Shift Happens!

The influence of dynamic energy contracts on electricity consumption in individual households in the Netherlands

Master thesis Complex System Engineering and Management

Faculty Technology, Policy and Management

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Abstract

This master thesis provides a review of dynamic energy contracts and their role in shifting electricity consumption in households in the Netherlands. In this research the mixed-methods approach is used to identify changes in electricity consumption behavior of consumers with a dynamic energy contract compared to consumers with a fixed energy contract. Dynamic energy contracts are recently introduced in line with the Clean Energy for all package of the European Commission (2019) and the need for more flexibility regarding electricity consumption in individual households. Qualitative research found that individual households are only willing to be flexible in their demand with activities that are not time-critical such as washing and cleaning, while there was almost no demand flexibility with activities such as cooking and watching television. Based on real-time consumer data of a Dutch energy supplier, a difference-in-difference (DiD) regression analysis is performed to analyze the effect of dynamic energy contracts on electricity consumption. This study revealed that consumers with a dynamic energy contract have a different consumption behavior pattern compared to their own behavior pattern under a different contract and compared to consumers with a fixed energy contract. These findings indicate that the dynamic energy contract can change the consumption behavior pattern of individual households, which can be explained by paying the hourly electricity price in this type of contract. This research can form an inspiration and knowledge base for future research that can elaborate on the role of dynamic energy contracts in demand load shifting.

Preface

With great pleasure, I hereby present my master thesis. With this project I conclude my studies in Complex System Engineering and Management.

The master thesis in front of you tries to create a clear picture of electricity consumption behavior changes of individual households when switching towards a dynamic energy contract.

Defining this thesis topic and choosing the research questions and methods was quite challenging. I wanted to perform a quantitative data-driven analysis, but also provide context which defined why this research has not been done yet, despite its significance in the current energy transition. Besides that, I really wanted to conduct my master thesis at an external energy company, which adds a lot of valuable opportunities. The process of writing this thesis and performing the analyses has been challenging at times, but I am very happy with the result I present to you now. I hope to not only contribute to increased attention towards dynamic energy contracts, but also to the crucial role we as energy consumers have in the energy transition. Besides that, I hope to inspire other researchers to dive deeper into possible recommended topics following from this master thesis.

I would like to express my immense gratitude to my graduation committee and my external supervisor at energy supplier Vandebron. I would like to thank my first supervisor, Rudi, for being my chair of the committee, providing me with very valuable insights and feedback, taking the time to have a biweekly meeting and always supporting my questions. My second supervisor, Enno, I would like to thank you for guiding me throughout the data-analysis, for taking the time to have separate meetings with me and explaining and providing me with valuable information regarding the extensive regression analysis.

To Hilde, my external supervisor, thank you for being my supervisor, helping me with the necessary data and connecting me with other professionals in the energy market. I immensely enjoyed our meetings, where there was always room for informal conversations as well. To everyone at Vandebron who helped me gain valuable insights for this research and whom I had the pleasure of interviewing, thank you so much.

Finally, my friends and family who have supported me throughout this whole journey. I would like to thank my mother and my sister for their unconditional support, interest, and love. I want to thank Bas for his continuous support and patience throughout the whole process and his motivational words that helped me keep going. I would like to thank my roommates and all my friends who provided their support, shaped my amazing study time in Delft and for the laughter they provided and distraction when needed.

Claire Wagener, April 15, 2024

Abbreviations

ACM = Authority for Consumers and Markets
CBS = Central Bureau of Statistics
RES = Renewable Energy Sources
PV = Photovoltaic
CO2 = Carbon Dioxide
DR = Demand Response
DSM = Demand Side Management
DER = Distributed Energy Resources
EE = Energy Efficiency
EV = Electric vehicle
DiD = Difference-in-Difference
RTP = Real Time Pricing
ToU = Time of Use
CPP = Critical Peak Pricing
PTR = Peak Time Rebate
CBL = Customer Baseline Load

Contents

1 Introduction

1.1 Introduction

Over the past years, energy markets have been evolving faster than ever. Since the Paris Agreement (2015), the need for more renewable energy sources has increased immensely. This is mainly due to the net zero goal of 2050, meaning net zero carbon dioxide (CO2) emissions globally by 2050. The development of renewable energy technologies has taken a flight in the Netherlands, with as frontrunner solar PV (photovoltaic) energy. At present, the Netherlands holds the record for the highest number of solar panels installed per inhabitant (van de Weijer, 2024). Due to the high increase in solar PV energy production in the Netherlands, larger fluctuations in electricity supply to the national power grid are becoming more apparent. These fluctuations require an increase in electricity transport during the peak of solar power generation, typically occurring during the sun's brightest hours. However, the grid operator is not able to rapidly expand the capacity, which results in an overload on the national grid, also known as congestion, (Netbeheer Nederland, n.d.). Besides that, during the sun's brightest hours, which are mainly midday hours, the overall grid demand is generally low (Stelmach et al., 2020), which results in a mismatch between electricity supply and demand. In addition to the increase in solar PV energy, other renewable energy technologies are also being developed, such as wind energy, hydrogen, and geothermal energy. The increase of these variable renewable energy sources (vRES) in the energy mix yields more flexibility in the energy market (Villar et al., 2018). This flexibility in the energy market is needed to accelerate the energy transition. However, to reap the full benefits of this flexibility, adjustments on the consumption side of the energy market are necessary.

In line with that, the European Union has implemented legislation, the Clean Energy for all Europeans' package, with the focus on the role and position of consumers in the energy transition. The key features of these regulations concentrate on empowering consumers with a more active role, increased choices and greater flexibility (European Commission, 2019). With the residential sector contributing to 34 percent of global energy consumption (Mata et al., 2020), it emphasizes the crucial need to enhance awareness and responsibility within this domain regarding their role in the energy transition. In order to integrate this flexibility in an efficient way in the energy market, flexibility options regarding energy consumption and production are needed, with the desired outcome that consumers should be able to actively participate directly in the energy market.

One of the flexibility options involves dynamic energy contracts. These contracts entail that individual households pay the electricity price that reflects the price variation in the spot markets, including the day-ahead and intraday market. The Electricity Directive (European Commission, 2019) mandates the implementation of dynamic energy contracts for suppliers in EU-countries by 2025, with a customer base of more than 200.000 customers.

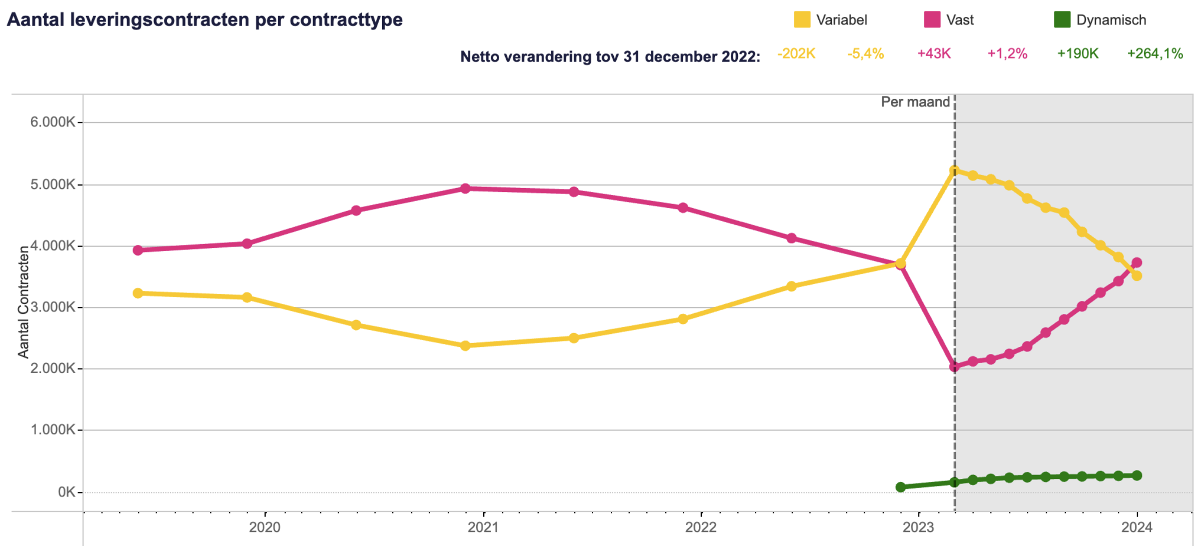

Figure 1. Number of energy contracts per contract type over the past few years in the Netherlands (ACM Monitor, February 2024)

The figure shows the different types of energy contracts and their market share in the Netherlands. There are three types of energy contracts displayed: fixed energy contracts (pink line), variable energy contracts (yellow line) and dynamic energy contracts (green line). Fixed and variable contracts are the most common contracts for consumers. In 2022, the dynamic energy contract was introduced in the Netherlands, initially adopted by smaller energy suppliers. By 2023 larger energy suppliers like Eneco and Vandebron also embraced this type of contract (Eneco, 2023; Vandebron, 2023).

The dynamic energy contract has been introduced in line with the values of the Clean Energy for all Europeans' package, with the main focus on more flexibility for consumers. The primary marketing proposition of this dynamic energy contract emphasizes the cost savings it offers to energy consumers. As previously mentioned, under this contract, consumers pay an hourly electricity price that corresponds to fluctuations in market prices. While this flexibility can be advantageous for reducing costs, it also presents a notable disadvantage. Given the nature of electricity as a necessity, consumers may face challenges as they need to continue consuming electricity regardless of its varying price. Besides that, the dynamic energy contract promotes pricing agility, enhances forecasting, greater choice and control for customers (Mecoms, 2023), and it gains the ability to optimize energy usage. To fully reap the promoted benefits of dynamic contracts, a change in behavior is necessary; consume electricity when the demand is low and the generation is high (Penttinen et al., 2020). This change in behavior, also known as demand load shifting, can also play a role in reducing the overload of the national grid. However, not all consumers are in the position to shift their energy demand towards different hours of the day. Therefore, it is important to keep in mind in which ways individual households are able to be flexible in their demand and how programs, such as demand side management, can play a role in the flexibility and load shifting of consumers.

The past year the dynamic energy contract took an immense flight in the Netherlands. Compared to March last year, the amount of households with a dynamic energy contract has more than doubled, which now leads to a market share of 3% (ACM, 2024). This number is relatively low compared to the market share of other existing energy contracts. Possible reasons for this are the newness and unfamiliarity of the contract among many households. In order to fully understand the consequences of dynamic contracts and how to maximize their benefits based on consumption behavior, more extensive research is necessary. By understanding dynamic energy contracts and their possible pricing structures, as well as examining the possibilities for households to be flexible in their demand, this study aims to provide valuable insights. Additionally, it analyzes whether consumption behavior patterns of households change under a dynamic energy contract. Combining these insights, this study aims to shed light on the relationship between dynamic energy contracts and consumer behavior in the Netherlands. In this research the focus will solely be on electricity. This decision arises from the consistent trend where more and more devices and appliances are undergoing electrification (International Energy Agency, 2022). It is anticipated that this trend will continue in the future.

1.2 Knowledge gap

The energy transition is in full swing and the need to become sustainable faster is growing. The current national and European energy policies face big challenges in the transition towards carbon-neutral power systems. The primary emphasis in addressing these challenges lies in enhancing flexibility within the energy system, both on the demand and generation side. This is crucial to ensure an efficient and secure energy supply for all consumers (Gržanić et al., 2022). It is known that regulatory frameworks have an influence on households' decision towards the energy transition (Aniello & Bertsch, 2023). Therefore, suitable and progressive regulations were needed, which resulted in the implementation of the Clean Energy for all Europeans' package (European Commission, 2019). This package of different energy directives shifted the focus of the energy market towards consumer protection and consumer empowerment. Right now, the government of the Netherlands is also in the process of approving a new law in the Netherlands that is in line with the objectives of the European Commission (Energiewet, 2023).

Aside from the change of focus in legislation, another trend has been happening the past years. The development of vRES continues to surge, leading to a continual increase in renewable energy generation. Due to this high amount of renewable energy generation, flexibility is the key for a reliable energy system (Paterakis et al., 2017). With the rise of flexibility in the energy markets, new technologies and tools, such as smart metering systems and smart grids, are necessary to accelerate the energy transition. This in combination with the need for more active consumers, the dynamic energy contracts are introduced. Over the past year the dynamic energy contract has taken a flight in the Netherlands. Dynamic energy contracts are a way to achieve energy efficiency maximization (Leal-Arcas et al., 2017), because of their real-time pricing component. Dynamic pricing can encourage consumers to transfer their consumption from peak hours to off-peak hours, due to higher electricity prices in peak hours compared to off-peak hours.

An additional strategy to increase consumer empowerment is demand side management (DSM). DSM consists of multiple strategies. The main objective of these strategies is to decrease energy consumption, particularly during peak hours (Batalla-Bejerano et al., 2020). Other goals include minimizing carbon emissions and offering consumers the option to choose their preferred energy source (Bakare et al., 2023). Energy suppliers benefit from DSM in mitigating risk associated with rising imbalance costs. It is expected that dynamic energy tariffs in combination with smart meters allow consumers to manage their demand efficiently (Frederiks et al., 2015). However, studies showed that the combination of smart meters and providing a dynamic energy contract is insufficient to convince most households to switch. Besides that, other barriers, such as the complexity of tariff information and the possible risks of dynamic pricing play a role in the transition to these new concepts (Lavrijssen & Parra, 2017; Aniello & Bertsch, 2023).

Research showed that households are only inclined to switch to a dynamic energy contract when they have the possibility to be flexible with their demand (Katz et al., 2018; Ghazvini et al., 2017). So, to fully capitalize on DSM strategies and dynamic energy contracts, it is necessary to understand the various ways households can be flexible in their electricity consumption. This consumption behavior is exceedingly intricate, and research showed that there is still a lot of uncertainty towards their behavior in this energy transition. Additionally, energy contracts are becoming more complex, and the options of different energy contracts are greater. This creates a higher risk for consumers to make wrong choices regarding their energy contract. This makes it crucial to ensure that new information through technological advancements, such as smart meters, is transparently and user-friendly presented to energy consumers. This presentation should empower consumers to verify, personalize and trust the relevant information. Otherwise, there is a genuine risk that consumers may not fully embrace the opportunities for consumer empowerment provided by technological innovations (Lavrijssen, 2017).

Based on the literature research above, the knowledge gap can be found in understanding consumer behavior in individual households in the Dutch energy market towards dynamic energy contracts, their possibilities to be more flexible with their demand and the impact of fluctuating prices on their consumption behavior.

An overview of all the selected articles and the methodology used to identify this research gap can be found in Appendix A.1.

1.3 Core concepts

In the literature review, used to identify the knowledge gap above, critical concepts have been found. These concepts require some additional information and will be explained more extensively.

1.3.1 Congestion

Congestion is a phenomenon that happens when a grid overload prevents electricity from reaching the consumer. This is due to transmission constraints: the demand for the transport of electricity is larger than the transmission capacity of the existing grid (withthegrid, n.d.). This occurs when there is a mismatch between electricity generation and consumption of electricity. Congestion has been happening over the past years more often due to multiple reasons. The electricity market went from a centralized energy system to a decentralized energy system, wherein consumers also contribute to energy generation. This shift is marked by a significant rise in solar PV energy. The generation of solar energy is always happening at the same time, whenever the sun is shining. This is however also the time that the demand load of consumers is relatively low, which results in a huge amount of energy generation that causes an overload on the national grid. This happens mostly in rural areas, where there used to be little transport of electricity. Besides that, large-scale solar parks are often built in these sparsely populated areas. This results in large solar peaks that the transmission grid is not built and prepared for. However, there is also congestion in urban areas. This can be mainly explained by the growing electrification of industry but also individual households with for example electric vehicles. This results in overall more traffic on the national grid, and therefore a higher risk of congestion. Currently, several provinces in the Netherlands are experiencing a peak load on their electricity grids, leading to a waiting list for services such as EV charging stations (NOS, 2023). Moreover, as noted by a grid operator in a conducted interview (ALL1), this surge in demand is significantly impacting the connection process for new houses to the electricity grid.

Congestion can result in voltage fluctuations, reduced system reliability and the need for additional infrastructure. Therefore, management of congestion is needed to ensure a reliable and efficient energy supply to meet the growing demand. There are in general two categories of congestion management methods: price-based method and incentive-based method. One of the price-based methods is dynamic tariffs for electricity. By giving insights into the dynamic prices throughout the day, consumption from energy will be shifted from peak hours (Shen et al., 2022) to off-peak hours, which will decrease the transmission load for several hours. It is expected that in the future congestion will escalate further (Alliander, 2024).

