Beyond Money

Exploring the Effect of Motivational Factors on Peak Hour Consumption in Norway's Residential Sector

Karen Helga Sigurgeirsdóttir

Beyond Money

Exploring the Effect of Motivational Factors on Peak Hour Consumption in Norway's Residential Sector

by

Karen Helga Sigurgeirsdóttir

in partial fulfillment of the requirements for the degree of

Master of Science

in Management of Technology

at the Delft University of Technology,
to be defended publicly on Wednesday, August 27, 2025, at 15:00.

Thesis Committee:

Chair and Second Supervisor: Prof. Dr. G. (Gerdien) de Vries, Faculty TPM, TU Delft

First Supervisor: Dr. E. (Enno) Schröder, Faculty TPM, TU Delft

Student Number:
6066917

TU Delft

Abstract

To handle surges in electricity demand during peak hours, utility companies often resort to meeting the excess demand by building additional capacity. The downside to this strategy is that a large proportion of the power generation capacity will become latently available, and thus not efficiently used. Another strategy is reducing peak hour electricity demand so that it meets the supply. Adjusting the demand to the supply is referred to as demand response (DR), and offers a significantly more environmentally friendly and sustainable approach to improving the efficiency of energy systems. In order to incentivise consumers to move their energy consumption to off-peak hours, or reducing it during peak hours, electric system operators and utility companies design DR programs that encourage consumers to change their energy usage patterns. One such program is the real-time pricing scheme, where electricity prices are adjusted dynamically, being higher during peak hours.

Real-time pricing schemes are designed around the principles of neoclassical economic theory, which assumes that consumers respond rationally to financial incentives. Studies investigating the elasticity of the own price of the demand for electricity in the residential sector have consistently shown small, but negative values, suggesting that financial motives do promote DR to a degree. However, research from environmental psychology suggests that non-financial motivations, such as environmental concern, also play a crucial role in shaping energy consumption behaviour.

This thesis investigates whether financial and environmental motivations influence how Norwegian households adjust their electricity usage during peak hours. Norway represents a unique case to study, as it is particularly well suited for DR programs. This was done using fixed-effect regression on a panel dataset consisting of the hourly electricity consumption of 1,136 households in Norway. Each regression model was characterised by different fixed effects, and each household was grouped by how they answered questions on what motivates them to partake in DR. In each model, groups corresponding to financial and environmental motivations were assigned a dummy variable which was interacted with indicators of peak hours, while all other households were used as a reference group. The resulting coefficients were analysed and discussed.

The baseline regression results show that neither households in the financially motivated group nor the environmentally motivated group appear to reduce their electricity consumption during peak hours by more or less than the reference group. This suggests that households adjusted their electricity consumption during peak hours in a similar way, despite differences in stated motivation. These findings are consistent for all models, except when the model included hour-level fixed effects, which control for each household's load structure. In that model, the coefficient on the interaction between the environmental group variable and the peak hour variable became significant at the 5% level, with a value of -0.0206. This effect corresponds to approximately double the electricity used by a single LED light bulb per hour. The robustness analysis supported these conclusions with a few minor exceptions.

Although the effect is significant, it is very small, making its practical relevance questionable. Furthermore, some limitations were opposed on this research by a relatively small sample size and the option for households to give multiple answers to motivational factors for partaking in DR. For these reason, this work can not provide definite answers to policy makers on whether DR programs are based on the correct assumptions, and whether focusing on the monetary incentives is most effective.

Keywords: Real-time pricing, Demand response, Peak-hour electricity consumption, Environmental psychology, Household energy use, Motivational factors

Awknowledgement

As I approach the end of my thesis journey, I want to take a moment to express my heartfelt gratitude to several individuals who have supported me along the way.

First, I would like to thank my primary supervisor, Enno Schröder. Your willingness to answer my questions and your constructive feedback were truly invaluable. I greatly appreciate your guidance and assistance throughout this process.

I would also like to extend my gratitude to my secondary supervisor, Gerdien de Vries, for your invaluable support and encouragement. Exploring a new research field was a rewarding experience, and your help and guidance greatly enhanced this journey.

I am incredibly grateful to my friends here in Delft and back home in Iceland, who have made this experience worthwhile by providing support when I needed it most. I want to give special thanks to my mom, dad, and my two siblings, who have always been there for me.

Lastly, I would like to express my deepest appreciation to my greatest supporter, Valdimar, who has stood by me every step of the way.

Karen Helga Sigurgeirsdóttir
Delft, the Netherlands
August 15, 2025

Contents

List of Figures

List of Tables

Acronyms

AI Artificial Intelligence. 68

CPP Critical-Peak Price. 6, 15, 16, 24, 70

DAG Directed Acyclic Graph. 29

DF Demand Flexibility. 5

DLC Direct Load Control. 5

DR Demand Response. 1, 2, 5, 67

EPI Environmental Performance Index. 63

EV Electric Vehicle. 33, 40, 42

GDP Gross Domestic Product. 25

MoT Management of Technology. 4, 71

MRS Marginal Rate of Substitution. 8

PBDR Price-Based Demand Response. 5, 6

RTP Real-Time Price. 1, 4, 6, 14–16, 22, 24, 70

TOU Time Of Use. 6, 15, 16, 24, 70

Chapter 1

Introduction

Global warming is a scientifically established threat to human civilisation. The cause of global warming is man-made, predominantly driven by over-consumption and production in wealthy societies. Scientists agree on the serious consequences of global warming. But, policymakers are, at the end of the day, responsible for avoiding the worst-case scenario. Towards this aim, policy makers have promoted efficient energy usage as an important strategy to reduce CO_2 emissions (European Commission, 2023). While the industry and commercial sectors are undoubtedly important parties in this effort, the residential sector also presents a significant opportunity for change. For example, households accounted for 25.8 % of the EU's final energy consumption in 2022 (European Commission, n.d.). For this reason, household electricity consumption contributes significantly to periods of peak demand. To handle these surges, utility companies are often required to build additional capacity to meet this demand during high-peak hours. This leads to a large proportion of the power generation capacity being latently available and thus not used efficiently (Haider et al., 2016).

The traditional solution to make the supply side manage the balance between the supply and demand side of the grid is inherently inefficient (Li et al., 2021). Instead of continuously increasing supply to meet the demand, Demand Response (DR) offers a more sustainable solution where the demand is adjusted to meet the energy supply (Haider et al., 2016). This adjustment can, for example, involve households moving their energy consumption to off-peak hours to reduce the demand for electricity during peak periods, a practice known as *load shifting* (Neukomm et al., 2019). In order to incentivise this behaviour, electric system operators and utility companies design DR programs to encourage consumers to change their energy usage patterns (Li et al., 2021). One example is the Real-Time Price (RTP) scheme, where electricity prices are adjusted dynamically, often on an hourly basis (Li et al., 2021).

Effective DR is becoming increasingly important, especially with the rise of renewable energy sources such as wind and photovoltaic energy. Because of the intermittent nature of these energy sources, they cannot reliably provide a constant energy supply. Therefore, there is a need to be able to adjust the demand to this variable renewable supply (Haider et al., 2016; Li et al., 2021). With growing technology advancements, such as in energy storage, electric vehicles, and smart metering, demand side management has become a viable solution to balance the grid (Li et al., 2021).

The electricity consumption patterns of Norwegian households and their responses to high electricity prices present a strong case for examining the effectiveness of demand response DR programs. Given that most Norwegian households have spot price contracts [1] and that every household is equipped with a smart meter, residential DR is a realistic approach (Hofmann & Lindberg, 2024b). Smart meters enable households to access real-time energy consumption feedback through various platforms, including websites, home displays, and mobile devices (Steg et al., 2015). Additionally, a high proportion of people own electric vehicles and heat their homes with electric heaters, which provides an opportunity for flexibility in terms of electricity demand (Hofmann et al., 2025). This combination of factors makes the Norwegian domestic electricity market uniquely positioned to be more flexible on the demand side, and thus, a compelling case for research.

As later described in Chapter 2, monetary incentives are the primary mechanism used to increase residential demand flexibility. This approach is based on the assumption of microeconomic theory, which views consumers as rational actors who aim to maximise their utility by weighing the expected cost and benefits of their actions (Chen et al., 2023; Gyamfi et al., 2013). Pricing policies are commonly thought to effectively motivate sustainable energy behaviour because people tend to be strongly motivated by financial gains. However, responses to such pricing policies are often weaker than expected (Steg et al., 2018). This can be explained by the fact that a range of other factors beyond financial incentives can influence pro-environmental behaviour. These factors include people's values, goals, beliefs, and norms, which are all considered in the field of environmental psychology (Steg et al., 2018).

It is therefore valuable to explore other motivational factors, especially to see if households motivated by environmental reasons consume less during high-price hours than those motivated by financial reasons. Beyond being an area of academic interest, this understanding is also essential for policymakers and industry. Without this understanding, policymakers are left without crucial input to design effective programs. This information would help answer the question of whether focusing on monetary incentives is most effective. In fact, some research has shown that environmental motives often play a bigger role and that financial motives are not always the way to promote sustainable energy behaviour (Asensio & Delmas, 2015; Sloot et al., 2019).

In simple terms, motivations can be defined as reasons people have to take part or not take part in particular behaviour (van Valkengoed et al., 2025). Therefore, whether or not people decide to take part in pro-environmental behaviour largely depends on their level of motivation (Steg et al., 2015). In the environmental context, people's motivation to act

[1] Spot price contracts are contracts where the cost of electricity varies hourly according to market price (Hofmann & Lindberg, 2024b).

environmentally can usually be split into three main categories.

First, people might be driven to act pro-environmentally because of the perceived costs and benefits of the behaviour. In this situation, people evaluate what they gain from the behaviour and weigh the benefits against the cost they must endure, for example, are motivated to lower their energy consumption because it saves them money.

Second, social motivation also plays a significant role in motivating people to act pro-environmentally. Social motivation refers to the fact that people are often motivated by the desire to fit in and to be accepted by others. For example, people might be motivated to recycle because everyone in their community is recycling to feel a sense of belonging or to avoid social disapproval. *Social Identity Theory* relates to this. Henri Tajfel and John Turner developed it in the 1970s. According to the theory, individuals define themselves based on the social groups to which they belong, such as nationality, religion, or occupation. These group memberships influence how the individual feels, thinks and acts (Hogg et al., 1995). When, for example, pro-environmental behaviour is part of the norm and values of a group that an individual strongly identifies with, they are more likely to adopt those behaviours to maintain group acceptance and align with the group's values.

Third, people might be motivated to act pro-environmentally because of moral motivation. In this situation, people are motivated to participate in a particular behaviour because they believe it is right. For example, a person is motivated to take the train when they visit another country, as opposed to an aeroplane, because they believe it is the right thing to do. They feel morally obligated to choose the more environmentally friendly option to protect the environment. This work will primarily focus on perceived cost and benefit and the moral motivation category, especially the moral motivation to protect the environment. In particular, it aims to explore which type of motivation is more or less critical for load-shifting behaviour, especially to see whether policies like demand response programs that target perceived cost and benefit motivation are effective (van Valkengoed et al., 2025).

No prior work has studied how different motivational factors, particularly monetary motives and environmental concerns, affect the load shifting of the Norwegian residential sector. This lack of understanding makes it difficult to assess whether DR programs are based on the correct assumptions and whether focusing on the monetary incentives is most effective. This lack of understanding leaves policymakers without critical insight to further refine and develop these programs. Therefore, there is a clear incentive to expand the body of knowledge about the effectiveness of DR programs. Norway represents a unique case to study, as it is particularly well-suited for DR programs. Therefore, regardless of whether this work concludes that non-financial motives are more effective or less effective, the findings will provide valuable insights for other countries under similar conditions.

Shedding light on how different motivational factors influence consumption during peak hours is the core research objective of the current work. In line with this objective, the main research question is:

RQ: *Do financial and environmental motivations influence whether, and to what extent, households reduce electricity consumption during peak hours?*

1.1 Master Program Relevance

There is a clear link between this master's thesis topic and the Management of Technology (MoT) master's program. The thesis examines how various motivations, specifically financial and environmental, influence electricity consumption during peak hours. The research is therefore aimed at investigating whether RTP demand response programs are built on the correct assumptions; that is, whether monetary incentives are the optimal policy instrument to make households consume less during peak hours.

This thesis topic, therefore, aligns significantly with the core of the MoT programs, which teach students how to analyse and understand technology as a strategic resource. Specifically, the thesis provides insight into how households in the Norwegian residential sector respond to the technological and policy mechanisms of RTP in a real-world context. It reflects the program's emphasis on connecting technology and user behaviour to support informed decision-making in both policy and business environments. Furthermore, the research methods used in this work highly align with methods and techniques taught in the MoT curriculum.

1.2 Structure of the Thesis

This thesis is structured as follows: Chapter 2 presents the theoretical foundation for this thesis, focusing on insights from economic theory and environmental psychology. The chapter also defines key concepts, such as RTP, and provides background about the context of this study. Chapter 3 outlines the methodology applied in this thesis and provides a detailed description of the dataset used for the analysis. Furthermore, this chapter presents descriptive statistics that both analyse the key variables and provide insight into the main groups studied in the thesis. Chapter 4, presents the regression results and a discussion about the results. Finally, Chapter 5 summarises the main findings and provides an answer to the research question. It further reflects on the implications of the results for policymakers and researchers, and outlines directions for future research.

Chapter 2

Literature Review

2.1 Demand Response and Demand Response Programs

Demand Flexibility (DF) is defined as the ability to shift or adjust energy consumption patterns in order to support and meet the electricity grid's need (Olawale et al., 2023). There are several modes in which households can provide demand flexibility, one of which is referred to as *load shifting*. Load shifting involves changing the timing of electricity use to decrease demand during peak hours (Neukomm et al., 2019). Through load shifting, a household adjusts its energy consumption in response to pricing signals or grid supply, a process known as Demand Response (DR) (Li et al., 2021). DR brings substantial benefits for utility companies, enabling them to reduce operational and capital costs, as well as their carbon footprint. Instead of building new generation plants to meet the demand at high peak hours, which is a time-consuming and capital-intensive solution, DR brings about an environmentally friendly and economically viable solution (Yan et al., 2018). To create incentives for DR, electric system operators and utility companies design DR programs that encourage consumers to change their energy usage patterns (Li et al., 2021).

DR programs can be divided into two primary types: **incentive-based** and **price-based** DR schemes [1]. These two schemes differ in the factors that motivate consumers to change their energy consumption behaviour. Under the incentive-based scheme, customers commit to reducing their energy usage as per the utility company's requests or contractual agreements. The agreement between the two parties grants the utility company a level of authority to directly disconnect, schedule, or reduce energy to save costs (Haider et al., 2016). An example of an incentive-based DR scheme is the Direct Load Control (DLC) scheme in which the utility company can remotely take control over specific high energy-consuming appliances of the customer to respond to reliability or demand issues (Yan et al., 2018).

The Price-Based Demand Response (PBDR) programs utilise electricity pricing as a con-

[1] From an economic standpoint, this naming convention is misleading since economists perceive price as incentives. The main distinction between the two is whether the incentives come from separate payments (incentive-based) or lower prices (price-based) (Yan et al., 2018)

trol signal and tariffs to incentivise consumers to change their electricity use (Bertoli, 2023; Yan et al., 2018). PBDR programs do not employ static tariffs; instead, the electricity tariffs dynamically respond to real-time fluctuations in electricity cost (Albadi & El-Saadany, 2008). By sending these price signals, the consumer is encouraged to shift or reduce their energy consumption from periods of high peak to off-peak hours, thus contributing to load balancing (Haider et al., 2016). Initially, PBDR programs were adopted in the industrial sector, where production costs are highly coupled to energy costs. Companies were willing to participate in the PBDR programs to take advantage of the low energy prices during off-peak hours. This was primarily pertinent to companies with high energy usage, such as chemical production companies (Yan et al., 2018). Although research on residential PBDR began in the 1980s, the research scale has historically been limited due to the lack of real-time monitoring of residents' electricity usage. However, the advent of smart metering and the subsequent improvement of infrastructure in residential areas have made real-time monitoring widely available (Yan et al., 2018) — providing the means necessary to realise residential PBDR adoption.

There are three main types of PBDR schemes: Time Of Use (TOU), Critical-Peak Price (CPP), and real-time price Real-Time Price (RTP) (Yan et al., 2018). Under a TOU scheme, utility companies offer customers different electricity prices based on time of use (e.g., on-peak vs. off-peak rates). Using a CPP scheme, utility companies raise electricity prices by a tangible amount during a specified period (CPP event) to drive down energy consumption (e.g., during the warmest hours in the summer). Lastly, the RTP scheme involves utilities dynamically modifying electricity prices at frequent intervals (e.g. per hour) (Li et al., 2021). The RTP scheme is particularly relevant since this thesis focuses on Norwegian households, where this scheme is widely adopted. The vast majority of households (75%) in Norway have spot price contracts: electricity contracts tied to the hourly electricity spot price (Hofmann & Lindberg, 2024b). This widespread adoption of spot price contracts makes Norway an ideal setting for examining the effectiveness of the RTP scheme.

Household energy behaviour is often studied from an economic perspective, analysing how the quantity demanded for electricity changes with income levels (*income elasticity*) or how demand for electricity changes with changing electricity prices (*price elasticity*). Another perspective is the social-psychological viewpoint. This involves the analysis of people's psychological and behavioural factors and their effect on decisions about efficient energy use (Gyamfi et al., 2013). A thorough review of these two perspectives is given in the following sections. Section 2.2 introduces the theoretical model and concepts which form the economic perspective. From this viewpoint, consumers are anticipated to respond to demand response programs, such as the real-time pricing scheme that uses price signals to influence consumer demand. Then, Section 2.3 covers insights and concepts from environmental psychology. This perspective explores how people's values, norms, beliefs, and other psychosocial factors influence their decisions to engage in pro-environmental behaviours, such as more efficient energy usage practices.

2.2 Economic theory

2.2.1 Neoclassical Theory of Consumer Demand

The neoclassical school of thought is the dominant framework for exploring the structure of the market economy. As a microeconomic theory, the neoclassical theory of demand is built upon a set of assumptions that shape its analysis of consumer consumption. It assumes *methodological individualism*, where each consumer acts independently, and the market demand is the aggregate of the demand of all individual consumers. The theory also posits that the consumer is *instrumentally rational*, meaning they allocate their entire income to maximise *utility* (Storm, 2021).

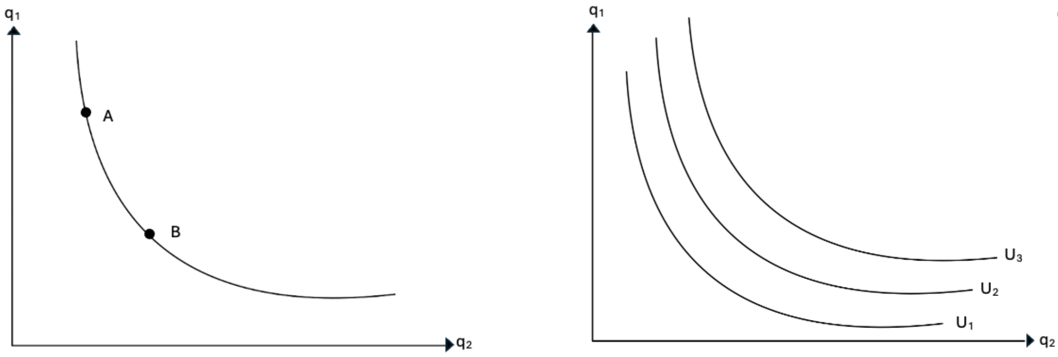
In this theory, consumers' *individual preferences* serve as the basis for making choices among different types of goods and services. These preferences are assumed to be *ordinal*, allowing consumers to compare and rank alternative consumption bundles. Furthermore, consumers are assumed to be *consistent* in their preferences. If the consumer prefers *consumption bundle* A over B, then the consumer will not, at a later point, opt for B over A. Preferences are also characterised by *transitivity*, that is, if a consumer prefers bundle A over B (A>B), and B over C (B>C), then the consumer will also prefer A over C (A>C) (Storm, 2021; Trigg, 2002).

To make optimal choices based on these preferences, and to select the consumption bundle that provides the highest utility, consumers are assumed to have *perfect information* regarding all available goods and services, relevant prices, and their income. These assumptions underpin the core principle of the theory: *consumer sovereignty*, where exogenous consumers' preferences determine what is produced of goods and services in the market (Storm, 2021; Trigg, 2002). To understand consumer decisions, the economic theory aims to frame the utility as a function of services and goods consumed. If the theoretical assumptions hold — i.e., the consumer has perfect knowledge, utility is ordinal, and the consumers' choices are both transitive and consistent — it is possible to create such a utility function (U). The function indicates the consumer's total utility as a function of amounts (q_i) of services and goods consumed, and can be written as:

$$U = f(q_1, q_2, q_3, ..., q_N) \tag{2.1}$$

In the equation, the subscripts denote commodity $i = 1, ..., N$ (Storm, 2021). This utility function must meet two conditions. First, the consumer's utility yielded by consuming one additional unit of a good (i.e., the marginal utility of the good) must be positive. This means that by consuming one additional unit of the good, the consumer will always experience a gain in utility, and more is always considered better. Second, marginal utility decreases as the quantity consumed of the good increases.

If the utility function (U) is known and the level of utility is fixed at a certain level, the *indifference curve* can be derived (Storm, 2021). It graphically represents the ranking of preferences, showing all combinations of goods and services that provide the same level of utility to the consumer (Bhattacharyya, 2019; Storm, 2021). The consumer is, therefore, indifferent between any of the points on the curve since they are all equally preferred. Figure 2.1a shows an indifference curve for the quantity of two goods (hypothetical *Good 1* and *Good 2*). In this case, the consumer does not have a preference between point A — representing a specific bundle of *Good 1* and *Good 2* — and point B, corresponding to a different bundle. This is because both points provide the same level of utility (Storm, 2021; Trigg, 2002).



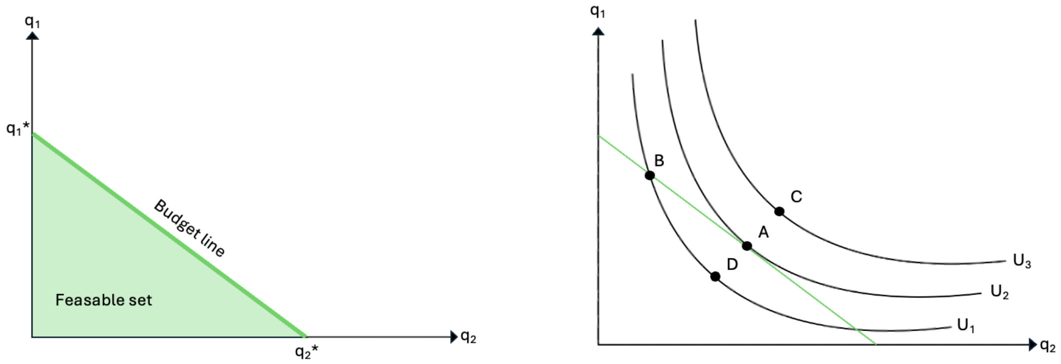
(a) Different bundles on the same indifference curve.

(b) Indifference map showcasing three different indifference curves.

Figure 2.1: Indifference map and different bundles. Figures are adapted Trigg (2002).

The slope of the indifference curve is called the Marginal Rate of Substitution (MRS). For two goods as depicted in Figure 2.1, the MRS of *Good 2* for *Good 1* represents the amount of *Good 1* that the consumer needs to give up for one additional unit of *Good 2* to stay on the same indifference curve. The indifference curve is convex to the origin, which means that the MRS declines as you move along the curve from left to right. This indicates that the amount of *Good 1* that the consumer is willing to give up for one additional unit of *Good 2* declines as the amount of *Good 1* declines (Storm, 2021; Trigg, 2002). For each utility function, it is possible to draw as many indifference curves as desired, and these form the *indifference map* where each curve represents a different level of utility (Storm, 2021). Figure 2.1b shows an indifference map displaying three different indifference curves. Each of the curves illustrates a range of combinations of the two goods that the consumer regards as equally satisfying, and each corresponds to a different utility (Storm, 2021; Trigg, 2002).

According to the neoclassical demand theory, the consumer maximises utility by reaching the highest possible indifference curve. For example, in Figure 2.1b, the consumer would prefer bundles on the indifference curve U_3 since the curve is associated with larger quantities of *Good 1* and *Good 2* compared to the other indifference curves. However, the consumer faces two main constraints when pursuing utility maximisation, which limit the consumer's ability to reach an ever higher indifference curve: the restriction of income and prices of the goods. These constraints determine all sets of consumption bundles that the consumer can afford, known as the *feasible consumption set*. The outer boundary of this set is the *budget constraint*, which shows all possible combinations of the two goods that exactly exhaust the consumer's income. In Figure 2.2a, the budget constraint is given by the indicated budget line, and the area under the line represents the feasible consumption set (Trigg, 2002). In the particular example illustrated in Figure 2.2a, the consumer can afford a maximum of $q1^*$ units of *Good 1* if they spend their entire income on *Good 1* and a maximum $q2^*$ units of *Good 2* if they spend their entire income on *Good 2*.



(a) Budget line and feasible consumption set.

(b) Utility maximised.

Figure 2.2: Budget line and utility maximisation. Figures are adapted from Trigg (2002).

Under the neoclassical framework, the consumer always spends their entire income on their own choice of a combination of goods on the budget line. This is because unspent income does not yield any utility, and more utility is always considered better (Storm, 2021). However, the exact point on the budget line is determined from the individual indifference map. The consumer maximises utility when the budget line is tangent to the highest possible indifference curve (Storm, 2021). For example, in Figure 2.2b, utility is maximised at point A, since the bundle associated with point A gives the highest possible utility. Whereas point B — corresponding to the same budget line as A — is associated with lower utility since it corresponds to a lower indifference curve. Indifference curves that lie further outside the budget constraints reflect a combination of unaffordable goods (e.g., point C), and those curves positioned closer to the origin indicate less desirable combinations (e.g., point D) that provide lower utility than the bundle selected at point A (Trigg, 2002).

To illustrate how this theory predicts how a consumer reacts to a price change, consider the case of two goods, *Good 1* and *Good 2*. Initially, the consumer budget constraints are given by the line B_1 and the consumer maximises its utility at point A, where the indifference curve and budget line are tangent (see Figure 2.3). Now, assume that the price of *Good 2* decreases. This change makes the original budget line shift to the right on the horizontal axis, becoming B_2. This enables the consumer to afford more quantities of the two goods. As a result, the consumer moves up to a higher utility curve, and now the utility maximisation point is at B. From the figure, it can be seen that in response to the reduction of the price of Good 2, the consumption increased from q_{2a} to q_{2b} (Trigg, 2002).

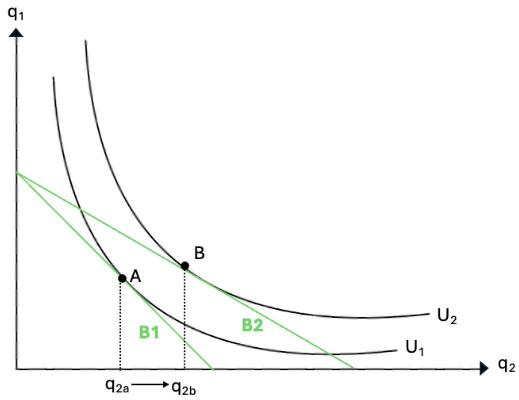


Figure 2.3: Impact of price decrease of *Good 2*. Figure adapted from Trigg (2002).

