our original version. This is especially the case for the homeowner subgroup (see Appendix B). The homeowner subgroup features many differences. While our advanced fixed effects do not indicate a response, the simple fixed effects method suggests renters engage in load shifting whereas home owners do not.

The difference in regression results suggests that our simpler model, which controls for less variation, is susceptible to omitted variable bias. As fixed effects terms demeans all observations, it controls for systematic differences in baseline consumption between households. However, since this FE term only controls for the mean household consumption, it does not account for household-specific consumption patterns throughout the day. For example, consider two households with the exact same mean electricity consumption. The first household has a daytime work schedule, while the other works night shifts. Although their total electricity might be the same, their hourly consumption patterns differ substantially[17]. As a result, consumption variation might just as well be caused by differences in daily routines, rather than a response to price changes. Without controlling for this, our model would suffer from omitted variable bias, leaving some household-specific heterogeneity unaccounted for, which explains the difference in estimates. Our time fixed effects could also explain the difference. As mentioned in Section 4.2.3, our household data originate from the two

[17]The differences in the consumption profile between households in our dataset are also described in Section 4.2.3 and Figure 9

Norwegian bidding areas, NO1 and NO5, which are approximately 300 kilometers apart (Oslo to Bergen). Weather events in NO1 do not have to coincide with those in region NO5. Households, therefore, do not experience the same event at the same time. If we assume they do, we misclassify our time fixed effects term, leading to biased estimates.

By controlling for household specific routines (ID-Hour) and time-related shocks in each region (PriceArea-DateTime), the original two-way fixed effects classification provides a more credible estimate of the causal effect. These differences highlight the existing heterogeneity in household responsiveness and the importance of strict two-way fixed effects assumptions in studies on household electricity consumption.

7.7.3 Clustered Standard Errors

As described in Section 5.2, standard errors are currently clustered at the household (ID) level. This reflects our assumption that the variation left unexplained by both the regressors and the two-way fixed effects is correlated within individual households (across different hours). A more restrictive assumption is that residual correlation arises only within the same household-hour combination (IDŒHour). In other words, the original assumption allows residuals at different hours (e.g., 7 PM and 10 PM) within a household to be correlated, while the more restrictive assumption limits correlation to residuals observed at the same hour across different days for that household. To assess the robustness of our original clustering assumption, we also report our results while clustering SEs at the IDxHour level in Appendix C.3.

Standard errors decrease for all estimates, which leads to higher statistical significance. This outcome is not surprising because clustering at a more restrictive level, increasing the amount of clusters, effectively assumes greater independence among observations. Interpreting these robustness results, we find stronger evidence of load-shifting behavior in both the EV and Smart Charging subgroups. Additionally, the results suggest that households actively monitoring prices engage in load shifting during weekends. Interestingly, we find no evidence of similar behavior on weekdays.

7.7.4 Peak/Off-Peak Definition

As indicated in Section 7.5, our approach to defining peak and off-peak hours comes with certain caveats. Currently, peak hours are defined as hours where prices were at least 20% above the average price of that day, and vise-versa for off-peak hours. To assess the robustness and sensitivity of our results, as well as the implications drawn from them, regarding the definition of Peak and Off-Peak hours, we re-estimated our models using two alternative classification approaches. First, we define peak and off-peak hours by a fixed set of hours: 4 PM - 8 PM for Peak hours, and 12 AM - 4 AM for off-peak. This approach ensures every day has both peak and off-peak hours, and there is no disparity in the amount of classified hours between the pre-treatment and treatment periods. Second, we adopt the same relative price-driven approach, but adjust the threshold to a more radical 50% instead of 20%. Regression results for these two options are displayed in Appendix C.4.

Re-estimating our models using two additional definitions yield consistent effect directions, suggesting robustness of our core findings. However, the estimated treatment effects size is observed to be sensitive to our classification strategy. Our fixed-hours approach consistently produces larger magnitudes, sometimes even twice as high, compared to the original approach. Peak hour reductions remain highest in the Smart Charging subgroup, with an average hourly reduction of 0.4614 kWh or nearly 11% under the new definition.

Interestingly, this suggests that households are responsive during late afternoon hours even when price levels do not exceed the 20% threshold relative to the daily average. Put differently, if the average household is sensitive to hourly price fluctuations, one would expect larger reductions in hours where the price is relatively high (>20%); yet, this does not seem to be the case. The larger consumption decrease for this peak hour definition could indicate that household routines are more flexible during this time window. Households could also be particularly responsive during common, well-known high-price hours out of habit, rather than due to daily monitoring of electricity prices. This observation and its interpretation present an interesting case for time-of-use (TOU) contracts[18]. Increasing the predictability of high-price electricity hours makes it easier for households to adapt their behavior, particularly among households without the enabling technology to automatically respond to hourly price fluctuations. Following this logic, TOU contracts could serve as an effective tool to incentivize consumer flexibility, while also reducing the cognitive burden associated with continuous price monitoring inherent in RTP contracts.

The strongest evidence for load shifting behavior, where off-peak consumption increases rather than decreases, disappears when defining off-peak as night hours. This may suggest that households do not shift consumption to night hours, and that our original definition may better capture the hours where actual load shifting occurs. When setting the threshold at 50% we see similar, slightly smaller, peak-hour reductions for average households and EV-owning households. These lower estimates are counterintuitive, as theory would suggest that larger intra-day price differences should provide greater incentives to shift consumption. This may indicate that households have already exhausted most of their flexibility at the 20% peak-hour threshold and are unable to reduce consumption further. Many other estimates are statistically insignificant, which may be due to the low number of peak-hour observations exceeding 50% above the average daily price.

The sensitivity of treatment effects to our peak/off-peak definition highlights the importance of accurately defining these hours to match them to research objectives. Our study primarily aims to investigate whether dynamic contract households (and subgroups) respond differently to a price shock. Therefore, the focus lies more on the direction of the effect and the relative differences across subgroups, rather than on the exact magnitude of the response in any particular hour classification. Since our key implications relate to whether and how different households adjust consumption in response to price shocks, rather than determining an exact kilowatt-hour shift, the observed sensitivity does not undermine our interpretation. However, as discussed above, interpreting the changing magnitudes across different peak hour classifications offers an interesting perspective on why the case for RTP contracts may be weaker than often assumed.

