

NHH



Switching behavior in the Norwegian electricity retail market

*The effect of Nord Pool spot prices on how households switch
electricity retailers*

Svetlana Olonina and Shokhrukh Pulatov

Supervisor: Morten Sæthre

Master thesis in Economics and Business Administration
Profiles in Economics & Energy, Natural Resources,
and the Environment

NORWEGIAN SCHOOL OF ECONOMICS

This thesis was written as a part of the Master of Science in Economics and Business Administration at NHH. Please note that neither the institution nor the examiners are responsible – through the approval of this thesis – for the theories and methods used, or results and conclusions drawn in this work.

ACKNOWLEDGMENTS

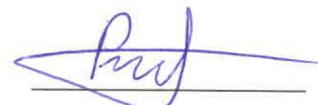
We would like to thank our supervisor Morten Sæthre from the Department of Economics, Norwegian School of Economics, for his patience and willingness to help us at all times and immense attention to detail. We have been touched and inspired by the energy and invaluable feedback we have received from him.

We are also grateful to our nearest for their support, to NHH for the emotionally rewarding ability to have a research journey partner, and to the city of Bergen for the perfect writing weather.

Stockholm-Tashkent, June 2018



Svetlana Olonina



Shokhrukh Pulatov

ABSTRACT

This paper has examined the relationship between Nord Pool spot prices on the Norwegian electricity market and the switching rate of residential consumers. Our research question was an attempt to find whether the electricity spot price can be a driver for the retailer switching among electricity consumers. Due to the popularity of spot-price contracts in the country, we assumed that higher spot prices may lead to an increased switching rate. Also, we made an assumption that Norwegian consumers may be forward-looking in their switching behavior. Meaning, spot price fluctuations may induce households to review their expected costs and switch the retailer before it changes the prices.

In the research, we used a combination of two panel data methods: Fixed Effects and Instrumental Variable approach. We constructed three models on the relationship between spot price and retailer switching, only one of which proved to be statistically significant. However, it did not show the result that we could consider to be economically viable; hence, we concluded that consumers in Norway are not forward-looking in their switching behavior and that spot prices do not influence switching rate.

KEYWORDS: switching behavior, Nord Pool spot price, Norwegian electricity market

CONTENTS

1.	INTRODUCTION	7
2.	DEREGULATED ELECTRICITY MARKET IN NORWAY	9
2.1	MARKET OPENING	9
2.2	ENTRANTS	10
2.3	OVERVIEW OF CONTRACTS	11
2.4	SPOT PRICE CONTRACTS	12
3.	RETAILER SWITCHING IN NORWAY: CONSUMER BEHAVIOR	15
3.1	SWITCHING PROCEDURE.....	15
3.2	SWITCHING PATTERNS	15
3.3	SWITCHING BEHAVIOR	17
3.4	SPOT-PRICE CONTRACTS AND SWITCHING IN PURSUIT OF LOWER ELECTRICITY PRICES.....	20
4.	RESEARCH QUESTION AND THE DATA	21
4.1	SWITCHING RATE	22
4.2	SPOT PRICES.....	24
4.3	HYDRO RESERVOIR LEVELS	25
4.4	SUMMARY STATISTICS AND EXPECTED RESULTS	26
4.5	DESCRIPTION OF THE VARIABLES.....	27
5.	METHODOLOGY	28
5.1	FIXED-EFFECTS METHOD	29
5.2	INSTRUMENTAL VARIABLES METHOD.....	31
6.	EMPIRICAL RESULTS AND DISCUSSION.....	35
7.	CONCLUSION	41
	REFERENCES.....	42
	APPENDIX.....	46

LIST OF FIGURES

FIGURE I — BIDDING REGIONS IN NORWAY, NORD POOL SYSTEM	13
FIGURE II — MONTHLY SHARE OF SWITCHES FOR HOUSEHOLDS AND BUSINESSES	16
FIGURE III — MONTHLY SWITCHING RATES IN NORWAY BY SPOT PRICE AREA, JAN 2011 – MAY 2015.....	23
FIGURE IV — MONTHLY ELECTRICITY SPOT PRICE FLUCTUATIONS IN NORWAY BY SPOT PRICE AREA, JAN 2011 – MAY 2015	24
FIGURE V – MONTHLY RESERVOIR CAPACITIES IN NORWAY BY SPOT PRICE AREAS, JAN 2011 – MAY 2015.....	25

LIST OF TABLES

TABLE I – ELSPOT DAY-AHEAD PRICES IN NOK/MWH IN NORWAY, WEEK 17, 2018.....	14
TABLE II – OVERVIEW OF THE DATA	26
TABLE III – MAIN RESULTS	36
TABLE IV – FIRST STAGE RESULTS	38
TABLE V – LAGGED PRICES REGRESSION MODEL	40

APPENDIX

TABLE A I – FIRST STAGE.....	46
TABLE A II – MAIN REGRESSION	46
TABLE A III – FIRST STAGE INCLUDING WEATHER VARIABLES	47
TABLE A IV – MAIN REGRESSION INCLUDING WEATHER VARIABLES	47
TABLE A V – MULTICOLLINEARITY AND SERIAL CORRELATION	48
TABLE A VI – SERIAL CORRELATION TESTS.....	48
TABLE A VII – FIRST STAGE WITH LAGGED RESERVOIR LEVEL VARIABLE.....	49
TABLE A VIII – MAIN REGRESSION WITH LAGGED RESERVOIR LEVEL VARIABLE.....	50

1. INTRODUCTION

Since the deregulation of the electricity sector in Norway in 1991, the power is sold to consumers using the market model. Now there are 120 electricity suppliers in Norway, and prices they offer vary to encourage electricity consumers to switch to their services (Forbrukerrådet, 2017). Consumers, on the other hand, have been slow in adapting to these changes (Littlechild, 2006): currently, 39% of consumers in Norway have not switched throughout the last five years (NVE, 2017). While the bigger, industrial consumers are more active on the power market, households are typically reluctant to switch from one electricity retailer to another (Waterson, 2003). Switching is made simple in the Norwegian market: a special online portal strompris.no allows consumers to compare prices and switch to another supplier quickly and hassle-free. The passive behavior of consumers is especially puzzling in this setting, as for consumers it is easy to switch retailers with all the opportunities given in the Norwegian market.

It is important to note that electricity is a highly homogeneous product, so price competition should be strong. Passive consumer behavior can also be observed with other products that have features of homogeneity, such as telecommunication or banking — few people tend to switch to similar services with a more attractive price. The case of inertia in switching to another retailer can also be observed in all other deregulated electricity markets in the world with Norway being among the most successful ones (Littlechild, 2006). Reluctant consumer behavior in the electricity sector is harmful to the open market system that the Norwegian electricity sector is supposed to be, which is why it is relevant to study consumer behavior in this market and the possible drivers for it to change.

While we give an overview of various psychological and economic factors that influence switching, in this work our primary focus is on one possible driver for consumers to switch — fluctuations in electricity spot price. The importance of our work hence lies in the fact that spot price is a crucial element of the electricity market as well as the basis for the most popular contract type among electricity consumers in Norway. Therefore, studying spot price relation to switching rate would foster understanding of the mechanisms of successful electricity market operation. Moreover, to our knowledge, spot price relationship to switching rate has not been investigated so far, while many other factors have been already researched to some extent.

We utilize data on monthly electricity spot prices obtained from Nord Pool, grid area demand, number of subscriptions and MWh consumption per month, number of switches per grid company per month — all being gathered from The Norwegian Water Resources and Energy Directorate (NVE). In our dataset we also use water reservoir levels for hydropower production, weather data for humidity, rain, temperature, and wind – gathered from YR.

In the research, we use two panel data methods: Fixed Effects and Instrumental Variable approaches. Our expected finding is that increase in spot price causes increase in consumer switching, as well as forward-looking behavior of electricity consumers on the electricity market in Norway. Our research, however, showed a different outcome: the increase in spot prices does not produce economically significant increase in switching rate. Neither did our study prove that Norwegian consumers are forward-looking in their switching behavior.