2.2.2 Household Production Theory and Energy Demand

The household production theory builds on the conventional microeconomic theory and provides a useful framework for understanding residential energy demand. The theory is based on two main functions: the **utility function** and the **production function**. The utility function contains two components, energy services (ES) and other goods (OG), and is expressed as (Filippini & Srinivasan, 2024):

$$U = u(ES, OG) \tag{2.2}$$

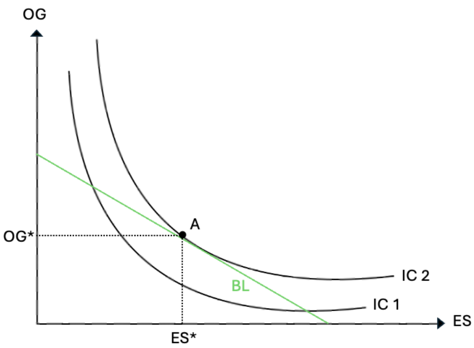
The production function represents the production of energy services (e.g., heating an apartment). The function includes two components that households generally use to produce energy services: energy (E) and capital stock (CS). Capital stock represents heating systems and appliances (e.g., electric stoves). The production function can be written as (Filippini & Srinivasan, 2024):

$$ES = f(E, CS) \tag{2.3}$$

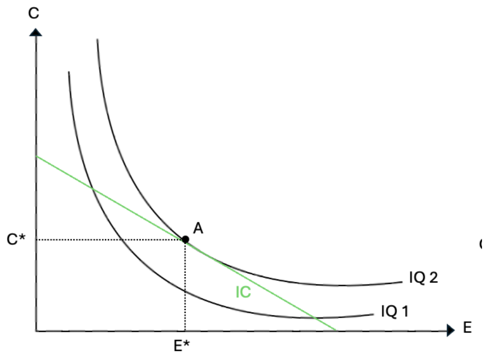
By putting equation 2.3 into equation 2.2, the household utility function becomes:

$$U = u(ES(E, CS), OG) \tag{2.4}$$

According to the conventional microeconomic theory, a household is assumed to maximise this utility function, which is restricted by the household's income level. This means that households choose an optimal combination of other goods (OG) and energy services (ES) that provides them with the highest utility. That is, the household maximises utility when the budget line is tangent to the highest possible indifference curve. In graphical terms, this occurs at point *A* in Figure 2.4a. The household production theory further posits that households achieve utility maximisation while minimising the cost of energy services production. *The isoquant curve* and *the isocost line* are two key concepts that explain how households minimise the cost of producing energy services (ES). In this context, the isoquant curve represents all possible combinations of energy (E) and capital stock (CS) that generate certain levels of energy services (ES). For example, if the energy service is heating a home, then every point on Isoquant 1 (IQ_1) in Figure 2.4b represents a different combination of E and CS that produces the same level of heat. Similarly, all points on Isoquant 2 (IQ_2) produce the same amount of heat, but at a lower level. The isocost line (IC), on the other hand, shows all combinations of energy (E) and capital stock (CS) that have the same cost (Kenton, 2024). The point where the isoquant curve is tangent to the isocost line represents the point where the production cost is minimised for the given level of energy services (Filippini & Srinivasan, 2024). Figure 2.4 graphically shows the two optimisation problems.



(a) Optimising consumption.



(b) Cost minimisation.

Figure 2.4: Household optimisation problems. Figures are adapted from Filippini and Srinivasan (2024).

To summarise, the household optimisation problem is maximising the utility function while adhering to both income restriction and cost-minimising constraints on production costs. When dealing with the household optimisation problem, it is essential to distinguish between short- and long-term constraints. In the long term, households can freely change and choose inputs in the production function of energy services. However, this flexibility is not granted in the short term since the capital stock is fixed and cannot be changed. That is because typical households do not have the capacity to react to electricity price increases in the short term, through means like purchasing new and more energy-efficient appliances (Filippini & Srinivasan, 2024).

The short-term capital stock constraint significantly influences how households react to energy price increases. Because households cannot optimise their capital stock by investing in more efficient appliances or insulation, their only option in the short term is to reduce their energy consumption. This situation is illustrated in Figure 2.5, where it is assumed that a household produces an energy service to heat an apartment to 20 °C during a certain hour with energy level E_1 and fixed capital stock $K*$. When the household faces higher electricity prices, its isocost curve changes from *IC1* to *IC2*. This is because, with the same budget constraint (cost), the household can afford less energy than before. Therefore, the household cannot maintain the previous output level and is forced to move to a lower isoquant curve. In this situation, the household will lower the heat in the apartment to 18 °C, with energy level E_2 and fixed capital stock $K*$ (Filippini & Srinivasan, 2024). A similar adjustment applies to other examples, such as EV charging. Suppose the household faces higher electricity prices during a certain hour. In that case, they will reduce their consumption and shift charging to lower-priced hours to fully charge their vehicle without exceeding their budget.

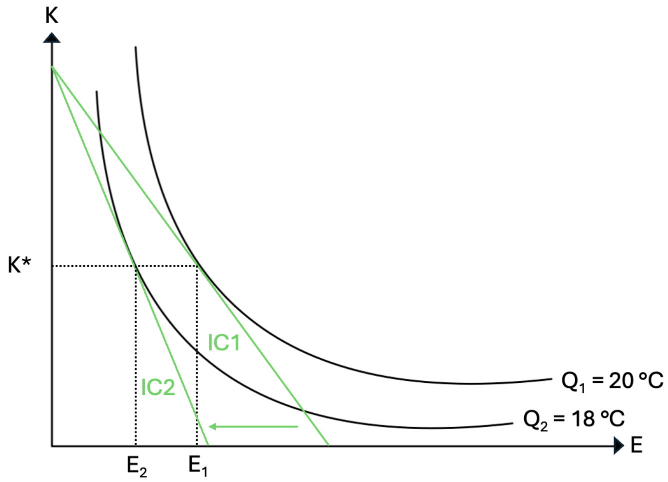


Figure 2.5: Impact of price increase on household energy demand. Figure is adapted from Filippini and Srinivasan (2024).

This thesis focuses on consumer behaviour under short-term constraints, since the aim is to analyse electricity demand over short time horizons. The optimisation problem that the household faces in the short term is given by (Filippini & Srinivasan, 2024):

$$\max \mathrm{U}(\mathrm{ES}(E, CS), OG) \tag{2.5}$$

$$\text{such that} \quad \mathrm{C}(P_E, P_{CS}, ES) + P_{OG} \times OG \leq Y$$

where P_E is the price of energy, P_{CS} price of capital stock, P_{OG} price of other goods, and Y is household income. Since the optimisation assumes a constant return to scale, it is possible to simplify the cost of producing energy services to the following formula (Filippini & Srinivasan, 2024):

$$\mathrm{C}(P_E, P_{CS}, ES) = P_{ES} \times ES \tag{2.6}$$

Solving the utility maximisation problem in equation 2.5 results in three demand equations for energy (E), energy services (ES), and other goods (OG).

$$ES = f(P_{ES}, P_{OG}, Y) \tag{2.7}$$

$$OG = g(P_{ES}, P_{OG}, Y) \tag{2.8}$$

$$E = h(P_E, \overline{CS}, ES, P_{OG}, Y) \tag{2.9}$$

Equation 2.9 gives the short-term energy demand of the household. From the equation, it can be seen that the energy demand depends on the price of energy (P_E), the fixed capital stock ($\overline{CS}$), energy services produced (ES), the price of other goods (P_{OG}), and the income of the household (Y). Researchers often use this simplified model in empirical research, along with control variables that capture geographical and technological factors (Filippini & Srinivasan, 2024). Furthermore, when the level of household energy services is unknown, socioeconomic variables can be used as a proxy to derive a prediction of ES. These variables are, for example, income, household size, age, and dwelling size (Filippini & Srinivasan, 2024).

2.2.3 Price Elasticity of Demand

In addition to theoretical models, extensive empirical research has been carried out in microeconomics to examine consumer demand and identify key factors driving purchasing decisions. This rich body of studies highlights three major factors that influence the demand: (1) ***cross-price elasticity of demand***: the proportional cjáhange in demand of one good in response to the proportional change in the price of another; (2) ***income elasticity of demand***: the proportional change in demand for one good due to a proportional change in consumers' income; and (3) ***own-price elasticity of demand***: the proportional change in the consumption of one good due to the proportional change in the price of the same good (Filippini & Srinivasan, 2024; Storm, 2021). If the value of the own-price elasticity of a good is between -1 and 0, the good is price-inelastic. However, if the value is below -1, the good is price-elastic (Storm, 2021). Studies often report price elasticity of demand when they explore the effect of higher electricity prices on consumer demand (Hofmann & Lindberg, 2024b).

This price elasticity of demand can be directly determined from the regression output when using the log-log functional form of the specified energy demand model. To give an example, consider the following energy demand model, where the variables are expressed in logarithmic form (Filippini & Srinivasan, 2024):

$$ln(E) = \beta_0 + \beta_{P_E} \times ln(P_E) + u \tag{2.10}$$

where u is the error term, E (dependent variable) is the energy demand and P_E (independent variable) is the price of energy. By running a regression (e.g. ordinary least squares) using this model, the own-price elasticity is given by the estimated coefficient $\hat{\beta}_{P_E}$. This is because when logs are used on both the dependent and independent variable, β_{P_E} is interpreted as the percentage change of the dependent variable for an increase of 1% in the independent variable (Stock & Watson, 2019). For example, if the estimated coefficient has a value of -0.35 in Equation 2.10, then the own-price elasticity of demand is also -0.35, meaning that a 1% increase in electricity price would lead to a 0.35% decrease in demand. Price elasticity of electricity demand can be analysed in the short-term, where consumers can not change their capital stock, and long-term (Hofmann & Lindberg, 2019).

2.2.4 Empirical Estimates of Residential Electricity Price Elasticity

Numerous studies have investigated the *own-price elasticity of the demand* for electricity in the residential sector. An international study by Csereklyei (2020) examined the short- and long-run price elasticities for countries in the European Union between 1996 and 2016 using data aggregated at the national level. Csereklyei (2020) conclude that the long-run price elasticity of the electricity demand was between -0.53 and -0.56. Furthermore, they found that the short-term price elasticity was -0.08, which would be considered highly inelastic (Csereklyei, 2020). Another study by Zhu et al. (2018) conducted a meta-analysis based on 103 articles about residential electricity demand. They found an average short-term price elasticity of -0.228 and a long-term price elasticity of -0.577. The articles in the meta-analysis were published between 1990 and 2017, employing data from various countries, which were either aggregated at the national or state/province level (Zhu et al., 2018).

There are some studies that focus their analysis of price elasticity on the Norwegian electricity market — the target market for analysis in this thesis. Hofmann and Lindberg (2019) studied the residential area of Oslo using aggregated hourly electricity demand data and found significant price elasticity estimates only for daily peak hours during the winter months, ranging from -0.011 to -0.075. However, they found that there was no short-term price elasticity on the coldest days with the highest electricity demand (Hofmann & Lindberg, 2019). Another Norwegian study conducted by Bye and Hansen (2008) worked with hourly data to estimate the price elasticity of the aggregate Norwegian electricity market and found that the short-term elasticity in response to variable spot prices was -0.02 during winter but zero during the summer. The study also concluded that the short-term price elasticity was lower during the weekends and decreased during winter night hours (Bye & Hansen, 2008).

As these results show, there is substantial variation in the estimated price elasticity of demand. In fact, estimates of the price elasticity of residential electricity demand vary considerably in the economic literature (Alberini et al., 2011). As suggested by Alberini et al. (2011) the differences can be explained by the different types of data used (e.g., *panel* vs. *time-series* vs. *cross-sectional*), sample period, aggregation level (e.g., *country level* vs. *household level*), and geographic context. Notably, all the previously mentioned studies of price elasticity utilised data that was aggregated on some level, whether national, regional, or city-wide. In contrast, this thesis will utilise disaggregated panel data at the household and hourly level. This is motivated by the objective to investigate *individual* household consumption behaviour during peak hours, which can only be interpreted to a limited degree from aggregated data. In addition, this thesis uses findings from existing studies that employ the same data format. The following section reviews evidence from studies investigating household-level data and how households respond to varying electricity prices. The section will therefore provide evidence of the impact of real-time pricing RTP, previously discussed in Section 2.1.

2.2.5 Evidence of the Effect of Real-Time Pricing

Many studies have analysed how households respond to time-varying price regimes, such as TOU, CPP, and RTP (see Section 2.1). Most of the evidence comes from experimental studies, often using randomised controlled trials where participants are randomly assigned to treatment and control groups (Harding & Sexton, 2017). Harding and Sexton (2017) reviews the results from dynamic pricing experiments conducted in the United States between 2005 and 2016. They find that almost all studies reported a reduction in peak electricity demand due to higher electricity prices, but the effects were generally modest. That is, household price responsiveness is typically low, with most reported price elasticities falling below 0.20 in absolute value. However, when enabling technologies were included, such as in-home displays or automation technologies, the response was significantly higher. But, their review focused primarily on consumer responses to CPP and TOU because few studies have investigated the effect of RTP in residential settings.

A comprehensive meta-analysis conducted by Faruqui et al. (2017) supports the finding that households reduce electricity consumption in response to higher prices during peak periods, and that enabling technologies significantly increase the treatment effect. This study analysed over 60 pilots with 337 pricing treatments conducted between 1997 and 2017 across nine countries, with the majority of these pilots occurring in the U.S. The average peak demand reduction across all treatments without enabling technologies was around 10%, while it was approximately 20% when such technologies were present. However, the results varied significantly between studies, with some reporting peak reduction as high as 50% and others no more than 2%. Nevertheless, the authors found that when they expressed the demand reduction as a function of the peak-to-off-peak price ratio, much of the discrepancy disappeared, and a consistent pattern emerged. The pattern indicated that higher price ratios result in larger demand reduction during peak hours. Similar to the review by Harding and Sexton (2017), this meta-analysis primarily examines household responses to CPP and TOU pricing schemes.

Although studies that have investigated the effect of RTP in the residential sector are scarce, they are not entirely absent. One such study was conducted by Allcott (2011). This randomised field experiment, conducted in Chicago in 2003, involved 693 households, with 103 assigned to a control group that remained on a standard flat-rate electricity contract. The remaining households were placed on a RTP scheme. The author observed hourly electricity consumption for all households over eight months. The main finding of this study was that households under the RTP scheme responded to price changes, exhibiting a price elasticity of approximately -0.1. Furthermore, they found that the households reduced their usage during high-price afternoon hours but did not significantly increase their consumption during low-price periods. The model used in this study included fixed effects for each hour in the dataset to account for time-varying factors common to all households (Allcott, 2011).

Wolak (2011) is another study that investigated whether residential electricity consumers adjusted their consumption in response to hourly electricity prices. The study analysed the behaviour of 1,245 customers from the District of Columbia, of which 388 were assigned to a control group and had a standard fixed electricity contract, while the rest were randomly assigned to three different pricing regimes, including RTP. Customers in the RTP group were notified of price increases with a 24-hour notice, using a so-called *high price warning*. Wolak (2011) estimated the hourly average treatment effect of these high-price warnings for customers on RTP. In their treatment effect model, they included hour-of-sample time effects and household-specific fixed effects to control for consistent differences in the hourly electricity consumption between the households. They found that customers on RTP reduced their usage by 3% during high-price events compared to the control group (Wolak, 2011).

A more recent experiment was conducted by Hofmann and Lindberg (2024a) involving 3,746 Norwegian households. This experiment took place over four months, from December 1st 2021, to March 26th 2022, across five regions. The households were randomly assigned to either a control group or a treatment group, where the latter was exposed to various price signals. However, this was not a pure RTP experiment; the design of the price signals aimed to mimic real-time pricing and is therefore relevant for this review. To estimate the household response to the price signals, the authors employed a panel-data fixed-effect model. The researchers included both household-specific fixed effects and time fixed effects in their analysis. However, the household-specific fixed effects used in this study served a broader purpose than controlling for variations in average hourly consumption among different households, which requires just one fixed effect per household. Rather, this structure included 24 fixed effects per household, providing the necessary controls for how each household typically uses electricity at each hour of the day. The time fixed effects were included for each hour in the dataset and were defined separately by region to control for external influences (e.g., weather) that affect electricity demand and differ between regions. The study found that average electricity demand across all price signals in peak hours was significantly lower, and the treatment group reduced their electricity consumption by 2.92% on average, compared to the control group. Hofmann and Lindberg (2024a) further found that when the price signal had a short peak price period and when the price signal exceeded 15 NOK/kWh[2], the household response increased. Therefore, this study demonstrates that households can and will manually respond to price signals, although the effect is limited. To fully exploit this potential, the authors recommend providing clearer price information and investment support schemes to incentivise the uptake of automation technologies that can enhance household price responsiveness.

The current section has demonstrated that consumers do respond to higher prices during peak hours. However, the magnitude of the response is generally small without supporting technologies. Most of the existing evidence comes from experimental studies, with a strong focus on TOU and CPP pricing, while studies that explore RTP remain limited. However, the RTP studies that were reviewed in the current section show that consumers respond to RTP-based strategies.

It is worth emphasising the advantages of panel data, as is the case for studies presented in

[2]NOK = Norwegian krone, the currency of Norway.

the current section. Panel datasets track multiple entities (such as households) over two or more time periods. This allows for examining trends across both time and entities. Furthermore, a panel dataset enables fixed-effect regression, making it possible to control for unobservable time-invariant variables. This is not possible in a cross-sectional dataset, which includes multiple entities at one point in time, where omitting relevant variables causes omitted variable bias (Stock & Watson, 2019).

2.2.6 Limitations of the Traditional Economic Theory

To close this discussion on the viewpoint of conventional economic theory, it is important to highlight the limiting assumptions of the traditional economic model. These are often criticised as being unrealistic by behavioural economists and psychologists. In particular, there are three core assumptions that distinguish the rational, utility-maximising *homo economicus* from the ”irrational” individual that is often studied in psychology (Jolls et al., 1998; Mullainathan & Thaler, 2000).

The first assumption is *unbounded rationality*. This refers to the idea that individuals have perfect information, can process it, and identify an optimal choice. Behavioural economists and psychologists challenge this notion and instead propose the concept of *bounded rationality*, first proposed by Herbert Simon (Jolls et al., 1998; Mullainathan & Thaler, 2000). Bounded rationality recognises that individuals are not only constrained by external factors (e.g., market prices and income) but also constrained by internal limitations such as knowledge and cognitive capacity (Simon, 2000). As a result, people often make decisions that are satisfactory instead of optimal, because they are unable to evaluate every possible option or outcome (Simon, 1956).

The second assumption is *unbounded willpower*. This assumption is related to the belief that once the optimum choice is identified, individuals will consistently choose it. This assumption is also contested, since individuals often make decisions that are not good for them in the long term. Even though they know what is the best option for them, they sometimes fail to choose it because of a lack of self-control. For example, people often eat too much or exercise too little, even though they know that it is not the best option for them (Jolls et al., 1998; Mullainathan & Thaler, 2000).

The third assumption is *unbounded self-interest*, which holds that individuals are primarily driven by self-interest and act to maximise their own utility. This, too, has been challenged because people often make selfless decisions and act in ways that benefit others or society at large (Jolls et al., 1998; Mullainathan & Thaler, 2000). This final assumption is particularly relevant when studying pro-environmental behaviour such as reducing electricity consumption during peak hours. These behaviours often involve personal sacrifice for collective benefit and therefore cannot be fully explained by traditional economic models. Therefore, it is important to consider alternative perspectives, such as those offered by environmental psychology, that address these limitations.

2.3 Environmental Psychology

Environmental psychology addresses psychological factors that are often overlooked by traditional economic models focused on rational and cost-benefit calculations. This field considers the complex interaction between the environment and humans (Kollmuss & Agyeman, 2002). Environmental psychologists study how effective different behaviour change strategies are in encouraging people to act pro-environmentally. To realise their analyses, they examine people's values, perceptions, actions, and attitudes (Abrahamse, 2019). This field of research acknowledges that although money is a very important driver of energy conservation behaviours, people are often motivated by things other than those that benefit themselves, such as financial gain or comfort (Abrahamse, 2019). As Steg (2023a) argued, when it comes to acting environmentally, people are not solely motivated by financial rewards or something that benefits their self-interest. This is, however, often assumed and therefore implied that to motivate people to act in pro-environmental ways, there is a need for external incentives, such as subsidies or rebates (Steg et al., 2015). Indeed, real-life examples show that money is an important driver of energy behaviour. One such example is the 2022 European gas crisis, where surges in gas prices led many households to reduce their energy usage. For example, in the Netherlands, household gas use dropped by 25% compared to the previous year, with many households reporting that they lowered their thermostat or took shorter showers to cut costs (Luther, 2022). However, in contrast to what many believe, people do not only participate in pro-environmental behaviour when it benefits themselves. Research has shown that people also care about the collective well-being of others, and people often choose to act pro-environmentally even when it is costly or inconvenient (Steg, 2023a).

It is helpful to distinguish between intrinsic and extrinsic motivation to understand why this is the case. Intrinsic motivation is rooted in the values and identity of the individual. For intrinsically motivated people, the motivation to participate in a particular behaviour comes from within. Therefore, these individuals do not need external rewards (i.e., financial incentives) because acting in line with their values and identity yields them intrinsic rewards and makes them feel good (Steg, 2023b; Steg et al., 2018). Intrinsic motivation is long-lasting and self-sustaining (Steg, 2023a), and is particularly important for stable pro-environmental behaviour. This is especially the case when the motivation is driven by a sense of moral obligation (obligation-based), rather than by the enjoyment of the behaviour itself (enjoyment-based) (Steg et al., 2016). On the other hand, motivation can also be extrinsic. In this scenario, individuals are motivated by external rewards or outcomes, rather than internal values or beliefs (Steg et al., 2018). In contrast to intrinsic motivation, extrinsic motivation is generally not a stable driver of sustainable energy behaviour (Steg et al., 2018).

To better understand where intrinsic motivation comes from and how it contributes to stable environmental behaviour, it is essential to further explore the role of individual values.

2.3.1 Values

Personal values are broad life goals that people aim to achieve. Values remain relatively stable over time, guide actions in various situations, and influence beliefs and behaviours (Bouman et al., 2018). A widely used framework to understand personal values is Schwartz's value theory (Steg & De Groot, 2012; Steg, Perlaviciute, et al., 2014). According to his theory, values can be clustered into a two-dimensional structure. The first dimension contrasts values associated with openness to change versus values that are associated with conservatism (i.e., preference for tradition and conformity). The other dimension contrasts *self-enhancement* values, which focus on personal interest, with *self-transcendence* values, which focus on the welfare of others(Steg & De Groot, 2012; Steg, Perlaviciute, et al., 2014). Values farther apart in the two-dimensional value space are more likely to conflict, and values closer are more likely to be compatible (Steg & De Groot, 2012). Schwartz's theory is widely used in environmental psychology research, particularly the self-transcendent versus self-enhancement dimension (Steg, Perlaviciute, et al., 2014). In this context, four types of personal values are considered particularly important in influencing energy behaviour and are among the most affected by climate action initiatives (Bouman et al., 2018; Steg, 2023b; Steg, Perlaviciute, et al., 2014; Steg et al., 2018). These values are *biospheric* and *altruistic*, which fall under the self-transcendence dimension, and *egoistic* and *hedonic* values, which fall under the self-enhancement dimension.

Hedonic values are concerned with emotional well-being and comfort. They make people strive to minimise effort and improve their feelings (Bouman et al., 2018; Steg, 2023b; Steg et al., 2018). ***Egoistic values*** places an emphasis on how people's actions and choices affect their resources or status (Bouman et al., 2018). These values, therefore, make people focus on how to increase their resources, such as wealth (Steg et al., 2018). ***Altruistic values*** centre on concern for fair treatment and welfare of other people (Bouman et al., 2018). Finally, ***biospheric values*** involve concern for the environment and how actions and decisions affect nature (Bouman et al., 2018; Steg et al., 2018). These values motivate individuals to engage in behaviour that is good for the environment, such as preventing pollution (Steg, 2023b). The stronger the biospheric values, the more likely the person is to take part in pro-environmental behaviour such as saving energy and using more sustainable transport modes (Steg, 2023b). For example, individuals might decide to consume less during high price hours because they believe it would protect the environment (biospheric values) or they might consume less to save money (egoistic values). Furthermore, different types of values are also found to affect the level of flexibility in energy use that the individual is willing to adopt (Cucuzzella et al., 2022). Flexibility has been shown to serve both self-transcendence values (biospheric and altruistic) by using energy more efficiently and reducing environmental impact. It has also been shown to support self-enhancement values (egoistic and hedonic) by making people save money or reduce effort. However, flexibility has also been seen to conflict with self-enhancement values when it limits personal comfort and control. Therefore, these findings suggest that the level of flexibility that individuals are willing to adopt depends on these competing values (Cucuzzella et al., 2022).

All individuals endorse all four types of values, but the extent to which they endorse specific values and how they prioritise them differ (Cucuzzella et al., 2022; Steg, 2023b; Steg et al., 2016, 2018). This suggests that when individuals are confronted with decisions involving value conflicts (that is, values that are far apart in the two-dimensional space discussed earlier), they tend to base their decision on the value that they deem most important. As a result, people with different value prioritizations arrive at different decisions (Steg & De Groot, 2012). For example, it is more likely that an individual who prioritises biospheric values would buy expensive organic products than an individual who prioritises egoistic values. While the person who prioritises egoistic values also endorses environmental values, they are more likely to view these products as too expensive and not worth the expense. The key difference between the two is how they prioritise their values (Steg & De Groot, 2012). Furthermore, people with strong biospheric values and weaker egoistic values are said to be more aware of the negative consequences of their behaviour on the environment, which influences their actions and behaviour (Steg et al., 2015).

Although values reflect general long-term goals and influence decision making, they do not determine what motivates people in a specific situation. This is where motivation becomes relevant. In fact, in this thesis, the results will be labelled in terms of motivations as reported by participants in the survey. Motives are situation-dependent and drive immediate behaviour (Steg et al., 2016). Therefore, to fully understand the link between values and behaviour, one needs to make a distinction between stable values and context-specific motives. Goal-Framing theory is one useful theory that does this and provides insight into how values influence behaviour through the activation of specific motives, or *goal frames* as they are termed in the theory. The following section introduces the Goal-Framing theory and its main concepts.

2.3.2 Goal Framing Theory

To better understand how values influence behaviour in certain situations, it is helpful to consider the Goal-framing theory (Lindenberg & Steg, 2007). According to this theory, goals reflect what motivates people in particular contexts, and values affect what goal is prioritised in a specific situation (Steg et al., 2016). Therefore, people's actions and decisions are determined by the goal (motive) that is most important for them in a given situation (Steg et al., 2016). There are three overarching goals. First, **the hedonic goal** refers to the goal of making oneself feel better in a particular situation, for example, to avoid some kind of effort and seeking direct pleasure. Second, **the normative goal** refers to the goal of doing the right thing and doing what is appropriate in a given situation. Third, **the gain goal** is the goal of increasing one's personal resources or to prevent a decrease (Lindenberg & Steg, 2007; Steg et al., 2016). All of the goals affect how people make decisions, but for any given situation, one of these goals is the focal goal, referred to as *the goal frame* in the theory (Lindenberg & Steg, 2007; Steg et al., 2016). This goal will have a greater impact on how the individual acts, thinks, responds to information, and considers alternatives than the other goals (do Canto et al., 2023; Lindenberg & Steg, 2007; Steg, Bolderdijk, et al., 2014). The other goals (i.e, background goals) may either increase or decrease the strength of the focal goal. If the other goals conflict with the focal one, they decrease its strength, whereas compatible goals compound their strength (do Canto et al., 2023; Steg, Bolderdijk, et al., 2014).