7.8 Broader Interpretation

Our findings suggest that dynamic contract households reduce their electricity consumption when exposed to higher and more volatile electricity prices. This confirms that price signals can incentivize more responsive consumption behavior and, in turn, help reduce peak loads. Shifting consumption from peak hours to off-peak hours appears to be more pronounced among households with higher consumption that have shiftable loads. In our study, this group was represented by households owning EVs. As suggested in previous literature, enabling technologies like smart charging appear to be very effective in facilitating consumption flexibility. Interpreting the direction of effects would advocate for incentivizing demand flexibility through dynamic contracts as a (partial) solution to overloaded power grids.

[18]Introduced in Section 2.3

A broad extrapolation of our results reveals the potential scale of the average effect. Assuming all households in the NO1 and NO5 regions were on dynamic contracts and uniformly exhibited the average peak hour reduction of 0.0886 kWh, this would translate into an estimated 3.3% reduction in average peak load. The 3.3% reduction is approximately equivalent to 57 MWH in aggregate hourly consumption per bidding area[19]. Such a reduction could relieve pressure on the power grid or create capacity to connect around 21,000 additional households in each region without requiring further grid investments. Although this might appear to be a promising result, the order of magnitude is rather disappointing. Although a 3.3% peak hour reduction is similar to the response found in other studies (Buckley, 2020; Hofmann & Lindberg, 2024), the magnitude is still lower than expected considering the exceptional nature of the price shock[20].

Low estimates could be (partially) explained by our econometric modeling approach, as suggested in Section 7.2.2. In addition, behavioral aspects could be constraining the very short-run response investigated in this study. The short-term hour-to-hour reduction investigated in this thesis allows for very little planning regarding electricity consumption. Households might be more responsive to multi-day trends rather than intra-day fluctuations. As suggested in Section 7.7.4, predictable peak price hours could contribute to increased demand-side flexibility. Core consumption like lighting, heating, or refrigeration can't easily be decreased hour-to-hour without inconvenience. Some households may therefore have limited flexibility in their electricity consumption.

Although the magnitude of effects is relatively small, it is a crucial confirmation on the existence of short-term demand-side flexibility. Our methodological approach ensures the estimated effect is more likely to be a conservative estimate rather than an overly optimistic one. Furthermore, short-run flexibility can form the building block for larger behavioral shifts in the long run. The average hourly response may therefore seem tiny, but when aggregated across many hours, and transitioned into a longer-term effect, the cumulative impact can still be substantial. Finally, the differences in estimates between subgroups highlight potential barriers and has the potential to guide policymakers to increase demand-side flexibility in the future.

7.9 Scientific Contribution

This study contributes to existing literature on residential electricity demand flexibility by examining how dynamic electricity pricing influences household consumption behavior. By comparing dynamic and fixed contract households, the study addresses a crucial knowledge gap: to what extent do dynamic price signals successfully encourage more flexible consumption patterns? Using high-frequency hourly data, we evaluated short-term price responsiveness and explored how household characteristics shape this response, as well as the prevalence of load shifting.

Using hourly data enables us to capture very short-term consumption responses in a highly relevant country context. Moreover, the price shock in our dataset approximates a natural experiment, providing a rare opportunity to deliver strong empirical evidence from a real-world setting. Our dual-model approach combines two perspectives, offering a deeper and more nuanced understanding of household responsiveness to the price shock.

[19] Based on an estimated average household peak-hour consumption of 2.702 kWh and total residential hourly consumption of 1,740 MWh during the pre-treatment winter period

[20] 250% increase in average hourly price and 85% increase in intra-day price volatility.

Compared to the original study by Hofmann and Lindberg, 2023, we make several scientific contributions. First, we calculate differential consumption reductions by comparing households on dynamic contracts with those on fixed contracts, isolating the effect of dynamic pricing on behavior. Second, we refined the time frame of interest by only focusing on official winter months (Dec-Feb). While the original study compared the price shock period (November 2021 to March 2022) with a broader reference period (October 2020 to July 2021), we instead compared two winter seasons directly, ensuring that all months in the treatment and reference periods overlapped. Third, while the original study relied on aggregated household consumption data, we use the available household-level data directly, allowing us to capture more granular effects. Finally, we employ advanced two-way fixed effects models that control for greater unobserved heterogeneity, thereby strengthening the causal interpretation of our results.

Our findings contribute to the literature by showing that households with dynamic electricity contracts reduced electricity consumption more than those with fixed contracts in response to intra-day price fluctuations during the 2021 price shock. We also find that sensitivity to a 1 NOK price increase was higher during the price shock period. While this aligns with previous studies, we provide additional empirical evidence highlighting the crucial role of enabling technology. Specifically, households with smart EV charging exhibited the largest consumption reductions. Finally, by combining our main results with robustness checks, we suggest that TOU contracts may be sufficient to encourage flexibility, potentially reducing the need for RTP contracts.

8 Conclusion

8.1 Summary of Findings

Using high-frequency Norwegian consumption and price data, enriched with household characteristics, this study contributes to the understanding of how dynamic pricing influences residential electricity consumption patterns. The following main research question guides this thesis:

How do dynamic electricity prices influence intra-day electricity consumption patterns among residential consumers?

Based on observational Norwegian data, this study provides empirical evidence that exposure to dynamic electricity prices during the winter season is associated with increased intraday hourly price sensitivity and a greater overall decrease in consumption in response to the 2021 energy price crisis, compared to households with fixed-price electricity contracts. Specifically, we expanded this analysis by investigating differences between peak and off-peak responsiveness and heterogeneity across household groups. Evidence reveals the existence of intraday price sensitivity by showing a 3.3% consumption decrease during hourly intraday price peaks, but no clear response when the intraday hourly price is relatively low. Moreover, separate subgroup regressions highlight different effect sizes, indicating heterogeneity in price responsiveness. The differential response during peak price hours is greater for households that own an EV and highest for households that charge this EV with smart technology. These two subgroups also exhibit strong evidence of load-shifting behavior, which suggests they are well-positioned to contribute to demand-side flexibility. Finally, households that actively monitor electricity prices also exhibit higher absolute peak consumption reductions.

8.2 Policy Implications

Although our results do not support the notion that the nationwide adoption of incentivizing demand flexibility through dynamic electricity contracts is likely to resolve the issue of overloaded power grids immediately, they could still have considerable potential in combination with supporting policies and technology. Our findings support evidence of consumer sensitivity to dynamic electricity prices. Households are shown to respond to intra-day peak prices by decreasing consumption. These behavioral responses strengthen the case for implementing or expanding peak-hour tariffs, complemented by off-peak discounts, as a means to encourage more flexible and efficient electricity usage. Widening the gap between peak and off-peak prices amplifies the financial incentive for households to shift consumption away from peak hours.