The structure of the thesis is as follows: in Chapter 2, we discuss deregulation of the electricity market in Norway, the reasons why and the way how it has been done, the results and the current state of the market. Chapter 3 is devoted to switching behavior on the Norwegian electricity retail market in relation to spot prices on electricity, as well as theoretical background for search and switching costs. We aim at studying the driver for consumers to switch and the factors that prevent them from doing this and to what extent these factors are important. Chapter 4 states our research question, hypotheses, and the data used in our research. In Chapter 5, we define the methodology and conduct the analysis, while Chapter 6 presents the empirical results and discussion. Finally, we draw conclusions, pinpoint limitations of our approach and make assumptions about possible future research.

2. DEREGULATED ELECTRICITY MARKET IN NORWAY

2.1 MARKET OPENING

Before the start of deregulation in 1991, the electricity retail market in Norway was vertically integrated and exhibited a number of problems. The incumbents were public utilities, and the government regulated the electricity prices, yet these regulations did not create equal conditions for all electricity users. The residential consumers paid much higher prices than the larger commercial ones, and electricity users in the remote areas had to pay extra due to longer proximity to the generation facilities. Hence, there was only one default option for the users, defined by their characteristics and location, with the price the incumbent was willing to impose on them. Innovation in the electricity sector did not seem to be in place, and no differentiation services were available. Investments in the industries were not efficient, because all the costs could be reflected in electricity prices. Lack of motivation for cost-efficiency made low-cost electricity projects less prioritized as well. The prices were not reflecting the scarcity of supply, so often consumers had to pay a lot while costs of power were not high, and underpay in case of electricity shortage (Johnsen, 2003). All those problems made conditions for electricity supply uneven across the users and called for changes in the market.

Norway was among the first places in Europe (after England and Wales) to start liberalization in the electricity sector. The deregulation process included unbundling (separation) of generation, transmission, distribution and sales activities on the market. The goal of the competitive retail market with a large number of suppliers is to transfer electricity from the wholesale to the retail level at low margins. However, those will stay low only when consumers penalize suppliers who set high prices by switching from them to other retailers (Olsen et al., 2006). Creating an open market would encourage consumers to choose the cheaper option and induce lowering the prices by the incumbents — they would not be able to enjoy extra revenues from the state-regulated non-competitive prices on the market (Littlechild, 2005). Electricity would be turned into a marketed product so that consumers could enjoy more competitive prices due to the growing number of new entrants on the market, that innovation process would be more active, and investments and projects would be cost-efficient compared to those under the vertically integrated market (Defeuilley, 2009). Olsen et al. (2006) argue that deregulation of the electricity retailing market would lead to

lower electricity prices in the geographically remote areas through the appearance of several electricity retailers there. The competition would allow to reduce the costs for consumers and help even out the costs throughout the whole country. The opening of the market would also create some new products and services, for example, risk management products (hedging). It would stimulate consumers to see that there are more possibilities than the incumbent offerings (Olsen et al., 2006).

Before the Energy Act of 1990 that came into force in 1991, Norway had regional markets, where utilities had both the right and obligation to supply all consumers with electricity, but then the Norwegian consumers became free to choose their electricity retailer as well as stay with the incumbent one. At first, the market was ineffective, as all consumers had to install new metering systems to measure the consumption hourly. Since its cost was too large, the vast majority of consumers preferred not to switch from the incumbent (Littlechild, 2006). In 1997-1999, the system of manual frequent metering was gradually replaced by profiling, which is the system of billing based on aggregate consumption profiles. The profile is the average consumption in the area for low-voltage consumers. The area is defined by the geographical configuration of the distribution network company (Johnsen & Olsen, 2008). Profiling gave the residential consumers a chance to start switching without considerable money losses, and this was when the residential electricity market started being effective (Littlechild, 2006).

Now electricity retailing market in Norway is well-functioning and is considered one of the more successful examples of electricity sector deregulation, but the picture is nuanced nevertheless.

2.2 ENTRANTS

The entrants on the newly deregulated market could be typically divided into two groups: 1) start-up companies, willing to take up their niche in the new market, and 2) bigger energy companies which previously operated in either other geographical regions or another energy sector, for example, oil and gas. At first, the market experienced an inflow of new entrants, over 150 companies operated in the market in 1996 (von der Fehr & Hansen, 2009). For the companies, it was not difficult to enter, but staying in business was a challenge. The stable demand for electricity limited the revenues, and low potential for differentiation of such a homogenous product as electricity hardly allowed for variety in the product offered

(Defeuilley, 2009). However, the companies have been approaching differentiation through taking up a niche, i.e., targeting specific consumers. They have been creating «best buys» for consumers depending on their geographic location, the average amount of electricity they consume or adding ancillary services the consumer might be interested in (Waterson, 2003). One example of differentiation is Fjordkraft: it offers electricity contracts that include additional benefits, such as cheaper internet service, petroleum at a lower price or extra EuroBonus points (Fjordkraft, 2017; Fjordkraft, 2018). Nevertheless, differentiation challenges squeezed some of the smaller entrants out of the market, and the bigger companies usually became the new "incumbents." Only two start-up entrants in the Norwegian electricity market managed to gain a large share of consumers, and both were then merged with incumbents (von der Fehr & Hansen, 2009). These challenges sunk the number of companies down to 130 in 2004, and in 2017 there are just over 100 companies in total. Only 39 retailers have over 10 000 customers, and they provide service to 90% of all end users in Norway. On average, the dominating supplier captures 56% of end users in each grid area (NVE, 2017).

2.3 OVERVIEW OF CONTRACTS

The unique feature of the electricity market in Norway is that no price regulations from the state have been in place after the deregulation, making price-forming fair and transparent for both suppliers and consumers (Amundsen & Bergman, 2006). There are three types of contracts available for the electricity users: Variable price contracts, spot-based offers, i.e., wholesale-based energy pricing, and fixed-term, fixed-price contracts. Under variable-price (default or standard) contract supplier can adjust the price, for example, due to the changed supply costs. There are, however, some restrictions to this: the supplier cannot change more frequently than every second week and must give consumers two-week notice of the change. A market-based or spot-price contract is based on weighted average from Nord Pool spot price plus a margin (markup added to each kWh) or commission (fixed extra monthly payment), and a fixed-price contract sets a price for an agreed period, mostly for one to three years (Johnsen & Olsen, 2008). Default suppliers tend to offer variable-price contracts, while alternative retailers stick to spot-price and fixed-price contracts (Littlechild, 2006). In 2015-2016 the share of offers for Spot-based contracts dominated the Norwegian market (ACER, 2015).

2.4 SPOT PRICE CONTRACTS

As mentioned before, spot-price offers are the most popular among consumers on the Norwegian electricity market. In this section, we will devote attention to why Norwegian consumers tend to choose spot-price contracts to gain a better understanding of the possible reasons for switching behavior.

First of all, on strompris.no there are two types of contracts that fall into spot price category: spot price and purchase price (innkjøpspris) contracts. Although they are presented together, there is a difference between them: while spot price bill will contain the average of the price for all the hours per month, the purchase price is added separately for each hour. (Strømpris, 2018) Normally, a purchase price offer is a bit more expensive than a spot-price one, adding up about 50-150 Norwegian kroner (NOK) to a yearly bill (Pedersen, 2018). Some electricity retailers often use this term interchangeably in their contract offer descriptions, for example, Telinet Energi and Norges Energi (NorgesEnergi, 2018; Telinet Energi, 2018). Further in this work, we will also consider those two types of contract to be the same.