According to the theory, the strength of each goal depends on the values that the individual prioritises (Steg et al., 2016). Each goal is supported by specific values: hedonic values align with the hedonic goal, egoistic values with the gain goal, and biospheric as well as altruistic values with the normative goal (do Canto et al., 2023). For example, individuals with strong egoistic values are more inclined to have a stronger gain goal compared to other goals. When the gain goal is dominant, individuals will focus on how their actions affect their personal resources and consider outcomes in terms of egoistic consequences, such as saving money. In contrast, individuals with strong biospheric values are more likely to have a stronger normative goal. When the normative goal is strongest, a person's behaviour is driven by a sense of doing what is right to do in a certain situation, such as protecting the environment (Steg et al., 2016). In the context of this thesis, when the household reports being motivated to reduce their electricity usage during high-price hours to save money on their electricity bill, this is interpreted as the gain goal being dominant. On the other hand, if the household reports being motivated to protect the environment, this is interpreted as the normative goal being dominant. This is based directly on participants' self-reported motivations, explained further in the Data chapter.

The relative strength of each goal also depends on situational factors (do Canto et al., 2023; Steg et al., 2016). These situational factors include cues and *symbols* in the environment. For example, normative symbols such as energy labels on household devices that inform consumers about energy efficiency can make people focus on the normative goal. In contrast, a symbol that emphasises the low price of a product can activate the gain goal by highlighting personal financial gain. Another situational factor is that people are often influenced by what other people around them are doing. For example, observing others violate social norms and not acting appropriately can weaken the normative goal of the individual in a given situation. The perceived cost of a behaviour is another situational factor that influences which goal becomes dominant. When a behaviour is seen as too costly, the gain goal can become stronger and push other goals to the background. This can even happen for individuals with strong biospheric values, where the increased strength of the gain goal pushes the normative goal to the background (Steg et al., 2016). To summarise, these situational factors explain why, in certain situations, individuals do not act according to their values that they prioritise and why individuals' preferences can differ across different situations (do Canto et al., 2023; Steg et al., 2016).

The relationships between the primary constructs of the goal-framing theory are depicted in Figure 2.6. Strategies to motivate pro-environmental behaviour often target the hedonic and gain goals of the individual (Steg et al., 2016). These strategies emphasise what the individual personally gains from participating in that behaviour. For example, real-time pricing schemes aim to motivate energy consumers to consume less during high-price hours and more during low-price hours because it is cheaper. However, research has shown that these

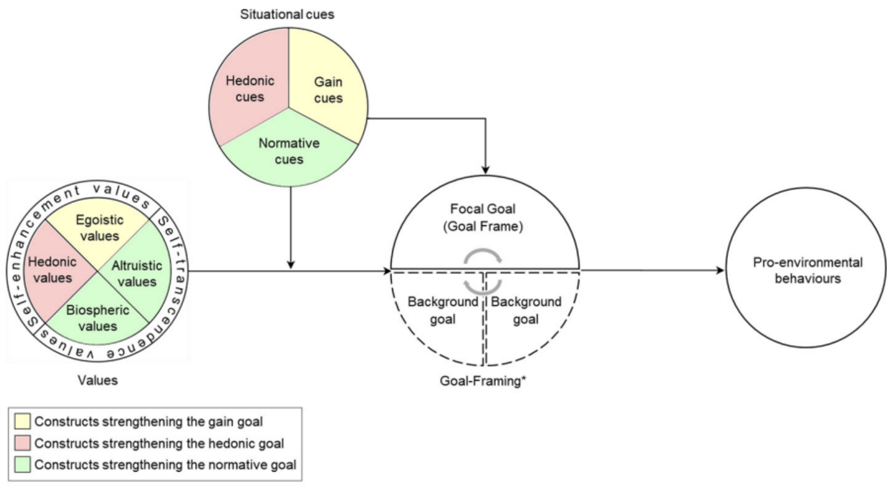


Figure 2.6: Visualisation of goal-framing theory. Reprinted from do Canto et al. (2023)

strategies are often not capable of encouraging stable pro-environmental behaviour because they limit people's focus to the personal benefits of the actions rather than what is considered the morally right action. This, in turn, strengthens hedonic and gain goals, making it possible for either goal to become the goal-frame and consequently reducing the influence of the normative goal (Steg, Bolderdijk, et al., 2014). Financial incentives can, therefore, shift people's decision-making from acting out of moral obligation to deciding to act based on what is to be personally gained (Steg et al., 2016). Therefore, this can cause those strategies to backfire. Research has shown that when hedonic and gain goals are strong, people will only participate in the behaviour when they consider it worth the effort. In contrast, this relation is less pertinent for people with strong normative goals (Steg, Bolderdijk, et al., 2014). This suggests that when strategies offer only small financial benefits, which is often the case for pro-environmental behaviour, emphasising the gain goal may not be effective since it can undermine the normative goal. Furthermore, the benefits are often too small to motivate actions on their own (Steg, Bolderdijk, et al., 2014). However, research has shown that strategies that offer small financial benefits can be successful when they can be seen as supporting the normative goal (Jakovcevic et al., 2014).

2.4 Research Gap

As previously mentioned, the RTP scheme utilises financial incentives to make household demand more flexible and react to the grid supply needs. It assumes that money is the most important driver in increasing residents' responsiveness and demonstrating demand-side flexibility. However, insights from environmental psychology show that individuals are not solely motivated to act pro-environmentally when it benefits themselves. Individual values play a key role in this determination. As covered in previous sections, the stronger the biospheric values a person has, the more likely they are to act in pro-environmental ways.

They act because it makes them feel good to act according to their values, and, therefore, they do not need external rewards. The link between values and behaviour is captured by Goal-framing theory, which posits that when the biospheric values are strong, the normative goal is more likely dominant, meaning actions are guided by a sense of doing the right thing rather than by, for example, financial gain.

Indeed, some studies have shown that financial motives are not always the strongest predictors of sustainable energy behaviour (Asensio & Delmas, 2015; Sloot et al., 2019). Sloot et al. (2019) explored what motivates people to be involved in community energy initiatives, for example, to invest in a local solar panel. In particular, they explored financial, environmental, and communal motives (e.g., engaging with the local community). They conducted three surveys in different neighbourhoods across the Netherlands, where information was collected about residents' motivations and indicators of involvement in community energy initiatives. The three surveys differed in terms of the stage of initiative development: the first one was conducted in a neighbourhood before it was launched, the second one was conducted in nine neighbourhoods shortly after launch, and the third one was conducted in 29 neighbourhoods where the initiative had been active for at least six months. They found that people reported financial and environmental motives as equally essential drivers for them to join the initiative, while communal motives were not ranked as critical. However, their analysis revealed that only environmental and communal motives were positively and uniquely related to different indicators of initiative involvement. Hence, suggesting that the importance of financial motives might sometimes be overrated.

Schwartz et al. (2015) examined how different framings of energy-saving program advertisements influenced the willingness and reasons for participants to join the program. They tested three types of advertisements. The first type emphasised monetary savings, the second type emphasised reduction of impact on nature, and the third type emphasised both. They found that an emphasis on monetary savings led to a significant decrease in willingness to join the program among participants compared to when environmental benefits were emphasised. They further found that participants were less likely to mention environmental concern when monetary savings were emphasised. This was also the case when environmental benefits were emphasised, in addition to financial savings in the advertisement. The authors point out that people often assume that monetary savings are a given in energy-saving decisions, and that their results suggest that if those monetary savings are emphasised too strongly, they might overshadow intrinsic environmental motivations. Therefore, it might be more effective to emphasise the environmental benefits of the program.

Asensio and Delmas (2015) performed a randomised control trial with 118 households, using real-time, appliance-level electricity data collected over eight months. Households were randomly assigned to one of three groups: the first one received messages regarding monetary savings, the second one received environmental and health-based messages, and the third group served as a control group. Using a difference-in-differences approach to estimate the treatment effect, they found that strategies that utilise environmental and health-based information are more successful in promoting energy conservation than those that utilise monetary saving information. They also found that the group that received messages related to health and the environment showed evidence of load shifting, whereas similar trends were not observed for people who received cost-saving messages. Based on these results, they note that when proposing conservation strategies, not only do price-based incentives need to be considered, but also incentives related to environmental or health reasons.

The different studies suggest that households respond differently to different incentives. However, it remains unclear if the personal motivation of households has a significant effect on a household's consumption during peak hours. Furthermore, it is not understood whether financial motives or environmental motives have a stronger effect on this behaviour. Taken together, this emphasises the gap in the literature that this thesis aims to address.

Beyond addressing the identified gap in the literature, this thesis makes several additional contributions. As reviewed in Section 2.2.5, most evidence on household responses to time-varying electricity pricing is based on experimental studies. In contrast, this thesis utilises observational data, providing a valuable alternative perspective. Experimental studies offer several advantages when studying household responses to variational pricing, such as being able to control the pricing signals. But they often rely on opt-in recruitment designs. For example, over 80% of the tested treatments in the meta-analysis by Faruqui et al. (2017) employ an opt-in recruitment design. As such, participants are aware that they are being observed and that their consumption data is being recorded. This may introduce a bias since the participants tend to be more aware of their energy consumption behaviour and showcase more conservative consumption as a result (Faruqui et al., 2017). This is referred to as the *Hawthorne Effect*, where individuals change their behaviour (typically leading to a perceived improvement) simply because they are being monitored (Perera, 2024).

Opt-in recruitment design can lead to other types of biases, for example *self-selection bias*. This occurs when individuals disproportionately choose to participate in a study, resulting in a sample that does not accurately represent the general population (Elston, 2021). Consequently, the results may be skewed toward a specific group of people. For example, Hofmann and Lindberg (2024a) acknowledges that their sample might suffer from self-selection bias since they employed voluntary participation in their study. Specifically, their sample might be skewed toward households strongly interested in electricity consumption, which might potentially inflate the observed level of demand response.

To minimise these biases, this thesis utilises observational data from households that are unaware of their consumption being monitored during the study period. This reduces the likelihood of both the Hawthorne effect and self-selection bias. Furthermore, this work studies a sample where the majority of households are exposed to RTP, which remains a relatively unexplored area (as per previous discussion in Section 2.2.5). To summarise, this thesis contributes to the limited RTP literature by providing insight based on real-world observational data, which distinguishes it from previous studies that are mainly experimental and limited to the analysis of CPP and TOU.

2.5 Context of the Study

This section provides a brief overview of the residential sector in Norway, outlines the structure of the country's power market, and discusses the unique context of the time period during which the data was collected that is used in this work.

Norway Residential Sector

As mentioned in Chapter 1, most Norwegian households have spot price contracts, and every household is equipped with a smart meter. Furthermore, households in Norway are highly electrified in their energy use. This makes the Norwegian residential sector uniquely positioned to monitor its electricity consumption and thus be flexible in its demand. However, this situation is not typical in all countries. Results from studies of the Norwegian market may therefore not generalise well to other countries that are not equipped with the same technology or the same capacity for flexible demand. As noted by Hofmann and Lindberg (2024a), research has shown that households that heat their houses with electricity and have electric vehicles have a higher response to varying prices of electricity than households that do not.

Norway is also one of wealthies country in the world, with a Gross Domestic Product (GDP)[3] per capita of 923,583 NOK ($\approx 83,000$ €) (Statistics Norway, 2025). With a population of around 5.6 million, the average yearly earnings are $704,700$ NOK ($\approx 60,000$ €) (Statistics Norway, 2025). In 2021, Norway was among the top three OECD countries in terms of median disposable household income [4](OECD, 2024). These economic factors are also important when considering the generalisability of findings to other regions.

Norwegian households typically use more electricity during the winter because of cold winters in Norway and the need for heating (Lee et al., 2022). This seasonal pattern is different from many other countries, where the electricity use peaks during summer due to air conditioning. For example, the majority of the studies in the meta-analysis conducted by Faruqui et al. (2017) were conducted during the summer period.

Electricity Generation and Market Structure

Norway is an energy-rich country which has access to an abundance of hydropower. In fact, most of the electricity produced in Norway is generated by hydropower. For example, in 2023, 89.1% of the electricity generation mix was from Hydropower (International Energy Agency, n.d.-b). Hydropower generation is determined by water inflow and installed capacity. However, since Norway has extensive water storage, they are largely able to mitigate this uncertainty in water inflows (International Energy Agency, 2022).

[3] A country's Gross Domestic Product (GDP) measures the aggregate income or value added produced by all inhabitants in a given year (Storm & Naastepad, 2021).

[4] Disposable household income is the amount of money a household has available to spend after paying direct taxes and social security contributions, and after receiving public cash transfers (OECD, 2024).

Norway is part of a Nordic power market along with Sweden, Denmark and Finland. As a result, Norway is also interconnected with several other European countries, for example, Russia and Germany (Norwegian Ministry of Energy, 2025). Although Norway is typically a net exporter of electricity, during the winter it relies on imports when water inflows are low (International Energy Agency, 2022).

Electricity is primarily traded through the *Nord Pool* power exchange, which handles more than 90% of the physical power trade in the region (International Energy Agency, 2022). The day-ahead market is the main market for power trading in the Nordic regions, and most of the trading in Nord Pool happens on this market. The day-ahead market determines the hourly electricity prices for the following day, and these prices form the basis of household spot price contracts (Norwegian Ministry of Energy, 2025).

Households in Norway do not all face the same electricity prices. Due to regional differences in weather conditions and limited transmission capacity, the country is divided into five bidding zones (Statnett, 2025):

- NO1 – Oslo
- NO2 – Kristiansand
- NO3 – Molde, Trondheim
- NO4 – Tromsø
- NO5 – Bergen

Figure 2.7 illustrates these zones. The southern regions (NO1, NO2, NO5) are highlighted in orange. Electricity conditions can differ significantly between the south and the north. This is because there is limited transmission capacity between the two regions. So, if there is a surplus production in the north, it cannot be easily transferred to the south. However, the southern regions have strong interconnection with Europe and therefore the prices in the south are linked to prices in continental Europe (International Energy Agency, 2022). The southern region of Norway was mainly affected by the European energy crisis, which is further discussed in the next section.

Unique Time Period: European Energy Crisis and the Pandemic

The dataset used in this thesis spans an unusual period, shaped by two major events: the European energy crisis and the COVID-19 pandemic.

Beginning in 2021, energy prices began to rise in Europe due to several factors. The energy supply was under significant pressure, driven by economic recovery after the pandemic, severe weather events, reduced investment in gas and oil production, and delayed maintenance. Additionally, Russia, one of the biggest exporters of fossil fuels, began to restrict gas supply to the rest of Europe, which further pushed up gas prices. The invasion of Ukraine by Russia escalated the situation into a broader European energy crisis. As the European Union imposed sanctions on Russia, gas supplies were further constrained, intensifying the crisis. Since natural gas often sets the marginal price in electricity markets, this led to

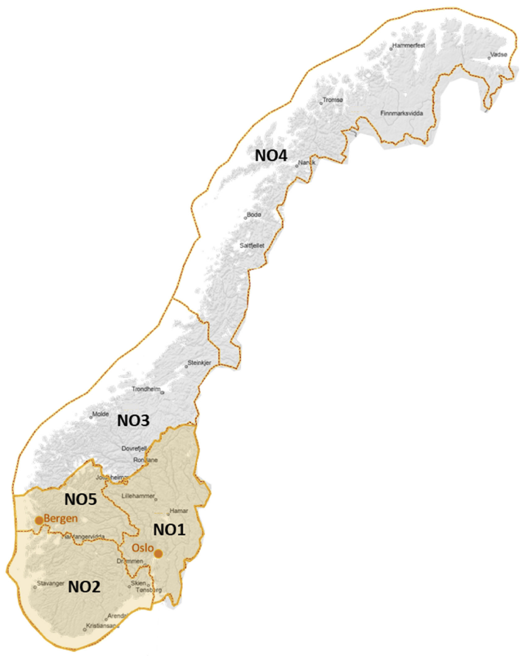


Figure 2.7: The five bidding areas of Norway. The southern part of Norway is highlighted in orange, where electricity prices increased following the European energy crisis. Reprinted from Hofmann and Lindberg (2024b)

a sharp increase in electricity prices across Europe (International Energy Agency, n.d.-a). Southern Norway (NO1, NO2, NO5) was mainly affected due to its strong interconnections with continental Europe and limited transmission capacity from the north (International Energy Agency, 2022). The situation was further worsened by low hydropower production in the North because of low precipitation (Hofmann & Lindberg, 2024b).

The period analysed in this thesis also coincided with the COVID-19 pandemic. During this time period, the Norwegian government issued policies designed to delay the outbreak of the virus (Government of Norway, n.d.). These include mandatory work-from-home policies and school closures, meaning that individuals were staying at home more than usual. This is important to keep in mind, as electricity consumption patterns during this period may not reflect normal conditions. However, the level of restrictions varied over time, and not all parts of the period were subject to strict lockdowns.

Chapter 3

Methods and Data

Quantitative analysis will be conducted to answer the questions posed in this thesis. This approach is appropriate as it allows for employing numerical data to analyse trends and estimate effects, central to this thesis. Regression models are estimated in the R programming language, employing a Norwegian dataset published in *Data in Brief* (Hofmann et al., 2023). The dataset comprises repeated hourly observations of individual household electricity consumption, along with data on household motivation to reduce their electricity consumption during peak hours, including both financial and environmental motivation. Section 3.1 introduces the methods used in the analysis and the econometric model employed in this research. Section 3.2 provides an in-depth description of the data. Section 3.3 presents detailed descriptive statistics of the main variables in the analysis, along with an in-depth examination of the primary groups studied.

3.1 Methods

To estimate whether different motivations (e.g., financial or environmental) explain whether and to what extent households reduce energy use in peak hours, an understanding of the effect of those motivational factors on peak hour consumption needs to be estimated. A multiple regression analysis provides a method to estimate this effect while controlling for other relevant factors that may influence consumption. However, the regression model must include all relevant variables to avoid omitted variable bias. One approach would be to run a cross-sectional regression, where one specific peak hour is selected in the dataset. Then, a comparison would be made between households with different stated motivations. That is, the regression model would be characterised as follows:

$$E_{peak_i} = \beta_0 + \beta_1 \times money_i + \beta_2 \times eco_i + controls_i + u_i \tag{3.1}$$

Where E_{peak_i} represents electricity consumption during the specified peak hour for a given household i, the variables $money_i$ and eco_i are binary variables equal to one if household i reports being financially or environmentally motivated, respectively. The term $controls_i$

represents all other relevant variables that may influence consumption. The regression coefficient β_1 can be interpreted as the average difference in electricity consumption during the peak hour for households motivated by financial reasons compared to those that are not. On the other hand, β_2 represents the average difference in electricity consumption for households motivated by environmental reasons compared with households that are not. Note that the group that is neither motivated by financial nor environmental reasons is represented by the intercept (β_0). This setup allows for the comparison between different motivational groups during the specified high peak hours. However, there are two things to note with this approach. First, the regression model must include all relevant variables to avoid omitted variable bias. Therefore, data on all *confounders*[1] that influence the dependent variable (here, peak hour consumption) need to be obtained. These factors include geographical, technological, and socioeconomic variables as discussed in Section 2.2.2. Obtaining data on the required controls can be challenging and sometimes unattainable. Second, this approach does not utilise the richness of the dataset. The dataset includes multiple households tracked over time and constitutes panel data. Therefore, performing *panel data analysis* constitutes a more detailed approach.

Fixed effect regression is a type of panel data analysis that addresses both limitations of the aforementioned cross-sectional method. First, it makes use of the whole dataset by incorporating repeated observations per household over time. Second, this approach allows for incorporating a household-specific intercept that absorbs all household-specific time-invariant factors (Stock & Watson, 2019). These household-specific intercepts are known as *entity fixed effects* and can be interpreted as the effect associated with belonging to a certain household (Stock & Watson, 2019). To put it differently, the entity fixed effect control for all variables that change between households but do not vary across time. Examples of variables that the fixed effect structure would account for are the insulation of the house, the type of appliances, or residential habits. Therefore, the need to control for any time-invariant factors that may influence the dependent variable is eliminated, thereby reducing the risk of omitted variable bias.

However, using fixed-effect regression brings about some challenges. Since household motivation is a time-invariant variable, its effect will be absorbed by the household-specific intercept. This means that it is impossible to estimate the direct effect of those variables on electricity consumption when using fixed-effect regression. This problem can be solved by interacting the motivation variables with a variable that varies with time. Therefore, it was decided to interact the motivation variables with a variable that defines what hours are peak hours. The peak hour variable varies with time, and therefore, the effect of the interaction between each motivational variable and peak hour will not be absorbed by the household-specific intercept. However, this method does come with a cost: it does not estimate the

[1] The term *confounder* comes from terminology used in the analysis of Directed Acyclic Graphs (DAGs). The term refers to variables that are associated with both the independent and dependent variables. These variables introduce an indirect association between the independent and dependent variables. Controlling for confounders closes the confounding (or *backdoor*) path, allowing for an unbiased estimate of the causal effect (Rohrer, 2018).

direct effect of motivation, but rather the difference in effect between groups. For example, suppose the group with financial motivation consumes 1 kWh less during peak hours and the reference group consumes 2 kWh less. In that case, the model estimates the 1 kWh difference between the groups but not their individual reductions.

Before presenting the baseline model in this work, it is essential to address the need to control for variables that are constant across households but vary with time, such as weather conditions and typical daily routines. This is essential as it prevents the analysis from being biased by these variables. This is done by adding *time-fixed effects* to the model (Stock & Watson, 2019). The model has a wide range of options when controlling for time. For example, it can control for variation across hours of the day, days of the week, and months, or even control for variation corresponding to every unique hour in the dataset (i.e., *full-time fixed effects*).

The baseline model in this work will include *year*, *month-of-year*, *day-of-the-week*, and *hour-of-day* fixed effects. These time-fixed effects capture general time trends that might bias the effect of motivational factors on peak hour consumption. The baseline model is given by:

$$\begin{aligned} \mathrm{E}_{it} &= \beta_1 \cdot \mathrm{peak}_t + \beta_2(\mathrm{money}_i \times \mathrm{peak}_t) + \beta_3(\mathrm{eco}_i \times \mathrm{peak}_t) \\ &+ \beta_4(\mathrm{both}_i \times \mathrm{peak}_t) + \alpha_i + \lambda_y + \tau_m + \sigma_w + \gamma_h + \varepsilon_{it} \end{aligned} \tag{3.2}$$

Here E_{it} represents electricity consumption for household i at hour t in the dataset. Variables $money_i$ and eco_i are the binary variables indicating whether household i is motivated by financial or environmental reasons. Furthermore, the variable $both_i$ is another binary variable that indicates whether household i is motivated by both financial and environmental reasons. The $peak_t$ variable is a binary variable indicating whether the hour is a peak hour. Note that the group that is neither motivated by financial nor environmental reasons is represented by the coefficient (β_1), which is the *reference group*. Household specific intercept is given by α_i, and the time-fixed effects are given by λ_y (year fixed effect), τ_m (month-of-year fixed effects), σ_w (day-of-week fixed effects), and γ_h (hour-of-day fixed effects). Lastly, ε_{it} is the error term that includes time-varying factors that are determinants of E_{it} but are not incorporated in the model as regressors (Stock & Watson, 2019).

Before moving on to the next section, which introduces the data used in this work, it is worth noting that the baseline model utilises the full sample of households with available consumption data. While it may seem reasonable to restrict the sample to only include households with spot price contracts (i.e., contracts that reflect price variation) or to periods with high electricity prices, such restrictions are less appropriate for households motivated by environmental reasons. Environmentally motivated households are expected to reduce consumption regardless of contract type or price incentives. Furthermore, as will be shown in the next section, the environmentally motivated group is very small. Therefore, if additional restrictions are imposed, the size of this group will be further reduced, thereby limiting the power of the analysis. Nevertheless, these dimensions, contract type and alternative periods will be explored in the robustness analysis section (Section 4.2). The dataset and the groups are further discussed in the next section (Section 3.2).

3.2 Data

Answering the main research question is fundamentally dependent on electricity demand data as well as data encapsulating what motivates households to decrease power consumption in high-price hours. The collection of electricity demand data is determined as an unfeasible strategy for the current work. So instead, data previously collected in Norway and made available in *Data in Brief*, an open-access, peer-reviewed journal, will be utilised [2]. The dataset was gathered to examine how households in Norway react to price shocks in electricity prices. It was part of the *iFlex* project by *Statnett*, the Norwegian transmission operator. The dataset (Hofmann et al., 2023) includes four types of data:

1. Survey responses from 4,446 households.
2. Hourly electricity consumption data from a subset of 1,136 survey respondents who consented to data collection.
3. Total hourly residential electricity consumption data per bidding area.
4. Day-ahead hourly electricity prices

Table 3.1 shows an overview of the main characteristics of each data type. In the current work, the main focus will be on the survey data, the individual electricity consumption data, and the electricity spot price data, which will be briefly introduced in the following sections.

Table 3.1: Overview of dataset characteristics, including sample sizes, observation counts, and recording periods. This table is adapted from table presented in (Hofmann & Lindberg, 2024b).

Data Type	Measurement Interval	Sample Size	Observations per Unit	Recording Period
Survey answers	N/A	4,446 households	1[a]	30.03.2022–03.05.2022
Individual electricity consumption	Hourly	1,136 households	13,128	01.10.2020–31.03.2022
Aggregated electricity consumption data	Hourly	5 bidding areas	27,048	01.07.2019–31.07.2022
Electricity spot prices	Hourly	5 bidding areas	27,048	01.07.2019–31.07.2022

[a] Each household completed one survey. The survey consisted of 35 questions, some of which allowed multiple responses, resulting in 106 response fields per household in the dataset.

3.2.1 Survey Data

The survey was conducted from March 30th to May 3rd 2022, via an online questionnaire by the research company *Ipsos*. The survey was sent out to a pre-recruited sample of households in the regions of Oslo (`NO1`), Trondheim (`NO3`), Tromsø (`NO4`), and Bergen (`NO5`), which correspond to different electricity bidding zones in Norway (Hofmann et al., 2023).

[2] https://www.sciencedirect.com/journal/data-in-brief

As discussed in Section 2.5, Norway is divided into five bidding zones to account for regional differences in electricity prices and supply. The survey was limited to four bidding zones, so one bidding zone, `NO2`, is not represented in the survey. However, as noted by Hofmann et al. (2023), the responses from the households in Bergen and Oslo should represent this missing bidding zone since both electricity prices and climate conditions are comparable.

A total of 4,446 households answered the survey, and Figure 3.1 shows the distribution of survey answers per region and the region distribution for the households with available consumption data. It can be seen that households that shared their demand data are only from Bergen (`NO5`) and Oslo (`NO1`). However, this should not be a concern, as only `NO1`, `NO2`, and `NO5` experienced a sharp increase in electricity prices, as discussed in Section 2.5. A total of 1,136 households had available and usable consumption data. As energy consumption data is essential to answer the research question, only these households are included in the proposed analysis.

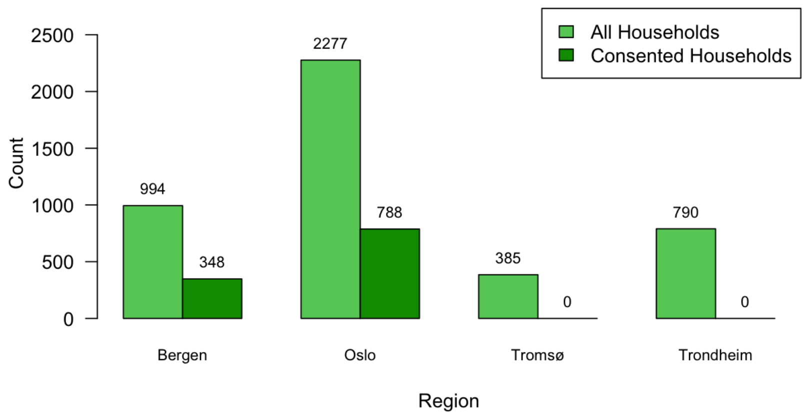


Figure 3.1: Distribution of survey respondents by region. The light green bars represent the total number of households that responded to the survey. The dark green bars represent the subset of those households that consented to share their electricity consumption data for analysis.