1.3.2 Demand Side Management (DSM)

Demand side management (DSM) is a new development that has enabled communication between energy suppliers and consumers (Bakare et al., 2023). There are three categories of DSM: demand response (DR), distributed energy resources (DER) and energy efficiency (EE). In this research the focus will be on DR and EE. There are multiple techniques of DSM, in which the most important one for this research is load shifting. This involves "changing the demand for loads from peak hours to off-peak hours" (Bakare et al., 2023). Although DSM has become more and more popular due to technological developments in smart grids, it is still unsure how consumers will react to these DSM techniques (Bakare et al., 2023). DSM programs encounter multiple challenges when aiming to influence the behavior consumption patterns of individual consumers, particularly in maintaining altered behavior over the long term (Breukers et al., 2013). However, research showed that whenever the consumers are better informed about the benefits of demand side management, they are more likely to shift or reduce their electricity usage (Oprea et al., 2021). A more extensive overview of the different DSM strategies is presented in Chapter 4.

1.4 Research questions

In attempt to close the defined knowledge gap, the main research question is formulated as follows:

"How do dynamic energy contracts influence consumption behavior of individual households?"

The main research question can be dissected into smaller questions. These sub questions will eventually answer the main question.

1. What are the possible pricing structures for dynamic energy contracts?

2. How do risk factors and benefits of dynamic energy contracts vary between energy consumers and energy suppliers?

3. What are the possibilities for individual households to be flexible in their demand?

4. Is there a difference in consumption behavior patterns between consumers with a dynamic energy contract and their behavior under their previous contract?

5. Does consumption behavior vary between consumers with a dynamic energy contract and those with a fixed energy contract under different real-time prices?

1.5 Relevance of this research

This research contributes to several important subjects regarding the energy transition. Besides that, this research aligns with the objectives and competencies of this master thesis guidelines, from the study Complex System Engineering and Management (CoSEM).

The active role of individual households in the energy transition is essential for accelerating the energy transition towards a carbon emission free future (European Commission, 2019). Therefore, various options for motivating flexibility in the energy consumption of individual households are introduced. One of these options is the dynamic energy contract. This research investigates the real consequences of introducing this type of energy contract. By conducting a mixed methods approach, combining a qualitative literature review and expert interviews with a quantitative regression, a clear view on the implementation of dynamic energy contracts is created. The results of this study are relevant for individual energy consumers (individual households), energy suppliers and policymakers and researchers within the energy domain. The findings give mainly specific information on the change in consumption behavior by adopting a dynamic energy contract. These insights can be useful to accelerate the implementation of dynamic energy contracts in the Netherlands. Additionally, they give insights into the types of households where dynamic energy contracts serve as a suitable form of DSM. The CoSEM program strives to provide its students with a profound understanding of complex societal technology systems for them to be able to develop personalized solutions to address the systems' problems. Throughout this master thesis research multiple skills and knowledge, acquired during the CoSEM program have been applied. Modeling skills, particularly in the data analysis and the Difference-in-Difference regression, using Python and SQL, but also skills regarding performing a structured literature review and conducting interviews with experts.

This research analyzes a complex, socio-technical system, examining how dynamic energy contracts influence consumption behavior, while considering other factors such as electricity prices, the influence of solar PV panels and external factors such as the temperature. These characteristics make this a highly complex system, in which the skills of the CoSEM program can be used efficiently to better understand the challenges and benefits that this system is likely to encounter and deliver in the future.

1.6 Thesis Structure

This report is divided into different parts. The second chapter outlines the research approach and research methods for this master thesis and elaborates on the utilized dataset. Hereafter, the chapters are divided into answering the different sub-questions proposed. The report will end with the discussion and limitations, followed by the overall conclusion of the research. Afterwards contributions and recommendations will be presented.

An overview of the research outline is displayed in the figure below.

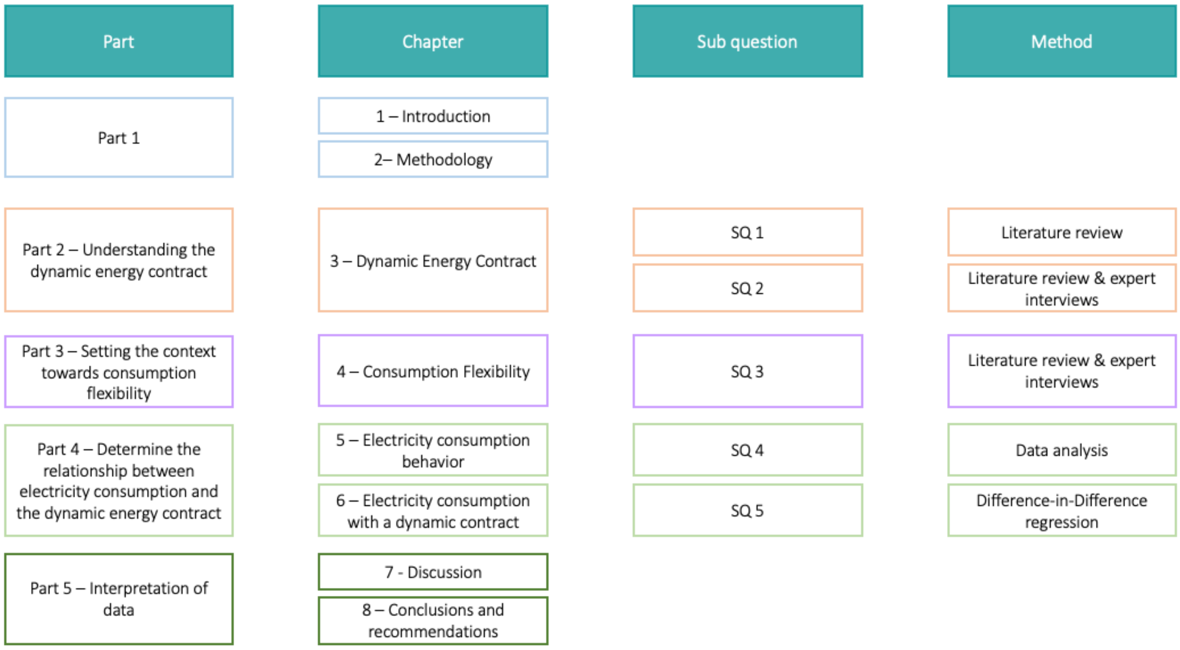

Figure 2. Thesis outline

2 Research approach and research method

In this chapter the chosen research approach and the thereby corresponding methods are explained. The type of research approach depends on the nature of the research project. The main objective of this paper is to gain insight in consumption behavior of individual households in response to electricity price fluctuations under dynamic energy contracts in the Dutch energy market. This objective consists of mainly three components. Firstly, it is about understanding the dynamic energy contract, and the advantages and risks that are associated with this type of contract, for consumers as well as suppliers. The second component is about gaining insight into the possibilities for individual households to be flexible in their energy demand. Finally, there will be an examination of consumption behavior of individual households both before and after adopting a dynamic energy contract, as well as a comparison of consumption behavior between consumers with a dynamic energy contract and those with a fixed energy contract.

2.1 Research approach: mixed method

Based on the three different components that this research will cover, a mixed-method research approach is used. This includes a qualitative research approach as well as a quantitative research approach. By combining both research approaches the development of a more comprehensive understanding of the research question can be formed (Kuhn, 2023). Besides that, it allows triangulation: the use of multiple sources to confirm research findings. This can increase the validity and reliability of the results (Creswell, 2009). A comprehensive situational analysis cannot be adequately conducted by relying solely on quantitative or qualitative methods, especially when trying to grasp the behavioral dynamics of individual consumers. There are a lot of different mixed-methods research designs. One of the most popular designs is the exploratory sequential design. This design involves two distinct phases. In the initial phase, qualitative data is collected and analyzed to explore a phenomenon, which in this research relates to consumption behavior of individual households. The second phase involves the collection and analysis of the quantitative data to confirm or generalize the findings from the first phase (Fetters et al., 2013). The nature of this design allows researchers to build upon qualitative insights, providing a more comprehensive and nuanced understanding of the research topic.

2.1.1 Qualitative research approach

The first part of this research will be explored through qualitative research. This approach is chosen because it is in nature descriptive: understanding the meaning of the different concepts and the process between the concepts (Atieno, 2009). This approach gives insight into the context and meaning of dynamic energy contracts, for consumers, suppliers and the Dutch energy market as a whole. By performing a literature review and expert interviews, valuable insights will be gathered about consumption behavior and flexibility of consumers towards their demand. A limitation of this approach is that especially interviews and the volume of other data is very time consuming. Besides that, the research quality is influenced by the individual skills of the researcher (Anderson, 2010). This last limitation will be applicable for every research in general.

2.1.2 Quantitative research approach

The second part of this research will be explored through quantitative research. This approach is chosen to gain insight in the consumption behavior patterns before and after a dynamic contract. Besides that, this approach will also be used to provide insights into the relationship between electricity consumption behavior under dynamic energy contracts and fixed energy contracts, and the thereby corresponding role of the electricity price. For this part of the research, smart-meter consumption data from the energy supplier Vandebron is used. This approach is very fitting here, since it is mostly used for research based on objective processes. Besides that, this approach is used to form a theory by testing prespecified concepts and using data-analysis to support that (Mason, 2013). This is applicable for this research since consumption behavior will be tested under different energy contracts, through data analysis of empirical data. A disadvantage of this approach is that it is very time consuming and data-heavy, which can result in high computation time of the analyses.

2.2 Research methods

The different sub questions will be answered by using various research methods. The mixed-method research approach requires both quantitative and qualitative data. This data is obtained through different sources.

Literature study

SQ1: What are the possible pricing structures for dynamic energy contracts?

To create an understanding of the dynamic energy contract as a dynamic pricing contract, a literature study is used to answer this sub-question. Mainly literature from academic journals and case studies are used to explain the different types of dynamic pricing.

(Grey) literature study and semi-structured interviews

SQ2: How do risk factors and benefits of dynamic energy contracts vary between energy consumers and energy suppliers?

SQ3: What are the possibilities for individual households to be flexible in their demand?

To answer the second and third sub question, a literature study is conducted, involving different types of sources. Mainly literature from academic journals is used to find the answers to the sub questions. Additionally, news articles are used to give more context to the current situation and position of dynamic energy contracts in the energy market.

For both sub questions semi-structured interviews are conducted with several stakeholders. Semi-structured interviews are exploratory interviews that are flexible and versatile (Magaldi & Beler, 2020). This makes this type of data collection very popular. A characteristic of this type of interviewing is that the questions are likely to vary in order and depending on the interviewees' responses (Magaldi & Beler, 2020). In the chosen mixed methods approach, these semi-structured interviews add depth to the quality of this research (Adams, 2015). In total, nine interviews were conducted. Four of these interviews were conducted with three different energy suppliers in the Netherlands: Vandebron, ANWB, and Essent. These interviews were done to get more insights in their perspectives towards the dynamic energy contract. Two interviews were done with net operators Stedin and Alliander. The remaining three interviews were conducted with individual households with a dynamic energy contract. All interviews aim to give more in-depth insights into the different perspectives towards dynamic energy contracts and to understand risks and benefits of both consumers and suppliers. Table 1 shows the reference code for each interviewee, their company, and their role within said company. To refer to interviews in the text, reference codes are used.

Table 1. Conducted interviews with their reference code

Role	Company	Reference code
Manager Portfolio	Vandebron	VDB1
Proposition Manager	Essent	ESS1
Growth Marketeer	ANWB	AB1
Proposition Manager	Vandebron	VDB2
Proposition Manager Flexible Energy Systems	Stedin	STED1
Energy Consultant	Alliander	ALL1
Customer dynamic contract	Vandebron	CUS1
Customer dynamic contract	Frank Energie	CUS2
Customer dynamic contract	Vandebron	CUS3

Data-analysis

SQ4: Is there a difference in consumption behavior patterns between consumers with a dynamic energy contract and their behavior under their previous contract?

To understand the possible differences in consumption behavior of customers with a dynamic energy contract compared to their previous contract, a data-analysis is conducted. This data-analysis is performed on real-time consumption data from individual households linked to energy supplier Vandebron.

Difference-in-difference (DiD) regression

SQ5: Does consumption behavior vary between consumers with a dynamic energy contract and those with a fixed energy contract under different real-time prices?

To answer the fifth sub question a DiD-regression is done. This DiD regression is conducted to determine a possible relationship between electricity consumption and the dynamic energy contract. The primary goal of the DiD regression is to compare the changes in outcomes over time between a treatment group that receives the intervention (households with a dynamic energy contract), and a control group (households with a fixed energy contract) that does not. The input data for this DiD regression is real-time consumption data from individual households linked to energy supplier Vandebron as well as multiple control variables. More information on the input data and the DiD method can be found in chapter 6.

3 Dynamic energy contract

This chapter answers the following sub questions:

What are the possible different pricing structures for dynamic energy contracts?

How do risk factors and benefits of dynamic energy contracts vary between consumers and energy suppliers?

The objective of this chapter is to give more context to the dynamic energy contract. For this part of the research a literature review is conducted combined with semi-structured interviews. When referring to the interviews, the reference codes will be used that were defined in table 1. The chapter will start with an overview of the different types of dynamic energy contracts. The second part of this chapter consists of a review of risk factors and benefits for both consumers and energy suppliers, to get a more in depth understanding of the different perspectives towards the dynamic energy contract in the Netherlands.

3.1 Pricing structures of dynamic energy contracts

To fully understand the context of dynamic energy contracts, it is important to understand which types of dynamic pricing such a contract can have. Increasingly, energy suppliers across various countries are embracing this form of energy contracts to provide to their customers. Besides that, it will be mandatory in 2025 for all energy suppliers in the European Union to offer at least one type of dynamic energy contract if their customer base is over 200.000 customers (Article 11.1 EU Electricity Directive, 2019). The four types of dynamic pricing are described below. These include real time pricing (RTP), time of use pricing (ToU), critical peak pricing (CPP) and peak time rebate (PTR).

3.1.1 Real Time Pricing (RTP)

RTP is defined as “a varying rate that allows prices to be adjusted regularly in a consistent interval of hour or few minutes to reflect real time structure” (Amin et al., 2020). In the Netherlands consumers with a dynamic energy contract will pay an hourly price for their electricity and a daily price for their gas consumption. As mentioned before, this research will focus only on electricity consumption, and therefore the RTP will be a price that varies hourly according to the spot price of electricity (Ruokamo et al., 2019). These spot prices are defined in the day-ahead market, and these prices are communicated to customers at 12pm for the following day.

RTP is the most efficient and purest form of dynamic pricing. In this type of pricing the price reflects the actual costs of supply (Amin et al., 2020; Dutta & Mitra, 2017), meaning that the spot price is equal to the marginal costs of electricity, since the electricity price changes in very small intervals. This also means that this is an effective type of pricing from the perspective of energy suppliers; they encounter less risk with volatile prices (Nezamoddini & Wang, 2017; Amin et al., 2020), which will be further explained in 4.2.2. For consumers, this type of pricing creates an opportunity to reduce their energy bill by changing their consumption behavior (Nezamoddini & Wang, 2017). However, there are also certain disadvantages of this type of dynamic pricing. Firstly, RTP is the most uncertain and risky option for consumers (Amin et al., 2020; Dutta & Mitra, 2017), and often the customers are not well informed about the billing process. Secondly, RTP schemes require advanced technology to communicate and manage the frequent price changes, intervals of one hour, to consumers (Dutta & Mitra, 2017). This involves a very high rate of data collection and data transfer, which is not always efficient. Besides that, these technological requirements for RTP pricing are associated with high costs, which can be considered as a barrier for its widespread adoption and acceptance (Nezamoddini & Wang, 2017).