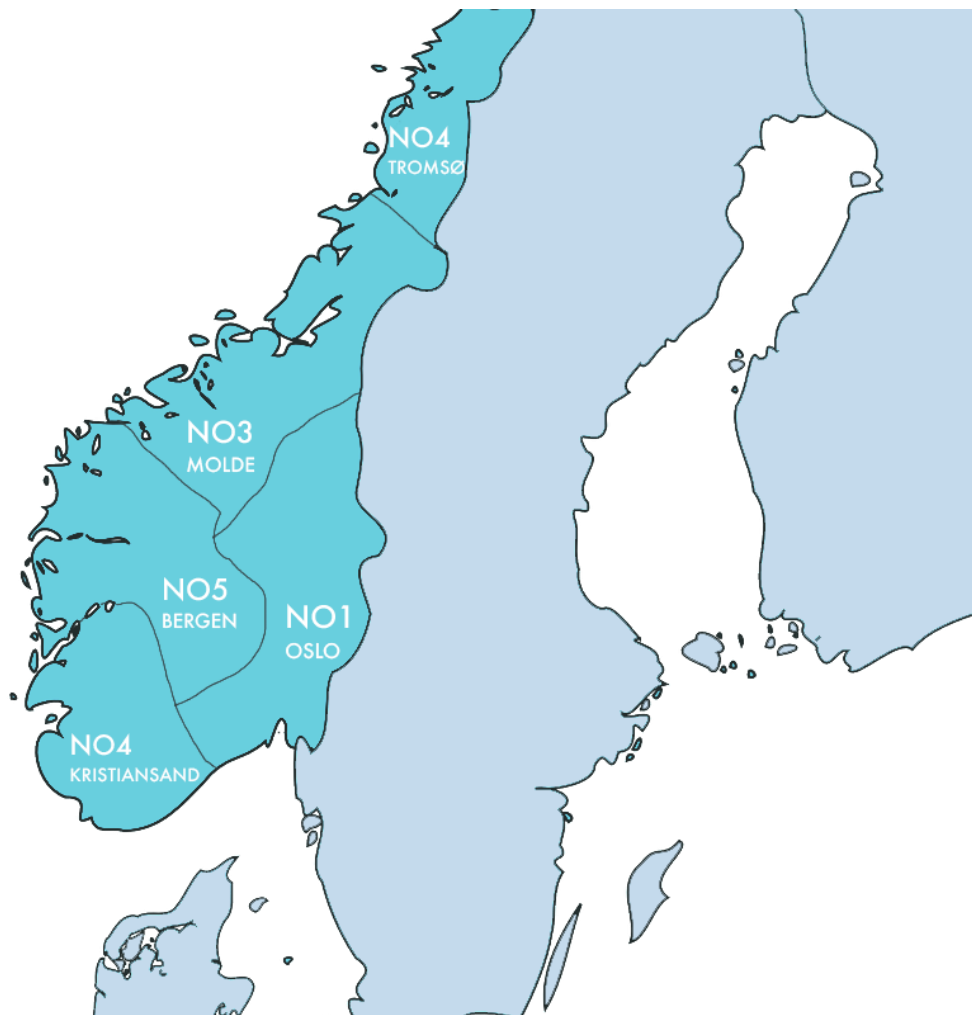
There are several reasons why Norwegian electricity consumers prefer spot-price contract in favor of other types. The primary driver for the choice is its low price compared to other contract types. On average, spot-price contracts are 15% cheaper than variable price contracts, and for an average-sized house could save up to NOK 2000 a year (Andersen, 2017; Øksnes, 2016). Moreover, even though ups and downs in the electricity spot price might bring substantial changes to the bill, in the long run, spot-price contracts turn out to be cheaper than other types. Spot price contracts also attract consumers, because it gives them relative independence from the provider: the only thing electricity provider controls for is the markup added to Nord Pool price. Therefore, it gives consumers room for relative control over electricity spending through monitoring spot price fluctuations. If price shows an upward trend, especially in the case of purchase price contracts, the consumer might lower the consumption or switch to another provider. Choosing spot-price for summertime allows to enjoy lower prices and choose less flexible options for the colder seasons.

Spot price contracts can be inconvenient to consumers that only have a specific available budget on electricity. Those usually choose other types of contracts, since spot price fluctuations bring different price on the bill each time. Electricity, however, constitutes such

a small share of consumer budget, that most consumers can spend extra money on the bill in one month to enjoy lower prices in another.

Another factor, promoting to choose in favor of spot price contract is that it creates the most favorable contract conditions notwithstanding the location of a consumer. In Nord Pool system, Norway is divided into five bidding zones, where spot prices typically differ from each other. These regions are named after the larger cities in the zone: Oslo (Eastern zone, also called N01), Kristiansand (South, N02), Molde (includes Trondheim, Midland, N03), Tromsø (North, N04), and Bergen (West, N05) (Strøm.no, 2018). The regions are displayed in Figure I below:

FIGURE I — BIDDING REGIONS IN NORWAY, NORD POOL SYSTEM



Source: Nord Pool

Usually, spot prices in the East and North regions are somewhat similar; Midland region tends to be the most expensive and south — the cheapest. However, it is not always the case: the table below shows spot prices for week 17 of 2018.

TABLE I – ELSPOOT DAY-AHEAD PRICES IN NOK/MWH IN NORWAY, WEEK 17, 2018

	Oslo	Kr.sand	Bergen	Molde	Tromsø
29/04/2018	338,78	338,78	338,78	338,78	342,1
28/04/2018	344,91	344,91	344,91	344,91	349,33
27/04/2018	358,34	358,34	358,34	358,34	360,49
26/04/2018	353,73	353,73	353,73	354,9	359,41
25/04/2018	355,46	355,46	355,46	355,02	360,83
24/04/2018	336,34	336,34	336,34	334,93	349,12
23/04/2018	335,97	335,97	335,97	335,97	356,56
Min	335,97	335,97	335,97	334,93	342,1
Max	358,34	358,34	358,34	358,34	360,83

Source: Nord Pool

The last week of April 2018 showed the highest price in the Northern region, while the cheapest was in Molde. The reasons for spot price differentiation by regions are the amounts of water in reservoirs and bottlenecks in the grid. Moreover, spot price varies from outside of Norway — it is Nord Pool supply and demand that is the defining factor. Different spot prices create cheaper and more expensive contract offers from retailers in different regions, but since fixed and variable price contracts, in the end, are also defined by the price at which retailers buy power, spot price contract remains the cheapest option notwithstanding the region.

3. RETAILER SWITCHING IN NORWAY: CONSUMER BEHAVIOR

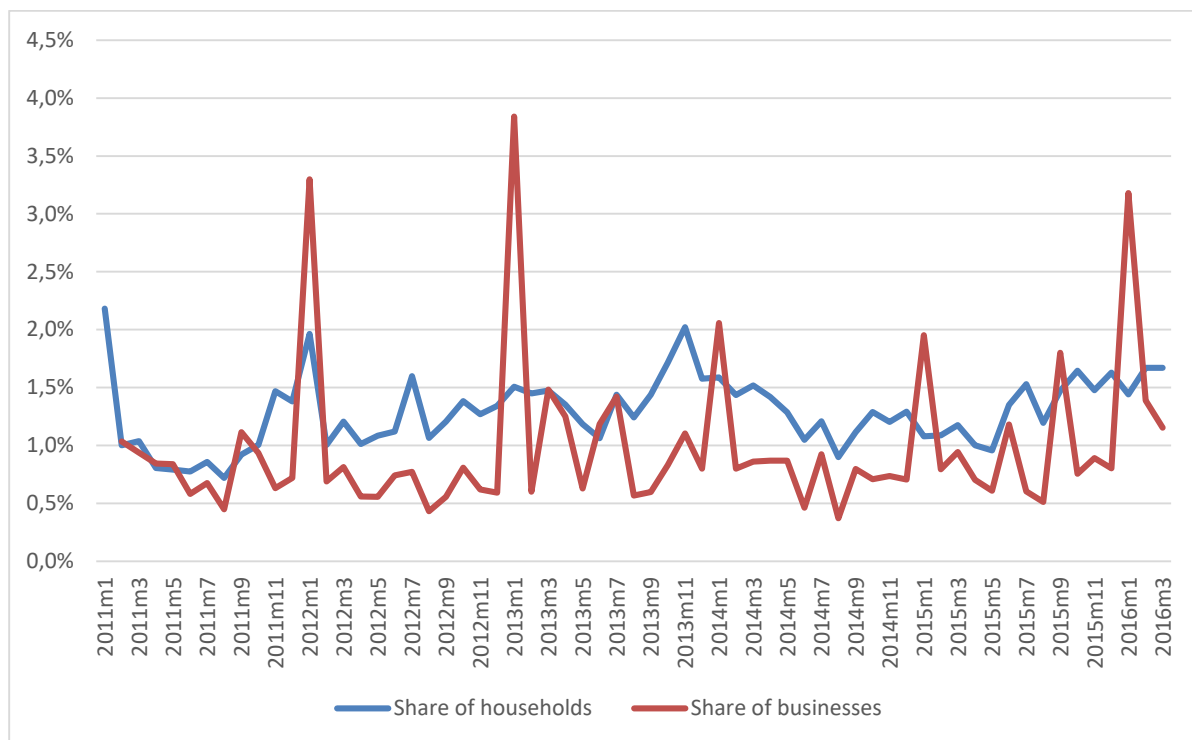
3.1 SWITCHING PROCEDURE

In Norway, the local distribution network operator plays a role of a supplier of last resort for those who have just moved or in between switches. The prices set distribution network operators are high to encourage consumers to search for better options. If the consumer wishes to switch the retailer, they can do it through a special online-based portal operated. Until 2016 it was operated by the Competition Authority (Konkurransetilsynet), but then the responsibility was transferred to the Consumer Council (Forbrukerrådet). There, the consumer can enter their address and get the comprehensive list of possible suppliers with the types of contracts and prices that they offer. Consumers can compare terms and conditions, and check whether the energy the retailer offers energy is from renewable sources. This can be ensured through guarantees of origin that the retailer can obtain through a third party. The consumers can fulfill switching with as little information as a personal number, birth date, and location. Unlike most other European countries, in Norway consumers have the right to switch the retailer any day, and switching is usually complete within a few days (ERGEG, 2007). The customer has the right to cancel the contract after having signed it, and the former supplier cannot object to the implementation of the switch, nor have they to pay for having switched — the procedure is completely free of charge.