Building on this, although not a primary focus of this study, evidence from our robustness analysis (Sec. 7.7.4) suggests that households may be particularly responsive during predictable high-price hours. This implies that, in the short to medium term, TOU contracts could provide sufficient incentives for households to reduce consumption. The simplicity of TOU contracts potentially enables broader household participation compared to the more demanding RTP contracts. They are also effective in achieving peak-load reductions, thereby helping to delay costly grid investments.

Looking forward, based on theory RTP contracts are expected to deliver greater economic efficiency by aligning consumption more closely with real-time supply-demand conditions. While households may currently be better suited to TOU contracts, policy interventions should nonetheless aim to enhance household responsiveness to RTP contracts. This is especially important as the share of intermittent electricity sources grows and enabling technologies become more prevalent. The effectiveness of RTP contracts, however, ultimately depends on household readiness and the widespread adoption of enabling technologies.

Policy interventions to accelerate the adoption of such technologies could increase household price responsiveness and flexibility, thereby improving household readiness to interact optimally with RTP contracts. While our smart-charging results already illustrate the potential of RTP contracts, similar gains may be achieved in other areas of electricity use, such as through smart thermostats, lighting, laundry, or cooking appliances.

8.3 Directions for Future Research

Despite the insights gained in this study, a comprehensive understanding of consumer price responsiveness under dynamic pricing contracts requires further research. First, the rich Norwegian dataset at our disposal features many characteristics that have been left unexplored. Future studies could leverage this data to increase understanding of the effects of dwelling characteristics, such as household size, residence size, and residence type. The socio-economic variables, income and education, could also be incorporated as explanatory variables. Further, analyzing demand-side flexibility in the context of heating consumption would be highly interesting given its importance in Norwegian electricity consumption.

While our findings contribute to existing knowledge, they also raise questions based on the limitations of this study. First, estimates are low relative to the severity of the price crisis, and could be biased toward highly responsive households. This potential bias, in particular, represents a limitation of our study. Future research could adopt a WLS method that assigns weights to households based on average consumption. This would yield more representative estimates for the average effect, accounting for the positive skew in our consumption data.

Second, a potential limitation of our study is the explicit focus on hour-to-hour consumption variation, which may overlook more complex behavioral responses that extend across multiple hours. Future researchers could introduce a time-lag to our models. Such an expansion would allow for delayed consumption responsiveness. Third, as mentioned in Section 5.5 and 7.5.3, a potential limitation of this study is our exogenous electricity price assumption. Future research could change our methodological approach towards 2SLS, taking an instrumental variable for electricity price, to investigate whether this changes our findings.

Finally, our subgroup analysis is conducted in separate regression models, limiting our ability to infer whether the difference between dynamic contract subgroups is statistically significant. Future research could investigate these within-dynamic contract household differences by using regression subgroups in a single model. This would enable researchers to directly compare estimates, whereas we can only make suggestive claims about the absolute magnitude of effects.

8.4 Final Statement

Our findings highlight that dynamic pricing encourages households to reduce consumption during peak hours, confirming that price signals can influence intraday electricity use. This responsiveness is strongest among households that actively monitor prices and those using smart EV charging, highlighting the importance of both awareness and enabling technologies. TOU contracts may currently provide sufficient incentives to encourage a demand response because of their simplicity and predictability. In the longer term, however, RTP type contracts have more potential to align consumption with real-time supply-demand conditions, particularly as intermittent electricity generation increases and enabling technologies become more widespread.

Policies that promote the adoption of smart technologies can further enhance consumer responsiveness. Demand response initiatives could specifically focus on raising awareness and enabling more households to directly monitor and engage with electricity price (signals). Although we find the effect to be more pronounced during weekends, the practical relevance lies in the flexibility of weekday consumption, as this is where grid stress is highest. The average weekday peak hour consumption reduction, is relatively low in magnitude, and unlikely to resolve issues of grid overload by itself. However, we should recognize that short-term consumption reductions can build towards higher long-term demand flexibility. Encouraging the adoption of dynamic electricity contracts and implementing policies to enhance responsiveness could be a meaningful part of a solution to help balance the grid.

Declaration of AI (assisted) technologies in the writing process

While preparing this work, I used *ChatGPT* and *Microsoft Copilot* to improve readability and language in general. I used language models to make my language less repetitive and more structured. I never performed such operations on full paragraphs but rather on individual sentences and words I wanted to have feedback on. Additionally, I used language models to provide me with feedback on general thesis structuring and potential missing content that would need elaborating on. I also used these tools to speed up repetitive tasks in the coding process (e.g., creation of figures). After using these tools, I carefully reviewed and edited the content as needed and take full responsibility for the content.

References

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://ideas.repec.org/a/eee/eneeco/v33y2011i5p870-881.html

Allcott, H. (2011a). Rethinking real-time electricity pricing. *Resource and Energy Economics*, *33*(4), 820–842.

Allcott, H. (2011b). Social norms and energy conservation. *Journal of Public Economics*, *95*(9-10), 1082–1095.

Auray, S., Caponi, V., & Ravel, B. (2019). Price elasticity of electricity demand in france [Cited by: 7; All Open Access, Bronze Open Access, Green Open Access]. *Economie et Statistique*, *2019*(513), 91–105. https://doi.org/10.24187/ECOSTAT.2019.513.2002

Azarova, V., Cohen, J. J., Kollmann, A., & Reichl, J. (2020). Reducing household electricity consumption during evening peak demand times: Evidence from a field experiment. *Energy Policy*, *144*, 111657. https://doi.org/https://doi.org/10.1016/j.enpol.2020.111657

Bedir, M., Hasselaar, E., & Itard, L. (2013). Determinants of electricity consumption in dutch dwellings. *Energy and Buildings*, *58*, 194–207. https://doi.org/https://doi.org/10.1016/j.enbuild.2012.10.016

Bergé, L. (2018). Efficient estimation of maximum likelihood models with multiple fixed-effects: The R package FENmlm. *CREA Discussion Papers*, (13).