3.1.2. Time of Use Pricing (ToU)

With ToU pricing, the consumers pay a different tariff for electricity in a different time block. The rates of the different blocks are based on historical conditions, instead of the current load curve, which was the case by RTP (Amin et al., 2020; Faria & Vale, 2011; Hung & Michailidis, 2018). Mainly there are three different intervals per day: peak interval, mid-peak interval, and off-peak interval (Jordehi, 2019). The tariffs are often high during peak hours and low during off-peak hours (Dutta & Mitra, 2017). This encourages the consumers to shift their demand load from peak hours to off-peak hours to pay a lower tariff. The idea of this type of dynamic pricing is to better reflect the price variations during different time periods of the day without capturing the day-to-day price volatility of supply costs (Paterakis et al., 2017). The main advantage of this type of pricing is that consumers have control over their own electricity bill, but without being exposed to the high price volatility that consumers experience with RTP. This makes this type of dynamic pricing more acceptable to individual households (Chen et al., 2021). Another benefit of this pricing scheme is its simplicity to comprehend, as ToU pricing portfolios frequently maintain consistent electricity prices within the same season (Yan et al., 2018). This encourages consumers participating in this pricing scheme to stick with this type of dynamic pricing. On the other hand, ToU tariffs reflect the longer-term electricity supply costs, which indicates that ToU prices cannot effectively regulate short-term loads. Therefore, ToU tariffs fail in guiding user behavior effectively in the short-term (Yang et al., 2021; Chen et al., 2021). However, ToU pricing can have efficiency gains on the medium- and long-term load control (Yang et al., 2021).

3.1.3. Critical Peak Pricing (CPP)

CPP is quite similar to ToU pricing, but the main difference is that CPP is based on forecasting high demand periods, not on historical conditions of the full day (Amin et al., 2020). CPP is used to capture the short-term costs of electricity supply in periods that are critical for the power system (Paterakis et al., 2017). This type of dynamic contract specifies the maximum number of days per year and the number of periods for which a CPP applies, known as ‘the critical days’ (Dutta & Mitra, 2017; Paterakis et al., 2017). However, this CPP rate is communicated to consumers on a very short notice, from several minutes up to several hours, before this rate applies, which distinguishes it from ToU pricing (Amin et al., 2020; Paterakis et al., 2017). CPP reacts to present conditions and not historic data, which is similar to RTP, which makes it more difficult to implement compared to ToU pricing (Faria & Vale, 2011). This type of pricing can also be considered as the hybrid option of RTP and ToU pricing. Often the CPP tariffs are higher than the ToU tariffs but are considered more effective to reduce the peak load (Amin et al., 2020; Dutta & Mitra, 2017; Yan et al., 2018). Besides that, the price forecasting for CPP is much more challenging than ToU pricing

(Amin et al., 2020). Additionally, the effectiveness in reducing peak load is significantly higher with CPP pricing than ToU pricing (Allehyani et al., 2024).

3.1.4. Peak Time Rebate (PTR)

This type of dynamic pricing works with a rebate instead of lower electricity tariffs for consumers. Consumers get a rebate for using electricity under a preset limit during peak hours (Schwarz et al., 2020; Amin et al., 2020; Saeed et al., 2015). As a result, consumers often see this type of payment more as a reward instead of an expense, where they are required to make higher payments during peak hours, akin to all other dynamic energy pricing contracts (Amin et al., 2020). For this kind of dynamic pricing, utilities need to accurately calculate the consumption level when not having this type of dynamic pricing; this is known as the customer baseline load (CBL) estimation (Schwarz et al., 2020). However, this estimation comes with multiple complications. First, the CBL is counterfactual, as it is impossible to observe what the consumer would have utilized on the previous rate. Secondly, the CBL is calculated based on historic data (Schwarz et al., 2020). This can complicate things, because the effectiveness of this pricing program, depends on the accuracy of the CBL estimation (Saeed et al., 2015; Amin et al., 2020). Besides that, other research showed that one-third of the payouts for residential customers are due to random variations in their usage, and not a reduction in their load in response to those price incentives (Williamson & Marrin, 2009). But PTR also offers benefits: it increases system reliability and reduces capacity needs (Earle et al., 2009). Besides that, it also offers a high bill steadiness to consumers (Amin et al., 2020).

3.2 Chosen type of dynamic pricing scheme: Real Time Pricing (RTP)

As mentioned above there are roughly four types of dynamic energy pricing possible for dynamic contracts. An overview of the types and their influence on multiple criteria are shown in the table below. The table is an extended version of the one presented in the literature review on dynamic pricing of electricity (Dutta & Mitra, 2017).

Table 2. Comparison of various dynamic pricing policies (based on Dutta & Mitra, 2017)

Policy	Economic efficiency consumer	Equity	Bill stability	Revenue stability	Initiate load shifting	Time base electricity rates
PTR	Good	Poor	Very good	Very poor	Poor	n.d.
CPP	Good	Average	Average	Good	Good	Present
ToU	Good	Good	Average	Average	Poor	Historical
RTP	Very good	Very good	Very poor	Very good	Very good	Present

In this research the focus will be on dynamic energy contracts with RTP. This is the only type of dynamic contract the Dutch suppliers offer to their customers. Besides the fact that RTP reflects the real cost of supply, it is also economically the most efficient way to implement dynamic contracts in the power market (Borenstein et al., 2002; Vickrey, 1992).

3.3 Risk factors and benefits of dynamic contracts

In this section a literature review is conducted, combined with semi-structured interviews to identify and explain the risks and benefits of electricity consumers and suppliers towards RTP dynamic energy contracts. This will give a more comprehensive understanding of the context of dynamic energy contracts and will provide the input for following steps of this research.

3.3.1 Consumers

In the past years, consumers have been more involved in the energy landscape than ever before. Awareness is created through international legislation, like the Electricity Directive of 2019, and through national legislation, for example by the development of the average energy bill which now happens twice a year instead of once (van Polen, 2020). Besides that, the energy crisis of 2022 has made a major contribution to consumers' awareness of their electricity consumption (Korras, 2022).

When choosing a dynamic energy contract, a consumer is forced to be a little risk-seeking, which can be a property that appeals to some customers in general (CUS3). Besides that, interviews showed that the most common reason for consumers to choose a dynamic contract is the innovation part of the dynamic contract next to the possibility to save more money (CUS1; CUS2; CUS3). Both customers of the energy supplier Vandebron also chose this type of contract with a sustainable motivation (CUS1; CUS3).

The main risk for energy consumers, individual households in this research, is price volatility (CUS1; CUS2; CUS3). Particularly during peak hours, wintertime and whenever there are unforeseen events regarding the energy market. It is not always possible to get a correct estimation of the supply and demand of energy, in which case the price of electricity can fluctuate a lot. This leaves the energy consumers extremely vulnerable, potentially exposing them to sudden spikes in electricity prices. Another risk and limitation for consumers is their knowledge regarding the price formation of electricity with a dynamic contract. There is uncertainty about the way their bill is composed (Amin et al., 2020). Often consumers choose a dynamic energy contract to save costs on their electricity bill, based on given information and often their historic usage. However, this can give a misplaced image of the amount of costs that consumers save with this new contract. On the other hand, dynamic energy contracts empower consumers with complete control over their energy bills, allowing them to pay solely for the electricity they use and when they use it. Therefore, dynamic energy contracts can have the possibility for consumers to save a lot of money on their energy bills, when electricity is used in hours where the electricity price is relatively low.

Over the past year, there has been a significant surge in the adoption of dynamic energy contracts. The number of households with such contracts has skyrocketed by 260% compared to the previous year (ACM, 2023). However, in recent months the growth of dynamic energy contracts has stagnated in the Dutch energy market (ACM, 2024). This could be explained by the season. During the winter the electricity prices are in general higher (VEH, n.d.), since people are spending more time at home and there is less generation of renewable energy which makes it more difficult to be efficient and flexible with your demand as a consumer. Besides that, other factors such as the uncertainty of the gas price due to geopolitical developments and lower prices for other types of energy contracts can also have an impact on the adoption rate of dynamic energy contracts.

3.3.2 Suppliers

The supplier's perspective towards dynamic energy contracts differs a lot from the perspective of an energy consumer. Suppliers with more than 200.000 customers are obliged to offer a dynamic contract to their customers (Article 11.1 EU Electricity Directive, 2019) by 2025. This does not necessarily mean that the dynamic contracts are always beneficial for suppliers, even though they have a lower risk towards price volatility than individual consumers. Right now, the majority of the energy suppliers in the Dutch market do not offer a dynamic contract yet to their customers.

The main risks for the suppliers are the cancellation risk of customers and the possible change in demand behavior of customers which has consequences for their forecast. With a dynamic energy contract, customers can cancel their contracts at any time, and switch towards another energy supplier very easily. This, combined with their possible change in their consumption behavior pattern can result in a mismatch between the now defined forecast models and the actual demand, which will cause difficulties for the energy supplier. On the other hand, dynamic energy contracts have less risk factors for suppliers compared to other energy contracts (VDB1; ESS1). For this type of contract, they only need to consider the imbalance risk between purchased energy and demand energy by the customers, while for other contracts they also need to take into account the demand variation risk, the power futures and the purchasing risk.

Research showed that supplier’s revenue is mainly impacted by households' local production (Miletíc et al., 2022). This is because their profit is dependent on electricity injections and imbalance settlements, which happens more often when consumers have a dynamic energy contract (Miletíc et al., 2022; Rautiainen et al., 2019).

3.4 Main conclusion chapter 3

This chapter revealed the different types of dynamic pricing and their characteristics. Besides that, it gave an in-depth overview of the risks and benefits of dynamic energy contracts for consumers as well as energy suppliers. This first section answers the following research questions:

What are the possible different pricing structures for dynamic energy contracts?

How do risk factors and benefits of dynamic energy contracts vary between consumers and energy suppliers?

The main findings from the research questions are summarized below.

Dynamic contracts make electricity consumption in households more flexible, which makes grid utilization more efficient. This flexibility is mainly existent in the fact that peak loads are spread more widely with dynamic pricing (Stute & Kühnbach, 2023).

The different dynamic pricing structures

There are mainly four different types of dynamic pricing structures: real time pricing (RTP), time of use pricing (ToU), critical peak pricing (CPP) and peak time rebate (PTR). The extent to which a consumer can realize savings through dynamic pricing is dependent on their ability to adjust the timing of their demand load (Azman et al., 2017). The RTP dynamic contract is the purest form of dynamic pricing since consumers pay the actual cost of supply and therefore the real price of electricity at each moment. Besides that, this is the only type of dynamic tariff that Dutch energy suppliers offer to consumers in their dynamic energy contract. The focus throughout this report will only be on this type of pricing. RTP has more advantages than other types of dynamic pricing, which is shown in table 2. The main advantage is economic efficiency for consumers, since they will be motivated to reduce their energy consumption during peak hours, when the price of electricity is high, to reduce their energy bill. This will positively affect the decrease of peak load on the national grid. Besides that, this form of dynamic pricing is fair and straightforward, as consumers have complete control and accountability for the electricity costs incurred during their usage. A disadvantage of RTP is the advanced technology such as smart metering, which involves a high rate of data collection and data transfer, which is not always efficient.

Risk and benefits for consumers and suppliers

The main risk for consumers with RTP dynamic energy contracts is the price volatility, which makes the consumer extremely vulnerable. The uncertainty surrounding future electricity prices necessitates the ability to cope with such unpredictability for consumers. Due to these risks, the willingness and acceptability of consumers to adopt these dynamic energy contracts is not optimal yet. The main benefit for consumers is their full authority over their own costs made by electricity consumption and therefore the possibility to save a lot of money on their energy bill. Dynamic energy contracts have different consequences for energy suppliers. For forecasting, the supplier only has to take into account the imbalance risk, while other energy contracts also demand more elaborate risks, such as purchasing risk and demand variations risk (VDB1). Dynamic energy contracts can cause possible changes in consumption behavior patterns of households. Additionally, consumers with a dynamic energy contract can cancel their contract at any time and switch to a different energy supplier. Both these factors have an influence on their energy forecast and pose the risk of a mismatch in the defined forecast models and the actual demand. It is expected by multiple Dutch energy suppliers that in the future eventually more consumers will make the transfer to dynamic energy contracts (VDB1; ESS1; AB1).

The literature studies and conducted interviews are clearly highlighting the potential of dynamic energy contracts. However, most literature research was conducted in geographic areas outside the Netherlands. On the other hand, all interviews held were with Dutch suppliers, consumers and experts on this subject, whose opinions and experiences corresponded to the reviewed literature. The remaining study will focus on the ways individual households can be flexible in their demand to fully reap the benefits of dynamic energy contracts and whether historic and real-time data in the Netherlands show the same results as the studies done in other geographical areas.

4 Consumption flexibility

This chapter answers sub-question 3:

What are the possibilities for individual households to be flexible in their demand?

This section covers additional context on flexible consumption for individual households. This analysis is based on a literature study of many academic papers, journals, governmental documents, and gray literature. Besides that, some supplementary insights into these findings will be provided by responses from the semi-structured interviews with consumers with a dynamic energy contract, as conducted in the previous chapter. To evaluate the potential flexibility in demand for individual households, it is crucial to gain a comprehensive understanding of the various energy-consuming activities and appliances within each household. This chapter will start with an overview of the various energy-consuming activities and appliances within households, exploring the degree of flexibility associated with each. Additionally, it will offer an overview of the different methods available for demand shifting in individual households. Furthermore, it will examine the factors influencing the flexibility of demand, thus contributing to a more comprehensive understanding of electricity consumers.

4.1 Flexibility options electricity consuming activities for individual households

Consumption flexibility is also known as demand response and is defined as 'the capacity to increase, decrease, or shift the consumption of domestic appliances over a period of time' (Sidqi et al., 2020). Demand flexibility is needed to accelerate the energy transition and to support the integration of RES (Darby 2017; Torriti et al., 2015; Yilmaz et al., 2019).

To understand the possibilities of flexibility in electricity demand, it is necessary to understand the different activities and appliances that consume electricity in an individual household. There are mainly five electricity consuming categories in Dutch households: lighting, space heating/cooling, hot water, electricity consuming appliances and others (Ortiz et al., 2017). An overview of the electricity consuming appliances and activities in Dutch households will be displayed in the table below. This table is constructed from the insights gathered in the literature study.

Table 3. Overview of electricity consuming activities and appliances (Ortiz et al., 2017; Eurostat, 2021)

Wet appliances	Dry appliances	Activities
Washer	Lighting	Cooking
Dishwasher	Air Conditioner/Heating	Leasuring: TV & Computer
Dryer	Boiler	Cleaning: Vacuum cleaner & Iron
Hot water	Fridge	
	Freezer	
	EV	

Research in the past focused a lot on discovering which activities and appliances are active during peak hours and which activities households are willing to shift to off-peak hours when given a price incentive.

The most electricity consuming activities from individual households during peak hours are cooking and watching television (Smale et al., 2017; Ozaki, 2018; Stelmach et al., 2020; Öhrlund et al., 2019). This is not surprising since most people come home at the same time, cook dinner and relax afterwards, before going to bed. A case study of two smart grid projects in the Netherlands showed that only a small portion of households were willing to shift their electricity consumption used for cooking and leisure activities, such as watching television (Smale et al., 2017). The individual households, which were all homeowners, consider control over the time of their cooking as very important and are therefore less willing to respond to price incentives. This perception is the same for individual households that consist of subsidized tenants (Schrammel et al., 2023). On the other hand, the shifting of domestic cleaning practices such as the dishwasher, dryer and washing machine were much more sensitive to price incentives. This can be explained by the absence of time sensitivity, in stark contrast to the time-critical nature of cooking. Additional research, conducted in various global regions, affirm a consistent trend towards electricity consumption shifting across the same activities. A survey study of 337 households in California revealed that around 80 percent of the households were willing to shift the use of their domestic cleaning appliances to off-peak hours, while only 22 percent of the households were willing to switch their cooking and watching television to a different time during the day (Stelmach et al., 2020). In the UK, an interview-based study of households who participated in a project with dynamic ToU pricing, indicated that individual households are only willing to shift household practices as long as it did not “ruin their quality of life” (Ozaki, 2018). This again resulted in the same outcome: households were more willing and able to shift cleaning tasks compared to cooking. The same findings were conducted from the three interviews with electricity consumers with a dynamic energy contract (CUS1; CUS2; CUS3). In Sweden, a study regarding consumption behavior during ToU tariffs was more extensively done, basing their conclusion on not only interviews, but also on activity-based diaries (Öhrlund et al., 2019). This study showed that individual households, even the ones that were retired, were not willing to shift the cooking and watching television. This indicates that individual households are not flexible regarding these activities, despite the price advantages and their (lack of) activity during the day. When considering appliances such as an EV and air conditioning, a case study in the US showed that the flexibility of demand of these appliances was higher than the wet appliances (Afzalan & Jazizadeh, 2019). This can be explained again by the less time-critical nature of these appliances. Other electricity-consuming appliances such as freezers, heating and lighting remain relatively constant throughout the day and constitute the largest portion of household electricity consumption (Eurostat, 2021).