3.2 SWITCHING PATTERNS

By the proportion of switching, Norwegian electricity retail market is considered second best working in Europe after the UK (Littlechild, 2006). The switching patterns for the residential and industrial consumers are depicted in Figure II.

FIGURE II — MONTHLY SHARE OF SWITCHES FOR HOUSEHOLDS AND BUSINESSES



Source: NVE

The trend in switching has been uneven both for residential and commercial consumers. In 2016, 21% of households and 13% of industrial consumers have switched their electricity retailers, and for the last four years, the trend went upwards. At the end of the second quarter of 2017, 1 031 000 Norwegian household customers had not exchanged power suppliers for five years or more. This corresponds to 39% of all Norwegian household customers (NVE, 2017). Norway has the highest electricity consumption in Europe, the second highest switching rate (ERGEG, 2007), and the electricity prices are low compared to income level. Industrial consumers in Norway are more active on the market than the residential ones. However, the rate of switching in Norway can hardly be called high and taking into account all the above-mentioned facts in this chapter, it is challenging to decide whether the purpose of opening the market has been reached. There are two main reasons for doubt: i) many consumers do not exercise their power to choose the electricity retailer and ii) the new entrants in the market fail to get sufficient business (Defeuilley, 2009). In the following section, we will discuss the causes and factors that contribute to the lack of switching behavior in Norway.

3.3 SWITCHING BEHAVIOR

As stated in the previous section, although switching rates in Norway compared to other European countries except for England are high, in absolute terms the situation is different — the market struggles to attract many consumers to switch their retailers (von der Fehr & Hansen, 2009). There are two ways consumers can foster the market competition themselves: 1) by regularly searching for the better electricity supply options and 2) by quickly responding to the price changing and actively exercising their right to switch the providers (Waterson, 2003). These actions describe ideal consumer-switching behavior for the market, yet such behavior is rarely the case. One of the first attempts to explain switching behavior was done by Keaveney (1995), his framework of switching included the perspective of the service but didn't take into account psychology and demographics of consumers. Psychology in economic settings is what behavioral economics study. Behavioral economics imply that consumer behavior can be affected by different biases that constitute a gap between rational choices and the one they actually make (Defeuilley, 2009). The model explaining consumer-switching behavior proposed by Bansal and Taylor (1999) took psychological factors into consideration. According to their service provider switching model (SPSM), switching behavior of the consumers is affected by service quality, service satisfaction, switching costs, attitudes towards switching, influence of the significant others.

The factors influencing switching can be categorized as psychological and economic (Basnal et al., 2005).

PSYCHOLOGICAL FACTORS of switching are more numerous and complex. They include:

1. CONSUMER LOYALTY

Loyalty to the supplier, and satisfaction attributed to it, shape consumer switching patterns. If the consumer's perceived happiness with the supplier is high, the loyalty towards it increases (Ek & Soderholm, 2008). With the increasing loyalty, the drive to switch goes down (Szymanski and Henard, 2001).

2. SOCIOECONOMIC AND DEMOGRAPHIC CHARACTERISTICS OF RESIDENTIAL CONSUMERS

The response is generally better within younger, more educated and wealthier consumers (Giulietti, M. et al., 2005). On the contrary, it is harder to encourage those who are less advantaged economically or have moved from the places where only a monopolist

incumbent is available (Hortaçsu, A. et al., 2015). When it comes to searching for the new suppliers, Giulietti et al. (2005) finds, however, that the relationship between income and search costs is U-shaped: consumers at the lower tier of the income tend to have higher switching costs, presumably due to lower levels of education, but those at the upper tier value their time higher (Waddams Price et al., 2013), which makes search costs high for them. Gender influences switching, too: men tend to be more positive towards switching than women (Gamble et al., 2009), which can be explained by the stronger proneness to competition observed in men's behavior rather than in women's (McDaniel and Groothuis, 2012).

3. SWITCHING IN THE ELECTRICITY SECTOR IN THE PAST

Consumers who have once switched within electricity sector tend to be more active on the market. This experience triggers "consumer learning" and makes users more likely to switch again (Hortaçsu et al., 2015). Most of the switches in the Norwegian retail market are conducted by the same consumers, too, but a lot of them constitute switching back to the previous supplier (NVE, 2017).

4. SWITCHING IN OTHER SECTORS

The tendency is so that in the electricity retailing sector those consumers are more prone to switching that have already done so within other sectors: telecommunications, banking, insurance or telephony (Defeuilley, 2009).

5. INFLUENCE OF THE PEERS

Peer effects and influence by significant others foster more active switching among the electricity consumers (Bansal et al., 2005).

6. SUPPLIER'S CHARACTERISTICS AND SERVICES

Such features as company's image (Peng & Wang, 2006), availability of ancillary services (Peng & Wang, 2006), active market communication (Wieringa & Verhoef, 2007), green energy offering and bundling of several energy sources within one company (Wieringa & Verhoef, 2007) affect switching behavior of the consumers.

ECONOMIC FACTORS determine monetary cost or benefit for consumers. They measure how investments made before entering the relationship with an alternative supplier brought the benefit afterward in the form of a better price. These investments include 1) search costs, 2) learning and transaction costs and 3) costs of substitution between suppliers.

Search costs in the electricity retailing market are typically associated with identifying the suppliers and comparing the offers (Defeuilley, 2009). Opening up of the markets of homogenous products requires policies that encourage consumers to switch — such as providing information and allowing a large number of companies to engage in supply. These should be the initially governmentally owned industries, where consumers are not used to exercising their power of choice (Waterson, 2003). Consumers need to be able to receive information about the suppliers, and this information should be trustworthy, accessible and comparable (NAO, 2008). On the website all the needed information about the retailers is available, fostering consumer learning. Moreover, consumers should receive the information, that outages and other problems with supply are not related to suppliers, which will likely weaken their attachment to the incumbent (Hortaçsu et al., 2015), and this information is provided at as well on the website. Consumers can find more detailed information about the service offerings on each supplier's website. While the website is within a few clicks for any internet user, the online procedure of comparing the offers can be done entirely there and would rarely take more than 30 minutes (von der Fehr & Hansen, 2009). However, sometimes search is not a problem, yet it is difficult to determine the choice, so consumers stick to what they have (Defeuilley, 2009) — they are reluctant to choose, which could reflect switching costs from a behavioral perspective. Some consumers explore the potential savings they could make but do not switch, which indicates the distinction between the two costs (Giulietti et al., 2005).

If costs outweigh the benefits, it is rational not to switch. The strongest driver to switch, according to Flores and Waddams Price (2013), is anticipated gains. The study by Gamble et al. (2009) showed that in neighboring Sweden perceived economic benefits from switching are relatively low in the markets for electricity. As Littlechild (2000) has stated, "the benefits of switching have to be large enough to induce customers to make the effort to switch." Giulietti et al. (2005) claim that most customers will tolerate having incumbent prices substantially above entrant prices because costs of switching are perceived higher than the prices and benefits are perceived as low.