Blazquez, J., Fuentes-Bracamontes, R., Bollino, C. A., & Nezamuddin, N. (2018). The renewable energy policy paradox. *Renewable and Sustainable Energy Reviews*, *82*, 1–5. https://doi.org/https://doi.org/10.1016/j.rser.2017.09.002

Bobbio, E. (2021). Fostering resiliency, the importance of the demand side. *IET Conference Proceedings*, *2021*(13), 179–192. https://doi.org/10.1049/icp.2021.2615

Borenstein, S. (2005). The long-run efficiency of real-time electricity pricing. *The Energy Journal*, *26*(3), 93–116. https://doi.org/10.5547/ISSN0195-6574-EJ-Vol26-No3-5

Borenstein, S. (2016). The economics of fixed cost recovery by utilities. *The Electricity Journal*, *29*(7), 5–12. https://doi.org/https://doi.org/10.1016/j.tej.2016.07.013

Borenstein, S., Jaske, M., & Rosenfeld, A. (2002). *Dynamic pricing, advanced metering, and demand response in electricity markets* (Working Paper No. CSEM WP 105). University of California Energy Institute.

Bosman, M. (2024, February). *Netcongestie: piekbelasting is het grootste probleem* [Accessed: 2025-03-31]. Rijksvastgoedbedrijf. https://www.rijksvastgoedbedrijf.nl/actueel/nieuws/2024/02/19/netcongestie-piekbelasting-is-het-grootste-probleem

Buckley, P. (2020). Prices, information and nudges for residential electricity conservation: A meta-analysis. *Ecological Economics*, *172*, 106635. https://doi.org/https://doi.org/10.1016/j.ecolecon.2020.106635

CBS. (2025, March). *Energiebalans; aanbod en verbruik, sector* [Accessed: 2025-04-24]. https://opendata.cbs.nl/statline/#/CBS/nl/dataset/83989NED/table?dl=21D0E

Chen, C.-f., Xu, X., Adua, L., Briggs, M., & Nelson, H. (2022). Exploring the factors that influence energy use intensity across low-, middle-, and high-income households in the united states. *Energy Policy*, *168*, 113071. https://doi.org/https://doi.org/10.1016/j.enpol.2022.113071

Commission, E. (2020). State of the union: Commission raises climate ambition. https://ec.europa.eu/commission/presscorner/detail/en/ip_20_1599

Dutta, G., & Mitra, K. (2017). A literature review on dynamic pricing of electricity [Cited by: 216; All Open Access, Green Open Access]. *Journal of the Operational Research Society*, *68*(10), 1131–1145. https://doi.org/10.1057/s41274-016-0149-4

Energie Nederland. (2021). *End consumers* [Accessed: 2025-03-31]. https://www.energie-nederland.nl/en/facts-figures/end-consumers

European Union. (2019). Directive (eu) 2019/944 of the european parliament and of the council of 5 june 2019 on common rules for the internal market for electricity and amending directive 2012/27/eu (recast). *EUR-Lex*. https://eur-lex.europa.eu/eli/dir/2019/944/oj/eng

Fabra, N., Rapson, D., Reguant, M., & Wang, J. (2021). Estimating the elasticity to real-time pricing: Evidence from the spanish electricity market. *AEA Papers and Proceedings*, *111*, 425–29. https://doi.org/10.1257/pandp.20211007

Faruqui, A., & George, S. (2005). Quantifying customer response to dynamic pricing. *The Electricity Journal*, *18*(4), 53–63. https://doi.org/https://doi.org/10.1016/j.tej.2005.04.005

Faruqui, A., & Sergici, S. (2013). Arcturus: International evidence on dynamic pricing [Cited by: 75]. *Electricity Journal*, *26*(7), 55–65. https://doi.org/10.1016/j.tej.2013.07.007

Faruqui, A., Sergici, S., & Warner, C. (2017). Arcturus 2.0: A meta-analysis of time-varying rates for electricity. *The Electricity Journal*, *30*(10), 64–72. https://www.sciencedirect.com/science/article/pii/S1040619017302750?via%3Dihub

Filippini, M., & Srinivasan, S. (2024). *An introduction to energy economics and policy*. Cambridge University Press. https://doi.org/10.1017/9781009471831

Frondel, M., Kussel, G., & Sommer, S. (2019). Heterogeneity in the price response of residential electricity demand: A dynamic approach for germany. *Resource and Energy Economics*, *57*. https://doi.org/10.1016/j.reseneeco.2019.03.001

Himmelweit, S., Simonetti, R., & Trigg, A. B. (2001). Microeconomics : Neoclassical and institutionalist perspectives on economic behaviour. https://api.semanticscholar.org/CorpusID:153841807

Hirth, L., Khanna, T. M., & Ruhnau, O. (2024). How aggregate electricity demand responds to hourly wholesale price fluctuations. *Energy Economics*, *135*, 107652. https://doi.org/https://doi.org/10.1016/j.eneco.2024.107652

Hofmann, M., Bjarghov, S., & Nessa, S. (2023). Norwegian hourly residential electricity demand data with consumer characteristics during the european energy crisis. *Data in Brief*, *51*, 109687. https://www.sciencedirect.com/science/article/pii/S2352340923007667

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

Hofmann, M., & Lindberg, K. B. (2023). Residential demand response and dynamic electricity contracts with hourly prices: A study of norwegian households during the 2021/22 energy crisis. *SSRN*. https://ssrn.com/abstract=4452761

Hofmann, M., & Lindberg, K. B. (2024). Evidence of households' demand flexibility in response to variable hourly electricity prices results from a comprehensive field experiment in norway. *Energy Policy*, *184*, 113821. https://doi.org/https://doi.org/10.1016/j.enpol.2023.113821

Hyundai Motors. (2022). *Hyundai legt zich toe op de ontwikkeling van vehicle-to-everything (v2x).* [Accessed: 2025-03-31]. https://hyundai-pers.nl/hyundai-legt-zich-toe-op-de-ontwikkeling-van-vehicle-to-everything-v2x/

Karatasou, S., & Santamouris, M. (2019). Socio-economic status and residential energy consumption: A latent variable approach. [Cited by: 45]. *Energy and Buildings*, *198*, 100–105. https://doi.org/10.1016/j.enbuild.2019.06.013

Krishnamurthy, C. K. B., & Kriström, B. (2015). A cross-country analysis of residential electricity demand in 11 oecd-countries [Cited by: 90]. *Resource and Energy Economics*, *39*, 68–88. https://doi.org/10.1016/j.reseneeco.2014.12.002

Møller Andersen, F., Gunkel, P. A., Bjerregaard, C., & Jacobsen, H. K. (2024). Changes in hourly electricity consumption profiles and price elasticities in denmark 20192022. *Energy*, *308*, 132798. https://doi.org/https://doi.org/10.1016/j.energy.2024.132798

Naastepad, C. W. M., & Storm, S. (2024). Mot112a economic foundation (2023/23q2) lecture note w-1 [MOT122A Economic Foundation W1].