The survey collected sociodemographic information about the respondents, including age and gender, for example. Table 3.2 shows the distribution of these characteristics for the estimation sample. The sample includes a higher proportion of men than women (approximately 58% men vs. 42% women). Furthermore, the largest age group for the sample is people 65 and over, and the smallest age group is people between 18 and 24 years of age. Approximately 70% of the respondents are above the age of 45. The average age of survey participants is approximately 54 years. This relatively high average age is most likely because the head of the household answered the survey, leading to a higher mean age. Table 3.2 further shows that the vast majority of the survey respondents own their residence and only a small proportion is renting their home (approximately 11%). Furthermore, the majority of households have a spot price contract, accounting for 63.12%.

Table 3.2: Distribution of selected characteristics of surveyed respondents in the estimation sample.

Respondents characteristics	**Households (N = 1,136)**
Gender	
Male	660 (58.10%)
Female	476 (41.90%)
Age	
18 to 24	19 (1.67%)
25 to 34	138 (12.15%)
35 to 44	186 (16.37%)
45 to 54	227 (19.98%)
55 to 64	221 (19.45%)
65 or over	345 (30.37%)
Do you own the residence?	
Yes	1010 (88.91%)
No	126 (11.09%)
Spot price contract	
Yes	717 (63.12%)
No	419 (36.88%)

The survey collected additional sociodemographic information at the household level, such as combined income and the highest education in the household. Table A.1 in Appendix A shows the distribution of those characteristics for the analytical sample. The table also shows other information collected in the survey, such as the number of residents in the home, the type and size of residence, and whether the household owns an Electric Vehicle (EV). From the table, it can be seen that most households comprise either one or two occupants, have a combined income between 500,000-1,499,999 NOK/year ($\approx 43,000 - 130,000$ €/year), and have a high level of education. Furthermore, most households live in an apartment block, and a high proportion of households own an EV.

The survey also includes questions on household electricity consumption, motivation for reducing consumption, and awareness of electricity prices. A table listing these questions can be found in Table A.2 in Appendix A. Given the nature of the study, particular attention is given to the question exploring different motivations that people had for consuming less energy during high-price hours. In particular, the question that asks: ***"What motivates you to reduce your power consumption in high-price hours?"***. This question was a multiple-choice question with eleven different answer options, addressing motivational factors such as environmental and financial ones. The answer options also included other types of motivations, and respondents could indicate if they were unsure about their motivation or not motivated at all (e.g., *"I don't know"* or *"None of the above"*). Figure 3.2 shows the distribution of responses to the question.

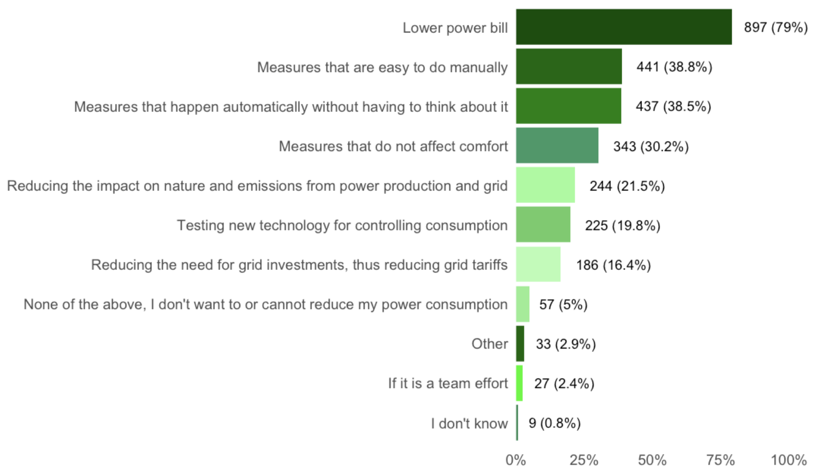


Figure 3.2: The distribution of household responses to what motivates them to reduce power consumption during high price hours (multiple choices allowed).

This survey question serves as the basis for classifying household motivations in the proposed regression analysis and creating the groups that the current work is interested in analysing. The answer option *"Reducing the impact on nature and emissions from power production and grid"* is used to capture the environmental motivation, and the answer option *"Lower power bill"* is used as an indication of financial motivation. Since this was a multiple-response question, respondents could select more than one motivation for reducing their electricity consumption during high-price hours. For example, 897 chose the financial motivation. Among those who selected this option, 215 individuals indicated it as their *only* motivation. On the other hand, a total of 244 households selected the environmental option, but only nine respondents chose it as their sole motivation. The households were split into groups based on how they responded to the motivational question.

Figure 3.3 shows how households were grouped based on how they answered the motivational question and if they selected the environmental option, the financial option, both of them, or neither. As a result of this design, there are four groups: `Monetary`, `Eco`, `Both`, and `Reference`. The `Reference` group contains households that selected neither the financial nor the environmental option. Each cell in the matrix represents one of these four groups. The number in each cell indicates the total number of households in that group, and the number in the parentheses reflects how many were only motivated by that specific motivation. Note that the groups are mutually exclusive in terms of their environmental and financial motivation. However, they are not strictly mutually exclusive in terms of other indicated motivations. This grouping focuses specifically on the two answer options relating to either a financial or an environmental motivation. Ideally, comparison would be made using respondents solely motivated by one motivation. However, given that the group solely motivated by environmental concern is very small ($N = 9$), the broader grouping is used to ensure sufficient sample size and meaningful analysis. Figure B.1 in the Appendix B shows the distribution of how many motivation options households selected (e.g., how many chose one, two, or more options), and the distribution of specific motivations among those who selected only one option.

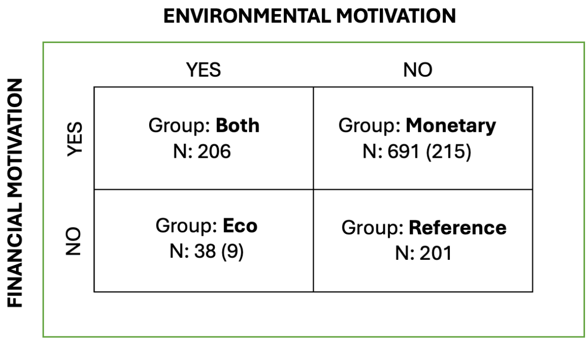


Figure 3.3: Overview of the four groups of the analysis. Each cell shows the number of respondents (N). Numbers in parentheses indicate those who selected only the corresponding motivation.

In the proposed regression analysis, these groups are captured by dummy variables, each corresponding to a different group. If a household falls into a specific group, they are coded as 1 for that specific dummy variable; otherwise, it is coded as 0. As a result, the model employs three dummy variables for representing the four groups, where the `Reference` group is, as the name suggests, used as a reference group. However, the primary focus of this analysis will be on the `Monetary` and `Eco` group. The creation of the `Both` group was performed to make the groups mutually exclusive regarding financial and environmental motivation.

3.2.2 Individual Consumption Data

The individual electricity consumption data was collected through smart meters from October 1st 2020, to March 31st 2022 (Hofmann et al., 2023). The electricity consumption data platform *Elhub* and local grid companies provided the data. In the survey discussed in the previous section, every respondent ($N = 4,446$) was asked if they consented to share their demand data. Out of all the survey respondents, $3,011$ households consented to share their data. However, data from many households were excluded due to the inability to match survey data to demand data, missing or duplicate values, and outliers. In total, $1,875$ households were excluded, and the final dataset for the demand data included $1,136$ households. The households that shared their demand data were from Bergen (`NO5`) and Oslo (`NO1`). Before proceeding, it is essential to note that the survey does not influence the demand data since the households were not aware that their electricity consumption data were being collected, since the survey was conducted after the time interval where the consumption data was collected (Hofmann et al., 2023).

Figure 3.4 shows the average hourly electricity consumption based on own calculations. The consumption patterns are plotted separately for winter and non-winter periods. The winter period is defined as November through March, following the approach used by Hofmann and Lindberg (2024b). The figure shows that consumption during the winter period is, unsurprisingly, significantly higher than in the non-winter period. Furthermore, the figure also shows that both curves follow a similar pattern, indicating that the daily shape of demand remains consistent across different seasons. This consumption pattern is expected, as it corresponds to a typical household routine where electricity usage peaks during the morning and early evening, when people are at home, but decreases during working hours, nights, and late evenings.

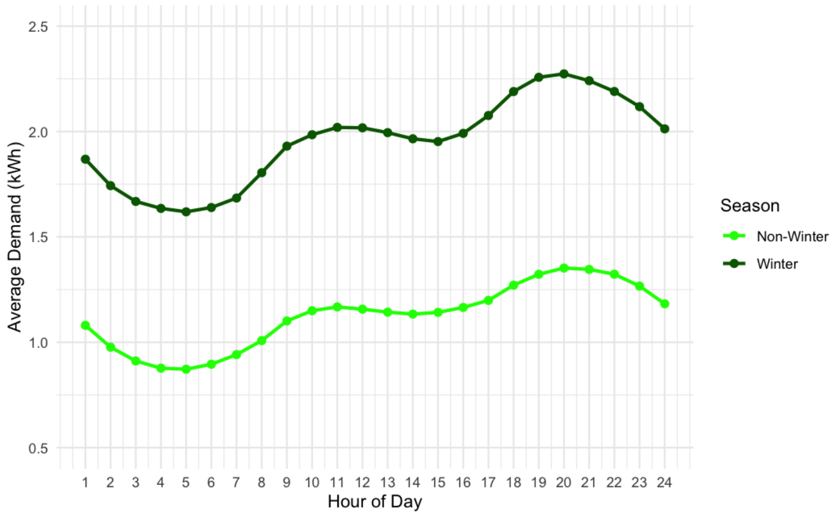


Figure 3.4: Average hourly electricity consumption, plotted separately for winter and non-winter periods.

To explore the difference in average consumption before and after the crisis, the average monthly electricity consumption was calculated across all households in the sample, combining data from both `NO1` and `NO5`. Figure 3.5 shows the average electricity consumption for each month of the collection period. In the figure, the winter period is highlighted in green (November to March), and the red dashed line indicates the point at which the price shock began (August 2021) (Hofmann & Lindberg, 2024b). The figure provides preliminary evidence [3] of a degree of energy conservation after the crisis, since the winter period following the price shock shows a lower peak in electricity consumption compared to the winter before the price shock. This can be clearly seen when the average hourly consumption before and after the crisis is compared. Figure 3.6 shows the average electricity consumption by the hours during the winter and non-winter period, both before and after the crisis. This figure demonstrates a similar trend as a result of the energy crisis: there seems to have been a reduction in the average consumption during the non-winter and winter months.

[3] The evidence is described as preliminary because it is based on descriptive statistics (i.e., average electricity consumption per hour) rather than formal statistical testing. To confirm that this observed conservation in electricity is due to the crisis, it is necessary to perform further analysis and statistical tests.

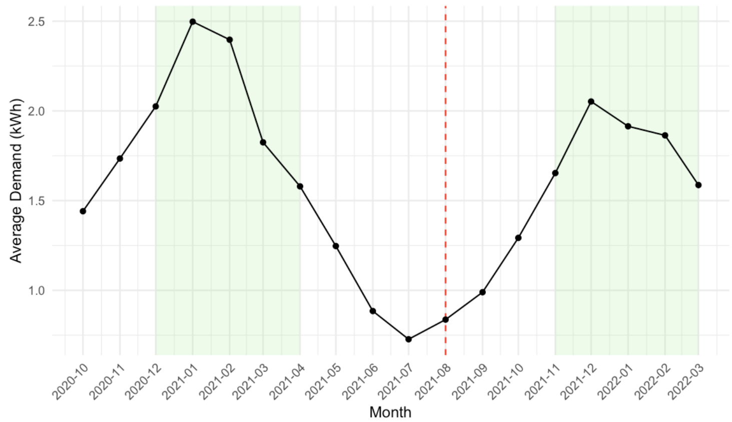


Figure 3.5: Average hourly electricity consumption by month, with the winter period (November to March) highlighted and a red dashed line indicating the onset of the price shock.

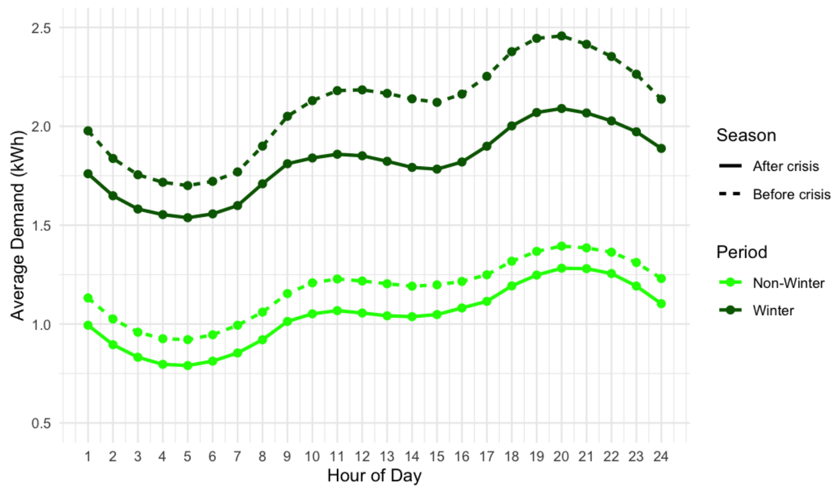


Figure 3.6: Average hourly electricity consumption by hour during the winter and non-winter periods, shown separately for the time before and after the crisis.

3.2.3 Price Data and Peak Hours Defined

Each of the five bidding zones' electricity spot price data was collected from July 1st 2019, to July 31st 2022. The price data was measured by the hour and retrieved from *Nord Pool* [4], which operates the leading power market in Europe and determines electricity prices in Norway (Hofmann & Lindberg, 2024b). Since the individual consumption data are limited to price zones `NO1` and `NO5`, the analysis of the price data will exclusively focus on those regions. Additionally, only price data from October 1st 2020, to March 31st 2022, will be employed, corresponding to the period during which the consumption data were collected.

[4]https://www.nordpoolgroup.com/

Figure 3.7 shows the average electricity price plotted per hour, separately for the periods before and after the energy crisis. The plots are further segmented by winter and non-winter periods. Therefore, four distinct periods can be considered: the non-winter and winter periods, both before and after the crisis. For each period, the four hours with the highest average price are indicated by red points. Different peak hours were defined for these periods because, as listed in previous sections, household consumption varied between them. These hours will be defined as the peak hours in the sample. Defining peak hours based on the price data is a valid design choice since the real-time pricing demand programs rely on energy prices to influence consumer behaviour. Table 3.3 gives a clear overview of the hours defined as peak hours for each period. In all periods except the non-winter period before the crisis, the peak hours include two hours in the morning and two hours in the evening. This is in line with the consumption pattern that was observed in the individual consumption data.

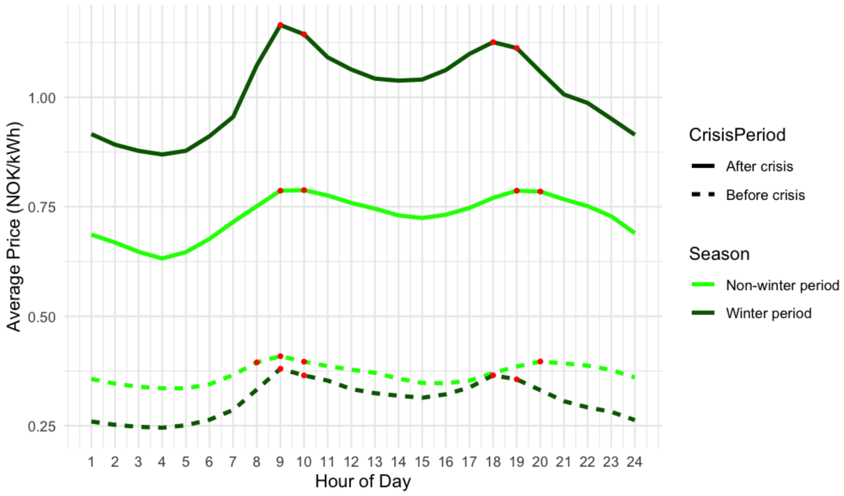


Figure 3.7: Average prices per hour before and after crisis, plotted separately for winter and non-winter periods. The top four most expensive hours per period are marked with a red point.

Table 3.3: Overview of what hours are defined as high price hours by time period.

	Before crisis	**After crisis**
Non-winter period	8,9,10,20	9,10,19,20
Winter period	9,10,18,19	9,10,18,19

Before proceeding to the next section, where the dataset and primary variable of interest will be further described, an alternative approach to defining peak hours is worth noting. This alternative definition will be used in the robustness analysis to test whether the baseline results are sensitive to how peak hours are defined. This approach follows the method used in Hofmann and Lindberg (2024b), who worked with the same data. They define an hour as a peak hour if the price of that hour (P_t) is at least 10% or 0.05 NOK/kWh higher than the average price of that day ($\bar{P}_d$). This yields a more sophisticated approach, in that it accounts for daily price fluctuations and only defines an hour as peak hour when there is a substantial deviation from the day's average price. This definition can be represented by the following equation:

$$\text{Hour}_t = \begin{cases} \text{peak hour}, & \text{if } P_t \geq \bar{P}_d + \max(0.05,\ 0.10 \cdot \bar{P}_d) \\ \text{off-peak hour}, & \text{otherwise} \end{cases}$$

3.3 Main variables and Descriptive Statistics

In Section 3.2, the data sources used to construct the main variables in the regression analysis were described. This included the survey responses, consumption data, and the spot-price data. Before turning to the descriptive statistics, it is worthwhile providing an overview of the main variables in the regression. Table 3.4 presents the main variables in the regression as well as their unit, label, and description. Although $Reference_i$ is included in the table for completeness, this variable serves as the reference group in the regression model. As such, it is not included as an independent variable in the regression model.

Table 3.4: Main variables in the regression analysis, including their labels, units, and descriptions.

Variable	Label	Unit	Description
Electricity consumption	E_{it}	kWh	Electricity consumed by household i during hour t
Peak hour dummy	$peak_t$	-	Equals 1 if hour t is a peak hour, 0 otherwise
Environmental motivation dummy	eco_i	-	Equals 1 if household i is environmentally motivated, 0 otherwise
Financial motivation dummy	$money_i$	-	Equals 1 if household i is financially motivated, 0 otherwise
Both motivations dummy	$both_i$	-	Equals 1 if household i is both financially and environmentally motivated, 0 otherwise
Other motivation dummy	$reference_i$	-	Equals 1 if household i is neither financially nor environmentally motivated, 0 otherwise

With the regression variables defined, the next step is to examine the descriptive statistics. Table 3.5 presents chosen descriptive statistics for the main variables used in the analysis. In the table, N represents the number of observations in the dataset, $i = 1,\ldots,n$ corresponds to n different households, and $t = 1,\ldots,T$ iterates over hours, where T is the total number of unique hours in the dataset. Note that the overall, between, and within statistics are only shown for the electricity consumption variable (E_{it}). The motivational variables are time-invariant, so including these statistics for them would be redundant. In other words, motivational variables are constant across time for each household. For the peak hour variable, this variable is constant across individuals. However, the electricity consumption variable varies with time and across households, making for a compelling analysis of between and within statistics as well.

Table 3.5: Descriptive statistics for the main variables used in the analysis.

Variable Label	Mean	s.d.	Min	Max	Observations
1. E_{it}					
Overall	1.582	1.603	0.000	19.638	N=14,913,408
Between households	-	1.153	0.104	5.867	n=1,136
Within households	-	1.113	–4.005	17.040	T=13,128
2. $peak_t$	0.167	0.373	0	1	N=14,913,408
3. eco_i	0.033	0.180	0	1	N=14,913,408
4. $money_i$	0.608	0.488	0	1	N=14,913,408
5. $both_i$	0.181	0.385	0	1	N=14,913,408
6. $reference_i$	0.177	0.382	0	1	N=14,913,408

Note: Electricity consumption (E_{it}) varies over time (t) and across households (i). The overall, between and within statistics are shown for that variable. N is the number of observations, n is the number of households, and T is the number of hours.

Table 3.5 shows that the overall electricity consumption ranged between a minimum of 0 kWh to a maximum of 19.638 kWh. This is a wide range, indicating high variability. The upper value of 19.638 kWh may, based on initial inspection, seem unusually high for a single hour. However, this level of consumption is plausible under certain conditions. Consider, for example, a household that is simultaneously (1) charging their EV, which typically draws between 7.4 kWh to 11 kWh; (2) operating high-power appliances, such as a washer, dryer, or a dishwasher; and (3) using electric heating (EVBox, n.d. Fjordkraft, n.d.). The high standard deviation of 1.603 compared to the mean of 1.582, shown in Table 3.5, further underlines the high variation observed in the data. Here, a few high outlier values of hourly electricity consumption positively bias the mean. For example, 95% of the electricity consumption data falls below 5 kWh and only a small proportion of the data has values over 10 kWh, or only 0.18 % of the sample.

The between statistics allows for a comparison of the means of each household with each other. Average hourly electricity consumption for each household in the dataset varies between 0.104 kWh to 5.867 kWh. Furthermore, the standard deviation is 1.153 kWh, indicating that the mean electricity consumption differs considerably between households. Lastly, the *within* statistics indicate how much, on average, the household deviates from its average consumption. The within-household standard deviation is 1.113 kWh, so the within-household variation is also substantial.

The other variables in the table are dummy variables. That is, the variables that indicate households' motivation (variables 3-6) and whether the hour is a peak hour. The proposed analysis focuses on the mean of these values, since the standard deviation is not informative for dummy variables. The mean value for a dummy variable indicates the proportion of the sample for which the variable takes the value one. From the mean values, it can be seen that approximately 60.8% of the sample falls into the `Monetary` group, 3.3% fall into the `Eco` group, 18.1% fall into the `Both` group and 17.7% fall into the `Reference` group. Since each household contributes the same number of observations (T is the same for each household), these proportions reflect the cross-sectional distribution of households across groups. It is interesting to note that a majority of the sample is motivated by money or financial reasons. Finally, for the peak hour variable ($peak_t$), 16.7% of the hours in the sample are defined as peak hours, corresponding to $4/24$ hours in a day being defined as peak hours.

3.3.1 Descriptive Statistics by Motivation Group

Here, a detailed coverage of the main groups of the analysis will be carried out to check whether some significant differences are observable between the groups. In Section 3.2.1, the sample was viewed as a whole, but here, the analysis considers separate groups. Table 3.6 shows some selected characteristics for each group of the analysis. The primary focus is on the `Monetary` and `Eco` groups, as in previous sections, where the other groups are included for clarity and reference.

Table 3.6: Selected characteristics of the surveyed respondents split by motivational group.

Characteristics	Monetary (N=691)	Eco (N=38)	Both (N=206)	Reference (N=201)
Gender				
Male	415 (60.1%)	18 (47.4%)	105 (51.0%)	122 (60.7%)
Female	276 (39.9%)	20 (52.6%)	101 (49.0%)	79 (39.3%)
Average Age	54.18 years	53.21 years	52.66 year	54.72 years
Residence Owner				
Yes	615 (89.0%)	37 (97.4%)	184 (89.3%)	174 (86.6%)
No	76 (11.0%)	1 (2.6%)	22 (10.7%)	27 (13.4%)
Spot price contract				
Yes	477 (69.0%)	17 (44.7%)	132 (64.1%)	91 (45.3%)
No	214 (31.0%)	21 (55.3%)	74 (35.9%)	110 (54.7%)

Gender Composition

From Table 3.6, the gender distribution of the groups can be seen. There appears to be a gender imbalance within the `Monetary` group, where roughly 60% of the group is male, whereas the `Eco` group reflects a more even gender balance. To test whether the gender distribution differs significantly between these two groups, a single linear regression was performed. The dependent variable in the regression was gender, coded as 1 for male and

0 for female. The independent variable was group membership, with households in the `Monetary` group coded as 1 and `Eco` group as 0. The regression coefficient for the independent variable represents the difference in the proportion of male respondents between the two groups, and the associated p-value indicates whether this difference is statistically significant. The regression included *heteroskedasticity robust standard errors* because the assumption of *homoskedasticity*: that the variance of the error term is constant across all values of independent variables (x), is rarely satisfied in real-world data (Stock & Watson, 2019).

Additionally, to assess whether the gender distribution differs significantly between the two groups and the `Reference` group, the same approach was used but with different group comparisons. In none of these experiments was the difference between genders statistically significant at the 5% level. These results can be seen in Table 3.7.

Table 3.7: Group comparisons in gender composition (percentage male), estimated via linear regression with robust standard errors.

Comparison (Group 1 vs. Group 2)	**Group 1** (% Male)	**Group 2** (% Male)	**Difference** (G1 – G2)	**Robust SE**	**p-value**
Monetary vs. Eco	60.1%	47.4%	12.7%	0.082	0.121
Monetary vs. Reference	60.1%	60.7%	-0.6%	0.039	0.871
Eco vs. Reference	47.4%	60.7%	-13.3%	0.088	0.131

Note. Differences are reported in percentage points. The heteroskedasticity-robust standard errors are based on the proportion differences estimated from the regression. The dependent variable is coded as one for male and zero for female. * p<0.05, ** p<0.01, *** p<0.001.

General Household Characteristics

From Table 3.6 it can be seen that the average age is similar across all groups, or around 50 years of age, and that the vast majority of all groups own their residence.

As for the dataset as a whole, further exploration of the household characteristics by motivational group was also carried out. Table A.3 in Appendix A shows the distribution of those characteristics for each group of the sample. The table indicates that both the `Monetary` and `Eco` groups, as well as the `Reference` group, are predominantly composed of households with 1 or 2 residents living in apartment blocks. Furthermore, a high proportion of all three groups reported being home more than 3 weekdays during the week on working hours in the winter period 2021-2022. However, in the `Eco` group and the `Reference` group, a significant proportion live in a residence of size $50\,\mathrm{m}^2$ to $99\,\mathrm{m}^2$, whereas the largest proportion of the `Monetary` group lives in residences of size $50\,\mathrm{m}^2$ to $159\,\mathrm{m}^2$. Finally, across the groups, a substantial proportion report owning an EV: 32.4% for the `Monetary` group and 26.32% for the `Environmental` group and 23.9% for the `Reference` group. This difference was tested using simple linear regression, with EV ownership as the dependent variable and group membership as the independent variable. The results showed that the 6.10% difference between the `Monetary` and `Eco` group was not statistically significant ($p = 0.41$). However, the difference of 8.5% between the Monetary and Reference group was statistically significant at the 5% level ($p = 0.015$).

Spot Price Contract Adoption

From Table 3.6, it can be seen that the majority of the Monetary group, approximately 70%, has a spot price contract. This is not the case for the Eco group and the Reference group, which reflects a more even balance between spot price contracts and alternative contracts. To test whether these differences between the groups are statistically significant, a single linear regression was performed. In addition to comparing the Monetary and Eco groups directly, comparisons between each of these groups and the Reference group were also conducted. The results can be seen in Table 3.8.

Table 3.8: Group comparisons in whether respondents have a spot price contract (percentage with contract), estimated via linear regression with robust standard errors.

Comparison (Group 1 vs. Group 2)	**Group 1** (% Spot Contract)	**Group 2** (% Spot Contract)	**Difference** (G1 – G2)	**Robust SE**	**p-value**
Monetary vs. Eco	69%	44.7%	24.3%	0.083	0.003**
Monetary vs. Reference	69%	45.3%	23.7%	0.039	0.000***
Eco vs. Reference	44.7%	45.3%	-0.5%	0.088	0.951

Note. Differences are reported in percentage points. The heteroskedasticity-robust standard errors are based on the proportion differences estimated from the regression. The dependent variable is coded as one for having a spot contract, zero otherwise. * p<0.05, ** p<0.01, *** p<0.001.