In addition to the different possibilities to shift demand there are various factors and characteristics that impact the willingness to shift. Multiple studies have been done regarding this subject. The most prominent factors influencing the willingness-to-shift of individual households are displayed in the table below.

Table 4. Factors influencing possibility and willingness to shift peak demand (Stelmach et al., 2020; Ozaki, 2018; Andersen et al., 2017; Mata et al., 2020)

Customer characteristics	Household properties	External factors
Children	Presence at home	Outdoor temperature
Income	Number of household members	
Gender	Smart technology	
	Square footage of home	

The various factors have been divided into three different categories: customer characteristics, household properties and external factors.

In California a study was conducted with 337 households to gain insights in the reaction of households towards dynamic pricing. The outcome of this research showed that various factors were positively associated with the willingness to shift their peak demand: more smart technologies in households, greater number of household members and less home square footage (Stelmach et al., 2020). The correlation between smart technologies and willingness to shift suggests that the presence of these technologies may facilitate shifting. For example, households in the UK mentioned during interviews that preset automatic reactions towards the electricity price from appliances would make “life a lot easier” (Ozaki, 2018). Furthermore, when households have more electric appliances such as an EV or an individual heat pump, their potential to be more flexible in their demand increases (Andersen et al., 2017; Wang et al., 2018). In the previously mentioned study in California, a correlation was identified solely between the number of household members and the willingness to shift, with no distinctions observed between households with and without children. However, studies conducted in the UK and the Netherlands found that households with children demonstrated less flexibility in shifting their peak demand to different hours (Torriti et al., 2015; Smale et al., 2017).

Other research confirmed again the positive relationship of smart appliances in households with the ability and willingness to shift peak demand (Yilmaz et al., 2019). A multinomial logistic regression identifies also other factors that increase the willingness to shift. Especially, the presence at home came out to be a significant determinant of load shifting. Smart appliances could increase the willingness and possibility to increase demand load shifting by helping households where there is less presence at home. Another factor that has been identified that influences household flexibility is the outside temperature (Mata et al., 2020). This is because this is the main factor contributing to the use of heating within an individual household. Whenever the temperature outside is higher, there is less need for heating and therefore households can be more flexible in their demand during the full day. This study focuses itself on four countries which improves the validity of the results.

Another factor influencing the willingness to shift their demand is the income of households. Lower income households were more willing to reduce their energy expenses (Iliopoulos et al., 2020), in order to save more money. On the other hand, low-income households often have fewer electric appliances to contribute to their flexibility (Gunkel et al., 2023; Ribó-Pérez et al., 2021), which shows that their willingness to shift needs to come from intrinsic motivation.

A field study on 71 Danish households revealed that gender plays a part in the flexibility of consumption and the willingness to shift (Tjørring et al., 2018). In this study households received incentivized text messages to shift their electricity consumption to other hours of the day. The result of this study showed that women significantly more responded to these messages. Targeting women increased the flexibility of the electricity consumption, since they were more willing to shift based on those messages.

Apart from various factors that can influence the willingness to shift peak demand of individual households, there are also extra incentives that can be given to increase the flexibility of demand. These will be discussed in the following paragraph.

4.2 Demand Side Management (DSM): contributing to demand flexibility

In order to get a grip on the demand of households, demand side management (DSM) can be used (Azarova, 2020). DSM aims at optimization of the electricity usage patterns of households to improve energy efficiency (Dong et al., 2022). Specifically, reducing peak consumption, since this is a key element in stabilizing the electricity grid (Azarova, 2020). Besides that, DSM can reduce electricity costs for consumers (Jasim et al., 2023). DSM requires changes of behavior patterns in everyday life, to get to a result (Friis & Christensen, 2016). There are different options for DSM, the types of DSM and their results in the past will be discussed below.

4.2.1 Economic incentives

The most dominant approach of DSM is providing economic incentives to households to change their behavior pattern (Friis & Christensen, 2016). Many studies have shown that this kind of incentive is the most effective incentive to influence the consumption pattern of households. Not only do economic incentives help with creating more awareness and stimulating active choices towards electricity consumption (Fjellså et al., 2021), they also impact load shifting. A study in Switzerland showed that there was a significant shift in consumption behavior when offering economic incentives to households, who normally pay a fixed tariff for their electricity (Weber et al., 2017). This study was conducted through a DiD regression in which they designed a control group and a treatment group. The treatment was designed in the form of a contest. Every month, a ranking would take place, and if your household were on top of the ranking, you received a higher financial price. This resulted in shifting consumption to times during the day when solar radiation takes place and reduced their consumption during peak hours. This is the same result for another study done by Faruqui et al. (2016) when offering economic incentives to households.

Not only do monetary incentives work effectively, but there is also a downside to this DSM strategy. In research conducted in Austria there was a so-called rebound effect: when the monetary incentives were no longer in place, the overall electricity consumption of those households increased during the peak hours (Azarova et al., 2020). This is not the effect that was intended by the researchers of this study.

4.2.2 Providing information

Providing information to end-users is a common way to change their knowledge and hopefully change their attitude towards their consumption behavior (Fjellså et al., 2021). This way of DSM is a relatively low-cost measure to take, which is possible on a large scale (Frondel & Kussel, 2018). Besides that, the same study in Germany showed that there is a significant difference in sensitivity to price changes; only households that were informed about electricity prices were sensitive to the changing prices (Frondel & Kussel, 2018). Incentivized text messages can also be classified as providing information to consumers. These incentivized text messages, suggesting shifting their electricity to non-peak hours of the day, have a bigger impact on female consumers than male consumers (Tjørring et al., 2018). The main reason behind this gender difference is that women often are more involved in household work tasks. However, when text messages were sent to the gender 'in charge' of that household task, both genders acted on it. Besides that, a newer study showed that text messages alone did increase the interest of households towards consumption reduction but does not have a significant effect on reducing the actual electricity load (Schrammel et al., 2023). Research from Weber et al. (2017) made the recommendation to improve households' knowledge by increasing the frequency of billing and to charge the actual amount of electricity used instead of the forecast.

4.2.3 Smart appliances

Smart meters and smart appliances are becoming more popular over the past years (CBS, 2022). Smart meters are meters that collect detailed information of consumption patterns of consumers (Jordehi, 2019; Azarova et al., 2020), for example their usage for every 15 minutes. Various research showed that the addition of smart meters and appliances, have a positive impact on the demand flexibility, since it increases consumer comfort in shifting their electricity load (Jasim et al., 2023). Besides that, they also have an impact on the load curve shape of households (Faruqui et al., 2016). A longitudinal study in the Netherlands showed that having a smart washing machine, shifted their laundry to during the day when renewable energy sources provided the electricity, and therefore their demand during peak-hours decreased (Kobus et al., 2015). This shift in behavior was the same during the full year, which indicated structural shift.

Smart appliances with shifting techniques are effective strategies to reduce the demand load of consumers (Avordeh et al., 2021). In this same study peak loads can be reduced to 45% when having time-triggered loads on refrigerators and air conditioning systems. However smart appliances and smart meters are not always as effective as described above. In a study in Germany, the saved costs of households with smart appliances were almost the same as the costs of smart metering technology per unit (Blaschke, 2022). This suggests that currently the costs of smart appliances are too high in order to significantly impact cost savings for consumers. This notion is reinforced by the fact that only 7% of households worldwide owned at least one smart appliance (Statista, 2023). However, this share is projected to triple over the next five years.

4.2.4 Social impulses

The above-mentioned DSM strategies are more common, but DSM strategies are broadening their tactics to pro-social impulses (Pratt & Erickson, 2020). This prosocial behavior that is incentivized by those impulses can be defined as any act designed to increase other's well-being (Tomasello, 2009), which is also known as altruism. Therefore, this DSM strategy is more social and less egoistic than the other ones. Research in behavioral economics has shown us that pro-social impulses have a significant effect on consumers' decision-making process (Kahneman, 2011). Not only does this influence the decision-making, but it also increases program effectiveness according to van der Werff et al. (2019) and White et al., (2019).

These outcomes are confirmed by a study done in the USA where they donated money to a charity whenever consumption was reduced during peak hours (Pratt & Erickson, 2020). The households participating in this research were informed of the hours in which they needed to limit their electricity consumption, a day before the study would take place. Results showed that there was a decrease of 13,5% in electricity consumption in those peak hours. This shows that, even though the consumers of those households did not benefit from this program at all, they were incentivized to reduce their consumption to help others. Additional research conducted in the Netherlands yielded similar results, but with a different prosocial impulse: the private commitment strategy. This approach required households to commit to altering their behavior. In this research participants were presented with a list of electrical appliances. They were asked to check the box next to all the appliances they committed to unplugging the following month. Afterwards, they were required to sign the online form with their name and the current date to enhance the private commitment and to foster greater active engagement. It was found that this strategy was effective only when the private commitment made was relatively effortful, meaning that changing their behavior needed to be a challenging task rather than an easy one (van der Werff et al., 2019). This private commitment made people more morally obligated to engage in the behavior that they committed to, which positively influenced overall energy savings behavior. However, pro-social impulses such as social norm interventions, do not seem to have a significant effect on this subject, since proactive environmental behavior, such as reducing energy consumption, is not widespread (Huber et al., 2018).

4.3 Main conclusions chapter 4

This chapter revealed the different possibilities for individual households to be flexible in their demand and how DSM strategies can contribute to this. This chapter answers the following research question:

What are the possibilities for individual households to be flexible in their demand?

An overview of the main findings is explained below.

Flexibility in individual households

Multiple studies have shown that there are a lot of different ways for individual households to be flexible in their demand. Multiple factors play a role in the flexibility of households and their willingness to shift their demand to off-peak hours. The presence at home during the day, the number of household members, the outdoor temperature and smart technology all exhibited a positive correlation with both the willingness and the ability to shift electricity consumption. Conversely, income and square footage of a home had a negative impact on these factors. Additionally, directing efforts towards women proves to be more effective than targeting men for electricity-consuming household activities. The most static activities, which do not really contribute to flexibility of demand are cooking and leisure activities at the end of the day. Households showed little to no motivation to change these habits despite the lower electricity price at different hours of the day. Conversely, they exhibited more flexibility with other activities such as cleaning, bathing and washing. These activities are perceived as less time critical. It is more challenging to change behavior when the activity is typically associated with a specific time frame. When households have an EV or an individual heat pump, there is also an increase of flexibility of demand.

Incentives for individual households to be more flexible

This chapter investigated four different DSM strategies: economic incentives, providing information, smart appliances and social impulses. Historically, economic incentives have proven to be the most effective among all DSM strategies, while providing information feedback has been observed to raise greater awareness but not necessarily result in a shift in electricity consumption in households (Weber et al., 2017; Yilmaz et al., 2019). It is most efficient to combine multiple strategies, which often happens. Energy monitoring technologies, such as smart meters, incentivizes customers to gain better knowledge and control over their electricity consumption (Caleno & Coppola., 2013). Recommendations to increase flexibility in households are more automation in appliances and offering an integrated, socially inclusive, and collectively motivated program to consumers.

The literature and conducted interviews are supporting each other regarding the different ways households can or cannot be flexible in their demand. This research shows that there is potential for more flexibility in individual households. This effect is heightened in the presence of DSM strategies, which provide incentives for households to reduce their demand during peak hours. The remaining study will focus on the role of dynamic energy contracts regarding the flexibility in electricity consumption of households.

5 Electricity consumption behavior

The objective of this chapter is to provide insights into the characteristics of electricity consumers and their behavioral patterns across different electricity contracts and different time periods. Emphasis will be placed on distinctions among consumer groups, setting the context for the following chapter.
This chapter will answer to the following sub question:

Is there a difference in consumption behavior patterns between consumers with a dynamic energy contract and their behavior under their previous contract?

5.1 Descriptive statistics

To provide a background for this analysis and before answering the sub question, various descriptive statistics of the different consumer groups will be presented. In this research two different consumer groups will be analyzed. Before performing the data analysis, it is necessary to have insights in the variations in properties among the different consumer groups. These observations provide insights into potential factors that may influence the consumption behavior patterns of individual households, within the two consumer groups. These findings can be utilized in the subsequent data analysis within this and the following chapter. An overview of the averages of several properties is presented in the table below. For a more complete overview of the 'average customer' per contract, the full consumer group of the energy supplier Vandebron is used.

Table 5. Customer insights of both consumer groups

	Dynamic energy contract (n=742)	Fixed energy contract, 3 years (n=62390)
Age	46.2 years	49.8 years
Male/Female	72,9% male, 27,1% female	59% male, 41% female
Solar Panels	34,1% solar panels	32,2% solar panels
Urban/Rural	60,7% Urban	49,4% Urban

When looking at the different characteristics of both consumer groups, the biggest contrast can be found in gender distribution. Besides that, customers with a dynamic energy contract are in general younger than customers with a fixed energy contract. These two findings can be explained by the fact that customers choose a dynamic energy contract mainly for the innovative part of this contract and are required to be a little risk-seeking, as indicated by the semi-structured interviews (CUS1; CUS2; CUS3). Besides that, there is also a difference in the location of the households of the customers; customers with a dynamic energy contract are more often living in an urban part of the country compared to customers with a fixed energy contract. The urban/rural distribution is determined using data provided by CBS (CBS, n.d.). The solar share in both consumer groups is quite similar. Based on the outcomes of the descriptive statistics, it can be concluded that both consumer groups are not the same. They differ on multiple characteristics, which might influence their electricity consumption.

5.2 Electricity consumption

To get a more complete overview of the differences of both consumer groups, their average electricity consumption is also analyzed. From this point onwards in the research, only a subset of the data is utilized for further analysis. From this point on in this study, only the subset of data is analyzed. The two different consumer groups used in this research are defined as follows:

Fixed: consumer group 1, n=863, fixed electricity contract in 2021 and 2023
Dynamic: consumer group 2, n=203, variable electricity contract in 2021 and a dynamic electricity contract in 2023

The subset of the consumer group 'Fixed' was randomly selected. The only requirement for this subset was that they had available smart meter data in 2021 and 2023, indicating that they had been a loyal customer of Vandebron for at least three years. The first 1000 households were chosen from the pool of customers meeting these criteria. This selection was entirely random, as running the query again would yield a different set of 1000 households. After cleaning and verifying all the data points, it was found that only 863 households had complete data for both years. Consequently, these 863 households were selected as the subset for further analysis.

The subset of the consumer group 'Dynamic' included all households that had a variable contract in 2021 and a dynamic contract in 2023. As shown in table 5, the total number of consumers with a dynamic contract in 2023 is only 742. After the requirement of being a loyal customer to Vandebron and having a smart meter, 253 customers remained. After cleaning and verifying all data points, it was found that only 203 households had complete data for both years. Consequently, these 203 households were selected as the subset for further analysis.

In this dataset the specific choice has been made to only consider the data from 2021 and 2023. The year 2022 has not been taken into account due to multiple reasons. The global conditions changed extremely in this year which resulted in the highest energy prices in a long time. Because of the energy crisis and the thereby associated high electricity prices, consumers were suddenly much more aware and invested in their energy consumption. Besides that, another choice is made to only consider the month September for both years. This is done with the knowledge that at that moment the customer base with dynamic energy contracts of Vandebron was at its highest when this research started. This decision is supported by the fact that Vandebron began offering this type of contract from May 2023. Therefore, there was no available data for customers with a dynamic energy contract before May 2023. Additionally, the summer months are less representative due to the long summer vacation and the prolonged absence of households at home.

The average electricity consumption for a day in September per consumer group is calculated and the outcomes are shown in table 6. Besides that, the percentage of electricity consumed in peak hours is also included.

Table 6. Average electricity consumption for both consumer groups 'Fixed' and 'Dynamic'

Average consumption /day	September 2021	September 2023	% consumed in peak hours 2021	% consumed in peak hours 2023
Fixed	28,1 kWh	27,1 kWh	56,7%	57,1%
Dynamic	37,4 kWh	34,9 kWh	54,7%	46,6%

The amount of electricity consumed varies significantly per consumer group. On average, Fixed has a lower electricity consumption compared to Dynamic. Nevertheless, the electricity consumption within both consumer groups remained relatively stable over the two years, with a slight overall decrease in consumption. Besides that, the amount of electricity consumed during peak hours is almost the same in both years for Fixed, while it differs a lot for both years in Dynamic. The electricity consumed during peak hours for Dynamic decreased by 8 percent. The shift in consumption is better visible in table 7.