NOS. (2023a). Deel nieuwe huizen almere niet aangesloten op stroom vanwege vol elektriciteitsnet. *NOS.nl*. https://nos.nl/artikel/2498097-deel-nieuwe-huizen-almere-niet-aangesloten-op-stroom-vanwege-vol-elektriciteitsnet

NOS. (2023b). Jetten wil bedrijven mogelijk verplichten in piekuren minder stroom af te nemen. *NOS.nl*. https://nos.nl/artikel/2494525-jetten-wil-bedrijven-mogelijk-verplichten-in-piekuren-minder-stroom-af-te-nemen

NOS. (2023c). Netbeheerder waarschuwt voor stroomtekort in 2030. *NOS.nl*. https://nos.nl/artikel/2459559-netbeheerder-waarschuwt-voor-stroomtekort-in-2030

NOS. (2023d). Te weinig stroom: Bedrijven verplicht minder elektriciteit? *NOS.nl*. https://nos.nl/nieuwsuur/artikel/2484088-te-weinig-stroom-bedrijven-verplicht-minder-elektriciteit

Ourahou, M., Ayrir, W., EL Hassouni, B., & Haddi, A. (2020). Review on smart grid control and reliability in presence of renewable energies: Challenges and prospects. *Mathematics and Computers in Simulation*, *167*, 19–31. https://www.sciencedirect.com/science/article/pii/S0378475418303045

Özkan, H. A. (2016). Appliance based control for home power management systems. *Energy*, *114*, 693–707. https://doi.org/https://doi.org/10.1016/j.energy.2016.08.016

Parrish, B., Gross, R., & Heptonstall, P. (2019). On demand: Can demand response live up to expectations in managing electricity systems? *Energy Research & Social Science*, *51*, 107–118. https://doi.org/https://doi.org/10.1016/j.erss.2018.11.018

Planbureau voor de Leefomgeving. (2024). Klimaatdoel 2030 raakt uit zicht; extra beleid met snel effect nodig. *Planbureau voor de Leefomgeving*. https://www.pbl.nl/actueel/nieuws/klimaatdoel-2030-raakt-uit-zicht-extra-beleid-met-snel-effect-nodig

Posit team. (2025). *Rstudio: Integrated development environment for r*. Posit Software, PBC. Boston, MA. http://www.posit.co/

Rabobank. (2024). The dutch electricity sector - part 3: Developments affecting electricity markets. *Rabobank.com*. https://www.rabobank.com/knowledge/d011428288-the-dutch-electricity-sector-part-3-developments-affecting-electricity-markets

Rijksoverheid. (2022). Ruimte voor duurzame energie. https://magazines.rijksoverheid.nl/ienw/duurzaamheidsverslag/2022/01/energietransitie

Rijksoverheid. (2024). Kabinet deelt toekomstig klimaatbeleid en bereidt alternatieve maatregelen naar 2030 voor. *Rijksoverheid.nl*. https://www.rijksoverheid.nl/actueel/nieuws/2024/10/24/kabinet-deelt-toekomstig-klimaatbeleid-en-bereidt-alternatieve-maatregelen-naar-2030-voor

Ruhnau, O., Lundström, L., Dürr, L., & Hunecke, F. (2023). Empirical weather dependency of heat pump load: Disentangling the effects of heat demand and efficiency. *2023 19th International Conference on the European Energy Market (EEM)*, 1–5. https://doi.org/10.1109/EEM58374.2023.10161914

Schofield, J., Carmichael, R., Tindemans, S., Woolf, M., Bilton, M., & Strbac, G. (2015). Experimental validation of residential consumer responsiveness to dynamic time-of-use pricing. *23rd International Conference on Electricity Distribution (CIRED)*.

Schulte, I., & Heindl, P. (2017). Price and income elasticities of residential energy demand in germany [Cited by: 115; All Open Access, Green Open Access]. *Energy Policy*, *102*, 512–528. https://doi.org/10.1016/j.enpol.2016.12.055

Sorrell, S. (2015). Reducing energy demand: A review of issues, challenges and approaches. *Renewable and Sustainable Energy Reviews*, *47*, 74–82. https://doi.org/https://doi.org/10.1016/j.rser.2015.03.002

Statistics Norway. (2025a). Electricity prices in the end-user market, by contract type 2012k1 - 2024k3. https://www.ssb.no/en/statbank/table/09364/

Statistics Norway. (2025b). Energy balance. supply and consumption, by energy product, contents, year and energy balance item. https://www.ssb.no/en/statbank/table/11561/tableViewLayout1/?loadedQueryId=10082787&timeType=item

Statnett. (2025, January). *Why we have bidding zones* [Accessed: 2025-04-03]. https://www.statnett.no/en/about-statnett/The-power-system/why-we-have-bidding-zones/

Strømtest.no. (2025). Variable price contracts [Accessed: 2025-06-03]. https://www.xn--strmtest-74a.no/en/stromavtale/variabel-pris-stromavtale/

TenneT. (2024). Next step to prevent electricity grid overload in utrecht province. https://www.tennet.eu/news/next-step-prevent-electricity-grid-overload-utrecht-province

TenneT. (2025, April). *Market types* [Accessed: 2025-04-24]. https://www.tennet.eu/market-types

Torriti, J. (2012). Price-based demand side management: Assessing the impacts of time-of-use tariffs on residential electricity demand and peak shifting in northern italy. *Energy*, *44*, 576–583.

Wang, Y., Lin, H., Liu, Y., Sun, Q., & Wennersten, R. (2018). Management of household electricity consumption under price-based demand response scheme [Cited by: 56]. *Journal of Cleaner Production*, *204*, 926–938. https://doi.org/10.1016/j.jclepro.2018.09.019

Wiesmann, D., Lima Azevedo, I., Ferrão, P., & Fernández, J. E. (2011). Residential electricity consumption in portugal: Findings from top-down and bottom-up models [Cited by: 173]. *Energy Policy*, *39*(5), 2772–2779. https://doi.org/10.1016/j.enpol.2011.02.047

Wooldridge, J. M. (2020). *Introductory econometrics: A modern approach* (Seventh). Cengage.