As shown in Table 3.8, the differences in the proportion of households with spot price contracts between the Monetary group and both the Eco group and the Reference group are statistically significant. The difference between the Monetary and Eco group is significant at the 1% level ($p = 0.003$), and the difference with the Reference group is highly significant ($p < 0.001$). In contrast, the difference between the Eco group and the Reference group is not statistically significant (p=0.951). These results indicate that there is a significant difference in the distribution of contract type between the groups. In particular, households in the Monetary group are more likely to have spot price contracts than those in the Eco group or Reference group. This makes intuitive sense, as people motivated by financial gain are expected to sign up for a spot price contract where they could save money by consuming less during high price hours. In contrast, those in the Eco group may aim to reduce consumption, regardless of whether they save or not, and therefore are less incentivised to have a spot price contract.

Income and Education Levels

Understanding differences in income and education levels between groups provides additional insight about the groups. Figure 3.8 shows the income distribution of the combined income of households per motivation group. This statistic is derived from the survey question asking about the combined household income. Overall, the distribution of combined income is relatively comparable across all groups, with some notable differences. For example, the `Eco` group has a notably high concentration in the 500,000-799,000 NOK/year bracket, or approximately 37%, whereas the `Monetary` group is spread more evenly across the income brackets. Furthermore, the `Eco` group has the highest proportion of households in the highest income group. However, it is essential to note that these statistics are based on combined income across households. That means that the differences between groups can also be attributed to household composition, specifically based on whether a household has a single or multiple income contributors.

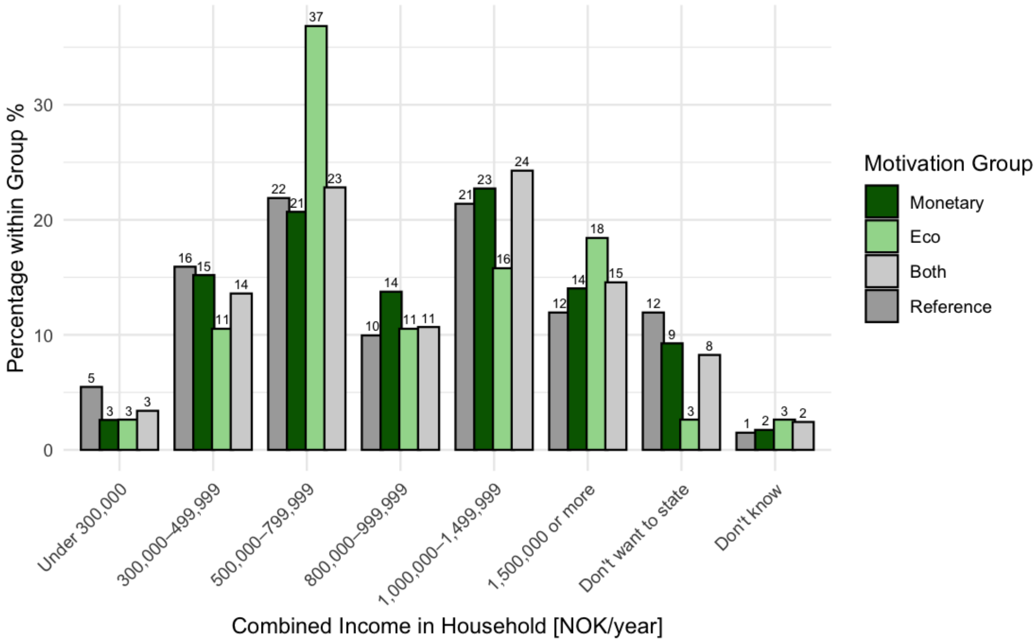


Figure 3.8: Income distribution by motivation group. Each bar represents the percentage of respondents within each motivation group who report a given combined household income level.

Figure 3.9 shows the distribution of highest household education level across motivational groups. This statistic is based on the survey question that asks about the highest level of education in the household. The figure illustrates clearly that the majority of all groups are concentrated in the higher end, which is associated with higher education. No group within the sample has a considerable proportion belonging to a low level of education. Each group, therefore, consists of households with relatively high levels of education. Here, the `Eco` group stands out and has approximately 68% of the group in the highest education category.

To test weather the observed differences in the proportion of households in the higher-degree category between the groups are statistically significant, simple linear regressions were conducted. Specifically, the analysis tested whether the 26% difference between the `Eco` group and `Monetary` group and the 33% difference between the `Eco` group and the `Reference` group were significant. Furthermore, the difference between the `Monetary` group and the `Reference` group was also tested. The results are displayed in Table 3.9,

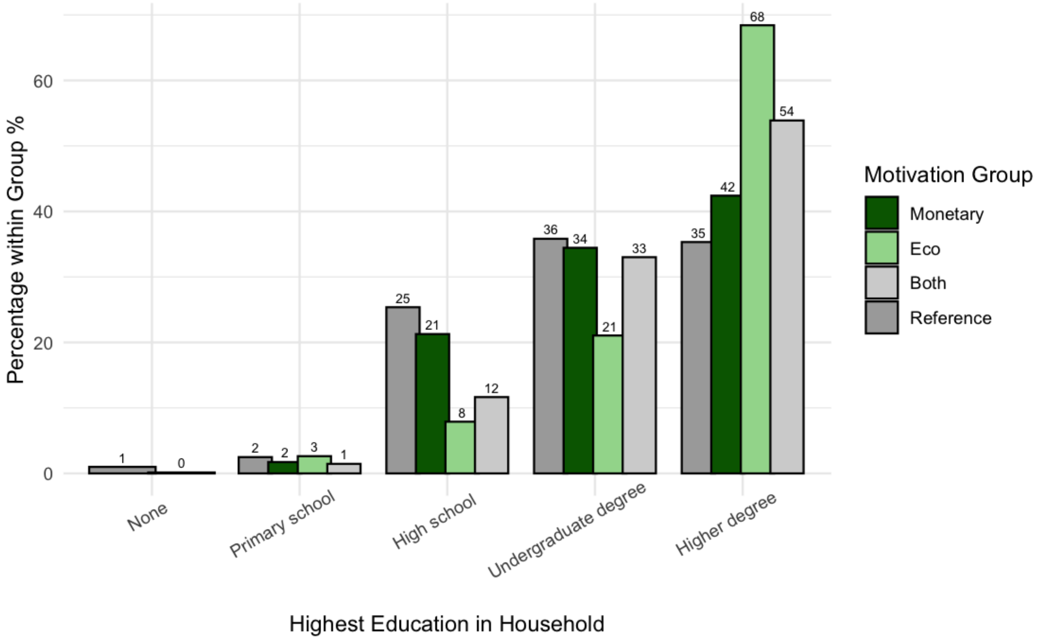


Figure 3.9: Education distribution by motivation group. Each bar represents the percentage of respondents within each motivation group reporting the given highest education level in their household.

and show that the difference between the `Eco` group and the other two groups are highly significant. However, the difference between the `Monetary` group and `Reference` group is not statistically significant. The fact that the `Eco` group is highly educated is in line with previous studies that have found a positive association between education level and environmental concern (e.g., (Meyer, 2015)).

Table 3.9: Group comparisons in whether households have a higher degree (percentage with higher education), estimated via linear regression with robust standard errors.

Comparison (Group 1 vs. Group 2)	**Group 1** (% Higher Education)	**Group 2** (% Higher Education)	**Difference** (G1 – G2)	**Robust SE**	**p-value**
Monetary vs. Eco	42.4%	68.4%	-26.0%	0.078	0.001***
Monetary vs. Reference	42.4%	35.3%	7.1%	0.039	0.067
Eco vs. Reference	68.4%	35.3%	33.1%	0.083	0.000***

Note. Differences are reported in percentage points. The heteroskedasticity-robust standard errors are based on the proportion differences estimated from the regression. The dependent variable is coded as one for households where the highest level of education is a higher degree, zero otherwise. * $p<0.05$, ** $p<0.01$, *** $p<0.001$.

Energy Monitoring and Behavioural Response

In addition to household characteristics and sociodemographic information previously discussed, it is also interesting to examine the respondents' answers to selected survey questions, which are listed in Table A.2 in Appendix A. The selected questions are listed in Table 3.10, along with the share of respondents of the `Eco`, `Monetary` group, and the `Reference` group that answered that question with a yes. These questions specifically refer to the winter period from November 2021 to March 2022.

Table 3.10: Share of "Yes" responses to selected survey questions by group (Monetary, Eco, and Reference).

Survey Question	Monetary (N = 691)	Eco (N = 38)	Reference (N = 201)
Did you monitor your power consumption this winter?	88.9% (N = 614)	57.89% (N = 22)	70.1% (N=141)
Did you monitor the variation in electricity prices from day to day and hour to hour this winter?	85.5% (N = 591)	63.2% (N = 24)	67.7% (N=136)
Did you take any measures to decrease or move power consumption from hours with high prices this winter?	86.5% (N = 598)	55.3% (N = 21)	52.2% (N=105)

Like illustrated in Table 3.10, the majority of the `Monetary` group answered all selected questions with a *yes*. That is, the majority of the `Monetary` group monitored power consumption, tracked variations in electricity prices, and took measures to decrease or shift their power consumption away from high-price hours during the winter period (November 2021 to March 2022). This is not surprising, given that the group is motivated by financial reasons and aims to save money on their electricity bill. To effectively do that, you need to monitor both your power consumption and electricity prices.

For the `Eco` group, more than half of the group answered all the questions affirmatively. Still, their level of monitoring and behavioural response is considerably lower than for the `Monetary` group. Over 60% of the `Eco` group monitored the variation in electricity prices even though this group is not motivated by cost savings on their electricity bill. At first, this might seem surprising, but the `Eco` group indeed needs to monitor the price variation to determine which hours are high-price hours, just like the `Monetary` group. However, their goals differ: while the `Monetary` group monitors prices to save money, the `Eco` group is presumably likelier to do so to identify peak hours to reduce consumption and minimise environmental impact. For the `Reference` group, more than half of the households answered all the questions affirmatively. The proportion of "Yes" responses was lower than in the `Monetary` group but higher than in the `Eco` group, except for the question on whether they took actions, where the `Eco` group had a slightly higher proportion.

To test whether the observed differences between the share of households that affirmatively responded to the selected survey questions across the groups are statistically significant, simple regression was performed as before. For each question, the difference between the groups was tested, and the results can be seen in Table 3.11. The results indicate that, for all three questions, the differences between the `Monetary` group and each of the two other groups are statistically significant. The table further shows that the difference between the `Eco` group and the `Reference` group is not statistically significant.

Table 3.11: Group comparisons in survey responses for three selected questions, estimated via linear regression with heteroskedasticity-robust standard errors.

Comparison (Group 1 vs. Group 2)	**Group 1** (% "Yes")	**Group 2** (% "Yes")	**Difference** (G1–G2)	**Robust SE**	**p-value**
Question: Did you monitor your power consumption this winter?					
Monetary vs. Eco	88.86%	57.89%	30.96%	0.081	0.000***
Monetary vs. Reference	88.86%	70.15%	18.71%	0.034	0.000***
Eco vs. Reference	57.89%	70.15%	-12.25%	0.087	0.157
Question: Did you monitor the variation in electricity prices from day to day and hour to hour this winter?					
Monetary vs. Eco	85.53%	63.16%	22.37%	0.079	0.005**
Monetary vs. Reference	85.53%	67.66%	17.87%	0.036	0.000***
Eco vs. Reference	63.16%	67.66%	-4.50%	0.085	0.597
Question: Did you take any measures to decrease or move power consumption from hours with high prices this winter?					
Monetary vs. Eco	86.54%	55.26%	31.28%	0.082	0.000***
Monetary vs. Reference	86.54%	52.24%	34.30%	0.038	0.000***
Eco vs. Reference	55.26%	52.24%	3.02%	0.088	0.732

Note. Differences are reported in percentage points. The heteroskedasticity-robust standard errors are based on the proportion differences estimated from the regression. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

The regression results provide an overall picture of how the groups differed in their responses. However, one pattern is worth noting: there appears to be a larger gap between monitoring and action (i.e., taking any measures) within the `Eco` group compared to the `Monetary` group. Of the `Eco` group, 62.2% monitored price variations, but only 55.3% took some measures. For the `Reference` group, this gap is even larger, with 67.7% reporting monitoring prices but only 52.2% taking measures. In contrast, 85.5% of the `Monetary` group monitored the price variation, and a slightly higher share (86.5%) reported taking measures. This could indicate that for the `Monetary` group, there is a more consistent link between awareness and action.

To investigate this further, the share of households that monitored prices but did not take any action was examined (Table 3.12). For the `Monetary` group, 7.67% of households monitored electricity prices without taking action. The proportion is higher in the other groups: 15.79% in the `Eco` group and 21.89% in the `Reference` group. Statistical tests show that the difference of 8.12% between the `Monetary` group and `Eco` group is not significant, while the difference of 14.2% between the `Reference` group and `Monetary` group is highly significant at the 0.01% level.

Table 3.12: Overlap between monitoring electricity prices and taking action to reduce or shift consumption from high-price hours, by group.

Category	**Monetary (N = 691)**	**Eco (N = 38)**	**Reference (N = 201)**
Both monitored and took action	77.86% (N=538)	47.37% (N=18)	45.77% (N=92)
Monitored only	7.67% (N=53)	15.79% (N=6)	21.89% (N=44)

Hourly Electricity Use

To conclude this review of the main groups of the analysis, the average electricity consumption by hour will be looked at in more detail and compared between the groups. Figure 3.10 shows the average consumption by hour for each group based on own calculations. Furthermore, the consumption patterns are plotted separately for winter and non-winter periods. As expected, all groups show higher consumption during the winter period than during non-winter periods. The figure shows that the average hourly consumption is highly similar between the `Eco` group and the `Reference` group. However, out of all four groups, the `Monetary` group has the highest average hourly consumption.

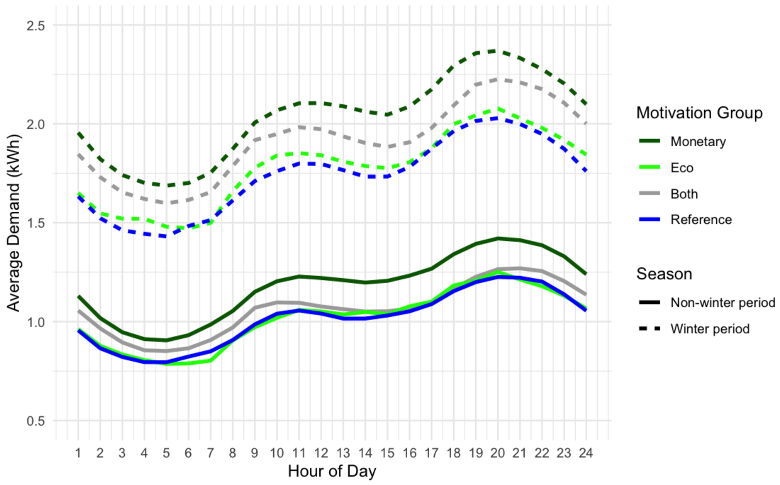


Figure 3.10: Average electricity consumption by hour by motivation group and season.

To further explore the difference in consumption between the groups, the average consumption during peak hours and all hours was calculated. This is depicted in Table 3.13. The `Monetary` group has the highest average consumption out of all groups, consuming approximately 14-17% more than the `Eco` and `Reference` group, across all periods.

Table 3.13: Average electricity consumption per hour by motivation group and season.

Hour type	Monetary		Eco		Both		Reference	
	Winter	Non-Winter	Winter	Non-Winter	Winter	Non-Winter	Winter	Non-Winter
Avg. per all hours [kWh]	2.04	1.18	1.78	1.02	1.91	1.06	1.74	1.01
Avg. per peak hour [kWh]	2.18	1.24	1.91	1.06	2.04	1.13	1.86	1.07

It can be seen that the `Monetary` group has a higher average electricity consumption than the `Eco` group and `Reference`, both during the winter and non-winter periods. However, from these results, it is not possible to conclude that the reported motivation drives this difference. Other factors might explain the gap. For example, the `Monetary` group might have more electric appliances, live in colder climates, or live in larger homes, as suggested in the earlier analysis. To isolate the effect of motivation itself, these factors need to be controlled for, as done in the regression analysis presented in the next chapter.

Chapter 4

Main Regression Results and Discussion

In the previous chapter, the methodology and the data used in this thesis were described. As listed in Chapter 3, fixed effect regression was performed using a dataset that includes individual household consumption data, motivational data, and data that defines hours as peak hours or not. The aim is to answer the research question: *Do financial and environmental motivations influence whether, and to what extent, households reduce electricity consumption during peak hours?* In the current chapter, the baseline results of the model are presented. Then, a robustness analysis of the baseline model is carried out. Finally, the chapter concludes with a discussion of the results.

4.1 Baseline Model Results

This section presents the regression results from the baseline model. As previously discussed in Section 3.1, the baseline regression includes all households in the dataset ($N = 1,136$), as well as the entire period of analysis, from October 1st, 2020, to March 31st, 2022. Therefore, the dataset included $13,128$ observations per household. Since there are $1,136$ households in total, the dataset includes $14,913,408$ observations. To reiterate, this route was chosen so the sample size of the `Eco` group would not be further restricted since it is already small.

Table 4.1 shows the regression results for the baseline model (see column 1). As discussed in section 3.1, the baseline model includes *year*, *month*, *weekday*, and *hour* time fixed effects. The baseline also includes unit fixed effects to control for time-invariant differences across households. The table includes additional entity and time fixed effect specifications. Specification (2) includes fewer time fixed effects, that is, it does not include the *hour* fixed effect. Specifications (3) and (4) include more granular fixed effects compared to the baseline. Specification (3) includes *region-time* fixed effects, which are time fixed effects that control for every hour in the dataset, uniquely so across regions, thereby controlling for differences based on weather conditions or other region-specific shocks. Specification (4) is the most granular and utilises the same time effects as (3), but also includes *hour-level* household fixed effects, following the approach taken by Hofmann and Lindberg (2024a). This fixed effects structure controls for the different load structures across households, as it includes 24 fixed effects per household.

Table 4.1: Regression results for the baseline model and additional specifications.

Dependent Variable: Electricity consumption per hour [kWh]				
Specifications:	(1)	(2)	(3)	(4)
Variables				
peak	0.0162	0.1136***	-	-
	(0.0130)	(0.0145)	-	-
peak × money	0.0143	0.0143	0.0129	0.0048
	(0.0161)	(0.0161)	(0.0160)	(0.0058)
peak × eco	0.0027	0.0027	0.0043	-0.0206*
	(0.0304)	(0.0304)	(0.0310)	(0.0095)
peak × both	0.0026	0.0026	0.0032	-0.0013
	(0.0188)	(0.0188)	(0.0186)	(0.0073)
Fixed Effects				
Unit	Yes	Yes	Yes	
Hour-level				Yes
Time Fixed Effects				
Year	Yes	Yes		
Month	Yes	Yes		
Weekday	Yes	Yes		
Hour	Yes			
Region-Time			Yes	Yes
Clustered SEs	Yes	Yes	Yes	Yes
Observations	14,913,408	14,913,408	14,913,408	14,913,408
$\bar{R}^2$	0.6267	0.6152	0.6441	0.6698

Notes: Standard errors clustered at the unit level are reported in parentheses. * p<0.05, ** p<0.01, *** p<0.001.

From the baseline model (1) in Table 4.1, it can be seen that the coefficient on the peak hour variable (*peak*) is positive and has a magnitude of 0.0162. This estimate corresponds to the coefficient β_1 in equation 3.2. Given this, and assuming that all other factors are constant, the `Reference` group consumes 0.0162 kWh more during peak hours relative to their off-peak usage. However, this coefficient is not statistically significant, which means that it is not possible to conclude that there is a significant difference in consumption during the specified peak hours and off-peak hours for the `Reference` group. As this specification includes hour-fixed effects, the model controls for any systematic pattern in electricity use at a given hour. In other words, this effect accounts for people's tendency to use more electricity during certain hours in the day. Therefore, what is left for the peak-hour variable to capture is any additional change in consumption specifically associated with the peak-hour classification, beyond what would normally be expected at that time of day.

The impact of removing the hour-fixed effect on the peak hour coefficient can be seen in specification (2) in Table 4.1. In this specification, the peak hour coefficient is statistically significant at the 0.1% level and has a magnitude of 0.1136 kWh. That is, during peak hours, the `Reference` group consumes 0.1136 kWh more than during off-peak hours while keeping all other factors constant. However, the model does not control for any systematic hourly consumption patterns, so the peak hour variable is picking up time-of-day variation that is unrelated to the peak hour definition. In other words, the coefficient reflects the regular daily variation in consumption rather than any behavioural response to peak hours. This, therefore, highlights the importance of including fixed effects that control for the hour of the day to make sure that the effect that is estimated is about the response to peak hours and not solely related to the time of day. For the other two specifications (3 and 4), the peak hour variable is omitted because it is collinear with the time fixed effects.

Next, the important coefficients on the interaction terms between the peak hour variable and the motivational variables are examined, specifically for ($peak \times money$) and ($peak \times eco$). These coefficients correspond to β_2 (financial interaction) and β_3 (environmental interaction) in Equation 3.2.

Beginning with specifications (1) and (2), it can be seen that neither the interaction between the peak hour variable and the financial motivation variable (*money*) nor the interaction with the environmental motivation variable (*eco*) is statistically significant. The estimated coefficients have standard errors that are as large as, or larger than, the coefficient values themselves. This indicates that there is a high degree of uncertainty around those estimates, and it is not possible to conclude that the difference between peak and non-peak consumption for the `Monetary` group or the `Eco` group is different from that of the `Reference` group. From Table 4.1, it can be further seen that the interaction terms remain stable across the first two specifications. However, when adding more granular time effects to the model (specifications 3 and 4), the coefficient on the interaction terms begins to change. In specification (3), *region-time* effects are added, so the model controls for anything that may vary as a function of region and time. That is, controlling for differences in weather conditions, the price of electricity, or any other time-varying regional shocks that might affect peak-hour consumption. However, in this specification, like the other ones, there are no significant results. However, when the *hour-level* fixed effects are added, the coefficient on the interaction for the `Eco` group becomes significant. In this specification, the model controls for each household's daily usage pattern. The coefficient on the environmental interaction is negative and has a value of -0.0206, which is significant at the 5% level. This indicates that, during peak hours, households in the `Eco` group use on average 0.0206 kWh less electricity relative to their off-peak usage, compared to the change observed for the `Reference` group, holding all other factors constant. Although this effect is statistically significant, it is very small in practical terms. When compared to the average hourly consumption for the `Eco` group across all hours, this effect corresponds to around a 1.5% decrease. To put this into perspective, this effect approximately corresponds to the electricity consumed by two typical LED light bulbs (0.010 kWh each) per hour (Marsh, 2024).

To look at how much variation the models explain, the $\bar{R}^2$ was also examined across the four specifications. The $\bar{R}^2$ value (the adjusted R^2[1]) is very similar across the four specifications. However, the highest value is obtained in specification (4) with a value of 0.6698. This value indicates that around 67% of the variation is explained by the model.

Before proceeding to the robustness analysis, it is essential to note that although specification (4) yielded a significant result for environmental interaction, it does not indicate any difference in consumption between the two main groups of interest (i.e. `Monetary` and `Eco`) during the specified peak hours. The same can be said for the other specifications, as no significant results were obtained.

4.2 Robustness of the Baseline Model Results

The baseline model results indicate that neither the `Eco` group nor the `Monetary` group changes its electricity consumption during peak hours in a way that is statistically different from the `Reference` group, except in specification (4) for the `Eco` group. However, it is important to verify the robustness of these results through a robustness analysis. There are multiple ways to perform such an analysis; one of which is running the model on different sub-samples of the dataset. In that case, robust results would be those that are similar to the original ones, across each sub-sample. In this scenario, the sample is first examined across different periods. Next, a subsample of households with spot price contracts is explored. Then the model will be run on the subset of households with a single motivation. Finally, the robustness of the results is evaluated against an alternative definition of the peak hour variable.

Before presenting the main results from the robustness analysis, one additional robustness analysis of the baseline results was conducted, which is not discussed in detail in this section. Specifically, the models were re-estimated using a dataset that excludes the weekends. The main motivation for testing this is that it is reasonable to assume that household load profiles differ significantly between weekends and weekdays. If such differences are substantial, then excluding weekends would allow the hour-fixed effect to capture a more stable and robust pattern, which may potentially affect the results. However, the results from this analysis showed that the baseline results remain robust even when weekends are excluded. A possible reason for this is that a large share of households in the dataset reported staying at home during working hours on more than three weekdays per week (as discussed in Section 3.3.1). As a result, the variation in load profiles between weekends and weekdays may be more limited than under normal circumstances. The results from this analysis are presented in Section C.5, Appendix C. Public holidays were also excluded in unreported regressions, with no effect on the results.

[1]Adjusted R^2 is a modified version of R^2 that accounts for the number of regressors. Unlike R^2, it can decrease when adding variables that do not improve the model fit, helping to avoid overestimating explanatory power (Stock & Watson, 2019).

4.2.1 Different Time Period

In this section, the robustness of the results is assessed across different periods. As shown in Section 3.2, average consumption varied between different periods. For example, the average consumption was higher during winter than in non-winter months. Furthermore, an analysis of the consumption data revealed that the average consumption was higher before the crisis compared to after it. The average hourly price for electricity was also shown to be significantly higher after the start of the crisis. In addition, as discussed by Hofmann and Lindberg (2024b), there was significant media coverage to educate households on how to change their electricity consumption and thus cut their electricity cost.

With all these factors in mind, it is plausible that households may not have acted before the crisis, or did so to a lesser degree, due to lower awareness and financial incentives. Therefore, it is essential to analyse whether the baseline results remain consistent across different periods. In total, four alternative periods were examined: 1) Winter period only, 2) The Period before the crisis, 3) The period after the crisis, and 4) Winter after the crisis. The results are presented in Table 4.2.

Table 4.2: Robustness of baseline results across different time periods.

Dependent Variable: Electricity consumption per hour [kWh]				
Specifications:	(1)	(1)	(1)	(1)
Periods:	Winter	Before the Crisis	After Crisis	After Crisis Winter
Variables				
peak	-	0.0466	-0.0050	-
	-	(0.0135)	(0.0143)	-
peak × money	0.0202	0.0152	0.0131	0.0099
	(0.0197)	(0.0168)	(0.0173)	(0.0209)
peak × eco	0.0151	0.0034	0.0020	0.0188
	(0.0382)	(0.0294)	(0.0343)	(0.0422)
peak × both	-0.0025	0.0151	-0.01301	-0.0212
	(0.0230)	(0.0203)	(0.0199)	(0.0238)
Fixed Effects				
Unit	Yes	Yes	Yes	Yes
Time Fixed Effects				
Year	Yes	Yes	Yes	Yes
Month	Yes	Yes	Yes	Yes
Weekday	Yes	Yes	Yes	Yes
Hour	Yes	Yes	Yes	Yes
Clustered SEs	Yes	Yes	Yes	Yes
Observations	8,233,728	8,288,256	6,625,152	4,116,864
$\bar{R}^2$	0.7036	0.6410	0.6233	0.6980

Notes: Standard errors clustered at the unit level are reported in parentheses. * p<0.05, ** p<0.01, *** p<0.001.

For each of these periods, the models have the same fixed effect structure as the baseline model in the previous analysis. It is important to note that in both the winter period model and the winter period after the crisis model, the peak hour variable is defined consistently across all households, making it collinear with the *hour* time fixed effects. Consequently, the peak hour coefficient has been excluded from those models. Alternative fixed-effects specifications were also tested for the post-crisis period, but none produced significant results, except for a small but statistically significant coefficient on the environmental interaction in specification (4). The results from these regressions can be found in Table C.1 in Appendix C.

The results from Table 4.2 show that the baseline results are robust across different time periods and that there is no significant difference in how the `Eco` and `Monetary` groups change their consumption during peak hours compared to the `Reference` group.