Table 7. Average consumption during peak and off-peak hours

Average consumption/day	2021		2023	
	Fixed	Dynamic	Fixed	Dynamic
Peak morning (6:00-10:00)	5,3 kWh	6,6 kWh	4,9 kWh	5,7 kWh
Peak evening (17:00-22:00)	10,6 kWh	13,9 kWh	10,6 kWh	10,5 kWh
Off-peak midday (11:00-16:00)	5,7 kWh	7,4 kWh	5,2 kWh	9,5 kWh
Off-peak night (2300-05:00)	6,5 kWh	9,5 kWh	6,4 kWh	9,2 kWh
Total	28,1 kWh	37,4 kWh	27,1 kWh	34,9 kWh

For Dynamic, the electricity consumption during peak hours in the morning as well as peak hours in the evening, has decreased. At the same time, the consumption during off-peak hours in both time periods has increased. The reason for this might be the fact that customers with a dynamic energy contract in 2023 pay the hourly electricity price for their electricity consumption. This will be investigated further in this chapter. The spot price of electricity is in general lower during the day since there is more generation of renewable energy. An extensive overview of the electricity spot price can be found in Appendix B.

Observing the average electricity consumption of both consumer groups reveals another noteworthy facet. The average consumption of both consumer groups is much higher than the overall average (7,9 kWh/day) in the Netherlands (Pure Energie, 2024). This much higher number of both consumption groups can be explained by the fact that a big part of the customers of the energy supplier Vandebron is only an electricity customer, 19,2 percent of the full customer base. There is always the possibility that these customers have a gas contract with a different energy supplier, but according to semi-structured interviews with various energy suppliers (VDB1; VDB2), this is often not the case. Another, more logical, reason for this could be the fact that those customers have electricity as their only source of energy in their household. This is more sustainable and will be expected to be the norm in the future (International Energy Agency, 2022). Vandebron is a green electricity supplier from local soil, appealing to customers who prioritizes sustainability and consequently prefer electricity over gas for their energy needs. Customers with a dynamic energy contract are even more likely to only have electricity as their only energy source, since 30,1 percent of these customers have an exclusive electricity contract, which was a pattern also observed among the interviewees (CUS1; CUS2; CUS3). Another reason might be the fact that customers who only have electricity as their energy source, often have solar panels and a heat pump, which increases their electricity consumption. Having an EV could also substantially impact electricity consumption of a household. Furthermore, other energy suppliers, such as ANWB, the market leader on dynamic energy contracts, confirm that a dynamic energy contract can be more beneficial if the overall consumption of electricity is higher (Voermans, 2023). Consequently, it is a logical outcome that the overall consumption of customers with a dynamic energy contract is higher than customers with a different energy contract.

5.3 Consumption behavior pattern

Based on the descriptive statistics from before, it is clear that there is a significant difference in the average electricity consumption per consumer group. The statistics have already been presented, but to better understand the differences during the day, the consumption behavior pattern of both consumer groups is displayed in the figures below.

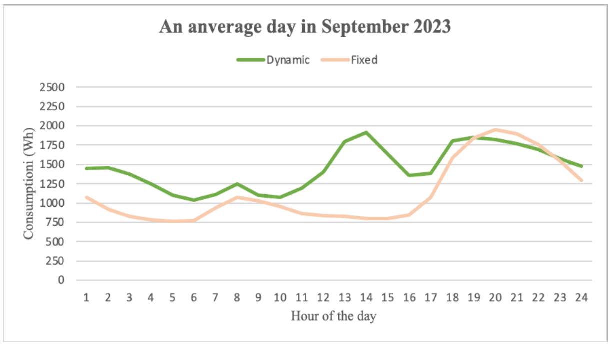

Figure 3. Consumption behavior patterns in 2021

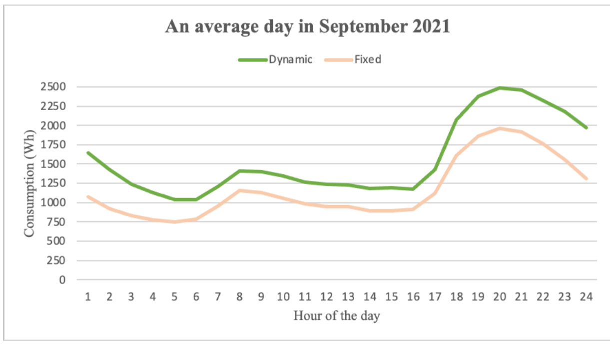

Figure 4. Consumption behavior patterns in 2023

In the figures above the consumption behavior patterns are shown for both consumer groups in the two different years. The key observation in figure 3 is the nearly identical consumption behavior pattern of both consumer groups in 2021, with the only distinction being that Dynamic consistently demonstrates a higher average consumption compared to Fixed. However, in 2023 (figure 4), the consumption behavior patterns diverge significantly. The most prominent distinction lies in off-peak hours during the day, particularly between 11:00 and 16:00, reaching a peak at 14:00.

Diving deeper into the average consumption of both consumer groups, there is an important factor revealed who has a major influence on the amount of electricity consumed. Analyzing variations among consumer groups with and without solar panels reveals that electricity consumption is significantly higher among customers with solar panels, in comparison to those without, which is shown in table 8.

Table 8. Consumption of electricity of both consumer groups with and without solar panels

Average consumption/day	Solar 2021	Solar 2023	Non Solar 2021	Non Solar 2023
Fixed	29,6 kWh	29,2 kWh	26,8 kWh	25,2 kWh
Dynamic	43,4 kWh	41,0 kWh	33,2 kWh	29,2 kWh

To get a better view on the differences between both groups, the average behavior pattern for both groups, with a distinction for solar and non-solar customers, in different years are presented in the figures below.

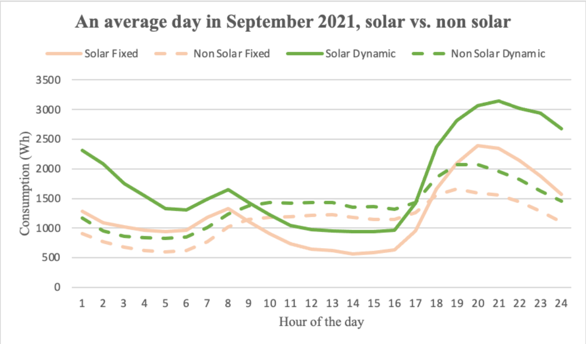

Figure 5. Consumption behavior patterns in 2021

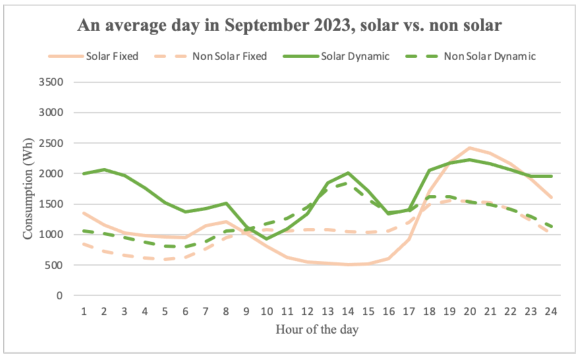

Figure 6. Consumption behavior patterns in 2023

When examining figure 5 (2021), the key observation is that customers in both consumption groups have the same consumption pattern. However, a distinction in consumption patterns between solar and non-solar customers is evident overall. Additionally, the figure confirms the generally higher electricity consumption of customers with solar panels. Figure 6 illustrates a different consumption pattern compared to their previous pattern. there is difference in consumption pattern between solar and non-solar customers in general. Besides that, there is also a difference visible between the solar customers and non-solar customers of the same consumer group. Again, the consumption of electricity for solar customers is higher than non-solar customers.

It is remarkable that overall customers with solar panels use in general more electricity. This is not specifically the case for these customers of this specific energy supplier but this applies to all individual households with solar panels in general (Deng & Newton, 2017; Hasan, 2023). Often customers install solar panels with the main motivation to save money (Alipour et al., 2022; Ugulu, 2019; Hansen et al., 2022), which is easier when you consume more electricity overall. Besides that, customers are consuming more electricity after installing the solar panels. Multiple studies have shown that after installing solar panels, households are increasing their electricity consumption (Beppler et al., 2021; D'Agosti & Danza, 2023). Additionally, earlier research, including in the Netherlands, even showed that solar panels have a rebound effect, meaning that the more solar energy households produce with their solar panels, the more their electricity consumption increases (Aydin et al., 2023; Beppler et al., 2021).

5.4 Main conclusion chapter 5

This chapter revealed the differences in characteristics of the consumer groups used in this research. Besides that, it gave an extensive overview of the electricity consumption for both consumer groups and revealed multiple factors that influence the electricity consumption.
This chapter answered the following research question:

Is there a difference in consumption behavior patterns between consumers with a dynamic energy contract and their behavior under their previous contract?

The main findings from the research question are summarized below.

Descriptive statistics
Customer insights revealed that electricity customers exhibit different values for the same characteristics, depending on the type of contract. It showed that customers with a dynamic energy contract are on average somewhat younger than customers with a fixed contract. Besides that, the dynamic energy contract is more frequently subscribed by male customers. This distinction in gender is much higher than in the consumer group with a fixed energy contract. The solar share for both energy contracts is similar, while customers with a dynamic energy contract are more often living in an urban area compared to customers with a fixed energy contract.

Electricity consumption
There is a large difference in electricity consumption of both consumer groups. The consumer group Dynamic, with a variable contract in 2021 and a dynamic energy contract in 2023, consumes around 1,3x times more electricity than the other consumer group in both years. In 2021, both consumer groups consumed most electricity in the peak hours, while in 2023, the consumer group with a dynamic energy contract consumed 8 percent less electricity in those peak hours, and more electricity in off-peak hours. The electricity consumption of both groups is much higher than the average electricity consumption of households in the Netherlands. This can be explained by the prevalence of customers in both consumer groups who solely use electricity as their energy source, often in conjunction with a heat pump. Another contributing factor could be the rising number of households owning electric vehicles (Statista, 2023). Additionally, Vandebron is more appealing to consumers with a sustainable motive, who prefer electricity over gas.

Consumption behavior pattern
Based on the analyzed electricity consumption, the different consumption behavior patterns in both years were constructed. In 2021, the patterns of both consumption groups were similar, with the only distinction that Dynamic consumed during all hours more electricity than Fixed. In 2023, the consumption patterns diverge immensely. The biggest difference in consumption is in off-peak hours during the day, between 11:00 and 16:00, reaching a peak at 14:00. When making a distinction between consumption patterns of solar and non-solar customers, there are a few striking differences. Customers with solar panels consume on average much more electricity than consumers without solar panels. This is due to the fact that customers overall choose for solar panels when they have a high electricity consumption. Additionally, research has

shown that customers are consuming more electricity after installing solar panels. The difference in the amount of electricity consumed is much higher in Dynamic compared to Fixed.

Based on the descriptive statistics and the electricity consumption during different hours, it is evident that there is a difference in consumption behavior patterns between consumers with different contracts. More importantly, there is a big difference in consumption behavior patterns between customers with a dynamic energy contract and their behavior under their previous contract (figure 4).

6 Electricity consumption with a dynamic contract

This chapter provides insights into the electricity consumption with a dynamic energy contract, and it will investigate a possible causal relationship between consumer behavior and the dynamic energy contract. This chapter will answer the following sub question:

Does consumption behavior vary between consumers with a dynamic energy contract and those with a fixed energy contract under different real-time prices?

For this analysis a difference-in-difference (DiD) regression is done. The data used for this analysis is the same data used for the consumption behavior patterns, but instead of averages, the consumption of each customer will be taken into account for this regression. This chapter will first explain the DiD regression method that is used. Secondly it will present all the input data used in the data analysis. Finally, the results of the regression analysis will be presented. The chapter ends with an overall conclusion.

6.1 Method

A regression analysis is chosen for this research to explore whether there is a causal relationship between one dependent variable and multiple independent variables (Gogtay et al., 2017). The primary goal of the DiD regression is to compare the changes in outcomes over time between a treatment group that receives the intervention, and a control group that does not. The intervention in this analysis is switching to the dynamic energy contract. In this research the control and treatment group are defined as follows:

Control group **Fixed**: consumer group 1, n=863, fixed electricity contract in 2021 and 2023
Treatment group **Dynamic**: consumer group 2, n=203, variable electricity contract in 2021 and a dynamic energy contract in 2023

The selection of this regression model is based on its ability to estimate causal effects, even in situations where the treatment and control group cannot be randomly chosen. In this study only electricity consumption data of one energy supplier, Vandebron, is analyzed. Additionally, individual households who opt for this energy supplier do not exhibit the average profile, as Vandebron is mainly focused on supplying sustainable energy. This method also helps control for potential confounding factors and time-varying trends.

The estimate of the causal effect in this analysis relies on observing changes in outcomes within the treatment group, under the assumption that any differences in these outcomes reflect pre-existing trends, and were not caused by the intervention.

The DiD regression analysis requires multiple key assumptions and conditions to be valid and provide unbiased estimates. The main requirements are:

- Parallel trends.

This assumes that in the absence of treatment, the baseline trend would have followed the same parallel trend over time. Meaning, that in the counterfactual world, where there was no change in treatment, the trend in outcomes between both consumer groups would have been the same on average over time.

- Treatment and control groups.

The data for this analysis is required to consist of both a control group (Fixed) and a treatment group (Dynamic).

- Stable treatment assignment.

This assumes that the assignment of treatment should be stable over time and not affected by the outcomes being studied. In this research the treatment assignment is not random, the treatment group was pre-defined, since the analysis is based on historic data from one energy supplier.

- Sufficient time periods.

The data for this analysis is required to have multiple time periods: before and after the introduction of the treatment. This is necessary to observe trends and differences. In this research all units from both consumer groups have data before and after the treatment (September 2021 and September 2023).

- No contamination.

This assumes that the control group cannot in any way be contaminated with any treatment effect. In this case that is impossible since the treatment consists of having a dynamic energy contract. The control group, customers with a fixed energy contract, remains unaffected by the treatment.

For this study the fixed effects method in the DiD regression is used. This makes it possible to regress the outcome on the treatment while controlling for all fixed characteristics of units and time periods (Bueno de Mesquita & Fowler, 2021). In this research multiple dummy variables are added to the dataset. First, a treatment variable and a time variable are included, which are extensively described in 6.2. Incorporating these dummy variables, also known as fixed effects, ensures the removal of all average differences between units and all average differences over time. Additionally, other variables, also known as control variables, are included in the dataset to enhance the identification of the causal effect of the treatment. By including these variables, there will be controlled for factors that could independently influence the outcome variable: the electricity consumption. The control variables in this research are the temperature per hour, the sunshine radiation per hour, the spot price of electricity and the characteristic whether the customer has solar panels or not. After performing the DiD regression, the regression model will be validated.

6.2 Input data

For the data analysis done in this chapter, various data sources are used. Some of the data is publicly available, while other data is provided from the energy supplier Vandebron.

Smart meter data Vandebron

Electricity consumption data of multiple households affiliated with energy supplier Vandebron is used. This data is obtained from smart meter data of every household. The data consists of consumption data of 1066 households (863 households Fixed and 203 households Dynamic) of every day in September in 2023 and 2021 for the hour 2pm. A part of these households had a variable energy contract before they switched to a dynamic energy contract in 2023 (treatment group), while the other part had a fixed energy contract in both years (control group). The consumption data is provided to the company by smart meters every 15 minutes. However, in this report, the consumption data is compiled into hourly data. All data is used anonymously and aggregated to hourly consumption data, and therefore will never be traceable to one individual customer.

As mentioned before, due to multiple reasons described in 5.2, only the month September for 2021 and 2023 has been taken into account. Furthermore, the decision was made to exclusively analyze the electricity consumption at 2pm every day. This selection was motivated by the fact that this hour typically coincides with the sun's brightest period, resulting in the highest solar electricity generation every day. Additionally, this timeframe often corresponds with the lowest electricity prices. Moreover, considering all hours from all customers would have been too data intensive.