3.4 SPOT-PRICE CONTRACTS AND SWITCHING IN PURSUIT OF LOWER ELECTRICITY PRICES

In 2.2.3 we have discussed the drivers for consumers to choose spot-price contracts over other types, and in 2.2.6 we took a closer look at the causes of passive and active switching behavior of electricity consumers. To further assess how spot-prices affect switching, we will now identify which goals can both active switching and choosing spot-price contract help to achieve.

First of all, monetary benefits for consumers are reflected in lower electricity price — both in the case of favoring spot-price contract and careful switching. Since in the long-term spot-price offers pay off better than other options, and switching to cheaper provider brings lower electricity bill, both of the actions have the same goal. However, cheaper contracts for switching do not always mean lower electricity prices than before. Some providers, for example, Agva Kraft or Teline Energi, tend to put up very attractive contracts to lend on top on strompris.no. These contracts turn to much less favorable conditions over time, causing higher prices than anticipated (Strømpris, 2018). What makes it extra challenging to choose the cheapest contract is the fact that taking all the contract conditions into account is time-consuming — some retailers have too many contracts offers at once on the market to allow for careful examination: for example, Agva Kraft offers 28 different contracts at the moment (Agva Kraft, 2018). To this end, switching in pursuit of lower electricity price does not always help achieve the goal if consumers do not carefully examine the contract conditions. Torstein van der Fehr and Vegard Hansen argue, that elasticity of demand in response to spot-prices in Norway is low and constitutes only 0,2. According to them, short-term spot-price peaks do not affect switching patterns of the consumers, but rising prices for longer periods of time puts a pressure on consumers to switch from spot-price contracts to other options. In the following chapter, we are going to further look into the relationship between spot-prices and consumer switching.

4. RESEARCH QUESTION AND THE DATA

As we set to explore how the consumers in the deregulated electricity market in Norway switch their electricity retailers, the sections above have provided a general background into the market structure and the potential factors affecting switching behavior of the consumers. The literature review has covered both monetary and psychological factors influencing the decision to switch, but in case of Norway, there might be another factor that plays a vital role in this process. Since the significant share of the electricity contracts issued to the household consumers is constituted by the spot price contracts, we expect Norwegians to be attentive to Nord Pool spot price fluctuations (ACER, 2015). Hence switching rates in Norway might be sensitive to the spot price dynamics.

Based on our research of the available literature, the relationship between the electricity spot prices and the switching of retailers has never been investigated. Observing how popular the spot price contracts are in Norway, it is interesting to identify whether the spot prices affect switching rates in the electricity market. It is uncertain whether the fluctuations in the spot prices are important enough to stimulate the consumers to change their electricity retailers to seek cheaper alternatives. Given that, according to Littlechild (2006), switching is one of the primary indicators of the deregulated market success, the absence of studies and the current popularity of spot-price contracts in Norway are the main motivating reasons for us to examine the relationship between switching and the spot prices. Hence, we define our research question as follows:

RESEARCH QUESTION: How do electricity spot price fluctuations influence electricity retailer switching rate among Norwegian consumers?

To answer our question, we need to formulate a testable hypothesis. Due to the lack of empirical research on the relationship, we base our hypothesis on logical conclusions from the analysis of electricity consumption patterns. Generally, when the electricity prices increase or when the consumers suddenly receive a large electricity bill, the consumers should more motivated to save on their electricity consumption (Flores and Waddams Price, 2013). A conventional way of doing this is through cutting on the electricity usage. However, in the deregulated market, the consumers have an additional choice: switch to a cheaper retailer or a cheaper contract if such are available. Therefore, we propose that there

should be a positive relationship between the switching rates and the electricity spot prices. Hence:

HYPOTHESIS 1: An increase in the spot prices is associated with an increase in the switching rates.

Due to some factors such as post-consumption electricity bills and consumer inattention to immediate changes in the spot prices, there might be some lag in the response of switching rates to changes in prices. As a part of our research question, we want to test the hypothesis of whether the Norwegian consumers are forward-looking or not. Hence:

HYPOTHESIS 2: An increase in the spot prices last month is associated with an increase in the switching rate in the current month.

To provide the answer to the research question, we have constructed a unique database by merging several datasets from different sources. This section presents explanations for the variables included in the models as well as a general summary of the statistics of the constructed dataset.

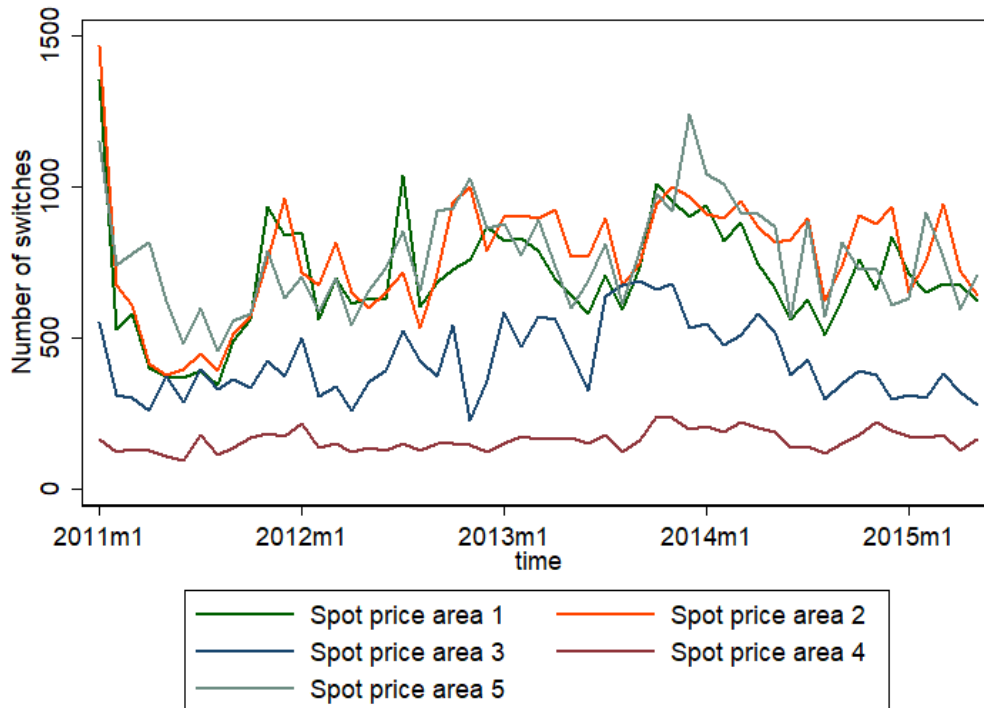
4.1 SWITCHING RATE

To conduct the analysis, we rely on the switching statistics in the electricity market provided by NVE. The switching statistics are represented as the number of switches per grid company every month from January 2011 to May 2015. In total, there are 45 grid companies in the dataset. Each grid operates within the specific area of the country. Electricity retailers may utilize more than one grid company's services since the retailers may offer their services within multiple cities in the country. The dataset allows us to perform the analysis on the grid company level, implying we cannot distinguish the retailers involved in the switching. The data registers only the act of switching completed between the retailers under the same grid company. It does not contain the data on switching between the contracts too. We only observe the monthly number of switches within each of the 45 grid companies.

As already mentioned in Chapter 2, there are five geographical areas in the dataset determined by Nord Pool spot price areas, from N01 to N05. Merging several datasets together allowed us to establish a link between the grids and one of the five areas they

operate in. Thus, in Figure III, we can observe the switching rates development in the five regions of Norway.