4.2.2 Spot Price Contract Households Subsample

To further investigate the robustness of the baseline results, a subsample of the data was analysed that included only households with spot price contracts. As noted in Section 3.2, 63.12% of the sample, totalling 717 households, possess spot price contracts. Among these households, 477 belong to the `Monetary` group, 17 to the `Eco` group, 132 to the `Both` group, and 91 to the `Reference` group.

This restriction (limiting the sample to households with spot price contracts) is especially relevant for the `Monetary` group since they only have a reason to change their electricity consumption if they are faced with a variation in electricity price. However, this is less relevant for the `Eco` group since they are expected to consume less during peak hour, irrespective of the electricity price. Nevertheless, the same restriction is applied to all motivational groups to facilitate easier comparison. This choice overlooks environmentally motivated households that do not have spot price contracts and may as well consume less during peak hours.

Results from Table 4.3 indicate that the model's outcomes are very similar when applied to the subsample of households with spot price contracts. The only significant result is obtained in specification (2), where hour-fixed effects are excluded from the model. The coefficient has a magnitude of 0.1305 and is significant at the 0.1% level, indicating that the `Reference` group consumes 0.1305 kWh more on peak hours than during off-peak hours while keeping all other factors constant. This value is of a similar magnitude to that obtained for the peak hour variable in the baseline regression results (see Table 4.1). However, as noted in Section 4.1, this specification does not account for any systematic hourly consumption patterns and therefore should be interpreted with caution.

Table 4.3: Robustness results using spot price contract subsample.

Dependent Variable: Electricity consumption per hour [kWh]				
Specifications:	(1)	(2)	(3)	(4)
Variables				
peak	0.0296	0.1305***	-	-
	(0.0227)	(0.0251)	-	-
peak × money	-0.0023	0.0023	-0.0024	0.0102
	(0.0264)	(0.0264)	(0.0264)	(0.0090)
peak × eco	0.0419	0.0419	0.0433	-0.0042
	(0.0553)	(0.0553)	(0.0560)	(0.0122)
peak × both	-0.0196	-0.0196	-0.0177	0.0002
	(0.0295)	(0.0295)	(0.0295)	(0.0106)
Fixed Effects				
Unit	Yes	Yes	Yes	
Hour-level				Yes
Time Fixed Effects				
Year	Yes	Yes		
Month	Yes	Yes		
Weekday	Yes	Yes		
Hour	Yes			
Region-Time			Yes	Yes
Clustered SEs	Yes	Yes	Yes	Yes
Observations	9,412,776	9,412,776	9,412,776	9,412,776
$\bar{R}^2$	0.6203	0.6092	0.6381	0.6644

Notes: Standard errors clustered at the unit level are reported in parentheses. * p<0.05, ** p<0.01, *** p<0.001.

From Table 4.3, it can be further seen that the interaction terms between the motivational groups and peak hour variable are statistically insignificant across all specifications. Considering the small sample size ($N = 17$), it is not surprising that the model does not yield any significant results for the `Eco` group. However, the `Monetary` group comprises a substantial number of observations, and the absence of significant results indicates that their change in electricity consumption from off-peak to peak hours is not measurably different from that of the `Reference` group. These findings suggest that even among households that are exposed to real-time pricing, neither financial nor environmental motivations appear to affect the change in electricity use from off-peak to peak hours compared to the `Reference` group. Thereby, the baseline results are robust when it comes to the type of contract that the household employs.

It can also be seen that the adjusted R^2 value increases slightly across the specification, where the highest value is obtained in specification (4) with a value of 0.6644; similar to what was obtained in the baseline regression. As an additional robustness test, the analysis was repeated for only the post-crisis period within the spot-price sample. Results remained consistent and are reported in Appendix C, Table C.2.

4.2.3 Single-Motivation Households Subsample

As an additional robustness check, a sub-sample of people who only reported one motivation for consuming less during peak hours was investigated. This is to see whether the results change when focusing on households that are exclusively motivated by a single motivation, and therefore ensuring that mixed motivations do not confound the effect. Figure B.1 in Appendix B shows the distribution of the selected motivations among households that chose only one option. From the figure and as previously seen in Section 3.2, there were in total 215 households that solely selected the financial option and only nine that selected just the environmental option. The figure further shows that there are a total of 351 households in the sample that selected only one motivation. Therefore, given the small sample size of the `Eco` group, the robustness test compares the `Monetary` group to the *other* households that did not report financial motivation, or $N = 136$ households. See Section B.1.2 in Appendix C for further details on this grouping. The results from the regression can be seen in Table 4.4, including four different specifications.

Table 4.4: Robustness results using single motivation sub-sample comparing the Monetary group to the rest (2 group specification).

Dependent Variable: Electricity consumption per hour [kWh]				
Specifications:	(1)	(2)	(3)	(4)
Variables				
peak	0.0064	0.0962***	-	-
	(0.0122)	(0.0141)	-	-
peak × money	0.0247	0.0247	0.0216	0.0172*
	(0.0202)	(0.0202)	(0.0201)	(0.0077)
Fixed Effects				
Unit	Yes	Yes	Yes	
Hour-level				Yes
Time Fixed Effects				
Year	Yes	Yes		
Month	Yes	Yes		
Weekday	Yes	Yes		
Hour	Yes			
Region-Time			Yes	Yes
Clustered SEs	Yes	Yes	Yes	Yes
Observations	4,607,928	4,607,928	4,607,928	4,607,928
$\bar{R}^2$	0.6147	0.6035	0.6331	0.6594

Notes: Standard errors clustered at the unit level are reported in parentheses. * p<0.05, ** p<0.01, *** p<0.001.

Results from Table 4.4 show that for specifications (1) through (3), the results remain consistent with the baseline results outlined in Table 4.1. In these specifications, the interaction between the financial motivation variable and the peak hour variable is positive and not statistically significant. However, for specification (4), the interaction between the peak variable and the financial motivation variable is statistically significant at the 5% level. The coefficient on the interaction is 0.0172. This indicates that, during peak hours, households in the `Monetary` group consume, on average, 0.0172 kWh more electricity relative to their off-peak usage, compared to the change observed for the `Reference` group, holding all other factors constant. This effect is smaller than the significant effect observed from the interaction between the environmental motivation variable and peak hour variable in the baseline results (see Section 4.1).

This effect approximately corresponds to the electricity used by 1.7 LED bulbs per hour. These results suggest that the baseline analysis may be influenced by households whose motivations were not purely financial or environmental. However, the obtained effect is minimal and therefore has limited practical relevance. Similar results were obtained when the same subsample was used and only periods after the crisis were tested. However, the previously significant interaction effect was no longer observed. For the regression results, refer to Table C.3 in Appendix C.

To further investigate households that reported on motivation, different groups were formed and tested to see if it altered the results. To reiterate, the regression represented in Table 4.4 compared the `Monetary` group to all other households that had only selected one motivation in the survey. However, an alternative grouping approach is possible, where the sample is split into a `Monetary` group, `Non-Monetary` group (households motivated but not for financial reasons), and `Unmotivated` group (people who selected an answer option that indicated that they are not motivated). Further explanations regarding this grouping can be found in Appendix B.

The results from this regression are presented in Table 4.5. For this alternative specification, just like the one previously described in the current section, the whole period was tested, as well as the period after the crisis. From these regression results, no statistically significant results were obtained for the interaction between the financial motivation variable and the peak hour variable. Therefore, it is not possible to conclude that the `Monetary` group's change in electricity consumption from off-peak to peak hours differs from households that are not motivated. Refer to Table C.6 in Appendix C to see the regression results for the period after the crisis.

Table 4.5: Robustness results using single motivation sub-sample comparing the Monetary group to Unmotivated group (3 group specification).

Dependent Variable: Electricity consumption per hour [kWh]				
Specifications:	(1)	(2)	(3)	(4)
Variables				
peak	0.0068	0.0967***	-	-
	(0.0196)	(0.0213)	-	-
peak × money	0.0243	0.0243	0.0223	0.0065
	(0.0257)	(0.0257)	(0.0256)	(0.0099)
peak × non-money	-0.0009	-0.0009	0.0012	-0.0207
	(0.0282)	(0.0282)	(0.0281)	(0.0112)
Fixed Effects				
Unit	Yes	Yes	Yes	
Hour-level				Yes
Time Fixed Effects				
Year	Yes	Yes		
Month	Yes	Yes		
Weekday	Yes	Yes		
Hour	Yes			
Region-Time			Yes	Yes
Clustered SEs	Yes	Yes	Yes	Yes
Observations	4,607,928	4,607,928	4,607,928	4,607,928
$\bar{R}^2$	0.6147	0.6035	0.6331	0.6594

Notes: The variable non-money is the group dummy for Non-Monetary group. Standard errors clustered at the unit level are reported in parentheses. * $p<0.05$, ** $p<0.01$, *** $p<0.001$.

It is worth noting that the subsample of single-motivation households that have spot price contracts were considered as well. This was done for both the 2-group specification and the 3-group specification. No significant results were observed on the interaction between the financial motivation variable and the peak hour variable. Refer to Table C.4 and Table C.7 in Appendix C to see the regression results.

4.2.4 Alternative Definition of the Peak Hour Variable

As a final robustness analysis, it was decided to look at an alternative definition of the peak hour variable. Specifically, to analyse whether a more price-dynamic peak variable would significantly alter the main results. As discussed in Section 3.2.3, the peak hour variable is defined from the four hours that have the highest average price for each period: the non-winter and winter periods, both before and after the crisis. But this approach does not account for intra-period price variation, thus it may fail to capture daily price dynamics. An alternative and more price-dynamic definition of the peak hour is where the peak hours are defined based on the average price for each day, following the approach of Hofmann and Lindberg (2024b). The results can be seen in Table 4.6.

Table 4.6: Robustness results using an alternative definition of the peak hour.

Dependent Variable: Electricity consumption per hour [kWh]				
Specifications:	(1)	(2)	(3)	(4)
Variables				
peak	0.0715***	0.1613***	-	-
	(0.0204)	(0.0211)	-	-
peak × money	0.0514*	0.0515*	0.0508*	0.0434*
	(0.0248)	(0.0249)	(0.0248)	(0.0206)
peak × eco	0.0070	0.0069	0.0077	0.0021
	(0.0533)	(0.0533)	(0.0535)	(0.0428)
peak × both	0.0307	0.0306	0.0309	0.0355
	(0.0311)	(0.0311)	(0.0310)	(0.0263)
Fixed Effects				
Unit	Yes	Yes	Yes	
Hour-level				Yes
Time Fixed Effects				
Year	Yes	Yes		
Month	Yes	Yes		
Weekday	Yes	Yes		
Hour	Yes			
Region-Time			Yes	Yes
Clustered SEs	Yes	Yes	Yes	Yes
Observations	14,913,408	14,913,408	14,913,408	14,913,408
$\bar{R}^2$	0.6271	0.6157	0.6441	0.6698

Notes: Standard errors clustered at the unit level are reported in parentheses. * p<0.05, ** p<0.01, *** p<0.001.

Table 4.6 shows that the findings are consistent with the baseline results, where there is no substantial and practically relevant difference between the groups. However, there are a few things about these results that differ slightly from the baseline results and warrant addressing. First of all, in this robustness analysis, in specification (1), the coefficient on the peak hour variable is positive and significant at the 0.1% level. This result can be attributed to the definition of peak hours used in this robustness analysis. Unlike the baseline, which uses a static definition, this model defines peak hours dynamically, based on daily price data. When controlling for systematic hourly consumption patterns, the model shows that housholds in the `Reference` group, on average, use 0.0715 kWh more during the defined peak hours compared to off-peak hours.

Furthermore, the results show that there is no significant difference in change from off-peak to peak hour consumption for the `Eco` group compared to the `Reference` group; an outcome consistent with the baseline results. However, for the interaction term between the financial variable and the peak hour variable, all four specifications result in a positive coefficient ranging from 0.043 to 0.051 kWh, all significant at the 5% level. That indicates that the `Monetary` group consumes, on average, around 0.05 kWh more electricity relative to their off-peak usage, compared to the `Reference` group. This is again a minimal effect, corresponding to the amount of electricity required to run approximately five LED bulbs for

1 hour. Overall, these results show that even when the peak hour variable is defined more dynamically and therefore reflects the electricity price more, there are no significant and practically relevant differences between the groups. For this specification, the period after the crisis was also tested and can be found in Table C.9 in Appendix C. Furthermore, the analysis of the subsample of only spot price contracts was also tested with this definition of the peak hours. The results confirmed the same conclusion: there is no significant difference in the change from off-peak to peak hour consumption when comparing the `Monetary` group to the `Reference` group and the `Eco` group to the `Reference` group. The regression results are presented in Table C.10 and C.11 in Appendix C.

In an unreported regression, a more stringent version of this dynamic definition of the peak hour was tested to check whether larger deviations from the daily average would have an effect. Instead of defining peak hours solely as those with prices at least 10% higher than the daily average, higher percentage thresholds were applied. As expected, stricter thresholds resulted in substantially fewer peak hours. For example, increasing the threshold from 10% to 50% reduced the number of peak hours from 2699 to 311. Thresholds above 50% would leave fewer than 100 peak hours per household and therefore were not tested. This pattern is evident in Figure 4.1, which shows the distribution of hourly price deviation from the daily mean, and Table 4.7, which lists the number of peak hours per region for each threshold. Specifications with thresholds between 20% and 50% were tested for both the full sample and the post-crisis period, for all households and also the subsample of spot price contract households. None of those resulted in significant deviations from the baseline results.

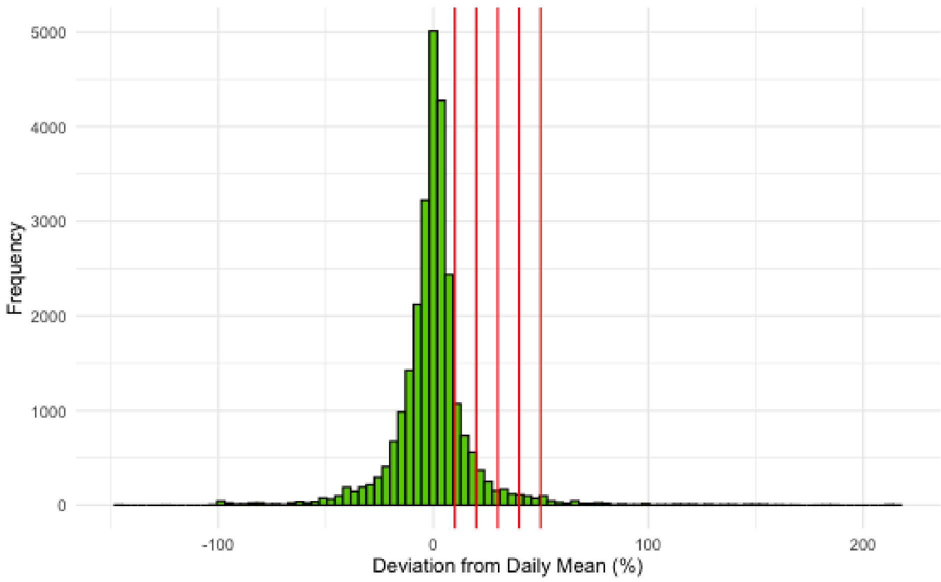


Figure 4.1: Distribution of hourly price deviations from daily mean. Red lines correspond to deviations of 10%, 20%, 30%, 40%, and 50% from the daily mean.

Table 4.7: Number of peak hours by threshold and price area.

Peak hour threshold	NO5	NO1	Total number of hours
10%	1298	1401	2699
20%	619	712	1331
30%	377	453	830
40%	236	292	528
50%	134	177	311
60%	98	138	236

Notes: Table reports the number of hours classified as peak hours under different percentage thresholds, by price area (NO5 and NO1) and in total.

4.3 Discussion

In the previous sections, both the baseline results and results from robustness analysis were presented. This section reflects on those results, summarises the main findings, and discusses the implications of those findings for this research. The current section begins with the summary and a discussion of the results for the `Monetary` group, followed by the `Eco` group. Then a general discussion about the results. Finally, the section concludes with a discussion about the main limitations of this work.

Monetary group

As evidenced by results previously reported in Table 4.1, households in the `Monetary` group do not appear to change their electricity consumption from off-peak to peak hours differently compared to the `Reference` group. These findings are consistent across the four specifications presented in the table, where each one corresponds to a different fixed effect structure. Notably, results in Section 3.2 showed that the `Monetary` group had higher baseline electricity consumption as well as higher consumption on average during peak hours. However, in the baseline regression, the difference between their peak hour and non-peak hour consumption was not significantly different from the same difference of the `Reference` group. In other words, the `Monetary` group's change in consumption from non-peak hour to peak hour was not statistically different from the `Reference` group.

The robustness analysis supported this conclusion. When the model is run on different periods and on the subsample of households that have a spot price contract, the coefficient on the interaction between the peak hour variable and the financial variable remained statistically insignificant. Two notable exceptions, however, were observed.

First, in the subsample of households that reported a single motivation, the coefficient on the interaction between the financial variable and the peak hour variable was statistically significant at the 5% level, with a value of 0.0172. This indicates that, during peak hours, households in the `Monetary` group consume, on average, 0.0172 kWh more electricity relative to their off-peak usage, compared to the change observed for the `Reference` group, holding all other factors constant. From a standard economic theory perspective, as reviewed in Section 2.2, one would expect financially motivated households to reduce their usage more during peak hours; however, the regression coefficient suggests the opposite. A possible interpretation of this result, based on environmental psychology, is that financially motivated individuals may only act when they perceive the financial benefit to be worth the effort (see Section 2.3). Perhaps, the financial benefit of the electricity bill was not worth the effort for the `Monetary` group. It is important to note that this significant effect was no longer observed during the period after the crisis. A plausible factor in this could be the fact that electricity prices rose significantly after the crisis; therefore, the `Monetary` group made an effort to reduce consumption, although not at a level higher than the reference group. Additionally, when the `Monetary` group was compared to the `Unmotivated` group in the 3-group specification, the interaction between the financial group variable and the peak hour variable was not statistically significant. So, neither during the whole period nor after the crisis was there any significant difference in the change from off-peak to peak hour consumption between the `Unmotivated` group and the `Monetary` group.

Second, when an alternative peak hour definition was applied to the full sample, the coefficient on the interaction between the financial variable and the peak hour variable was statistically significant at the 5% level, with a value of about 0.05. Similar results were obtained when looking at the post-crisis period, although the estimated effect was smaller (around 0.03). For this definition, the peak hours were defined more dynamically; therefore, they would require more flexibility and effort from households. From an environmental psychology perspective, it is plausible that financially motivated people found the added effort not worth the savings on the electricity bill, leading to a smaller reduction (or a greater increase) in consumption compared to the `Reference` group. This effect was not significant, however, when the subsample of spot-price households was analysed.

Eco Group

For the `Eco` group, the baseline regression results showed no significant difference in the change from off-peak to peak-hour consumption compared to the `Reference` group. However, when the model included hour-level fixed effects, which control for each household's load structure (specification 4), the coefficient on the interaction between the environmental group variable and the peak hour variable became significant at the 5% level, with a value of -0.0206. This finding persisted in the robustness analysis, when limited to the post-crisis period, suggesting some stability. Further robustness checks using specification (4) for different periods (e.g., the post-crisis winter or winter period) could not be conducted due to collinearity between the interaction term and the more detailed fixed effects.

However, it was tested whether this effect would remain when the model was constrained to the spot contract subsample. But this effect was not observed under these conditions, and the coefficient on the interaction between the peak hour variable and the environmental variable was insignificant. This may have been caused by the low representation of environmentally motivated households; an effect exacerbated when limiting the sample to spot price contract households.

To summarise, the results do not show any practically relevant difference between the `Eco` group and the `Reference` group. This may be a result of a hypothetical *floor effect*: the `Eco` group has already modified their consumption to the highest degree, and they can not perform any additional actions.

General Discussion

The results show that the `Monetary` and `Eco` groups reduced peak-hour usage neither more nor less than the `Reference` group. However, it is essential to reiterate that the model employed in this study does not estimate the absolute difference between the groups. Therefore, the model does not indicate whether each group consumed less during peak hours, but it does tell us the difference between the reductions. Thus, the results from this thesis do not exclude the possibility that all groups consumed less during peak hours. For example, if all groups in the analysis reduced the consumption by 1kWh, then the findings would be the same. The results of this thesis only indicate that the difference in baseline consumption and peak hour consumption between the groups is not statistically significant.

While a few specifications in the robustness analysis produced statistically significant interaction terms, they were all very small in size and therefore not deemed practically relevant. Furthermore, when running many regression analyses, it is not surprising that occasionally one gets a statistically significant effect by chance. Importantly, these occasional significant effects do not alter the main conclusion of this thesis.

It is also important to reflect on the possible introduction of a biasing effect in this thesis. Section 2.4 discusses the use of observational data, and how that reduces the possibility of *selection bias*, since experimental studies often employ an opt-in recruitment design. However, there is also a possibility that the data used in this thesis reflects some degree of selection bias. For example, households are asked ex-post if they are willing to share their demand data. The use of ex-post data can be beneficial because it eliminates observational bias. However, the fact that participants are asked to share their data after the fact does not eliminate the possibility that only those who behaved efficiently chose to share their information, while those who did not may have refused to share their data.

It is also relevant to reflect on the generalisability of the results of this thesis and whether similar results in other countries would be expected. Given that this work draws on research conducted by Dutch researchers, it is natural to ask whether the results based on Norwegian households would hold in the Dutch context. There are several similarities between the two countries: both are high-income societies, have well-developed electricity systems, ambitious climate targets, and strong environmental performance as reflected by the Environmental Performance Index (EPI) (Block et al., 2024; International Energy Agency, n.d.-b, n.d.-c).

However, notable structural differences may affect the generalisability of the findings. In

Norway, the residential sector relies predominantly on electricity to heat its houses and water, with electricity making up approximately 83% of total residential consumption (International Energy Agency, n.d.-b). On the other hand, in the Netherlands, the largest source of energy in the residential sector is natural gas, and electricity accounts for just about 20% (International Energy Agency, n.d.-c). This suggests that Norwegian households might have stronger incentives to reduce their electricity during peak hours, given that electricity constitutes a much larger share of their total energy consumption.

The carbon intensity of electricity generation also differs significantly between the two countries. Around 99% of Norway's electricity generation comes from renewable sources, predominantly hydropower (International Energy Agency, n.d.-b), while in the Netherlands, nearly half of electricity generation is from non-renewable sources, with natural gas being the largest contributor (International Energy Agency, n.d.-c). This means that in the Netherlands, environmentally motivated households might perceive greater climate benefits from reducing their electricity use during peak hours compared to their Norwegian counterparts. Conversely, financially motivated people in the Netherlands might be less motivated to reduce their peak-hour consumption, as electricity constitutes a smaller share of their energy bill. Taken together, this could indicate that the magnitude of the differences between the motivational groups might differ between the countries.

The collection period of the dataset used in this thesis is also worth noting. The period was marked by both an energy crisis in Europe and the COVID-19 pandemic. It is very possible that in more typical circumstances, the results would have been different. During this period, electricity prices were unusually high, and many people were spending more time at home. In addition, as discussed by (Hofmann & Lindberg, 2024b), there was substantial media coverage and public information campaigns on how to reduce electricity costs. Under normal conditions, when electricity prices are lower and there is little to no media coverage about reducing electricity consumption, financially motivated people might be less inclined to reduce their consumption, which would potentially result in a clearer difference between the motivational groups. Furthermore, in normal times (i.e., times not marked by COVID-19 restrictions), daily routines and electricity use patterns would differ and therefore potentially result in different results.

Limitations of Study

To close this chapter, the main limitations of the study are addressed.

The first limitation is related to the motivational survey question. The key variable used to capture the motivation of the households is based on a single question in the survey: *"What motivates you to reduce your power consumption in high price hours?"*. Importantly, this question allows the respondents to choose multiple options, directly acknowledging that individuals are often driven by more than a single factor. This aligns with insights from environmental psychology, in particular the Goal-framing theory, which suggests that in a given situation all three goals (i.e., the hedonic goal, the normative goal, and the gain goal) affect individual decision making (Lindenberg & Steg, 2007; Steg et al., 2016). However, the theory proposes that one of these goals is the focal goal, which is most influential in the decision making (Lindenberg & Steg, 2007). The survey question does not capture this nuance. The data alone is insufficient to make a determination of which motivation (or goal) is focal for each household. For example, suppose a household selected the environmental option, as well as three other answer options. In that case, there is no way to determine whether it was the dominant motive in the situation or whether it was the other motivation that the respondent selected.

The second limitation also relates to the motivational survey question and, in particular, who answers it. The motivational question in the survey was answered by a single household member. This might mean that the reported household motivation might not reflect the overall motivation of the household. Relying on the motivation of one person in the household to reflect the overall household motivational profile might be overly simplistic; the electricity consumption is shared among people who live in the household. Furthermore, since the motivational question was only asked once, this study assumes that household motivation remains constant throughout the entire analysis period. This may not be realistic since motivations can change due to changes in personal circumstances.

The third, and final limitation is the small sample size of the `Eco` group. Of the total 1,136 households in the dataset, 244 selected the environmental reason as one of their motivation. However, the vast majority of this group also selected the financial option (206 households), leaving the `Eco` group with only 38 households. This relatively small sample size increases the likelihood of Type II errors, which is the error of failing to detect an effect even if one exists (Columb & Atkinson, 2016). This highlights a significant limitation of the study when it comes to the `Eco` group.

Section 5.4 outlines potential avenues for future research to address these limitations.

Chapter 5

Conclusion

This chapter provides a concluding answer to the stated research question. The current work is then considered from a policy-based perspective, followed by a discussion of its scientific contributions. Finally, avenues for future research are listed, and the chapter is closed with a final reflection from the researcher.

5.1 Answering the Research Question

This work aimed to answer the following research question: *"Do financial and environmental motivations influence whether, and to what extent, households reduce electricity consumption during peak hours?"*. To answer this question, this work used a large dataset on 1,136 Norwegian households and performed fixed-effect regression. This method was used to see whether the change in electricity consumption from off-peak to peak hours for households motivated by environmental reasons or financial reasons differed significantly from the reference group.

The descriptive results showed that a greater proportion of the `Monetary` group than that of the `Eco` group claimed to decrease or shift their power consumption from high-price hours, as well as to monitor their consumption and electricity prices. However, from the calculated average consumption by the hour, the `Monetary` group had the highest average electricity consumption compared to the other groups, including the `Eco` group. Although this offers a valuable insight into the dataset, more detailed analysis through regression analysis is needed to conclude if motivation has an effect on electricity consumption when other relevant factors are controlled for.

Based on the regression results presented in Section 4.1 and 4.2, there is no consistent evidence that financial or environmental motivations substantially affect how household electricity consumption changes from off-peak to peak hours. Although some significant results were obtained — such as the `Eco` group when hour-level fixed effects are added to the model and the `Monetary` group when only a subsample of 1 motivation households are analysed — the results are not consistent across other specifications. Furthermore, both effects are notably small in practical terms. Given the lack of consistency and practical significance, the findings of this work do not support the conclusion that financial or environmental motivations meaningfully drive household electricity use during peak periods.

Although the obtained results do not confirm that either motivations substantially influence peak hour consumption, there is one noteworthy observation that emerges from the data that warrants further discussion. A tiny proportion of households in the subsample that selected only one motivation chose the environmental option: only nine households. This number is remarkably small compared to the number of households within the same subsample that chose the financial option. In fact, the subset of households that selected only one option within the `Monetary` group is nearly 24 times larger than for the `Eco` group, comprising 215 households.

This can be rationalised through the lens of Goal-framing theory. Because these households only selected a single motivation, it is reasonable to interpret their selected motivation as their focal goal (motivation) in this given context. Therefore, out of the 351 households that selected only one option, 215 chose the financial option as their focal goal. This is a large proportion of the subsample, approximately 61%.