Weather data

For the weather data, multiple variables have been taken into account: the temperature per hour and the amount of sunshine per hour (on a scale of 1 to 10). The data provided by the KNMI (Koninklijk Nederlands Meteorologisch Instituut) is used for this analysis (KNMI, 2021; KNMI, 2023). The weather values of the KNMI measured in the Bilt are considered, due to its central location. This location is considered representative of the average Netherlands (KNMI, n.d.). The assumption is made here that those weather conditions are the same for all customers in the customer base from Vandebron. However, these weather conditions differ for the years 2021 and 2023, which will be considered.

The inclusion of weather data in this analysis serves to control for potential differences in electricity consumption stemming from varying weather conditions. For instance, when the outside temperature is lower, households tend to consume more electricity due to heating purposes. Moreover, increased sunshine hours result in greater generation of renewable energy during the day, leading to lower electricity prices during those hours. These factors can significantly influence the electricity consumption patterns of households.

EPEX Spot Price

With dynamic energy contracts the price for electricity is similar to the spot price of electricity at every given hour. Therefore, it is necessary to take the varying prices into account. The EPEX spot price for electricity (EPEX, n.d.) for every day and year chosen (description above) at 2pm is taken into account. Other costs such as the fixed contribution customers pay to Vandebron for each kWh are not included.

The spot price of electricity is included in this analysis, as this research will explore the influence of the electricity price on electricity consumption.

Dummy variables

Additional input data are some dummy variables which are also added to the dataset:

- Solar/No Solar. For every household in the dataset, it is defined whether they have solar panels. This will be displayed with the value 1 if the household has solar panels and with the value 0 when the household does not have solar panels. Households with solar panels typically exhibit higher electricity consumption on average compared to households without solar panels (Deng & Newton, 2017; Hasan, 2023). This dummy variable is included to account for potential differences in electricity consumption stemming arising from the presence or absence of solar panels.

- Treatment variable. This variable is necessary to perform the DiD regression analysis. The value 1 is given to the treatment group: CG2, who has a variable contract in 2021 and a dynamic energy contract in 2023. The value 0 is given to the control group (CG1), which are the households who in both years had a fixed energy contract.

- Time variable. This variable is necessary in order to perform the DiD regression analysis. The variable is defined as 'D2023'. The value 1 is given to all data points that are measured in 2023. The value 0 is given to all data points measured in 2021.

6.3 DiD regression analysis

For this research multiple programming languages were used to provide the correct dataset and to perform the right analysis. The dataset is constructed using SQL (Structured Query Language). A subset is created from all customer data available in the data warehouse (Snowflake) of the energy supplier Vandebron. To perform the Difference-in-Difference (DiD) regression, Jupyter Notebook is used with the programming language Python. In Jupyter Notebook the necessary packages for data gathering, data cleaning, statistical and correlation analysis, and data visualization are imported. These packages include pandas, matplotlib, numpy, sklearn, scipy, statsmodels and seaborn. Other descriptive statistics analyses are performed in Excel.

Before performing the DiD regression analysis, it is essential to consider the potential presence of heteroscedasticity, which implies that the variance of errors may not remain constant across all levels of the independent variables. Additionally, there is the likelihood of autocorrelation, indicating that errors may not be entirely independent of each other. Given that this research does not utilize a completely random sample of households in the Netherlands and relies solely on data from a single energy supplier, the potential for such biases is apparent. Besides that, the DiD regression analysis requires time-series data. In time-series, autocorrelation can also be a concern. Heteroscedasticity can affect the efficiency and reliability of the coefficient estimates and can lead to incorrect standard errors. To check this phenomenon in this model, the White test for heteroscedasticity has been performed. This test is performed in Jupyter Notebook and resulted in a high positive value of the White test statistics, with a very low p-value. This indicates that this result is significant, and that there is the case of heteroscedasticity. To make the model more robust and reliable, heteroskedasticity- and autocorrelation-consistent (HAC) standard errors have been used in the DiD regression. HAC standard errors can in this case provide more robust and reliable standard errors (Newey & West, 1987).

6.3.1 Results

The DiD regression is performed multiple times, in which each time another control variable is added to the regression. First, the DiD regression is performed as if there are no control variables, only including the treatment variable, time variable and the interaction variable. Afterwards the control variables are added to the regression one by one. As mentioned before, four control variables are in total added to the dataset: spot price, having solar panels or not, the temperature per hour and the solar radiation per hour. The results of the DiD regression can be found in the table below.

Table 9. Results of regression analysis

	Model 1		Model 2		Model 3		Model 4		Model 5	
	Dependent Variable = Electricity Consumption at 2pm									
	Coef (std err)	P-value	Coef (std err)	P-value	Coef (std err)	P-value	Coef (std err)	P-value	Coef (std err)	P-value
Constant	851.65 (9.835)	0.000	1046.56 41.165)	0.000	1251.22 (41.017)	0.000	1526.95 (62.251)	0.000	1479.73 (63.322)	0.000
Treated	292.88 (25.238)	0.000	292.88 (25.241)	0.000	274.98 (24.962)	0.000	274.98 (24.822)	0.000	274.98 (24.764)	0.000
After	7.81 (15.877)	0.623	-62.80 (19.917)	0.002	-62.80 (19.767)	0.001	-33.24 (20.202)	0.100	-42.67 (20.215)	0.035
Interaction	513.07 (58.897)	0.000	513.07 (58.646)	0.000	513.07 (58.648)	0.000	513.07 (58.568)	0.000	513.07 (58.520)	0.000
Spot price			-1.55 (0.319)	0.000	-1.55 (0.319)	0.000	-1.52 (0.318)	0.000	-1.82 (0.323)	0.000
Solar/No Solar					-446.02 (15.875)	0.000	-446.02 (15.868)	0.000	-446.02 (15.864)	0.000
Temperature							-13.88 (2.312)	0.000	-7.08 (2.706)	0.009
Sunshine									-11.23 (2.291)	0.000
Observations	63960		63960		63960		63960		63960	
R-squared	0.014		0.015		0.027		0.028		0.028	
Df Model	3		4		5		6		7	

The outcomes of the DiD regression are significant, since the p-value for every coefficient is lower than 0.05. The change in electricity consumption within this dataset is also depending on changes in the control variables. Based on the results of the DiD regression, the following interpretation of coefficients can be done:

- Constant. There is an average electricity consumption of 1479,73 Wh at 2pm in the control group (Fixed), before the treatment period, in 2021, holding all other variables constant. The value of this coefficient is large and increases when more control variables are added. This could indicate that the additional control variables account for factors that contribute to higher baseline electricity consumption.

- Treated. The average electricity consumption in the treatment group (Dynamic) is 274.98 Wh higher compared to the control group (Fixed), before the treatment, in 2021. This is the baseline difference. This coefficient is relatively consistent throughout the different models. This indicates that the difference in electricity consumption between the Dynamic and the Fixed consumption group before the treatment period remains stable, even when more control variables are added. This suggests a robust treatment effect.

- After. The average electricity consumption has decreased with 42,67 Wh in the control group after the treatment period in 2023 compared to 2021, holding all other variables constant. The value of this coefficient is varying across the different models. This suggests that the change in electricity consumption for the Fixed consumer group after the treatment period, in 2023, fluctuates depending on the control variables included in each model. This may reflect on the electricity consumption after the treatment.

- Interaction. The interaction coefficient captures the treatment effect. This represents the differences in the change in electricity consumption between the Dynamic customer group and the Fixed customer group after the treatment period, compared to before the treatment period. The treatment effect is an increase of electricity consumption of 513,07 Wh at 2pm. The interaction coefficient is constant across all models and indicates that the treatment effect remains consistent. This suggests that the treatment, switching towards a dynamic energy contract, has a significant impact on the electricity consumption.

- Spot price. When the price of electricity increases with one unit (one euro), the electricity consumption on average decreases with 1,82 Wh, holding all other variables constant.

- Solar/No Solar. The difference in electricity consumption between households with solar panels and without solar panels is 446,02 Wh, holding all other variables constant. Households with solar panels consume on average at 2pm 446,02 Wh more electricity.

- Temperature. When the temperature increases with one unit (one degree Celsius), the electricity consumption in households on average decreases with 7,08 Wh, holding all other variables constant.

- Sunshine. When the sunshine radiation increases with one unit, the electricity consumption decreases on average with 11,23 Wh, holding all variables constant.

The consistent treatment effect across models, as indicated by the constant coefficient for the interaction term, suggests that the treatment has a robust and significant impact on the electricity consumption of households. Besides that, all coefficients in the final model (5) are statistically significant which indicates that each variable included in the model has an effect on the electricity consumption. It suggests that when the value of each of these control variables change, the electricity consumption in households also changes. It is unlikely that these changes have occurred by chance alone.

6.3.2 Validation of model

In order to validate the model, multiple validation tests have been performed.

Parallel trends: baseline trend
In this study the electricity consumption is not the same in the control and treatment group beforehand. This makes it more challenging to assume parallel trends. To support this parallel trend assumption, a baseline trend is added to the model. When looking at the average electricity consumption of both consumer groups (table 6), the electricity consumption of the consumer groups Fixed and Dynamic are not the same, independent of the treatment. In order to compensate for this difference, a baseline trend is added to the DiD regression. By incorporating the baseline differences, there will be accounted for the initial disparities between consumer groups Fixed and Dynamic. This way we can control for the pre-existing differences in electricity consumption between both groups. This baseline trend helps support the parallel trends assumption.

Placebo test
To test the robustness of this model, a placebo test is conducted. This involves performing the same DiD regression analysis on a placebo treatment group that did not actually receive the treatment. The objective is to evaluate whether the estimated treatment effect in the analysis is statiscally significant compared to what would be expected by chance. Different units are randomly assigned to a placebo treatment group, and the DiD regression, including all control variables is performed again. The outcomes of this placebo regression analysis can be found in Appendix C. When comparing the coefficient of the Treated variable (274.98) in the normal DiD regression to the placebo_treatment coefficient (-24.53), a substantial difference is evident. The coefficient of the treated variable in the main analysis is statistically significant and notably larger than the placebo effect. This provides evidence in support of a true treatment effect. The interaction effect in the placebo analysis is not statistically significant. These results suggest that there is no significant treatment effect in the placebo treatment group, which supports the validity of the estimated treatment effect in the main DiD regression analysis. Additionally, the control variables in the placebo test show significant effects on the electricity consumption, indicating their importance in explaining the variability in the outcome.

6.4 Main conclusions chapter 6

This chapter investigated the difference of consumption behavior between two consumer groups. And whether this difference can be explained by the dynamic energy contract. For this research a DiD regression analysis was conducted, and multiple validation methods have been performed to make this model more robust.

This chapter answered the following research question:

Does consumption behavior vary between consumers with a dynamic energy contract and those with a fixed energy contract under different real-time prices?

The main findings from this chapter are summarized below.

A DiD regression analysis is conducted to investigate whether there is a causal relation between the electricity consumption and the dynamic energy contract. In this analysis multiple control variables were added to the model to make the model more robust. The results from the DiD regression showed that all coefficients in the model were statistically significant. The treated variable showed a high positive value, indicating that there is a baseline difference in electricity consumption between both consumer groups. Households in the consumer group Dynamic consume on average, before the treatment almost 275 Wh electricity more compared to the Fixed consumer group. The value of this coefficient remains stable which indicates a robust treatment effect. The after coefficient reflects the change in electricity consumption for the control group after the treatment period. This suggests that average electricity consumption of the control group has decreased with almost 43 Wh in 2023 compared to 2021. The value of this coefficient is varying across the different models and indicates that the change in electricity consumption for the Fixed consumer groups depends on the different control variables included in each model. The value of the interaction coefficient has a high positive value, which is exactly the same across all models. This interaction term represents the differences in change in electricity consumption between the Dynamic customer group and the Fixed customer group after the treatment period, compared to before the treatment period. The treatment effect is an increase of around 513 Wh in electricity consumption at 2pm.

All control variables are statistically significant but have relatively low coefficient values, except the dummy variable of having solar panels. Households with solar panels consume on average 446 Wh more electricity compared to households without solar panels. While this difference is substantial, it is consistent with the results showcased in table 8 (chapter 5) and therefore not unexpected.

The placebo test done for this analysis suggests that there is no significant treatment effect in the placebo treatment group, which supports the validity of the estimated treatment effect in the main analysis.

This analysis showed that there is indeed a significant difference in electricity consumption between consumers with a dynamic energy contract and consumers with a fixed energy contract.

7 Discussion

This section reflects on the methodology used in this research and discusses the limitations of the model and the implications of these limitations. Additionally, this chapter provides suggestions for further research.

7.1 Reflection on the methodology

7.1.1 Mixed-methods approach

The mixed-method approach used in this research proved to be well-fitting for the purpose of this study. This approach allows for combining qualitative and quantitative research data which gives a more comprehensive understanding of this research subject. The energy market is a very complex system, especially with the ongoing changes in technology, policies, and the role of consumers. By combining both data sources, it results in a better understanding of the behavioral dynamics of individual consumers. A limitation of this approach is that it is very time-consuming and data intensive.

The qualitative part of this research was time-consuming by not only finding and analyzing the right references and sources, but also by performing multiple semi-structured expert interviews. The planning, preparation and the development of the interviews are time intensive. Writing this master thesis at an energy supplier proved to be very beneficial regarding obtaining interviews with multiple experts and electricity consumers. The quantitative part of this research was both time-intensive as data-intensive, and therefore also computer-resource intensive. The quantitative consumption data was provided by the energy supplier. However, this data was not perfectly organized, which took multiple days to subtract the right data. The total database of the energy suppliers consisted of over 20 billion rows of information, making it impossible to derive data insights from this dataset, since it would likely take over 24 hours computation time per insight. Therefore, a subset of data was created. Generating this subset took over 34 hours, which made this a very computer-resource intensive project.

For other energy suppliers, it could be much more data-intensive to perform analyses which require smart meter consumption data, if they have a bigger customer base.

7.1.2 DiD regression analysis

The DiD regression analysis has proven to be an appropriate data-analysis approach for this research. This statistical data-analysis offers an advantage due to the well-established grounding of its methods in the existing literature. In this study the main object was to explore a causal relationship between the electricity consumption pattern and the type of energy contract. The DiD regression analysis allows us to use a time and treatment variable to explore this. Besides that, this model is able to estimate causal effects when the treatment and control group cannot be randomly chosen. This is a huge advantage of this analysis, since for this study there was only access to the database from one energy supplier. Additionally, this analysis also gives the opportunity to control for other variables who might have an impact on the electricity consumption. This way there will be controlled for factors that could independently influence the electricity consumption. A disadvantage of this method is that it requires a lot of assumptions in order to perform the analysis and get robust results. This has been dealt with in the validation phase. Overall, this method was found suitable for the intended purpose.

7.2 Discussion of limitations

7.2.1 Limitations of DiD regression analysis

1. Selection bias input data

In this research there is only electricity consumption data taken into account from one energy supplier. Additionally, this energy supplier has a very specific customer base, since they offer electricity that is truly sustainable and generated on Dutch soil. This cannot represent the total population in the Netherlands and can only draw conclusions for the total customer base of Vandebron. However, these specific customers may offer a more suitable base for this study. They are likely to be driven by green behavior and sustainability, making them potentially more receptive to adjusting their demand load to off-peak hours, especially given that these hours often coincide with increased generation in renewable energy.

2. Limited input data

As mentioned before, this study had only access to the electricity consumption data of one energy supplier. This results in not being able to take into account all possible variables that can impact the flexibility and electricity consumption of individual households. Therefore, it was only possible to work with information and variables that were already provided by the energy supplier. This resulted in the fact that only limited characteristics of the individual households were considered in this analysis. Due to this lack of information, it is unclear which type of households were considered, whether they had any knowledge regarding this subject and what their motivations were for choosing this type of contract.

7.2.2 Limitations of qualitative approach

1. Researcher bias

For the qualitative part of this research information conducted from literature review and interviews with experts is used. As previously noted, most of the expert interviews were carried out with individuals who had connections, either direct or indirect, with employees of the energy supplier Vandebron. This gives the potential risk of focusing solely on like-minded people and may not fully present the expert community of the Netherlands. In this study this also resulted in only interviews with males as customers with a dynamic energy contract. As mentioned in the descriptive statistics, there are more males than females choosing for this type of contract. This might be because of the innovative nature of this contract and the requirement to be a little risk-seeking. This property is more often attributed to men, compared to women (Dawson, 2023; Harris & Jenkins, 2006). Furthermore, the literature used in this study is often found through snowballing, providing increased chances of discovering relevant literature that aligns with this study's focus, rather than exploring literature that might present opposing perspectives.