World Economic Forum. (2021). Fostering effective energy transition 2021 edition. *World Economic Forum*. https://www3.weforum.org/docs/WEF_Fostering_Effective_Energy_Transition_2021.pdf

Zhu, X., Li, L., Zhou, K., Zhang, X., & Yang, S. (2018). A meta-analysis on the price elasticity and income elasticity of residential electricity demand [Cited by: 87]. *Journal of Cleaner Production*, *201*, 169–177. https://doi.org/10.1016/j.jclepro.2018.08.027

A Survey Questions

The dataset used for this Thesis includes a survey that explores household characteristics. A full list of all questions in this survey is presented below.

Age?
Gender?
City?
Q1: Did you monitor your power consumption this winter?
Q2: How did you acquire information about your power consumption?
Q3: Why did you not monitor your consumption?
Q4: Did you monitor the variation in electricity prices from day to day and hour to hour this winter?
Q5: How did you acquire information about the electricity prices?
Q6: Why did you not monitor the electricity prices?
Q7: Did you take any measures to decrease or move power consumption from hours with high prices this winter?
Q8: Which measure did you implement?
Q9: Do you know how much the household has saved on the power bill as a result of the measures?
Q10: About how much has the household saved per month this winter as a result of the measures?
Q11: Do you feel that the measures you implemented were worth the savings on the power bill?
Q12: Why did you not take any measures?
Q13: What motivates you to reduce your power consumption in high price hours?
Q14: How much do you agree or disagree with the following statement? People who adjust their power consumption based on price should be able to save on their power bill.
Q15: Would you or have you used a free information service that alerts you of high price hours the following day?
Q16: How many persons does your household consist of, including yourself?
Q17: What age are the inhabitants of you household, including yourself?
Q18: Imagine you can buy smart devices for 5,000 NOK that will reduce your power bill by automatically shifting parts of you consumption away from high price hours - without reducing comfort. How much would you have to save every year to do it?
Q19: How many weekdays (Mon-Fri) on average was there anyone home in the day (9 a.m. to 4 p.m.) this winter (Nov-Mar)?
Q20: What is the highest education in the household?
Q21: What is the combined gross income of the household?
Q22: What type of residence do you live in?
Q23: How big is the residence?
Q24: Do you own the residence?
Q25: Do you have a rental unit in the residence?
Q26: Does the rental unit have its own power meter?
Q27: How is the residence heated?
Q28: How is the tap water heated?
Q29: Do you own one or more electric car that is at least sometimes charged at home?
Q30: How is the car or cars normally charged?
Q31: Do you control the car charging to avoid hours with high prices?
Q32: What type of power contract do you have?

B Home Ownership Results & Analysis

Table 8: Home Ownership Subgroup Results

Dependent Variable:	Demand (kWh)			
Model:	(DID - Weekday)	(DID - Weekend)	(Comp - Weekday)	(Comp - Weekend)
HomeOwner Subgroup				
HomeOwner - Peak	-0.0916***	-0.1120**	-0.0288***	-0.0519**
	(0.0303)	(0.0481)	(0.0092)	(0.0236)
HomeOwner - OffPeak	-0.0220	0.0217	-0.0227	0.0154
	(0.0311)	(0.0340)	(0.0196)	(0.0299)
Renter - Peak	-0.0574	-0.0515	-0.0186	-0.0177
	(0.0484)	(0.0648)	(0.0148)	(0.0321)
Renter - OffPeak	-0.0345	0.0176	-0.0273	-0.0229
	(0.0401)	(0.0420)	(0.0254)	(0.0386)
Fixed-effects				
ID-Hour	Yes	Yes	Yes	Yes
PriceArea-DateTime	Yes	Yes	Yes	Yes
Fit statistics				
Observations	2,497,536	1,014,624	2,497,536	1,014,624
R^2	0.77711	0.76907	0.77711	0.76907
Within R^2	2.47×10^{-5}	2.37×10^{-5}	2.99×10^{-5}	2.39×10^{-5}

Clustered (ID) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Homeowners demonstrate a statistically significant decrease in peak consumption, while consumption response by renters is never statistically different from zero. Hourly peak consumption decreased by an average of 0.0916 kWh during weekdays and 0.1120 kWh in weekends. Off-peak homeowner estimates did not show a significant consumption response. Similarly, complementary model results show that homeowners are significantly more responsive during peak hours than renters, as renters show no significant consumption reductions in peak periods.

When focusing on the price responsiveness of homeowners as opposed to households that rent their homes, results indicate that only homeowners respond to the price shock by decreasing average hourly consumption in peak hours. Moreover, this peak hour reduction is higher in absolute magnitude compared to the average household's peak reduction, suggesting that homeowners may be more responsive. As homeowners have full control over both appliance and dwelling factors (such as type of heating and dwelling insulation), this could explain the increased response. Homeowners could be better equipped to respond to price changes compared to the average household. Evidence on the ability of home ownership to moderate the extent to which households shift consumption from peak to off-peak hours is not as strong as it was for EV owning households. Although homeowners exhibit peak consumption reductions, no significant increase in off-peak hours is observed. As mentioned before, this does not rule out load shifting behavior altogether, but does suggest load shifting is less pronounced than it was for EV households.

Estimates for renters were very low, and insignificant, suggesting renters with dynamic contracts did not respond differently to the price shock compared to renters with fixed contracts. Furthermore, it highlights the difference in consumption flexibility between homeowners and renters, a finding also reported by Frondel et al., 2019. The behavior of renters could be explained by the structure of rental agreements, where electricity costs could be included in a fixed rent. In such cases, the landlord is the actual holder of the dynamic pricing contract. As a result, renters are effectively shielded from real-time price signals and are not directly exposed to the price shock, thereby reducing their incentive to adjust their consumption. Though, based on the structure of the survey and alternative answer, it seems unlikely renters would say they have a dynamic price contract if, in reality, they pay a fixed rate. A more plausible explanation could be that renters have limited control over usage. Renters are likely to live in buildings where (water) heating is shared with the whole building, limiting their influence on consumption. Additionally, neither landlords nor renters are strongly incentivized to invest in energy efficiency upgrades or technological improvements to their dwellings. This could lead to a situation where renters have minimal capacity to respond to price changes, or move specific consumption to off-peak hours.