FIGURE III — MONTHLY SWITCHING RATES IN NORWAY BY SPOT PRICE AREA, JAN 2011 – MAY 2015



Source: NVE

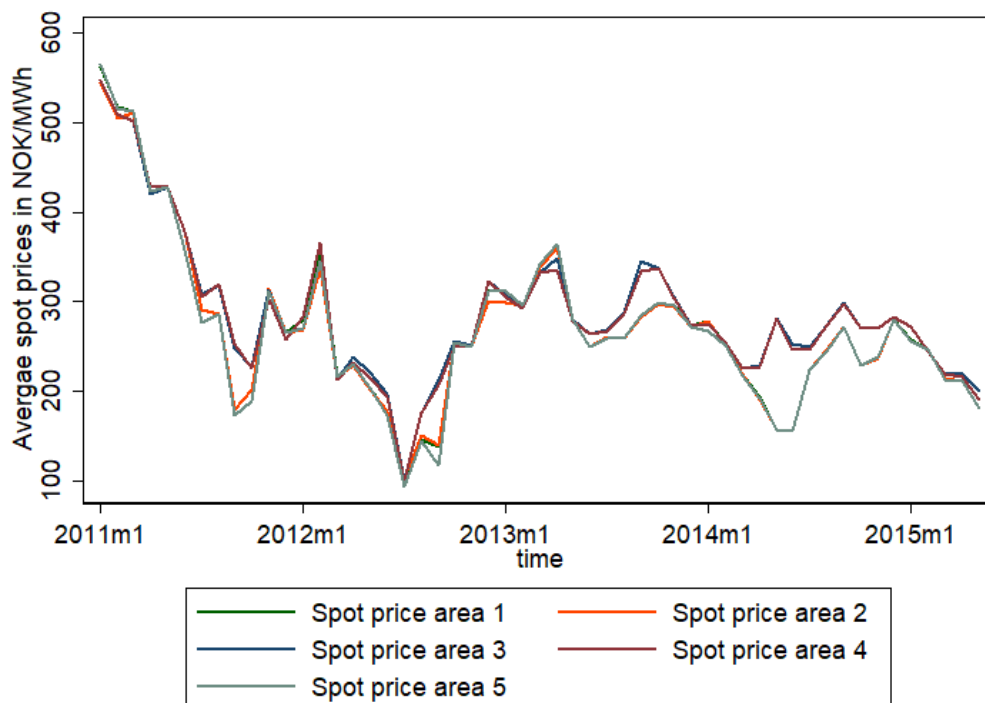
As the graph suggests, Oslo, Kristiansand, and Bergen have relatively higher numbers of switches per month compared to Trondheim and Tromsø. It is not surprising that cities with bigger population have a higher share of switching. However, it also might be due to a greater choice of electricity retailers in the bigger cities. In late 2013, Bergen shows an unusually high number of switches, which is a definite outlier compared to the rest of the data. Since we could not find any justification for this from the past events, we suppose it to be a data entry error and treat it by deleting that observation.

For the analysis, we have used each grid company's switching rate as a dependent variable which is obtained by dividing the number of switches by the number of subscriptions. This allows us to control for the size differences among the grids and stabilizes the variable of switching.

4.2 SPOT PRICES

In the analysis, we use Nord Pool electricity spot prices specified for above mentioned five spot price areas in Norway for the period from January 2011 to May 2015. The prices are in NOK per MWh of electricity. As shown in Figure IV, the prices follow almost identical trend in all the regions throughout the analysis period. There are small differences in some periods, probably caused by weather condition fluctuations, which influence the power demand and supply, leading to various prices in different regions.

FIGURE IV — MONTHLY ELECTRICITY SPOT PRICE FLUCTUATIONS IN NORWAY BY SPOT PRICE AREA, JAN 2011 – MAY 2015



Source: NVE

Given that more than 90 percent of power generation in Norway is based on hydro resources, weather conditions in the regions exert significant influence on the spot price formation. Increased demand during colder times and reduced supply of electricity during scarce rainfall or frozen mountain tops, result in increased spot prices for the electricity.

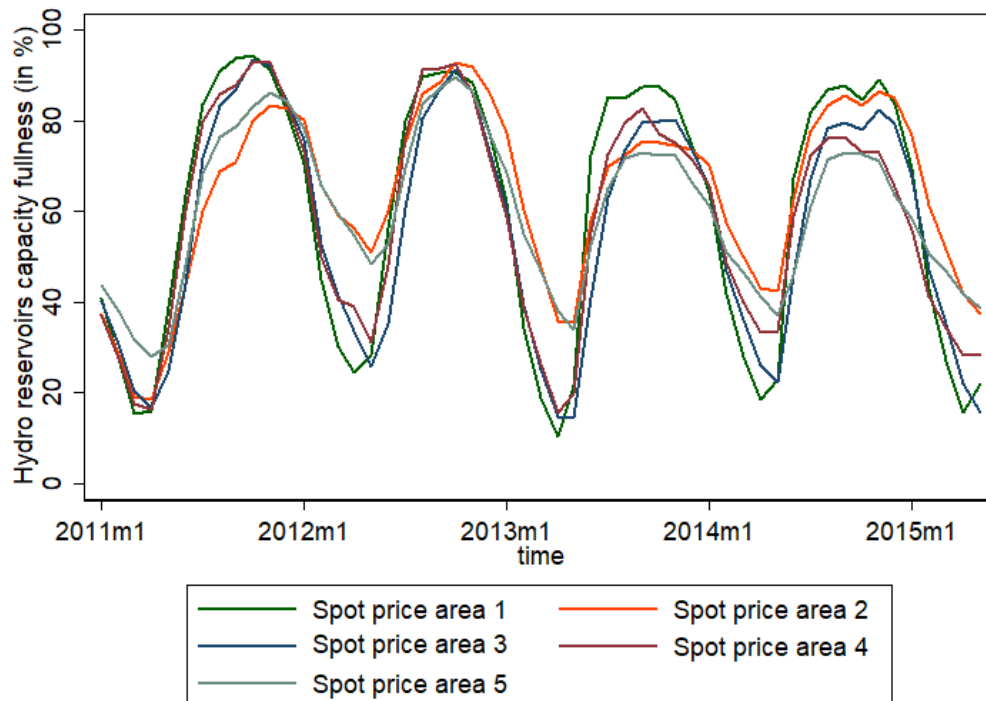
Due to the close correlation of spot prices with demand side factors, using the spot prices as an independent variable in the analysis may result in erroneous estimates. The reason for this is a possible dependence of switching on the same demand side factors. It is hard to specify

these factors and, more importantly, find their measurements. Therefore, they are assumed to be in the error term of the model. Using spot prices directly in such model will lead to endogeneity problem. One of the effective ways to overcome this problem is to use instrumental variable approach, which requires finding an appropriate instrument. In our case, we believe that hydro reservoir levels can be a valid instrument.

4.3 HYDRO RESERVOIR LEVELS

Nord Pool specifies five hydro reservoir capacities corresponding to the five spot price areas for the period from January 2011 to May 2015. These reservoirs play a vital role in power generation process. The power generation depends on how much water is in the reservoirs. A full reservoir means ample capacity to produce electricity, hence lower electricity prices. This close dependence on spot prices makes this variable of hydro levels potentially a valid instrument for our analysis. We assume that consumers do not take into consideration the hydro reservoir levels when deciding on the consumption of the electricity. If it is indeed so, then this should ensure the exogeneity of the variable.

FIGURE V – MONTHLY RESERVOIR CAPACITIES IN NORWAY BY SPOT PRICE AREAS, JAN 2011 - MAY 2015



Source: NVE

As expected, Figure V illustrates strong seasonality effect of the hydro reservoir levels in all five regions. The reservoirs start to fill up as the weather gets warmer, reach their peak in summer and gradually fall towards winter. This emphasizes the importance of including time variables into the model to control for the seasonality.

4.4 SUMMARY STATISTICS AND EXPECTED RESULTS

This subsection provides an overview of the whole dataset which is used in the analysis. The final dataset is constructed by using geographical area and time indicators to tie up all the pieces of information into one complete dataset. The grid company's ID and time variable were used to set up the panel dataset. The total number of observations is not the same for all variables because some of them do not overlap in some periods. For example, weather indicators such as temperature and rainfall data are available from January 2013 to May 2015 only.

TABLE II – OVERVIEW OF THE DATA

Variable	Observations	Mean	Std. Dev.	Min	Max
Number of switches	2316	540.070	1242.453	8	15808
Subscriptions	2316	50191.120	84803.290	7960	622655
Switching rate	2316	0.008	0.006	0.001	0.104
Spot price	2385	277.988	87.190	93.240	565.610
Hydro reservoir levels	2385	59.022	25.133	10.200	94.525
Market share	2316	0.023	0.039	0.004	0.276
Rainfall (mm)	1305	81.834	68.727	0.000	512.100
Average temperature	1186	6.121	6.283	-5.570	20.844

Source: YR, NVE

4.5 DESCRIPTION OF THE VARIABLES

Below you will find the overview of the variables that we use further in our research.

THE NUMBER OF SWITCHES depicts how many switches were made within one grid company in one month.

SUBSCRIPTIONS represent a monthly number of subscribers of each grid company.