As Section 2.3.2 addressed, the situational factors influence the relative strength of each goal. Therefore, the strong preference for the financial motivation option may result from the way demand response programs, particularly real-time pricing schemes, highlight the opportunity to save on energy bills. This emphasis is a type of situational factors that presumably activate *the gain goal*. In the next section, this finding will be discussed in more detail and what implications it may have for policy.

5.2 Implication for Policy

This work can not provide a definitive answer to policymakers on whether Demand Response (DR) programs are based on the correct assumptions and whether focusing on monetary incentives is the most effective approach. If the data had shown that the `Monetary` group reduced the consumption significantly more than the `Reference` group, it would have supported the current policy focus on financial incentives. This would then have offered an insight into whether focusing on financial motivation is an effective strategy. On the other hand, if the `Eco` group had reduced their consumption significantly and to a meaningful amount compared to the `Reference` group, it would have suggested that alternative motivational strategies would be effective. For example, by targeting the environmental motivation of households.

Although regrettably, this work cannot offer a clear recommendation, like those mentioned in the examples above, the current work still provides valuable insights. A notable observation is that a high proportion of the households that selected only one motivation in the survey selected the financial option, while very few selected the environmental option. This might be the result of certain situational factors like those discussed in Section 2.3.2. That is, the fact that these demand response programs focus on the potential savings on the electricity bill may explain why so many households selected the financial option. However, the `Monetary` group does not reduce their consumption during peak hours more than the reference group, even though these programs (i.e., real-time pricing schemes) are designed to appeal to this motivation. This might be explained by the fact that when people have a strong gain goal (financial motivation), they tend to only participate in the behaviour if it is worth the effort. Perhaps the financial gain in this case was not worth the required effort. On the other hand, people with a strong normative goal are less sensitive to this effect (Steg, Bolderdijk, et al., 2014).

Some of the households might respond more strongly if these programs placed a higher emphasis on environmental reasons for shifting electricity use from peak hours. This is not to suggest removing the financial incentive altogether. Still, it might be a better strategy to combine financial incentives with normative ones to make people more environmentally motivated. Indeed, research has shown that strategies that offer small financial incentives are successful when they are accompanied by some normative motive as well (Jakovcevic et al., 2014).

At the same time, it is important to note that a change in individual behaviour is not enough. Although encouraging households to consume less during peak hours is helpful, the broader energy system must also change and help facilitate change in individual behaviour. It would be unfair to place all the responsibility on the households and expect them to be motivated enough to change their behaviour. Every stakeholder in the system needs to make adjustments for demand response programs to be truly effective.

For policymakers, this means not only relying on households to reduce their consumption through dynamic electricity pricing, but also supporting measures that offer more flexibility to users. One promising avenue is the integration of automation and Artificial Intelligence (AI) technologies, which can play a significant role in shifting load from peak hours without relying solely on behavioural change. As seen in the literature, the response of the household is significantly higher when automation technologies are used (see Section 2.2.5). Where this technology can make the biggest impact is dependent on several factors. Exploration of the end-use of electricity consumption gives a clearer idea of the potential of automation because some functions are more complex to shift than others. In 2023, the electricity consumption in EU households had the following split: space heating (62.5%), water heating (15.1%), lighting and electrical appliances (14.5%), cooking (6.5%), space cooling (0.6%), and other end use (0.8%) (European Commission, n.d.).

From these statistics, lowering space heating would have the largest impact on overall energy consumption. For example, heat pumps can be programmed to operate at a lower level or briefly interrupted during periods of high electricity prices (Šajn, 2016). Water heating, the second largest end-use, is also well suited for automation, because water heaters can store hot water, and therefore heating can be shifted to off-peak hours (Moreau, 2011).

Electrical appliances account for a substantial part of the end-use of electricity. Appliances such as dishwashers, tumble dryers, and washing machines are examples of appliances that use substantial electricity but have flexible loads. That is, they do not need to be operated at strictly set times. Smart functions allow the consumer to set a preferred completion time, with the appliance automatically selecting the optimal time to complete the task (Šajn, 2016). However, concerns such as leaving appliances running while away from home or the need to unload the machines promptly can introduce barriers to uptake.

Cooking remains a highly human-centred activity that relies heavily on household routines. There are, nonetheless, some smart cooking utilities (e.g. ovens that allow for remote activation). However, these are typically used for home assistance, rather than scheduling energy consumption. So, cooking offers a less limited potential for automation.

People's willingness to purchase smart appliances also depends on the costs. When the Norwegian households, that were analysed in this thesis, were asked how much annual savings on their energy bill would justify purchasing a smart device for 5,000 NOK (≈ 420€), the majority reported needing savings above 1,000 NOK and nearly half required savings of more than 2,000 NOK. This highlights the fact that the affordability of automation technologies is essential, as also noted by Hofmann and Lindberg (2024a), who recommended investment support schemes for automation technologies. Furthermore, research shows that user acceptance decreases if technology requires substantial changes in habits or comfort (Šajn, 2016).

There is an additional catch that must be considered. A potential negative consequence of this energy scheduling technology is an unintended incentive for increased usage (Šajn, 2016). For example, households with good insulation may take advantage of low-price hours to preheat their home, potentially resulting in higher consumption despite lower cost. Similarly, an appliance waiting for a start signal may remain in standby mode, therefore using more electricity.

This highlights an important aspect: although automation offers great potential to boost household response to increased electricity prices — thereby reducing the stress on the grid — it comes with its challenges. Their success depends on avoiding the rebound effect, affordability, and making sure that the technology has minimal effect on the comfort and routines of households.

5.3 Scientific Contribution

This thesis is different from most other studies in the prior literature in that it evaluates electric consumption from the perspective of the end-user's motivational factors. In doing so, this thesis grounds the evidence in the theory of environmental psychology, which is often overlooked when scheduling systems are evaluated. There are, however, studies that have analysed the effect of different incentives. But none, as far as the researcher is aware, employs data based on self-reported motivational factors collected *after* the usage period to assess their impact on peak-hour consumption. By doing so, this thesis avoids any possible bias arising from subjects' being primed by their predetermined motivations; the subjects were unaware at the time-of-use that their survey responses would be collected. However, an important limitation, as addressed in Section 4.3, is that this thesis uses secondary data. The survey was, therefore, not designed with this specific research in mind, and the questions designed to capture respondents' motivation might be insufficient.

Furthermore, this thesis adds to the limited literature of observational studies that examine the effectiveness of dynamic electricity pricing. Most evidence of household responses to time-varying electricity prices is based on experimental studies. Thereby reducing self-selection bias that is often present in experimental studies because they often have an opt-in recruitment design. Furthermore, as this study utilises data where households were not aware that they were being monitored, it reduced the likelihood of observer bias, or the *Hawthorne Effect*. However, it is important to note that this study might contain some selection bias. Given the fact that households were asked afterwards if they were willing to share their demand data, it is possible that only people who behaved very efficiently decided to share their demand data.

Lastly, this thesis adds to the limited RTP literature as most of the previous studies have examined Critical-Peak Price (CPP) and Time Of Use (TOU) price schemes. The EU issued a directive (EU 2019/944), which requires member states to ensure that end-users with smart meters are able to request a dynamic electricity price contract (such as Real-Time Price (RTP)) from at least one supplier (European Union, 2019). This makes studying RTP particularly policy-relevant, as it provides direct evidence of how households respond to such pricing schemes. Although previous research studying CPP and TOU offers valuable insights, they do not address this specific policy context.

5.4 Future research

The limitations addressed in the previous chapter, specifically Section 4.3, provide valuable input for future research.

One future research direction can address one of the main limitations of this study, namely, the motivational survey question. It is recommended that future researchers design the question in a way that allows for estimating the relative importance of each motivation. For example, respondents could be asked to rank their selected motivation in order of importance. Another solution would be to use a 7-point Likert scale [1] which would make it possible to determine survey respondent's level of agreement with various statements that would address the motivation to consume less on peak hours. Such refinement would allow future research to identify the focal goal (motivation), providing greater confidence that households assigned to a particular group are primarily driven by that motivation.

[1] A 7-point Likert scale is a rating scale that can be used to capture the extent of a respondent's agreement or disagreement with a statement, typically ranging from (1) strongly disagree to (7) strongly agree (Taherdoost, 2019).

Future research can also address the limitation that the motivational question is only asked to one household member. This could be addressed by only looking at single-person households or by collecting responses from all household members who influence electricity use. Doing so would more accurately estimate the overall motivation of the household.

Another potential avenue for future research is to address the limitation of this study related to the small sample size of the Eco group. Researchers could for example employ more targeted sampling strategies to try to obtain a more balanced sample.

5.5 Final Reflection from the Researcher

As a final part of this thesis, I want to reflect on the process and share what I have learned throughout this journey. Both concerning the method and theory that I was introduced to and learned to apply.

First of all, having only worked with cross-sectional data, the introduction of new analytical techniques for panel data was a great learning experience. It opened my eyes to methods that I believe will be useful in my future career, especially if I decide to pursue a role in data analysis. Specifically, the method of fixed-effect regression. This method showed me how it is possible to control for unobserved characteristics that remain constant over time within each entity, as well as for external factors that vary over time and affect all entities.

Second, the thesis introduced me to another theoretical perspective: environmental psychology. As a Management of Technology (MoT) student specialising in economics and finance, this perspective was novel to me and introduced me to several new concepts and ideas. In my master's program, I have become familiar with decision-making through rational utility maximisation and financial incentives. In contrast, environmental psychology highlights that although money is an important driver, it is not the only one. For example, people are often motivated by normative concerns, such as to protect the environment. This perspective was therefore very eye-opening for me. In retrospect, I believe that combining these two distinct theoretical approaches added value to my thesis.

Lastly, before I started working on this thesis, I assumed that a good research project needed to produce statistically significant results. Therefore, I was pretty concerned when my analysis did not yield strong or consistent effects. However, through discussion with my supervisors, I concluded that non-significant results are also meaningful. They also provide valuable insight and raise essential questions. Reflecting on why I did not get any strong effect, pushed me to think more critically about the data, methods, and limitations of the study. Therefore, obtaining no statistical results ultimately pushed the thesis to a higher level.

Bibliography

Abrahamse, W. (2019). *Encouraging pro-environmental behaviour: What works, what doesn't, and why*. Academic Press.

Albadi, M., & El-Saadany, E. (2008). A summary of demand response in electricity markets. *Electric Power Systems Research*, *78*(11), 1989–1996. https://doi.org/10.1016/j.epsr.2008.04.002

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

Allcott, H. (2011). Rethinking real-time electricity pricing. *Resource and Energy Economics*, *33*(4), 820–842. https://doi.org/10.1016/j.reseneeco.2011.06.003

Asensio, O. I., & Delmas, M. A. (2015). Nonprice incentives and energy conservation. *Proceedings of the National Academy of Sciences of the United States of America*, *112*(6), E510–E515. https://doi.org/10.1073/pnas.1401880112

Bertoli, E. (2023). *Demand Response*. IEA. https://www.iea.org/energy-system/energy-efficiency-and-demand/demand-response

Bhattacharyya, S. C. (2019). *Energy economics: Concepts, issues, markets and governance* (2nd ed.). Springer Nature.

Block, S., Emerson, J. W., Esty, D. C., de Sherbinin, A., Wendling, Z. A., et al. (2024). *2024 environmental performance index*. Yale Center for Environmental Law & Policy. New Haven, CT. https://epi.yale.edu

Bouman, T., Steg, L., & Kiers, H. A. L. (2018). Measuring values in environmental research: A test of an environmental portrait value questionnaire. *Frontiers in Psychology*, *9*, 564. https://doi.org/10.3389/fpsyg.2018.00564

Bye, T., & Hansen, P. V. (2008). *How do spot prices affect aggregate electricity demand?* (Discussion Papers No. 527). Statistics Norway, Research Department. Oslo.

Chen, C.-F., Xu, X., Cao, Z., Mockus, A., & Shi, Q. (2023). Analysis of social–psychological factors and financial incentives in demand response and residential energy behavior. *Frontiers in Energy Research*, *11*, 932134. https://doi.org/10.3389/fenrg.2023.932134

Columb, M. O., & Atkinson, M. S. (2016). Statistical analysis: Sample size and power estimations. *BJA Education*, *16*(5), 159–161. https://doi.org/10.1093/bjaed/mkv034

Csereklyei, Z. (2020). Price and income elasticities of residential and industrial electricity demand in the European Union. *Energy Policy*, *137*, 111079. https://doi.org/10.1016/j.enpol.2019.111079

Cucuzzella, M., Bouman, T., Kosaraju, K. C., Schuitema, G., Lemmen, N., Johnson-Zawadzki, S. J. Z., Fischione, C., Steg, L., & Scherpen, J. M. A. (2022). Distributed Control of DC Grids: Integrating Prosumers' Motives. *IEEE Transactions on Power Systems*, *37*(4), 3299–3310. https://doi.org/10.1109/TPWRS.2021.3109024

do Canto, N. R., Grunert, K. G., & Dutra de Barcellos, M. (2023). Goal-framing theory in environmental behaviours: Review, future research agenda and possible applications in behavioural change. *Journal of Social Marketing*, *13*(1), 20–40. https://doi.org/10.1108/JSOCM-03-2021-0058

Elston, D. M. (2021). Participation bias, self-selection bias, and response bias. *Journal of the American Academy of Dermatology*, *85*(5), 1052–1053. https://doi.org/10.1016/j.jaad.2021.07.059

European Commission. (2023). Energy Efficiency Directive. https://energy.ec.europa.eu/topics/energy-efficiency/energy-efficiency-targets-directive-and-rules/energy-efficiency-directive_en

European Commission. (n.d.). Energy consumption in households. https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Energy_consumption_in_households

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 [CELEX number: 32019L0944]. https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:32019L0944

EVBox. (n.d.). *The beginner's guide to charging your electric car*. https://evbox.com/en/complete-guide-to-charging-your-electric-car

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://doi.org/10.1016/j.tej.2017.11.003

Filippini, M., & Srinivasan, S. (2024). *An introduction to energy economics and policy*. Cambridge University Press.

Fjordkraft. (n.d.). *Elektriske apparater: Hvor mye strøm bruker ulike elektriske apparater?* https://www.fjordkraft.no/strom/stromforbruk/elektriske-apparater/

Government of Norway. (n.d.). Timeline: News from Norwegian ministries about the coronavirus disease COVID-19 [Accessed August 5, 2025]. https://www.regjeringen.no/en/topics/health-and-care/public-health/timeline-for-news-from-norwegian-ministries-about-the-coronavirus-disease-covid-19/id2692402/

Gyamfi, S., Krumdieck, S., & Urmee, T. (2013). Residential peak electricity demand response—Highlights of some behavioural issues. *Renewable and Sustainable Energy Reviews*, *25*, 71–77. https://doi.org/10.1016/j.rser.2013.04.006

Haider, H. T., See, O. H., & Elmenreich, W. (2016). A review of residential demand response of smart grid. *Renewable and Sustainable Energy Reviews*, *59*, 166–178. https://doi.org/10.1016/j.rser.2016.01.016

Harding, M., & Sexton, S. (2017). Household response to time-varying electricity prices. *Annual Review of Resource Economics*, *9*(1), 337–359. https://doi.org/10.1146/annurev-resource-100516-053437

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. (2024a). 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/10.1016/j.enpol.2023.113821

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://doi.org/10.1016/j.dib.2023.109687

Hofmann, M., Bjarghov, S., Sæle, H., & Lindberg, K. B. (2025). Grid tariff design and peak demand shaving: A comparative tariff analysis with simulated demand response. *Energy Policy*, *198*, 114475. https://doi.org/10.1016/j.enpol.2024.114475

Hofmann, M., & Lindberg, K. B. (2024b). Residential demand response and dynamic electricity contracts with hourly prices: A study of Norwegian households during the 2021/22 energy crisis. *Smart Energy*, *13*, 100126. https://doi.org/10.1016/j.segy.2023.100126

Hogg, M. A., Terry, D. J., & White, K. M. (1995). A tale of two theories: A critical comparison of identity theory with social identity theory. *Social Psychology Quarterly*, *58*(4), 255–269. https://doi.org/10.2307/2787127

International Energy Agency. (2022). *Norway 2022: Energy policy review*. OECD Publishing. https://doi.org/10.1787/7411c642-en

International Energy Agency. (n.d.-a). *Global energy crisis: How the energy crisis started, how global energy markets are impacting our daily life, and what governments are doing about it* [Accessed August 5, 2025]. https://www.iea.org/topics/global-energy-crisis

International Energy Agency. (n.d.-b). *Norway* [Accessed August 5, 2025]. https://www.iea.org/countries/norway

International Energy Agency. (n.d.-c). *The Netherlands* [Accessed August 5, 2025]. https://www.iea.org/countries/the-netherlands

Jakovcevic, A., Steg, L., Mazzeo, N., Caballero, R., Franco, P., Putrino, N., & Favara, J. (2014). Charges for plastic bags: Motivational and behavioral effects. *Journal of Environmental Psychology*, *40*, 372–380. https://doi.org/10.1016/j.jenvp.2014.09.004

Jolls, C., Sunstein, C. R., & Thaler, R. (1998). A behavioral approach to law and economics. *Stanford Law Review*, *50*(5), 1471–1550. https://doi.org/10.2307/1229304

Kenton, W. (2024). *How an Isoquant Curve Explains Input and Output*. Investopedia. https://www.investopedia.com/terms/i/isoquantcurve.asp

Kollmuss, A., & Agyeman, J. (2002). Mind the gap: Why do people act environmentally and what are the barriers to pro-environmental behavior? *Environmental Education Research*, *8*(3), 239–260. https://doi.org/10.1080/13504620220145401

Lee, M. H. L., Ser, Y. C., Selvachandran, G., Thong, P. H., Cuong, L., Son, L. H., Tuan, N. T., & Gerogiannis, V. C. (2022). A comparative study of forecasting electricity consumption using machine learning models. *Mathematics*, *10*(8), 1329. https://doi.org/10.3390/math10081329

Li, H., Wang, Z., Hong, T., & Piette, M. A. (2021). Energy flexibility of residential buildings: A systematic review of characterization and quantification methods and applications. *Advances in Applied Energy*, *3*, 100054. https://doi.org/10.1016/j.adapen.2021.100054

Lindenberg, S., & Steg, L. (2007). Normative, gain and hedonic goal frames guiding environmental behavior. *Journal of Social Issues*, *63*(1), 117–137. https://doi.org/10.1111/j.1540-4560.2007.00499.x

Luther, L. (2022). Families around the Netherlands turn down the thermostat to save on heating bills. *Holland Times*. https://www.hollandtimes.nl/2022-edition-9-november/families-around-the-netherlands-turn-down-the-thermostat-to-save-on-heating-bills/

Marsh, J. (2024). *How many watts does a light bulb use?* EnergySage. https://www.energysage.com/electricity/house-watts/how-many-watts-does-a-light-bulb-use/

Meyer, A. (2015). Does education increase pro-environmental behavior? Evidence from Europe. *Ecological Economics*, *116*, 108–121. https://doi.org/10.1016/j.ecolecon.2015.04.018

Moreau, A. (2011). Control strategy for domestic water heaters during peak periods and its impact on the demand for electricity. *Energy Procedia*, *12*, 1074–1082.

Mullainathan, S., & Thaler, R. H. (2000). *Behavioral economics* (Working Paper No. 00-27). MIT Department of Economics. https://doi.org/10.2139/ssrn.245828

Neukomm, M., Nubbe, V., & Fares, R. (2019). Grid-Interactive Efficient Buildings. https://doi.org/10.2172/1508212

Norwegian Ministry of Energy. (2025). *The power market*. Energy Facts Norway. https://energifaktanorge.no/en/norsk-energiforsyning/kraftmarkedet/#:~:text=About%20Energy%20Facts%20Norway

OECD. (2024). *Society at a glance 2024: Oecd social indicators*. OECD Publishing. Paris. https://doi.org/10.1787/918d8db3-en

Olawale, O. W., Gilbert, B., & Reyna, J. (2023). Aggregate residential demand flexibility behavior: A novel assessment framework. *Sustainable Energy Technologies and Assessments*, *56*, 103073. https://doi.org/10.1016/j.seta.2023.103073

Perera, A. (2024). *Hawthorne effect: Definition, how it works, and how to avoid it*. Simply Psychology. https://www.simplypsychology.org/hawthorne-effect.html

Rohrer, J. M. (2018). Thinking clearly about correlations and causation: Graphical causal models for observational data. *Advances in Methods and Practices in Psychological Science*, *1*(1), 27–42. https://doi.org/10.1177/2515245917745629

Šajn, N. (2016). *Smart appliances and the electrical system* (tech. rep. No. EPRS Briefing ENPE 595.859). European Parliamentary Research Service. https://www.europarl.europa.eu/thinktank/en/document/EPRS_BRI(2016)593519

Schwartz, D., Bruine de Bruin, W., Fischhoff, B., & Lave, L. (2015). Advertising energy saving programs: The potential environmental cost of emphasizing monetary savings. *Journal of Experimental Psychology: Applied*, *21*(2), 158–166. https://doi.org/10.1037/xap0000042

Simon, H. A. (1956). Rational choice and the structure of the environment. *Psychological Review*, *63*(2), 129–138. https://doi.org/10.1037/h0042769

Simon, H. A. (2000). Bounded rationality in social science: Today and tomorrow. *Mind & Society*, *1*(1), 25–39. https://doi.org/10.1007/BF02512227

Sloot, D., Jans, L., & Steg, L. (2019). In it for the money, the environment, or the community? motives for being involved in community energy initiatives. *Global Environmental Change*, *57*, 101936. https://doi.org/10.1016/j.gloenvcha.2019.101936

Statistics Norway. (2025). Ssb. https://www.ssb.no/en

Statnett. (2025). *Why we have bidding zones*. https://www.statnett.no/en/about-statnett/The-power-system/why-we-have-bidding-zones/

Steg, L. (2023a). Intrinsic motivation to act pro-environmentally. In B. Gatersleben & N. Murtagh (Eds.), *Handbook on Pro-Environmental Behaviour Change* (pp. 28–37). Edward Elgar Publishing. https://doi.org/10.4337/9781800882133.00009

Steg, L. (2023b). Psychology of Climate Change. *Annual Review of Psychology*, *74*, 391–421. https://doi.org/10.1146/annurev-psych-032720-042905

Steg, L., Bolderdijk, J. W., Keizer, K., & Perlaviciute, G. (2014). An integrated framework for encouraging pro-environmental behaviour: The role of values, situational factors and goals. *Journal of Environmental Psychology*, *38*, 104–115. https://doi.org/10.1016/j.jenvp.2014.01.002

Steg, L., & De Groot, J. I. M. (2012). Environmental values. In S. Clayton (Ed.), *The oxford handbook of environmental and conservation psychology* (pp. 81–92). Oxford University Press. https://doi.org/10.1093/oxfordhb/9780199733026.013.0005

Steg, L., Lindenberg, S., & Keizer, K. (2016). Intrinsic motivation, norms and environmental behaviour: The dynamics of overarching goals. *International Review of Environmental and Resource Economics*, *9*(1-2), 179–207. https://doi.org/10.1561/101.00000077

Steg, L., Perlaviciute, G., & Van der Werff, E. (2015). Understanding the human dimensions of a sustainable energy transition. *Frontiers in Psychology*, *6*, 805. https://doi.org/10.3389/fpsyg.2015.00805

Steg, L., Perlaviciute, G., van der Werff, E., & Lurvink, J. (2014). The significance of hedonic values for environmentally relevant attitudes, preferences, and actions. *Environment and Behavior*, *46*(2), 163–192. https://doi.org/10.1177/0013916512454730

Steg, L., Shwom, R., & Dietz, T. (2018). What Drives Energy Consumers? Engaging People in a Sustainable Energy Transition. *IEEE Power and Energy Magazine*, *16*(1), 20–28. https://doi.org/10.1109/MPE.2017.2762379

Stock, J. H., & Watson, M. W. (2019). *Introduction to econometrics* (4th). Pearson.

Storm, S. (2021). Introduction theories of consumer demand [Lecture Note MOT1421-W-1].

Storm, S., & Naastepad, C. W. M. (2021). Background lecture note on the corona-lockdown recession [Lecture note, TPM022A-W-1].

Taherdoost, H. (2019). What is the best response scale for survey and questionnaire design: Review of different lengths of rating scale/attitude scale/likert scale. *International Journal of Academic Research in Management*, *8*(1), 1–10.

Trigg, A. B. (2002). Consumer sovereignty. In S. Himmelweit, R. Simonetti, & A. Trigg (Eds.), *Microeconomics: Neoclassical and institutionalist perspectives on economic behaviour* (pp. 27–58). Cengage.

van Valkengoed, A. M., Perlaviciute, G., & Steg, L. (2025). Representing the drivers of lifestyle change in Integrated Assessment Models using theories from environmental psychology: introducing the Motivation, Agency, and Past Behaviour (MAP) framework. *Environmental Research Communications*, *7*(3), Article 032001. https://doi.org/10.1088/2515-7620/adb9bf

Wolak, F. A. (2011). Do residential customers respond to hourly prices? evidence from a dynamic pricing experiment. *American Economic Review*, *101*(3), 83–87. https://doi.org/10.1257/aer.101.3.83

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

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. *Journal of Cleaner Production*, *201*, 169–177. https://doi.org/10.1016/j.jclepro.2018.08.027

Appendix A

Supplementary Tables

This appendix presents additional tables that provide supplementary information for the analysis. It includes tables with information regarding:

- Selected characteristics of household residents in the analytical sample (see Table A.1).
- Questions on the survey that addressed energy consumption awareness and behaviour (see Table A.2).
- Selected characteristics of residents by group (see Table A.3)

Table A.1: Selected characteristics of household residents in the analytical sample.

Household characteristic	Households (N = 1,136)
Number of residents	
1	351 (30.90%)
2	452 (39.79%)
3	159 (14.00%)
4	125 (11.00%)
5 or more	49 (4.32%)
Weekdays at home (9-16)	
ca. 0	129 (11.36%)
ca. 1	119 (10.48%)
ca. 2	111 (9.77%)
ca. 3	131 (11.53%)
ca. 4	117 (10.30%)
ca. 5	516 (45.42%)
Don't know	13 (1.14%)
Combined income	
Below 300,000 NOK/year	37 (3.26%)
300,000–499,999 NOK/year	169 (14.88%)
500,000–799,999 NOK/year	248 (21.83%)
800,000–999,999 NOK/year	141 (12.41%)
1,000,000–1,499,999 NOK/year	256 (22.54%)
1,500,000 or more	158 (13.91%)
Don't know / Prefer not to say	127 (11.18%)
Highest education	
No completed education	3 (0.26%)
Primary school (10 yrs)	21 (1.85%)
High school (11–13 yrs)	225 (19.81%)
Univ. undergraduate (1–3 yrs)	386 (33.98%)
Univ. higher degree (4+ yrs)	501 (44.10%)
Type of residence	
Detached house	256 (22.54%)
Semi-detached house	64 (5.63%)
Townhouse / small houses (3+)	222 (19.54%)
Apartment block	562 (49.47%)
Other	32 (2.82%)
Size of residence	
Under 50 sqm	96 (8.45%)
50–99 sqm	477 (41.99%)
100–159 sqm	352 (30.99%)
160+ sqm	206 (18.13%)
Don't know	5 (0.44%)
Electric car ownership	
Yes	341 (30.02%)
No	795 (69.98%)

Table A.2: Survey questions on energy consumption awareness and behaviour.