Renters are remarkably insensitive to price fluctuations. While it's important first to understand the root causes of this observation, enabling more flexible consumption among renters has strong potential to enhance the overall effectiveness of dynamic pricing.

C Robustness Results

C.1 Parallel Trends Assumption

Table 9: Robustness Results Parallel Trends Assumption

Dependent Variable:	Demand (kWh)			
Model:	(DID - Weekday)	(DID - Weekend)	(Comp - Weekday)	(Comp - Weekend)
Variables				
$D_i^{\text{DynamicContract}} \times D_t^{PriceShock}$	0.0358	0.0583	0.0342	0.1178
	(0.0397)	(0.0378)	(0.0623)	(0.0883)
Fixed-effects				
ID-Hour	Yes	Yes	Yes	Yes
PriceArea-DateTime	Yes	Yes	Yes	Yes
Fit statistics				
Observations	1,248,768	507,312	1,248,768	507,312
R^2	0.81756	0.80907	0.81756	0.80907
Within R^2	4.31×10^{-5}	0.00011	1.86×10^{-5}	9.8×10^{-5}

Clustered (ID) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

C.2 Fixed Effects

Table 10: Simple Fixed Effects Regression Results

Dependent Variable:	Demand_kWh			
Model:	(DID - Weekday)	(DID - Weekend)	(Comp - Weekday)	(Comp - Weekend)
Variables				
$D_i^{DynamicContract} \times D_t^{\text{PriceShock}}$	-0.0815*	-0.0930**	-0.0494**	-0.0672**
	(0.0471)	(0.0455)	(0.0227)	(0.0293)
Fixed-effects				
ID	Yes	Yes	Yes	Yes
DateTime	Yes	Yes	Yes	Yes
Fit statistics				
Observations	2,497,536	1,014,624	2,497,536	1,014,624
R^2	0.74156	0.73274	0.74156	0.73274
Within R^2	0.00018	0.00023	0.00020	0.00024

Clustered (ID) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 11: Simple Fixed Effects Regression Results - Subgroups

Dependent Variable:	Demand (kWh)			
Model:	(DID - Weekday)	(DID - Weekend)	(Comp - Weekday)	(Comp - Weekend)
Variables				
Peak Hour	-0.0111	-0.0896**	-0.0097	-0.0415**
	(0.0272)	(0.0407)	(0.0090)	(0.0198)
OffPeak Hour	0.0473	0.0076	0.0213	0.0016
	(0.0299)	(0.0444)	(0.0180)	(0.0374)
Appliance Subgroups				
EV - Peak	-0.1755***	-0.0561	-0.0561***	-0.0274
	(0.0553)	(0.0708)	(0.0158)	(0.0347)
EV - OffPeak	0.2082***	-0.0587	0.1099***	-0.0392
	(0.0644)	(0.0687)	(0.0380)	(0.0583)
SmartCharge - Peak	-0.2533**	-0.2795	-0.0852**	-0.1436
	(0.1234)	(0.1785)	(0.0340)	(0.0877)
SmartCharge - OffPeak	0.5340***	0.4516**	0.2708***	0.2809*
	(0.1451)	(0.1934)	(0.0869)	(0.1484)
HomeOwner Subgroup				
HomeOwner - Peak	-0.0094	-0.0876**	-0.0093	-0.0409**
	(0.0277)	(0.0413)	(0.0092)	(0.0201)
HomeOwner - OffPeak	0.0424	-0.0008	0.0184	-0.0024
	(0.0307)	(0.0450)	(0.0184)	(0.0379)
Renter - Peak	-0.0275	-0.1099*	-0.0140	-0.0479
	(0.0501)	(0.0660)	(0.0154)	(0.0326)
Renter - OffPeak	0.0979**	0.0983*	0.0513*	0.0449
	(0.0445)	(0.0573)	(0.0276)	(0.0505)
Awareness Subgroup				
ActiveMonitoring - Peak	-0.1568***	-0.1456***	-0.0478***	-0.0704***
	(0.0357)	(0.0401)	(0.0105)	(0.0197)
ActiveMonitoring - OffPeak	0.0236	0.0297	0.0099	0.0266
	(0.0433)	(0.0469)	(0.0262)	(0.0387)
Fixed-effects				
ID	Yes	Yes	Yes	Yes
DateTime	Yes	Yes	Yes	Yes
Fit statistics				
Observations	2,497,536	1,014,624	2,497,536	1,014,624

Clustered (ID) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

C.3 Clustered Standard Errors

Table 12: Robustness Baseline Results IDxHour Clustered SE's

Dependent Variable:	Demand (kWh)			
Model:	(DID - Weekday)	(DID - Weekend)	(Comp - Weekday)	(Comp - Weekend)
Variables				
$D_i^{\text{DynamicContract}} \times D_t^{PriceShock}$	-0.0830***	-0.0945***	-0.0523***	-0.0694***
	(0.0118)	(0.0118)	(0.0060)	(0.0079)
Fixed-effects				
ID-Hour	Yes	Yes	Yes	Yes
PriceArea-DateTime	Yes	Yes	Yes	Yes
Fit statistics				
Observations	2,497,536	1,014,624	2,497,536	1,014,624
R^2	0.77715	0.76913	0.77716	0.76913
Within R^2	0.00021	0.00027	0.00025	0.00029

Clustered (IDxHour) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 13: Robustness Subgroup Results IDxHour Clustered SE's