SWITCHING RATE is derived from the two variables mentioned above: the number of switches divided by the number of subscriptions. This transformation allows the results to be comparable between the grid companies. We use the switching rate variable as the dependent variable in the analysis.

SPOT PRICE variable contains monthly spot prices of electricity in NOK/MWh for five regions in Norway. For the analysis, we have transformed the spot prices into logarithmic form to accentuate relative price volatility compared to absolute terms. As per our hypothesis, we expect to reveal a positive sign of the coefficient of this variable.

HYDRO RESERVOIR LEVELS show the percentage of capacity fullness of reservoirs in five areas corresponding to five spot price areas. The variable is used as an instrument for the prices. We expect that lower reservoir levels should lead to higher prices and vice versa.

RAINFALL AND AVERAGE TEMPERATURE are the weather controls indicating levels of rainfall much rained in millimeters per month and the average temperature in Celsius in each spot price area. We expect that higher rainfall lowers the electricity prices through fuller hydro reservoirs. The temperature in Norway may influence both demand and supply of electricity. People tend to use more electricity to heat up their houses and offices in cold seasons, thus driving up the demand and prices. While in warmer seasons, higher temperatures melt down the ice in the mountains, increasing the inflow into the hydro reservoirs and driving the prices down.

5. METHODOLOGY

The main purpose of this research is to identify the relationship between the Nord pool spot prices and the electricity retailer switching rate of consumers in Norway. The structure of the data at hand allows us to take advantage of panel data methods to investigate the question. The switching statistics have been recorded within each grid company on a monthly basis, therefore, grid companies' ID and monthly time variable are used to set up the panel dataset.

Using the methodology developed below, we are going to test the hypothesis that when spot prices increase, the switching rates across Norway also increase. We believe that since the majority of the electricity contracts in Norway are spot price based contracts, the consumers' behavior should be more sensitive to the fluctuations in the Nord Pool prices. We expect that this sensitivity will be at least partially revealed through changes in the switching rates. We will take advantage of panel data set and implement fixed effects and instrumental variables regression models to test the hypothesis.

In non-experimental studies such as ours, it is beneficial to have the possibility to implement panel data analysis techniques. It is common practice in such studies to statistically control for other variables to obtain the results comparable to those that could be obtained from a randomized trial. Statistical control indeed can be a useful technique, but it has two major limitations. First, in practice it is hard to control for all variables in the environment, there will always be some that are left unattended. The omission of an important variable can cause a severe bias in estimating the real effect of included variables (Wooldridge, 2006). In our case, there may be some demand factors that influence both price and switching, characteristics specific to grid companies or it may be region specific features that stay unchanged over time. Second, even though we identify all the variables for statistical control, we may not be able to measure and explicitly include all of them in the model. Some variables are just hard to measure, others may have an imperfect measurement, which also can lead to biased estimates. For example, measuring consumer loyalty or customer support quality in each grid company.

5.1 FIXED-EFFECTS METHOD

Fixed-effects (FE) method offers one way to deal with omitted variable bias. The dataset meets the two major requirements of FE, namely time series nature of observations and the variability in the independent variables within the grid companies, which we will refer to as entities. FE can control for all possible time-invariant characteristics of entities even without measuring them.

Based on Stock and Watson's (2006) explanation of fixed effects regressions, there must be a number of intercepts in the FE regression model, for each entity respectively. These intercepts can be represented in the model as binary variables which absorb the effect of omitted variables that vary among the entities but are constant over time. Consider the regression model in equation (1) with switching rate as a dependent variable and log of electricity spot prices as observed regressor denoted as Y_{it} and X_{it} , respectively:

$$Y_{it} = \beta_0 + \beta_1 X_{it} + \beta_2 C_i + u_{it} \quad (1)$$

Where C_i is an unobserved variable that differs from one grid company to another but is stable over time (for example, C_i may represent cultural attitude toward switching retailers in each region, customer support quality in each company. While these characteristics can change over longer time, we assumed they could be stable over the five years period included in this study). The model should estimate β_1 , the effect of electricity spot prices on switching holding constant the unobserved characteristics C_i .

Because C_i varies among the entities but is constant over time, the equation (1) can be rewritten as:

$$Y_{it} = \beta_1 X_{it} + \alpha_i + u_{it}, \quad (2)$$

Where let $\alpha_i = \beta_0 + \beta_2 C_i$. Equation (2) is the general representation of FE regression model with $\alpha_1, \dots, \alpha_n$ as unknown intercepts to be estimated. Other observed variables that can determine Y , and are correlated with u and time-variant, can be included in the regression model to avoid omitted variable bias.

Similarly, as fixed-effects can control for time-invariant variables, so can time-fixed-effects control for variables that stay unchanged over entities but vary over time. For example,

market regulations for electricity retailers can improve market conditions and simplify consumer switching. As a result, market conditions may change over time, but most likely they will affect switching rates in each grid company.

Combined entity and time fixed effects regression model is more appropriate to use in our case because we want to avoid both types of omitted variables, those that are constant across the entities but change over time and those that are constant over time but change across the entities. The general specification of such model is:

$$Y_{it} = \beta_1 X_{it} + \alpha_i + \delta_t + u_{it}, \quad (3)$$

Where α_i is the grid company fixed effects and δ_t is the time fixed effect. Other observed covariates influencing Y can be included in the model as additional regressors as in equation (4):

$$Y_{it} = \beta_1 X_{it} + \beta_2 W_{1t} + \dots + \beta_k W_{kt} + \alpha_i + \delta_t + u_{it}, \quad (4)$$

Where W_1, W_2, \dots, W_n are additional regressors such as regional temperature or rainfall.

ASSUMPTIONS OF THE FIXED EFFECTS REGRESSION

THE FIRST ASSUMPTION: given all time values of observed regressor for the entity, the error term must have a conditional mean of zero:

$$E(u_{it} | X_{i1}, X_{i2}, \dots, X_{iT}, \alpha_i) = 0 \quad (5)$$

The assumption holds when there is no omitted variable bias. We will include all the necessary variables and control for others using time fixed effects to satisfy this assumption.

THE SECOND ASSUMPTION: the variables are identically and independently distributed (i.i.d.) across entities for $i = 1, \dots, n$. The assumption holds if the entities are randomly sampled from the population. Since the data was collected by NVE for monitoring the whole market condition in the country, this assumption seems to be satisfied.

THE THIRD AND FOURTH ASSUMPTIONS: there are no large outliers in the data and there is no perfect multicollinearity.

THE FIFTH ASSUMPTION: conditional on the regressors, there is no autocorrelation in the errors u_{it} in the FE regression model. This assumption arises in FE regression due to time dimension of the data. Some part of the error term u_{it} consists of time-variant factors that determine Y_{it} but are not included in the model. Such factors may include weather shock: unusually hot or rainy weather in Bergen or Kristiansand could result in lower electricity prices and lower electricity demand, which potentially may change the switching rates. If the error term u_{it} consists of weather factors that are serially correlated over time, conditional on the regressors and the entity fixed effect, then u_{it} is autocorrelated over time and the fifth assumption does not hold. If the tests reveal the presence of serial correlation, a possible solution may be to include the weather factors explicitly into the model. We suspect that it is the case in our model and therefore prepared several weather variables to use in the model.

Despite the advantages of entity and time fixed effects, the FE regression uses up too many degrees of freedom and is not capable of controlling for omitted variables that change both across the entities and over time. In our case, such variables may be demand-side factors that can impact both electricity prices and switching behavior across grid companies and over time. Thus, there remains the need for the approach that can remove the impact of unobserved omitted variables which could not be eliminated by FE regression. A powerful and universal method for such case is the instrumental variable approach.

5.2 INSTRUMENTAL VARIABLES METHOD

Instrumental variables (IV) regression approach provides an effective way to evaluate a consistent estimator of the unknown population coefficient when the independent variable is correlated with the error term (Woldridge, 2006). We believe the variation of the X , electricity spot prices, has two parts, the one that is correlated with demand side factors which are in the error term u and the other part which is not correlated with u . The correlated factors may include the regional development of electricity retailers or the regional markets, differences and evolution of offered contracts in one region with another. If we have information that could isolate the correlated part of the variation in X , then we could focus on uncorrelated variations to obtain unbiased estimators. This is the working principle of IV regression. The information about the uncorrelated part of the X can be obtained from one or more supplementary variables, called instrumental variables. In our estimations, we are using

water reservoir levels in five regions corresponding to five spot price regions. The reservoir level seems to be a good predictor of electricity prices in Norway since the more than 90 percent of power generation is provided by hydro sources.