Survey Questions
Did you monitor your power consumption this winter?
How did you acquire information about your power consumption?
Why did you not monitor your consumption?
Did you monitor the variation in electricity prices from day to day and hour to hour this winter?
How did you acquire information about the electricity prices?
Why did you not monitor the electricity prices?
Did you take any measures to decrease or move power consumption from hours with high prices this winter?
Which measure did you implement?
Do you know how much the household has saved on the power bill as a result of the measures?
About how much has the household saved per month this winter as a result of the measures?
Do you feel that the measures you implemented were worth the savings on the power bill?
Why did you not take any measures?
What motivates you to reduce your power consumption in high price hours?
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.
Would you or have you used a free information service that alerts you of high price hours the following day?
Imagine you can buy smart devices for 5,000 NOK that will reduce your power bill by automatically shifting parts of your consumption away from high price hours—without reducing comfort. How much would you have to save every year to do it?
How is the residence heated?
How is the tap water heated?
How is the car or cars normally charged?
Do you control the car charging to avoid hours with high prices?
What type of power contract do you have?

Table A.3: Selected characteristics of residents by group.

Household characteristic	Monetary	Eco	Both	Reference
Number of residents				
1	197 (28.5%)	14 (36.8%)	67 (32.5%)	73 (36.3%)
2	264 (38.2%)	13 (34.2%)	89 (43.2%)	86 (42.8%)
3	107 (15.5%)	4 (10.5%)	27 (13.1%)	21 (10.4%)
4	91 (13.2%)	5 (13.2%)	18 (8.7%)	11 (5.5%)
5 or more	32 (4.6%)	2 (5.3%)	5 (2.4%)	10 (5.0%)
Weekdays at home (9–16)				
ca. 0	70 (10.1%)	7 (18.4%)	23 (11.2%)	29 (14.4%)
ca. 1	70 (10.1%)	5 (13.2%)	27 (13.1%)	17 (8.5%)
ca. 2	71 (10.3%)	5 (13.2%)	20 (9.7%)	15 (7.5%)
ca. 3	75 (10.9%)	3 (7.9%)	33 (16.0%)	20 (10.0%)
ca. 4	78 (11.3%)	3 (7.9%)	20 (9.7%)	16 (8.0%)
ca. 5	322 (46.6%)	14 (36.8%)	82 (39.8%)	98 (48.8%)
Don't know	5 (0.7%)	1 (2.6%)	1 (0.5%)	7 (3.5%)
Type of residence				
Detached house	169 (24.5%)	7 (18.4%)	42 (20.4%)	38 (18.9%)
Semi-detached house	44 (6.4%)	0 (0.0%)	9 (4.4%)	11 (5.5%)
Townhouse	139 (20.1%)	7 (18.4%)	42 (20.4%)	34 (16.9%)
Apartment block	319 (46.2%)	24 (63.2%)	106 (51.5%)	113 (56.2%)
Other	20 (2.9%)	0 (0.0%)	7 (3.4%)	5 (2.5%)
Size of residence				
Under 50 sqm	47 (6.8%)	2 (5.3%)	19 (9.2%)	28 (13.9%)
50–99 sqm	276 (39.9%)	20 (52.6%)	91 (44.2%)	90 (44.8%)
100–159 sqm	230 (33.3%)	8 (21.1%)	58 (28.2%)	56 (27.9%)
160+ sqm	135 (19.5%)	7 (18.4%)	37 (18.0%)	27 (13.4%)
Don't know	3 (0.4%)	1 (2.6%)	1 (0.5%)	0 (0.0%)
Electric car ownership				
Yes	224 (32.4%)	10 (26.3%)	59 (28.6%)	48 (23.9%)
No	467 (67.6%)	28 (73.7%)	147 (71.4%)	153 (76.1%)

Appendix B

Supplementary Information

B.1 Motivational Question

B.1.1 Distribution and Composition of Stated Motivations

Figure B.1 presents two elements. First, the distribution of how many options the households selected for the motivational question: ”What motivates you to reduce you power consumption in high price hours? Second, the breakdown of selected motivations among those who selected only one option.

From the distribution of the number of option selected, it can be seen that the largest proportion of households selected one option, or 351 households (30.9%). However, a considerable proportion of the households selected between two and four motivations.

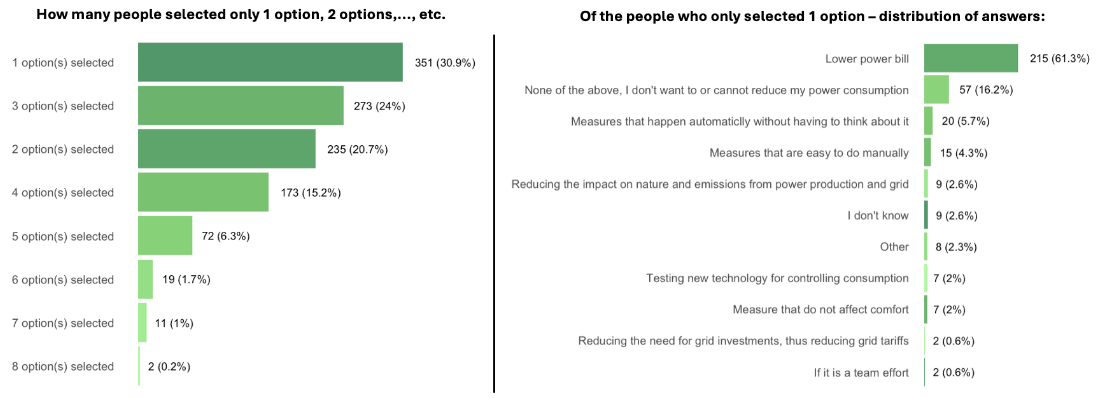


Figure B.1: Left: Distribution of the number of motivation options selected by households for the motivational question. Right: Distribution of selected motivations among households that chose only one option.

B.1.2 Groupings of Single-Motivation Households

This section will explain the two alternative groupings for the single-motivation households. First, the specification with two groups is explained and then the specification with three groups.

Figure B.1 shows that for households that selected only one motivation, the majority chose the financial motivation option, or 215 households out of 351. However, the number of households that selected only the environmental option is small (N=9). Therefore, in the robustness analysis that uses the subsample of households motivated by one motivation, the `Monetary` group (N=215) is compared to the rest of the households (N=351-215=136). When only looking at households with spot price contracts, the number of households in each group is: 145 in the `Monetary` group, and 59 in the comparison group.

When working with a subsample of the data that only includes households with one motivation it is possible to test the model with alternative grouping. Alternative grouping that was tested was with the following three groups:

1. **Monetary group (N=215):** Households that selected the financial option.
2. **Non-Monetary group (N=70):** Households that stated that they were motivated but not for financial reasons. These motivations include answer options:
    - ”Measures that happen automatically without having to thing about it”
    - ”Measures that are easy to do manually”
    - ”Reducing the impact on nature and emissions from power production and grid”
    - ”Other”
    - ”Testing new technology for controlling consumption”
    - ”Measures that do not affect comfort”
    - ”Reducing the need for grid investments, thus reducing grid tariffs”
    - ”It is a team effort”
3. **Unmotivated group (N=66):** Households that stated that they are not motivated and do not know what their motivations are. These include the answer options:
    - ”None of the above. I don’t want to or cannot reduce my power consumption.”
    - ”I don’t know”

When only looking at a subsample of households that have spot-price contracts the number of households in each group are: 145 in the `Monetary` group, 28 in the `Non-Monetary` group and 31 in the `Unmotivated` group.

Appendix C

Additional Regression Results

C.1 Different Time Period

Whole Dataset after the price crisis

Table C.1 presents the baseline regression results using a dataset that only includes observations after the crisis.

Table C.1: Baseline Regression results ran on the dataset after the crisis.

Dependent Variable: Electricity consumption per hour [kWh]				
Specifications:	(1)	(2)	(3)	(4)
Variables				
peak	-0.0050	0.1304***	-	-
	(0.0143)	(0.0155)	-	-
peak × money	0.0131	0.0131	0.0122	0.0034
	(0.0173)	(0.0173)	(0.0172)	(0.0081)
peak × eco	0.0020	0.0020	0.0030	-0.0322*
	(0.0343)	(0.0343)	(0.0348)	(0.0140)
peak × both	-0.0130	-0.0130	-0.0126	-0.0171
	(0.0199)	(0.0199)	(0.0199)	(0.0095)
Fixed Effects				
Unit	Yes	Yes	Yes	
Hour-level				Yes
Time Fixed Effects				
Year	Yes	Yes		
Month	Yes	Yes		
Weekday	Yes	Yes		
Hour	Yes			
Region-Time			Yes	Yes
Clustered SEs	Yes	Yes	Yes	Yes
Observations	6,625,152	6,625,152	6,625,152	6,625,152
$\bar{R}^2$	0.6233	0.6132	0.6363	0.6662

Notes: Standard errors clustered at the unit level are reported in parentheses. * p<0.05, ** p<0.01, *** p<0.001.

C.2 Spot Price Contract Households Subsample

Spot price contract after crisis

Robustness results by running the model with households that have spot price contract and after the crisis.

Table C.2: After crisis – Spot price contract subsample.

Dependent Variable: Electricity consumption per hour [kWh]				
Specifications:	(1)	(2)	(3)	(4)
Variables				
peak	0.0199	0.1519***	-	-
	(0.0250)	(0.0270)	-	-
peak × money	-0.0120	-0.0120	-0.0120	0.0147
	(0.0285)	(0.0285)	(0.0285)	(0.0126)
peak × eco	0.0527	0.0527	0.0534	-0.0387
	(0.0625)	(0.0625)	(0.0630)	(0.0251)
peak × both	-0.0404	-0.0404	-0.0394	-0.0054
	(0.0318)	(0.0318)	(0.0320)	(0.0141)
Fixed Effects				
Unit	Yes	Yes	Yes	
Hour-level				Yes
Time Fixed Effects				
Year	Yes	Yes		
Month	Yes	Yes		
Weekday	Yes	Yes		
Hour	Yes			
Region-Time			Yes	Yes
Clustered SEs	Yes	Yes	Yes	Yes
Observations	4,181,544	4,181,544	4,181,544	4,181,544
$\bar{R}^2$	0.6134	0.6039	0.6266	0.6577

Notes: Standard errors clustered at the unit level are reported in parentheses. * p<0.05, ** p<0.01, *** p<0.001.

C.3 Single-Motivation Households Subsample

C.3.1 Results with 2 groups

This section presents the results of a robustness analysis using the subsample of households that selected only one motivation. In this analysis, the model compares the `Monetary` group to all remaining households, resulting in two distinct groups. Furthermore, a restriction is also tested where only spot price contract households within the one-motivation households are considered.

2 groups - After the crisis

Table C.3: After crisis – 1 option selected and 2 groups: Monetary vs. the rest.

Dependent Variable: Electricity consumption per hour [kWh]				
Specifications:	(1)	(2)	(3)	(4)
Variables				
peak	-0.0067	0.1120***	-	-
	(0.0148)	(0.0157)	-	-
peak × money	0.0185	0.0185	0.0163	0.0065
	(0.0219)	(0.0219)	(0.0219)	(0.0111)
Fixed Effects				
Unit	Yes	Yes	Yes	
Hour-level				Yes
Time Fixed Effects				
Year	Yes	Yes		
Month	Yes	Yes		
Weekday	Yes	Yes		
Hour	Yes			
Region-Time			Yes	Yes
Clustered SEs	Yes	Yes	Yes	Yes
Observations	2,047,032	2,047,032	2,047,032	2,047,032
$\bar{R}^2$	0.6096	0.5998	0.6225	0.6542

Notes: Standard errors clustered at the unit level are reported in parentheses. * p<0.05, ** p<0.01, *** p<0.001.

2 Groups (spot contracts) - Whole period

Table C.4: Whole period (spot contracts) – 1 option selected and 2 groups: Monetary vs. the rest.

Dependent Variable: Electricity consumption per hour [kWh]				
Specifications:	(1)	(2)	(3)	(4)
Variables				
peak	0.0285	0.1197***	-	-
	(0.0217)	(0.0266)	-	-
peak × money	0.0002	0.0002	-0.0009	0.0203 .
	(0.0310)	(0.0310)	(0.0314)	(0.0121)
Fixed Effects				
Unit	Yes	Yes	Yes	
Hour-level				Yes
Time Fixed Effects				
Year	Yes	Yes		
Month	Yes	Yes		
Weekday	Yes	Yes		
Hour	Yes			
Region-Time			Yes	Yes
Clustered SEs	Yes	Yes	Yes	Yes
Observations	2,678,112	2,678,112	2,678,112	2,678,112
$\bar{R}^2$	0.6060	0.5945	0.6251	0.6522

Notes: Standard errors clustered at the unit level are reported in parentheses. * p<0.05, ** p<0.01, *** p<0.001.

2 Groups (spot contracts) - After crisis

Table C.5: After crisis (spot contracts) – 1 option selected and 2 groups: Monetary vs. the rest.

Dependent Variable: Electricity consumption per hour [kWh]				
Specifications:	(1)	(2)	(3)	(4)
Variables				
peak	0.0299	0.1433***	-	-
	(0.0274)	(0.0315)	-	-
peak × money	-0.0159	-0.0159	-0.0159	0.0135
	(0.0360)	(0.0360)	(0.0361)	(0.0154)
Fixed Effects				
Unit	Yes	Yes	Yes	
Hour-level				Yes
Time Fixed Effects				
Year	Yes	Yes		
Month	Yes	Yes		
Weekday	Yes	Yes		
Hour	Yes			
Region-Time			Yes	Yes
Clustered SEs	Yes	Yes	Yes	Yes
Observations	1,189,728	1,189,728	1,189,728	1,189,728
$\bar{R}^2$	0.5934	0.5830	0.6070	0.6405

Notes: Standard errors clustered at the unit level are reported in parentheses. * p<0.05, ** p<0.01, *** p<0.001.

C.3.2 Results with 3 groups

This section presents the results of a robustness analysis using the subsample of households that selected only one motivation. In this analysis, the model compares the `Monetary` group to two other groups: the `Non-Monetary` group and the `Unmotivated` group. This results in 3 distinct groups. Furthermore, a restriction is also tested where only spot price contract households within the one-motivation households are considered.

3 Groups - After the crisis

Table C.6: After crisis – 1 option selected and 3 groups: Monetary, Non-Monetary, and Unmotivated.

Dependent Variable: Electricity consumption per hour [kWh]				
Specifications:	(1)	(2)	(3)	(4)
Variables				
peak	0.0021	0.1208***	-	-
	(0.0250)	(0.0268)	-	-
peak × money	0.0097	0.0097	0.0083	-0.0065
	(0.0308)	(0.0308)	(0.0308)	(0.0141)
peak × non-money	-0.0170	-0.0170	-0.0155	-0.0253 .
	(0.0317)	(0.0317)	(0.0318)	(0.0138)
Fixed Effects				
Unit	Yes	Yes	Yes	
Hour-level				Yes
Time Fixed Effects				
Year	Yes	Yes		
Month	Yes	Yes		
Weekday	Yes	Yes		
Hour	Yes			
Region-Time			Yes	Yes
Clustered SEs	Yes	Yes	Yes	Yes
Observations	2,047,032	2,047,032	2,047,032	2,047,032
$\bar{R}^2$	0.6096	0.5998	0.6225	0.6542

Notes: Standard errors clustered at the unit level are reported in parentheses. * p<0.05, ** p<0.01, *** p<0.001.

3 groups (spot contracts) - Entire sample period

Table C.7: Whole period (spot contracts) – 1 option selected and 3 groups: Monetary, Non-Monetary, and Unmotivated.

Dependent Variable: Electricity consumption per hour [kWh]				
Specifications:	(1)	(2)	(3)	(4)
Variables				
peak	0.0375	0.1287**	-	-
	(0.0354)	(0.0396)	-	-
peak × money	-0.0088	-0.0088	-0.0105	-0.0002
	(0.0427)	(0.0427)	(0.0431)	(0.0145)
peak × non-money	-0.0190	-0.0190	-0.0203	-0.0431*
	(0.0527)	(0.0527)	(0.0530)	(0.0194)
Fixed Effects				
Unit	Yes	Yes	Yes	
Hour-level				Yes
Time Fixed Effects				
Year	Yes	Yes		
Month	Yes	Yes		
Weekday	Yes	Yes		
Hour	Yes			
Region-Time			Yes	Yes
Clustered SEs	Yes	Yes	Yes	Yes
Observations	2,678,112	2,678,112	2,678,112	2,678,112
$\bar{R}^2$	0.6060	0.5945	0.6251	0.6522

Notes: Standard errors clustered at the unit level are reported in parentheses. * p<0.05, ** p<0.01, *** p<0.001.

3 groups (spot contracts) - After crisis

Table C.8: After crisis (spot contracts) – 1 option selected and 3 groups: Monetary, Non-Monetary, and Unmotivated.

Dependent Variable: Electricity consumption per hour [kWh]				
Specifications:	(1)	(2)	(3)	(4)
Variables				
peak	0.0568	0.1703**	-	-
	(0.0478)	(0.0524)	-	-
peak × money	-0.0429	-0.0429	-0.0429	-0.0058
	(0.0552)	(0.0552)	(0.0554)	(0.0205)
peak × non-money	-0.0568	-0.0568	-0.0568	-0.0404 .
	(0.0610)	(0.0610)	(0.0611)	(0.0232)
Fixed Effects				
Unit	Yes	Yes	Yes	
Hour-level				Yes
Time Fixed Effects				
Year	Yes	Yes		
Month	Yes	Yes		
Weekday	Yes	Yes		
Hour	Yes			
Region-Time			Yes	Yes
Clustered SEs	Yes	Yes	Yes	Yes
Observations	1,189,728	1,189,728	1,189,728	1,189,728
$\bar{R}^2$	0.5934	0.5830	0.6070	0.6405

Notes: Standard errors clustered at the unit level are reported in parentheses. * p<0.05, ** p<0.01, *** p<0.001.

C.4 Results Using Alternative Peak Hour Definition

This section presents the results of a robustness analysis using an alternative definition of the peak hour variable. Results in this section used data from all household after the crisis and then tested separately data from the subsample of household with spot price contract both for the entire sample period and after the crisis.

The full sample restricted to the post-crisis period

Table C.9: Alternative peak hour definition – After crisis and all households.

Dependent Variable: Electricity consumption per hour [kWh]				
Specifications:	(1)	(2)	(3)	(4)
Variables				
peak	0.0514***	0.1496***	-	-
	(0.0151)	(0.0160)	-	-
peak × money	0.0372*	0.0373*	0.0370*	0.0321*
	(0.0184)	(0.0184)	(0.0184)	(0.0127)
peak × eco	0.0018	0.0018	0.0021	-0.0004
	(0.0443)	(0.0443)	(0.0445)	(0.0314)
peak × both	0.0048	0.0047	0.0049	0.0191
	(0.0227)	(0.0227)	(0.0227)	(0.0165)
Fixed Effects				
Unit	Yes	Yes	Yes	
Hour-level				Yes
Time Fixed Effects				
Year	Yes	Yes		
Month	Yes	Yes		
Weekday	Yes	Yes		
Hour	Yes			
Region-Time			Yes	Yes
Clustered SEs	Yes	Yes	Yes	Yes
Observations	6,625,152	6,625,152	6,625,152	6,625,152
$\bar{R}^2$	0.6235	0.6133	0.6363	0.6662

Notes: Standard errors clustered at the unit level are reported in parentheses. * p<0.05, ** p<0.01, *** p<0.001.

The spot price contract subsample over the entire sample period

Table C.10: Alternative peak hour definition – Entire sample period and spot price.

Dependent Variable: Electricity consumption per hour [kWh]				
Specifications:	(1)	(2)	(3)	(4)
Variables				
peak	0.1047***	0.1953***	-	-
	(0.0311)	(0.0320)	-	-
peak × money	0.0123	0.0123	0.0123	0.0136
	(0.0357)	(0.0357)	(0.0357)	(0.0293)
peak × eco	0.0395	0.0394	0.0398	0.0015
	(0.0960)	(0.0959)	(0.0962)	(0.0718)
peak × both	-0.0080	-0.0081	-0.0076	0.0078
	(0.0440)	(0.0440)	(0.0440)	(0.0366)
Fixed Effects				
Unit	Yes	Yes	Yes	
Hour-level				Yes
Time Fixed Effects				
Year	Yes	Yes		
Month	Yes	Yes		
Weekday	Yes	Yes		
Hour	Yes			
Region-Time			Yes	Yes
Clustered SEs	Yes	Yes	Yes	Yes
Observations	9,412,776	9,412,776	9,412,776	9,412,776
$\bar{R}^2$	0.6207	0.6097	0.6381	0.6644

Notes: Standard errors clustered at the unit level are reported in parentheses. * p<0.05, ** p<0.01, *** p<0.001.

The spot price contract subsample restricted to the post-crisis period

Table C.11: Alternative peak hour definition – after crisis and spot price.

Dependent Variable: Electricity consumption per hour [kWh]				
Specifications:	(1)	(2)	(3)	(4)
Variables				
peak	0.0710**	0.1682***	-	-
	(0.0227)	(0.0238)	-	-
peak × money	0.0079	0.0079	0.0079	0.0163
	(0.0260)	(0.0260)	(0.0260)	(0.0173)
peak × eco	0.0660	0.0659	0.0660	0.0203
	(0.0797)	(0.0797)	(0.0799)	(0.0514)
peak × both	-0.0237	-0.0239	-0.0238	0.0047
	(0.0321)	(0.0321)	(0.0322)	(0.0224)
Fixed Effects				
Unit	Yes	Yes	Yes	
Hour-level				Yes
Time Fixed Effects				
Year	Yes	Yes		
Month	Yes	Yes		
Weekday	Yes	Yes		
Hour	Yes			
Region-Time			Yes	Yes
Clustered SEs	Yes	Yes	Yes	Yes
Observations	4,181,544	4,181,544	4,181,544	4,181,544
$\bar{R}^2$	0.6136	0.6039	0.6266	0.6577

Notes: Standard errors clustered at the unit level are reported in parentheses. * p<0.05, ** p<0.01, *** p<0.001.

C.5 Excluding weekends

This section presents the results of a robustness analysis using subsample of the dataset where weekends are excluded. First the analysis using data from all households (full sample) are presented both for the entire sample period and then after the crisis. Then the results using data from subsample of households that have spot price contracts are presented for the whole period and then period after the crisis.

C.5.1 Full sample

Here are the results when we exclude the weekends. This subset includes all households regardless of contract.

The full sample for the entire study period

Table C.12: Excluding weekends – Whole period and all households.

Dependent Variable: Electricity consumption per hour [kWh]				
Specifications:	(1)	(2)	(3)	(4)
Variables				
peak	0.0066	0.1309***	-	-
	(0.0150)	(0.0166)	-	-
peak × money	0.0239	0.0239	0.0231	0.0579 .
	(0.0185)	(0.0185)	(0.0185)	(0.0296)
peak × eco	0.0136	0.0136	0.0144	0.0056
	(0.0371)	(0.0371)	(0.0373)	(0.0621)
peak × both	0.0140	0.0140	0.0143	0.0486
	(0.0217)	(0.0371)	(0.0216)	(0.0377)
Fixed Effects				
Unit	Yes	Yes	Yes	
Hour-level				Yes
Time Fixed Effects				
Year	Yes	Yes		
Month	Yes	Yes		
Weekday	Yes	Yes		
Hour	Yes			
Region-Time			Yes	Yes
Clustered SEs	Yes	Yes	Yes	Yes
Observations	10,660,224	10,660,224	10,660,224	10,660,224
$\bar{R}^2$	0.6297	0.6191	0.646319	0.676033

Notes: Standard errors clustered at the unit level are reported in parentheses. * p<0.05, ** p<0.01, *** p<0.001.

The full sample restricted to the post-crisis period.

Table C.13: Excluding weekends – After crisis and all households.

Dependent Variable: Electricity consumption per hour [kWh]				
Specifications:	(1)	(2)	(3)	(4)
Variables				
peak	-0.0108	0.1441***	-	-
	(0.0164)	(0.0178)	-	-
peak × money	0.0206	0.0206	0.0205	0.0031
	(0.0199)	(0.0199)	(0.0199)	(0.0095)
peak × eco	0.0135	0.0135	0.0136	-0.0532**
	(0.0424)	(0.0424)	(0.0425)	(0.0200)
peak × both	-0.0032	-0.0032	-0.0031	-0.0226*
	(0.0233)	(0.0233)	(0.0233)	(0.0108)
Fixed Effects				
Unit	Yes	Yes	Yes	
Hour-level				Yes
Time Fixed Effects				
Year	Yes	Yes		
Month	Yes	Yes		
Weekday	Yes	Yes		
Hour	Yes			
Region-Time			Yes	Yes
Clustered SEs	Yes	Yes	Yes	Yes
Observations	4,743,936	4,743,936	4,743,936	4,743,936
$\bar{R}^2$	0.6266	0.6174	0.6391	0.6747

Notes: Standard errors clustered at the unit level are reported in parentheses.
* p<0.05, ** p<0.01, *** p<0.001.

C.5.2 Spot price contract subsample

Here are the results when we exclude the weekends. This subset includes all households that have a spot price contract.

The spot price contract subsample for the entire study period

Table C.14: Excluding weekends – Whole period and spot price households.

Dependent Variable: Electricity consumption per hour [kWh]				
Specifications:	(1)	(2)	(3)	(4)
Variables				
peak	0.0201	0.1488***	-	-
	(0.0264)	(0.0290)	-	-
peak × money	0.0053	0.0053	0.0053	0.0115
	(0.0306)	(0.0306)	(0.0306)	(0.0429)
peak × eco	0.0576	0.0576	0.0580	-0.0159
	(0.0665)	(0.0665)	(0.0668)	(0.1021)
peak × both	-0.0069	-0.0069	-0.0064	0.0025
	(0.0342)	(0.0342)	(0.0343)	(0.0529)
Fixed Effects				
Unit	Yes	Yes	Yes	
Hour-level				Yes
Time Fixed Effects				
Year	Yes	Yes		
Month	Yes	Yes		
Weekday	Yes	Yes		
Hour	Yes			
Region-Time			Yes	Yes
Clustered SEs	Yes	Yes	Yes	Yes
Observations	6,728,328	6,728,328	6,728,328	6,728,328
$\bar{R}^2$	0.6234	0.6133	0.6404	0.6705

Notes: Standard errors clustered at the unit level are reported in parentheses. * $p<0.05$, ** $p<0.01$, *** $p<0.001$.

The spot price contract subsample restricted to the post-crisis period

Table C.15: Excluding weekends – After crisis and spot price households.

Dependent Variable: Electricity consumption per hour [kWh]				
Specifications:	(1)	(2)	(3)	(4)
Variables				
peak	0.0159	0.1673***	-	-
	(0.0291)	(0.0316)	-	-
peak × money	-0.0073	-0.0073	-0.0073	0.0151
	(0.0333)	(0.0333)	(0.0333)	(0.0150)
peak × eco	0.0717	0.0717	0.0714	-0.0565.
	(0.0755)	(0.0755)	(0.0755)	(0.0311)
peak × both	-0.0297	-0.0297	-0.0302	-0.0130
	(0.0372)	(0.0372)	(0.0374)	(0.0165)
Fixed Effects				
Unit	Yes	Yes	Yes	
Hour-level				Yes
Time Fixed Effects				
Year	Yes	Yes		
Month	Yes	Yes		
Weekday	Yes	Yes		
Hour	Yes			
Region-Time			Yes	Yes
Clustered SEs	Yes	Yes	Yes	Yes
Observations	2,994,192	2,994,192	2,994,192	2,994,192
$\bar{R}^2$	0.6170	0.6081	0.6297	0.6663

Notes: Standard errors clustered at the unit level are reported in parentheses. * p<0.05, ** p<0.01, *** p<0.001.

Appendix D

Reflection on the use of Artificial Intelligence

In the preparation of this work, I used ChatGPT as a supportive tool. Specifically for reviewing written text, correcting grammar, and suggesting improvements to enhance readability. I carefully reviewed all suggestions made and therefore, I take full responsibility for this work. Furthermore, I used ChatGPT for additional help, such as refining plots in R and also to generate code for tables in LaTeX that fit the aesthetics that I was looking for. To summarise, ChatGPT was used as a supportive tool and not a tool to generate content.