Dependent Variable:	Demand (kWh)			
Model:	(DID - Weekday)	(DID - Weekend)	(Comp - Weekday)	(Comp - Weekend)
Variables				
Peak Hour	-0.0886***	-0.1068***	-0.0279***	-0.0489***
	(0.0143)	(0.0287)	(0.0042)	(0.0139)
OffPeak Hour	-0.0231*	0.0214	-0.0231***	0.0121
	(0.0137)	(0.0198)	(0.0087)	(0.0176)
Appliance Subgroups				
EV - Peak	-0.1502***	-0.1610***	-0.0497***	-0.0781***
	(0.0188)	(0.0358)	(0.0055)	(0.0176)
EV - OffPeak	0.1440***	0.0936***	0.0683***	0.0850***
	(0.0239)	(0.0319)	(0.0143)	(0.0273)
SmartCharge - Peak	-0.1899***	-0.2910***	-0.0651***	-0.1465***
	(0.0457)	(0.0860)	(0.0129)	(0.0428)
SmartCharge - OffPeak	0.3249***	0.3944***	0.1487***	0.2349**
	(0.0725)	(0.1186)	(0.0429)	(0.0946)
HomeOwner Subgroup				
HomeOwner - Peak	-0.0916***	-0.1120***	-0.0288***	-0.0519***
	(0.0144)	(0.0290)	(0.0043)	(0.0140)
HomeOwner - OffPeak	-0.0220	0.0217	-0.0227**	0.0154
	(0.0139)	(0.0201)	(0.0089)	(0.0178)
Renter - Peak	-0.0574***	-0.0515	-0.0186***	-0.0177
	(0.0202)	(0.0369)	(0.0061)	(0.0181)
Renter - OffPeak	-0.0345**	0.0176	-0.0273**	-0.0229
	(0.0174)	(0.0238)	(0.0110)	(0.0217)
Awareness Subgroup				
ActiveMonitoring - Peak	-0.1628***	-0.1582***	-0.0486***	-0.0770***
	(0.0131)	(0.0222)	(0.0039)	(0.0109)
ActiveMonitoring - OffPeak	-0.0014	0.0388*	-0.0054	0.0347**
	(0.0151)	(0.0209)	(0.0091)	(0.0174)
Fixed-effects				
ID-Hour	Yes	Yes	Yes	Yes
PriceArea-DateTime	Yes	Yes	Yes	Yes
Fit statistics				
Observations	2,497,536	1,014,624	2,497,536	1,014,624

Clustered (IDxHour) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

C.4 Peak/OffPeak

Table 14: Robustness Results Fixed Peak/OffPeak Hours

Dependent Variable:	Demand (kWh)			
Model:	(DID - Weekday)	(DID - Weekend)	(Comp - Weekday)	(Comp - Weekend)
Variables				
Peak Hour	-0.1145**	-0.1564***	-0.0589***	-0.0954***
	(0.0542)	(0.0539)	(0.0215)	(0.0319)
OffPeak Hour	-0.0455	-0.0448	-0.0387	-0.0352
	(0.0494)	(0.0490)	(0.0347)	(0.0350)
Appliance Subgroups				
EV - Peak	-0.3962***	-0.3931***	-0.1635***	-0.2227***
	(0.0721)	(0.0739)	(0.0324)	(0.0465)
EV - OffPeak	0.0431	0.0200	0.0282	0.0204
	(0.0690)	(0.0662)	(0.0505)	(0.0505)
SmartCharge - Peak	-0.4614***	-0.5705***	-0.2005***	-0.3588***
	(0.1593)	(0.1630)	(0.0640)	(0.0997)
SmartCharge - OffPeak	-0.0108	0.0153	-0.0216	0.0069
	(0.1439)	(0.0955)	(0.1022)	(0.0743)
HomeOwner Subgroup				
HomeOwner - Peak	-0.1360**	-0.1764***	-0.0658***	-0.1055***
	(0.0547)	(0.0545)	(0.0218)	(0.0323)
HomeOwner - OffPeak	-0.0540	-0.0532	-0.0442	-0.0403
	(0.0500)	(0.0496)	(0.0351)	(0.0354)
Renter - Peak	0.1181*	0.0598	0.0153	0.0137
	(0.0706)	(0.0688)	(0.0302)	(0.0416)
Renter - OffPeak	0.0460	0.0454	0.0204	0.0196
	(0.0643)	(0.0629)	(0.0461)	(0.0462)
Awareness Subgroup				
ActiveMonitoring - Peak	-0.1961***	-0.1843***	-0.0942***	-0.1150***
	(0.0531)	(0.0519)	(0.0236)	(0.0317)
ActiveMonitoring - OffPeak	-0.0733	-0.0788*	-0.0489	-0.0525
	(0.0498)	(0.0455)	(0.0359)	(0.0334)
Fixed-effects				
ID-Hour	Yes	Yes	Yes	Yes
PriceArea-DateTime	Yes	Yes	Yes	Yes
Fit statistics				
Observations	2,497,536	1,014,624	2,497,536	1,014,624

Clustered (ID) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 15: Robustness Results 50% Peak/OffPeak Hours

Dependent Variable:	Demand (kWh)			
Model:	(DID - Weekday)	(DID - Weekend)	(Comp - Weekday)	(Comp - Weekend)
Variables				
Peak Hour	-0.0806**	-0.0306	-0.0251**	-0.0123
	(0.0357)	(0.0595)	(0.0110)	(0.0243)
OffPeak Hour	0.0164	-0.0457	0.0107	-0.0973
	(0.0814)	(0.0685)	(0.0529)	(0.1487)
Appliance Subgroups				
EV - Peak	-0.1150**	-0.0704	-0.0413***	-0.0303
	(0.0512)	(0.0904)	(0.0153)	(0.0363)
EV - OffPeak	-0.1435	0.0023	-0.0931	0.0061
	(0.1479)	(0.1344)	(0.0960)	(0.2922)
SmartCharge - Peak	-0.1306	-0.2775	-0.0468	-0.1184
	(0.1101)	(0.2053)	(0.0333)	(0.0836)
SmartCharge - OffPeak	-0.8953***	0.6607	-0.5813***	1.437
	((0.2745)	(0.4968)	(0.1783)	(1.080)
HomeOwner Subgroup				
HomeOwner - Peak	-0.0821**	-0.0394	-0.0256**	-0.0161
	(0.0361)	(0.0602)	(0.0111)	(0.0246)
HomeOwner - OffPeak	0.0130	-0.0579	0.0085	-0.1239
	(0.0824)	(0.0697)	(0.0535)	(0.1514)
Renter - Peak	-0.0649	0.0654	-0.0201	0.0286
	(0.0488)	(0.0878)	(0.0151)	(0.0356)
Renter - OffPeak	0.0536	0.0859	0.0348	0.1897
	(0.1105)	(0.0769)	(0.0717)	(0.1671)
Awareness Subgroup				
ActiveMonitoring - Peak	-0.1560***	-0.1721***	-0.0492***	-0.0693***
	(0.0338)	(0.0510)	(0.0104)	(0.0206)
ActiveMonitorng - OffPeak	-0.1284	0.0403	-0.0834	0.0886
	(0.0785)	(0.0840)	(0.0510)	(0.1826)
Fixed-effects				
ID-Hour	Yes	Yes	Yes	Yes
PriceArea-DateTime	Yes	Yes	Yes	Yes
Fit statistics				
Observations	2,497,536	1,014,624	2,497,536	1,014,624

Clustered (ID) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*