2. Generalizability

In found literature, research analyses are often done on small samples, which gives the risk that the outcomes may not be representative of the full population. An example of this has been found in multiple different academic journals. Based on the studies of Torriti et al. (2015) and Smale et al. (2017) the presence of children decreases the flexibility of electricity consumption of a household in peak hours. While in the study of Stelmach et al. (2020) there was no impact found on the electricity consumption regardless of the presence or absence of children. These differences can be attributed to possible differences in the definition of children, other characteristics of the individual households or other factors such as the demographic areas the studies are conducted. This shows that results from previous done studies do not have to be the case in this research.

7.2.3 Limitations of quantitative approach

1. Ethical limitations

The data that is chosen for this study does not include all properties of households that were available, because of the ethical implications. In order to take into account for example the city that customers live in, their age and the number of persons per household, specific approval from all customers is necessary. This was impossible to perceive on such short notice and could also impact the number of customers that could have been taken into account for this study.

2. Limited input data

In this research the scope is limited to the month September for only the years 2021 and 2023 and the hour 14:00. This could have been more elaborate, by also considering all other hours of the day and the month September 2022. It was chosen not to include all other hours of the day because the data-analysis was already time consuming, data intensive and computer-resource intensive. September 2022 has not been taken into account because of the data intensiveness, but also due to another reason. In 2022 the energy prices were insanely high due to the energy crisis. Besides that, due to these immense high prices individual households were suddenly much more aware of their energy bill, their energy consumption, and their energy supplier. On the other hand, in 2021 the world was still in the middle of the COVID-19 crisis, which could also have impacted the electricity consumption, since households would spend more time at home. It is difficult to say whether this year would be more representative for the 'general' electricity consumption, since every year was and will be different.

3. Simplification of energy market

The energy market is very complex. There are many variables that can influence the electricity consumption of individual households. In this study multiple control variables have been added to the dataset to make the outcome more robust. However, there are numerous other factors that can influence a change in electricity consumption. These factors include the energy crisis, technological developments, and other personal characteristics of households. These factors are too difficult to implement, and the assumption in this study is done as if these factors are always constant over time. One of the personal characteristics of individual households that have a significant influence on the flexibility of electricity consumption is knowledge and affinity with new technologies and sustainability (Kowalska-Pyzalska, 2018; Frondel & Kussel, 2018). Other personal characteristics that could have an impact on the electricity consumption of households are the number of people in a household, the type of house that they live in, whether they have an EV and whether they have a heat pump. Given the limited time and resources it was impossible to take all those personal characteristics into account, due to not available data yet. Therefore, it was chosen to only focus on the variables that were available and not consider other factors.

7.3 Recommendations for future research

- This study focuses on dynamic energy contracts, which is a relatively new energy contract. Right now, only a small number of households in the Netherlands have adopted this kind of energy contract. In this study only consumption data of one energy supplier have been analyzed. Since this is an energy supplier with quite a specific customer base, it would be interesting to expand the consumption data. Future research could investigate electricity consumption data of multiple energy suppliers. A suggestion would be to take at least one energy supplier who has a large market share, as well as one supplier that is not specifically focused on renewable and sustainable energy. This can give a more representative result for all Dutch households.

- This study solely focuses on the hour 14:00, since in that hour the biggest change was visible for this customer base. However, this could be different for other households. Therefore, it is recommended to include multiple hours in future research. By including this, research can be conducted based on peak hours and off-peak hours, to investigate whether there really is a shift in consumption behavior. This can support analysis on whether dynamic energy contracts shift behavior from peak hours to off peak hours.

- This study showed that the biggest difference in electricity consumption between the two consumer groups was at 2pm. The hour with the most renewable energy generation is not necessarily 2pm and the electricity price is not the cheapest at 2pm (Appendix B). It is recommended to investigate why the. Biggest change in consumption behavior is happening at exactly at 2pm.

- The conducted DiD regression analysis could be extended to more control variables based on consumer characteristics and other external factors such as technological developments, or the possibility of other energy contracts. Many literature studies showed different characteristics that can influence consumption behavior: income (Iliopoulos et al., 2020), knowledge regarding dynamic pricing (Frondel & Kussel, 2018), number of household members (Stelmach et al., 2020) and the square footage of a house (Stelmach et al., 2020). It might be interesting to take these into account for future research.

- The dataset analyzed for this study is divided into a control and treatment group. However, the control and treatment group have not been selected on the same personal characteristics. For future research it would be recommended to include a control group with the same type of characteristics as the treatment group to make the research more robust and the results more reliable. This is because when both groups have similar personal characteristics, it strengthens the validity of the counterfactual assumption necessary for the DiD regression. If this is not the case, the estimated treatment effect may be biased.

- Flexibility of consumers in this research has been based on electricity consumption appliances and activities in households. The different activities and appliances mentioned in this study have been based on one reference, while controlling the outcomes with multiple references. However, it is recommended to make this overview more extensive to get a more accurate view on the overall electricity consumption of households.

- Different DSM techniques have been reviewed and explained. However, it remains untested whether the findings from the literature review would have the same effect on Dutch households and this specific customer base. Future research could concentrate on dividing the customer base into distinct groups, each subjected to different DSM strategies and additionally analyzing the differences in consumption behavior between those groups. From such investigations, conclusions could be drawn regarding the most advantageous DSM strategy for the customer base in the Netherlands.

- In this research the focus has solely focused on the dynamic RTP structure. This choice has been made, since this is the only dynamic price structure energy suppliers offer to their customers. Expanding this research to different geographical areas where other types of dynamic pricing contracts are offered, it might be interesting to make a distinction between the different types of dynamic pricing and their influence on electricity consumption behavior.

- This research focused on the change in consumption behavior between consumer groups and the consumption behavior pattern of customers with a dynamic energy contract compared to their behavior pattern under their previous contract. However, consequences of this behavior change in terms of electricity costs for the individual households have not been investigated. Future research could investigate the savings options of dynamic energy contracts. It is recommended to consider when their previous contract was concluded, since this influences their energy bill. If their contract was concluded in 2022, the fixed contract prices would have been much higher, compared to a few years before.

- In this research the influence of national policies has not been taken into account. However, they might have a large impact on the consumption behavior of customers. Right now, a new energy bill (Proposal Energiewet, 2023) is being made. A part of this new policy is phasing out the netting scheme, which has large consequences for customers with solar panels. Other policies such as costs for supplying energy to the grid as a customer can also impact choices of customers towards new technologies, their energy contract, and their consumption.

- Right now, only a very small market share of the total energy contracts is dynamic. However, due to multiple defined advantages it might grow immensely in the future. However, it is unclear whether this would be beneficial for the energy transition. In that case, a large part of the customers would change their behavior patterns and new consumption peaks may arise at different hours. Future research could investigate possible consequences of the changing behavior pattern, based on insight of this study.

8 Conclusion and recommendations

This final chapter will provide insights and conclusions based on the findings presented throughout this study. The first part of this chapter will give an overview of the main research findings and will answer the main research question: *'How do dynamic energy contracts influence consumption behavior of individual households?'*. In the second part of this chapter the contributions of this research will be discussed. Finally, recommendations for policy makers and energy supplier companies will be presented.

8.1 Overview of main research findings & answer to the main research question

The purpose of this research study was to gain insights into the impact of dynamic energy contracts on electricity consumption behavior patterns in individual households. By using a mixed method approach a comprehensive understanding of the research context could be formed. The quantitative part of this analysis was performed on real time electricity consumption data of customers from energy supplier Vandebron. The different sub questions are divided between different parts of the research, as displayed in figure 2 (chapter 1).

This research started with an introduction of the subject and an explanation of the methodology and research approaches used. The second part of this research began with a thorough analysis of the dynamic energy contract. The different types of dynamic pricing were identified, and the choice was made to focus only on RTP dynamic pricing contracts. Additionally, the differences of benefits and risks of this dynamic energy contract between energy suppliers and energy consumers, in this case individual households, were explained. Literature review and expert interviews were conducted to find the answers to this phase.

Part 3 of this research was also conducted with qualitative research. This part of the research consisted of a thorough analysis of consumption flexibility. It gave an overview of the different energy consuming activities and appliances in individual households and explained different factors that have influence on the consumption flexibility of households towards these activities and appliances. Additionally, the research focused on different DSM strategies that can influence the flexibility of individual households and gave an in-depth analysis on the different types of DSM strategies and their effectiveness in previously done studies.

The fourth part of this research deployed data analysis to determine the relation between electricity consumption and a dynamic energy contract. This part of the research is conducted through a difference-in-difference (DiD) regression analysis. By using a control and treatment group and two different time periods a causal relationship can be tested between the change in electricity consumption behavior and the dynamic energy contract. After performing the data analysis, validation tests have been performed to check the robustness of the model.

Combining the different phases resulted in the knowledge and data evidence that can aid policymakers and energy suppliers in their position towards dynamic energy contracts and their influence on electricity consumption in individual households. Combining all results from the different research phases together, resulted in a set of main findings that can give an answer to the main research question:

"How do dynamic energy contracts influence consumption behavior of individual households?"

To answer this question, multiple parts of research are completed. First, the in-depth research on dynamic energy contracts is described. Secondly, the context towards electricity consumption flexibility is presented. From there, a DiD regression analysis is performed. Multiple sub questions were answered in order to answer the main research question. These answers are included in the conclusion of each chapter. An overview of the main findings answering the sub questions are presented below.

The main findings from part 2:

- The RTP type of dynamic pricing is focused on in this research. This type of dynamic pricing reflects the real cost of supply, and it is the most economically efficient way to implement dynamic contracts in the power market. However, it also has the highest type of price volatility for consumers.

- Electricity consumers mainly choose a dynamic energy contract because of the possibility to save more money on their energy bill, their attraction to the innovative part of the dynamic contract and the possible contribution to a more sustainable way of electricity consumption of the dynamic energy contract.

- Dynamic energy contracts bring different risks for energy suppliers. For their forecast they only must consider the imbalance risk between purchased energy and demanded energy by consumers. Other risks are the possibility of consumers to cancel their dynamic energy contract at any given time.

The main findings from part 3:

- Qualitative research revealed that individual households are most flexible with activities that involve wet appliances such as washing, cleaning and showering. This can be explained by the less-critical time nature of these appliances. With other activities such as cooking and leisure, which involves watching television, individual households are less willing to shift their electricity consumption.

- Different factors can influence the flexibility in electricity consumption of a household. Presence at home during the day, the number of household members and smart technology increased the willingness of households to be more flexible in their demand. On the other hand, income and square footage of a home decreased the flexibility of demand of those households. Meaning when income was higher and homes were larger, the willingness of those households to shift their demand became less.

- Economic incentives are the most effective way to influence the demand shifting of households. Other DSM strategies such as providing information are creating greater awareness but do not lead to shifts in electricity consumption. However, the efficiency of demand load shifting is maximized when multiple DSM strategies are combined.

The main findings from part 4:

● Electricity consumption of customers with a dynamic energy contract is much higher than customers with a fixed energy contract. The households of the Dynamic consumer group had a higher electricity consumption compared to households of the Fixed consumer group, before the treatment period.

● The electricity consumption in both consumer groups was much higher for individual households with solar panels compared to households without solar panels, before and after the treatment.

● Customers with a dynamic energy contract are overall younger and living more often in urban areas, compared to customers with a fixed energy contract. The share of males that concluded this type of energy contract is much higher compared to their share with a fixed energy contract.

● The amount of electricity consumed during peak hours is much higher in 2021 for the treatment group than in 2023, even though the total amount of electricity consumed did not decrease significantly. The main shift in electricity consumption in the treatment group was from the evening peak to off-peak hours during the day, with the largest difference at 14:00.

● The DiD regression results show that all models are statistically significant. The treatment variable has a high positive coefficient (275) which confirms that the treatment group has a higher electricity consumption, of 275Wh on average at 2 pm, compared to the control group, before the treatment.

● The interaction coefficient captures the treatment effect and shows that there is an increase in electricity consumption of 513 Wh. This represents the differences in the change in electricity consumption between the Dynamic consumer group and the Fixed consumer group, compared to before the treatment period. The interaction coefficient is constant across all models and is statistically significant. This suggests that switching towards a dynamic energy contract has a significant impact on the electricity consumption.

● The DiD regression model showed heteroscedasticity and the possibility of autocorrelation. To make the model more reliable and robust HAC standard errors have been used in this regression model. Additionally, a baseline trend is added to the model to account for disparities in electricity consumption between the two consumer groups before the treatment. Afterwards a placebo test has been performed, with the desired outcomes, confirming the robustness of the model.

Based on these findings, several main conclusions can be drawn from this study. First, a gap between the benefits and risks of dynamic energy contracts is observed between energy consumers and energy suppliers. For energy consumers, in this study individual households, dynamic energy contracts give them full control over their energy bills, but on the other hand they experience a high volatility, because of the hourly electricity price. Conversely, dynamic energy contracts pose different risks for energy suppliers. They only need to consider imbalance risk and no other risks such as demand variation risk and purchasing risk when making the forecast. On the other hand, consumers can cancel their dynamic energy contract at any time and are able to switch to a different supplier whenever they want to.

Secondly, DSM strategies have the potential to enhance the willingness to shift demand of individual households. However, some activities are more amenable to influence than others. Research showed that households are not willing to shift activities characterized by strict time constraints, such as cooking and evening leisure activities like watching television. Additionally, there are multiple factors that can influence the flexibility of electricity consumption. Although the outcomes of the literature review can differ, due to the subsets used in those studies, the overall findings are in line with research from Ozaki (2018), Andersen et al. (2017), Wang et al. (2017), Iliopoulos et al. (2020), Gunkel et al. (2023) and Ribó-Pérez et al. (2021). These studies showed that the number of smart appliances in a household has a positive correlation with flexibility of energy consumption, while income was negatively related to the flexibility of energy consumption. Although economic incentives are the most effective strategy to influence demand load shifting of individual households, it is more efficient in the long-term to combine the strategies: economic incentives, provide information, increase smart appliances in households and give households pro-social impulses.

With the above information in mind, a qualitative analysis was conducted on households' consumption data associated with various energy contracts. The customer base is different between households with a dynamic energy contract and households with a fixed energy contract. The electricity consumption is higher for households with a dynamic energy contract, and they are overall younger and more often living in urban areas. To explore whether the differences in electricity consumption can be explained by the different energy contract, a DiD regression analysis was performed.

The DiD regression model required multiple steps, which involved adding more and more control variables to each model. All coefficients of the final model turned out to be statistically significant. The treatment and interaction variable both have a high positive coefficient value which confirms that the treatment, switching to a dynamic energy contract, is associated with higher electricity consumption at 2pm and that this change is unlikely to have occurred by chance. This robustness of the model is increased by performing multiple validation tests.

This study aimed to gain insights into the impact of dynamic energy contracts on electricity consumption behavior patterns in individual households. With this research the change in consumption behavior of households is confirmed by switching to a dynamic energy contract. The research resulted in enriching the current knowledge of dynamic energy contracts, the possibilities, and drivers of demand flexibility of households and the relationship between dynamic energy contracts and demand load shifting of households. The mixed methods approach and the DiD regression analysis have shown to be appropriate methods to answer the main research question and were able to grasp the nature of demand flexibility and the role of dynamic energy contracts in Dutch households.

The method presented several limitations that need to be considered when interpreting the result of this study. First, the data utilized in this study consists of consumer data of one energy supplier. Second, the change in electricity consumption behavior found in this study is for the hour 14:00. This does imply change in behavior, however a conclusion on shifting energy from peak to off-peak hours cannot be made on this one hour. Third, the characteristics of individual households are simplified. Future research can address these limitations, by adding more personal characteristics and more consumption data of different energy suppliers to the regression model. This will increase the robustness of the research findings.

8.2 Contributions of this research

This study gained insights in the perspective of individual households towards dynamic energy contracts and the consequences in behavior when switching to a dynamic energy contract, which contributes to its societal relevance.

Since the implementation of the Clean Energy for all Europeans' package (European Commission, 2019), the emphasis has been placed on control for the individual consumer and the flexibility of demand in order to accelerate the energy transition. Part of this new plan will be achieved through the implementation of dynamic energy contracts. The research aimed to fill an existing gap on understanding electricity consumption behavior of households with a dynamic energy contract, based on the fluctuating electricity price and their possibilities to be more flexible in their demand. No previous study has been conducted in the Netherlands that investigated the impact of dynamic energy contracts on the consumption behavior pattern, using real time data of individual households. In the literature, multiple studies have been found but these were mainly focusing on data from a survey, or a panel and therefore the customer base does not reflect the same customer base in this study. Only households who were willing to join the survey are taken into account, while in this research the customers have chosen the dynamic contract, regardless of a survey or panel and the thereby associated benefits.

This study contributed to the fact that it made observations of the differences in factors that can influence flexibility of demand. These differences are caused by the subgroup analyzed for each study and can therefore change, depending on the geographical area of the study and the type of households involved. Whilst this study did not analyze all possible factors of influencing flexibility of demand, the analysis already demonstrates that there are differences in previous findings. This shows that the factors can also differ from factors that have not been revealed yet in the Netherlands.

Finally, his research showed that there is a change in consumption behavior patterns of individual households before and after adopting a dynamic energy contract. By combining the real-time quantitative consumption data with qualitative literature review and expert interviews, a complete image of dynamic energy contracts in the Dutch energy market is outlined. The results of this study provide input for governmental bodies to consider these impacts of dynamic energy contracts in forming more sophisticated policies and incentives. Besides that, it provides the energy supplier with insights of the consumption behavior of their customers and can form a reference to improve their business proposition.

8.3 Recommendations for policy makers and the energy supplier

The identified changes in consumption behavior patterns emphasized the need for knowledge and attention by policy makers in the Netherlands towards dynamic energy contracts. Dynamic energy contracts cause changes in consumption behavior, using more electricity during off-peak hours during the day, which could play a part in congestion management and increase the flexibility of electricity consumption.

Recommendations for policy makers:

1. Future policy interventions on dynamic energy contracts should be addressing the awareness of individual households about dynamic energy contracts. This research has shown that it is possible to change the electricity consumption pattern of individual households with a dynamic energy contract. If policy makers intend to have this result, they should inform households better. If individual households are not well-informed about this contract, they are unlikely to choose this contract in the future. This can stagnate the growth of this contract and fasten the energy transition.

2. The generated insights into the different DSM strategies to influence load shifting gave a good overview of the possible strategies, but there is more attention needed to understand the effectiveness of these strategies in the Netherlands. The government has multiple ways of reaching their target group with their intentions, but more focus should be on the efficiency of these strategies, and whether individual households act on their intended objective.

3. All research emphasized the role of smart appliances in accelerating the flexibility of demand, and their impact on load shifting. To deploy dynamic energy contracts on a larger scale, smart home energy systems are needed. Policies and incentives are advised to focus on deploying smart appliances on a greater scale, by for example investing in new technologies, or working together with energy providers to create greater awareness towards smart appliances.

By creating greater awareness, towards the dynamic energy contract, combined with other incentives, such as financial incentives or easier available smart appliances, policymakers might be able to overcome the current boundaries of individual households towards dynamic energy contracts. Earlier research showed that regulatory frameworks have an influence on households' decision towards the energy transition (Aniello & Bertsch, 2023). Therefore, by implementing this in an efficient manner in new policies, it can play a bigger role in accelerating the Netherlands towards a more sustainable future.

On the other hand, energy suppliers also play an important role in shaping the perception of dynamic energy contracts among individual households and will also be affected by the findings of this research. Therefore, multiple recommendations for energy suppliers are also identified:

1. Consumption behavior of customers with dynamic energy contracts differs from consumption behavior of households with fixed energy contracts. When a bigger part of the customer base of energy suppliers will switch to the dynamic energy contract it will impact their standard way of working. Reassessment of demand forecast, risk management and profit margins become necessary. Adjustment to the business proposition may be required in order to stay financially competitive, without incurring losses.

2. This research revealed the consumption behavior patterns of households with different energy contracts. If Vandebron wants to pursue a higher customer share with a dynamic energy contract, it is recommended to inform their customers on a personal level. By informing them about the advantages of dynamic energy contracts, the strategies to optimize their electricity consumption and reducing their electricity expenses. The information shared with customers should be on a personal level. For example, if their customer has solar panels, arguments for choosing a dynamic energy contract differ from households without solar panels. If the electricity consumption of the customer is higher due to an EV other arguments

should be used to convince the customer. By engaging and informing the customers personally, they could pursue the customer base they want to achieve.

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Appendix A.1 Methodology literature review

The literature review for the knowledge gap (chapter 1.2) is based on a literature search, which was carried out in a semi-structured way. The scope of the literature is quite broad and therefore different core concepts were used to find the scientific articles. The main literature source that was used in this review was the online database Scopus. Three different search strings were used to find the suitable literature: 'consumer behavior AND electricity consumption', 'dynamic pricing AND consumer behavior' and 'flexibility households AND electricity demand'. Additional articles and papers were found by snowballing and using an alternative database such as Google Scholar. The full overview of the literature review process can be seen in the figure below.

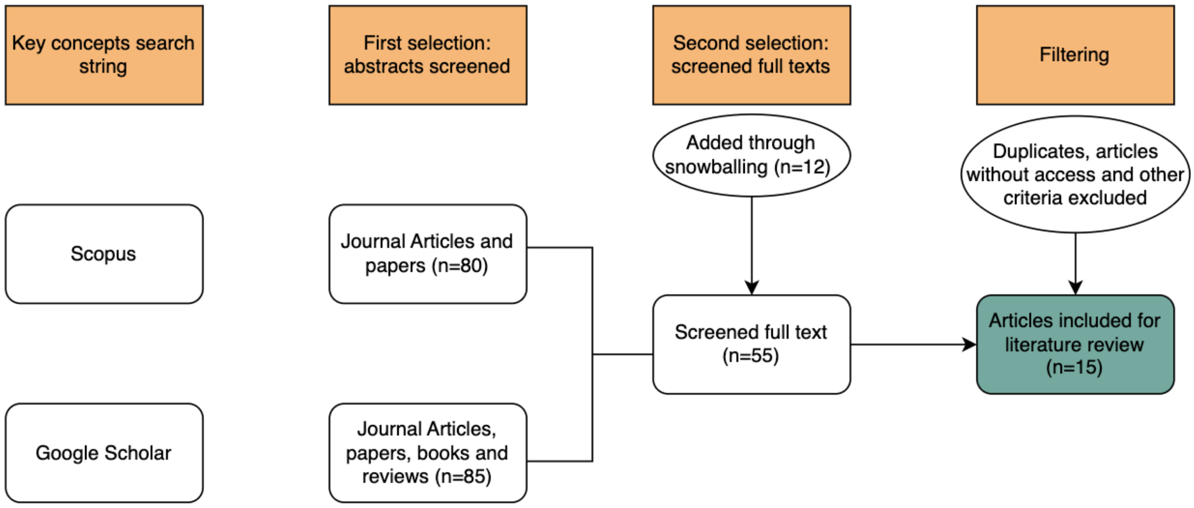

Figure 7. Literature Review Process

Since dynamic energy contracts and consumption behavior are broad topics, a lot of useful information could not be found by just using the search strings in Scopus. Therefore, the search has been expanded with Google Scholar. This gave a broader perspective, but also provided a lot of articles and papers that were not useful for this research. The main excluded types of literature were the ones that were mainly focused on the evaluation of energy sharing and trading energy in smart communities.

Appendix A.2 Literature findings

All selected articles used to identify the knowledge are presented in the table below. The table is sorted by the alphabetical name of the author. It shows the main features of the article and the research content of the conducted study or review.

Table 10. Literature review

Article	Main features	Research content
Aniello & Bertsch, 2023	Households, PV prosumers, Germany, Home Energy Systems	The influence of regulatory frameworks on households' perspectives towards the energy transition
Bakare et al., 2023	Demand Side Management, Smart Grids, Energy Efficiency	The examination of DSM categories and techniques and their challenges and solutions for the future
Batalla-Bejerano et al., 2019	Smart Meter, Consumer Behavior, Dynamic pricing, Literature Review	Analysis of consumption behavior in response to dynamic pricing
Breukers et al., 2013	Energy Behavior, Demand Side Management, Socio-technical Approach	Understanding energy consumption behavior from a socio-technical perspective
Frederiks et al., 2015	Consumer Behavior, Household Energy Consumption, Behavioural Economics	Understanding energy-related behavior by understanding insights from behavioral economics and psychology
Ghazvini et al., 2019	Demand Response, Smart Meter, Home Energy Management System	Demand response implementation in smart households
Gržanić et al., 2022	Prosumers, Dynamic Pricing, Systematic Review, Aggregation	Review of different options for prosumers to exploit their potential, such as dynamic contracts
Katz et al., 2018	Dynamic Pricing, Electricity Consumers, Renewable Energies, Household Behavior, Denmark	The concept of switching costs (dynamic pricing) to explain consumers' behavior in Denmark
Lavrijssen, 2017	Legislation, Consumer Behavior, Energy Policy, EU	Review of EU energy legislation and their impact on consumers participation
Lavrijssen & Parra, 2017	Consumer Empowerment, Electricity Regulation, Energy Transition, EY	Review and analysis of main radical innovations in electricity market that can influence empowerment of energy consumers and prosumers

Leal-Arcas et al., 2017	Prosumers, EU, Renewable Energy, Energy Security	Analysis of challenges and opportunities of prosumers in the EU
Oprea et al., 2021	Demand Side Management, Consumers’ Behavior, Smart Meter	Analysis on smart meter data to examine consumers’ behavio and the role of DSM
Paterakis et al., 2017	Demand Response, Flexibility, Renewable Energy Sources,	Review of demand response technologies and the motivations and barriers whether to adopt such as system
Pereira & Marques, 2023	Energy Poverty, Dynamic Pricing, US, Renewable Energy Sources, Smart Meter	Dynamic pricing can reduce energy poverty in the US
Ruokamo et al., 2019	Dynamic Pricing, Consumer Behavior, Willingness to Adopt, Finland	Analysis on households' willingness to adopt dynamic pricing in Finland
Shen et al., 2022	Dynamic Tariff, Congestion Management Distribution System Operator	Proposed coordination scheme of dynamic tariff and scheduled reprofiling product to manage congestion

Appendix B. Electricity spot prices

The spot price of electricity is in general lower during the day, since there is more generation of renewable energy. To prove this, the average electricity spot prices per hour of every month from the year 2023 are displayed below.

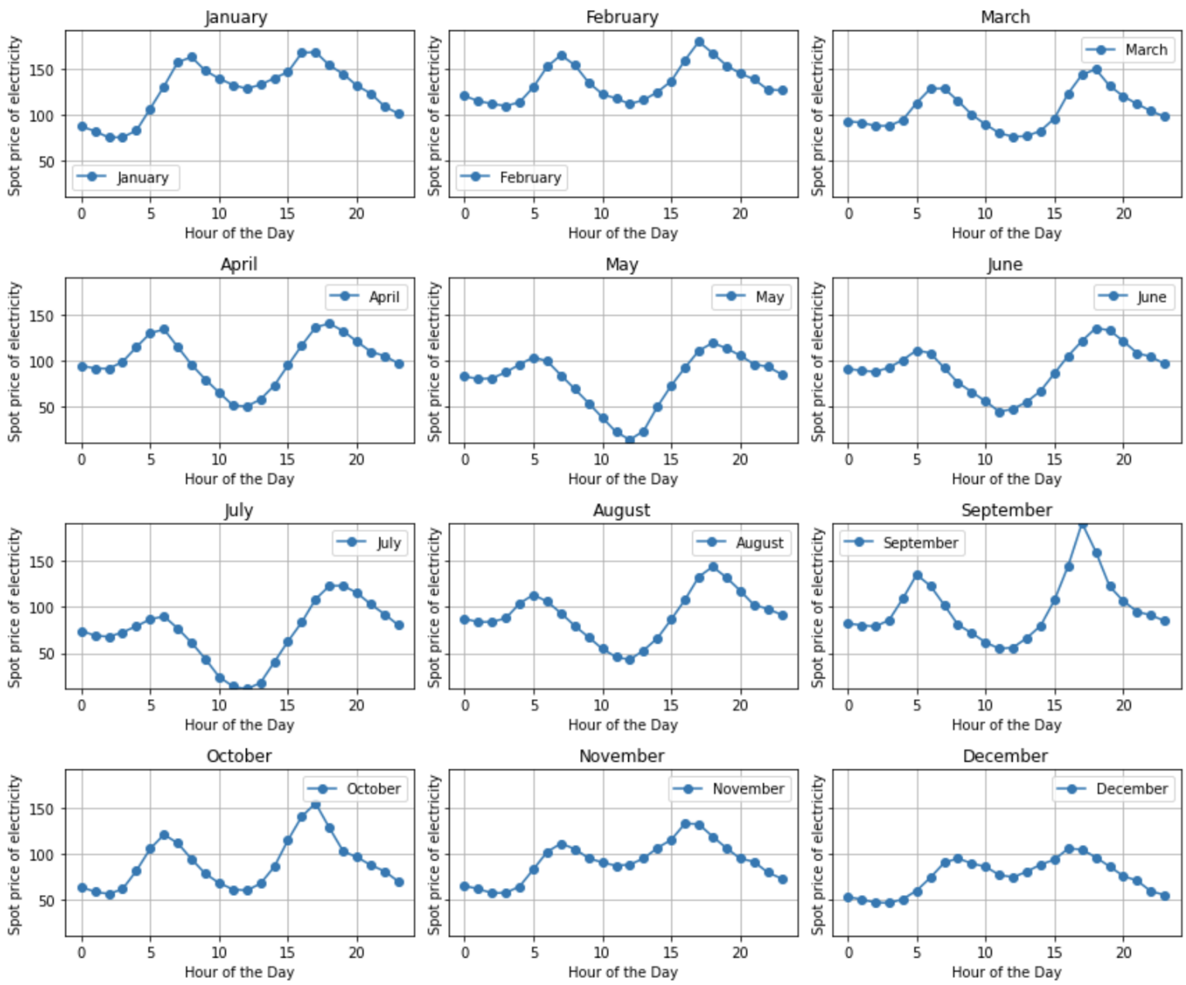

Figure 8. The average electricity price per month in 2023

In the figure above it is clear that the electricity price in every month has the same pattern. During the hours 10:00 and 15:00 the electricity price is in general lower during the peak hours. The only difference that is visible is that in the winter months the overall average electricity price is higher than in the summer months.

Additionally, the average electricity price of all months together is plotted in one graph, to get a better view on the patterns when compared to each other. In figure 8 it is visible that all months have the same pattern: lower prices during off peak hours during the day (between 11:00-16:00) and higher electricity prices during peak hours in the morning and in the evening.

Figure 9. The average spot price of all months in 2023

Appendix C. Placebo test DiD regression

In this Appendix the results from the placebo test of the DiD regression analysis is presented.

Table 11. Results of placebo regression analysis

	Model 1		Model 2		Model 3		Model 4		Model 5	
	Dependent Variable = Electricity Consumption at 2pm									
	Coef (std err)	P-value	Coef (std err)	P-value	Coef (std err)	P-value	Coef (std err)	P-value	Coef (std err)	P-value
Constant	920.45 (13.041)	0.000	1115.78 (42.461)	0.000	1322.56 (42.162)	0.000	1598.17 (63.397)	0.000	1550.69 (64.482)	0.000
Placebo_treatment	-26.21 (18.010)	0.146	-26.39 (18.016)	0.143	-25.45 (17.785)	0.152	-25.08 (17.776)	0.158	-24.53 (17.765)	0.167
After	-13.40 (21.929)	0.541	-84.74 (25.939)	0.001	-84.53 (25.750)	0.001	-55.16 (26.169)	0.035	-64.72 (26.146)	0.013
Placebo_interaction	42.51 (31.338)	0.175	43.76 (31.354)	0.163	43.347 (31.136)	0.164	43.70 (31.124)	0.160	43.94 (31.117)	0.158
Spot price			-1.55 (0.320)	0.000	-1.55 (0.319)	0.000	-1.52 (0.319)	0.000	-1.82 (0.322)	0.000
Solar/No Solar					-449.29.02 (15.973)	0.000	-459.29 (15.966)	0.000	(-459.29) (15.962)	0.000
Temperature							-13.88 (2.328)	0.000	-7.08 (2.726)	0.009
Sunshine									-11.23 (2.300)	0.000
Observations	63960		63960		63960		63960		63960	
R-squared	0.014		0.000		0.014		0.014		0.015	
Df Model	3		4		5		6		7	