First, let us explain the general mechanism of how IV regression can provide consistent estimates through Two-Stage Least Squares method and how IV approach incorporates with FE regression model. Based on the equation (4), where X_{it} , spot price variable, might be correlated with the error term u_{it} , but W_{1t}, \dots, W_{mt} are not.

The first stage regression of 2SLS relates spot prices to all exogenous regressors and the instrument Z , reservoir levels in water dams:

$$X_{it} = \pi_0 + \pi_1 Z_{it} + \pi_2 W_{1t} + \dots + \pi_m W_{mt} + v_{it} \quad (6)$$

Where $\pi_0, \pi_1, \dots, \pi_m$ are unknown coefficients and v_{it} is an error term. The model in equation (2.44) is also called reduced form equation for X . The predicted \hat{X}_{it} from the reduced form is then used to replace X_{it} in the second stage of the 2SLS method:

$$Y_{it} = \beta_1 \hat{X}_{it} + \beta_2 W_{1t} + \dots + \beta_k W_{mt} + \alpha_i + \delta_t + u_{it}, \quad (7)$$

This is the general model that is used in the estimation process of this research.

The model with lagged spot prices is also specified to see whether electricity consumers change their retailers with some time lag. Since we cannot directly include the lagged variable of spot prices, we perform the first stage of the 2SLS with lagged versions of logarithmic spot prices and lagged reservoir levels:

$$X_{i(t-1)} = \pi_0 + \pi_1 Z_{i(t-1)} + \pi_2 W_{1t} + \dots + \pi_m W_{mt} + v_{it}, \quad (8)$$

Then, use the predicted $\hat{X}_{i(t-1)}$ from the reduced form in the second stage regression model:

$$Y_{it} = \beta_1 \hat{X}_{i(t-1)} + \beta_2 W_{1t} + \dots + \beta_k W_{mt} + \alpha_i + \delta_t + u_{it}, \quad (9)$$

This model can imply whether electricity consumers need more time to comprehend the market signal and adjust their preferences towards cheaper retailers.

VALID INSTRUMENT

There are some complications in finding a good instrumental variable. The instrument must satisfy the relevance and exogeneity conditions to qualify as a valid instrument.

Instrument relevance: $\text{corr}(Z_i, X_i) \neq 0$.

Instrument exogeneity: $\text{corr}(Z_i, X_i) = 0$.

The degree of relevance of an instrument can be observed from how strongly the variation in the instrument is related to the variation in the endogenous regressor. The related part of the variation is exogenous only if the instrument is also exogenous. This exogenous variation is used to estimate the unbiased effect of spot prices on the switching rates. The relevance of an instrument can be tested in the first stage of the 2SLS method while the exogeneity of an instrument can be supported only by sound judgment and expert knowledge of the topic (Wooldridge, 2006).

The instrument that we use is the reservoir levels in the water dams in five regions, corresponding to the five spot price areas. These reservoirs are used as the source of hydropower production in Norway. Consequently, they can exert significant influence on the supply side and in determination of the electricity prices. This sounds a reasonable justification of their relevance but are they exogenous enough to be a suitable instrument is a different question. The problem with using spot prices in the model was that they could be correlated with the error term, particularly with unobserved demand side factors. The reservoir levels variable does not entirely solve the problem in this case. Factors such as weather conditions still can impact both switching rates and reservoir levels at the same time. However, we have the data on temperature and rain precipitation for all five regions. We use these two variables as control variables in the model and believe that they will make our instrument exogenous. However, we need to be careful about multicollinearity issue in this case. Severe multicollinearity, with Variance Inflation Factor (VIF) of over 10, may cause an increased variance of the estimates and make them sensitive to even slightest changes in the model. As a result, the coefficients are unstable, switching signs, and the statistical power of the analysis is weak (Wooldridge, 2006).

If an instrument fails the relevance condition, it is called a weak instrument. Estimation with weak instruments may lead to severely biased estimators of the 2SLS model. One way to check the weak instrument assumption is to check the statistical significance of the

instrument in the first stage regression model. If there are more than one instruments for one endogenous variable, then F-statistics can be computed and tested against the hypothesis that all coefficients of instruments are zero. There is a rule of thumb that if the first-stage F-statistic is larger than 10, the assumption of weak instruments may be safely rejected (Wooldridge, 2006).

In summary, the estimation part of this research uses FE and IV regression methods to consistently estimate the true influence of the electricity spot prices on the switching behavior of electricity consumers. The main rationale behind using these methods is based on avoiding omitted variable bias by employing entity and time fixed effects for both factors that vary across the entities but not over time and that vary over time but not across the entities. Besides, to control for factors that can vary over time and across the entities, we use IV regression method.

6. EMPIRICAL RESULTS AND DISCUSSION

In this chapter, we provide the analysis of the models proposed in the methodology section and present the test results concerning the model quality. First, we introduce the estimates from the IV regression model using logarithmic spot prices instrumented by hydro reservoir levels. We will provide the first stage results to assess the relevance of the proposed instrument before we move to the examination of second stage estimates. We also present models with added control variables such as average temperature and average monthly precipitation and argue for the exogeneity of our instrumental variable. We have also performed multicollinearity and serial correlation tests to select the right model specification. The test results will be presented in this section as well. To test our second hypothesis of forward-looking consumers, we use one period lagged variable of spot prices instrumented by the one period lagged hydro reservoir levels. Finally, we check the robustness of our results by adding additional control variables such as the average markup of the retailers and the market share of the grid companies. The pros and cons of the specified models and the variables are discussed at the end of this chapter.

Since the focus of the thesis is to find an answer to our research question, we concentrate our attention on the instrumented spot price variable. Mainly we are concerned with its sign and significance level. We cannot directly compare our results with any earlier research on this topic, because no previous works are investigating the relationship between the electricity spot prices and the switching rates. Therefore, we base our judgment of the expected slopes and the significance on implications from the economic theory.

Table III shows the final results from the three model specifications. The models use IV estimation and Fixed Effects. The models differ in the specification of the time effects; Model 1 includes only monthly dummy variables, which control for the seasonality effects. Such effects may be caused by monthly weather patterns, potentially higher switching rates in Januaries because people may want to start a new year with different retailers, or possibly higher switching rates when people move to new houses more often during the year. In Model 2 we added yearly binary variables to control for the annual trend of the switches and the prices. Finally, Model 3 includes monthly and full-time binary variables which may account for much more detailed variations in the dataset. However, including full-time

effects may have both positive and negative impact which will be discussed later in the chapter.

Model 1 shows that the effect of the spot prices on the switching rate is significant at 10% significance level. The results are interpreted in percentage points because of the construction of the variables and are described as - one percent increase in the spot prices will lead to 0.412 percentage point increase in the switching rate. Both the significance and the magnitude of the effect do not allow us to establish a causal interpretation between the two variables. The other two models estimate the coefficient to be insignificant at 90% confidence level and their magnitude is twice as low as compared to the first model.

TABLE III – MAIN RESULTS

Variable	(Model 1) Switch rate	(Model 2) Switch rate	(Model 3) Switch rate
Log of prices	0.004* (0.002)	0.002 (0.007)	0.027 (0.025)
Rain (mm)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
Month	✓	✓	✓
Year		✓	
Full time			✓
Observations	1,260	1,260	1,260
Root MSE	0.00369	0.00366	0.00398
AIC	-10561.80	-10579.26	-10340.11
BIC	-10494.99	-10502.18	-10185.94
Number of ID	45	45	45

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

The variable for rainy weather does not have any effect on the switching rates. We have left only rain variable and excluded the average temperature variable due to multicollinearity issues. Further details of the multicollinearity tests are presented later in the chapter. The purpose of including the weather variables is to ensure that the instrument is indeed exogenous during the estimation. The variable of hydro reservoir levels does not suffer from the demand side unobservable factors, but it still depends on the weather factors. The same

weather factors may influence the switching rates, hence, including them as control variables may help us get more accurate estimations.

We have decided to use three criteria to assess which model is better in terms of statistical power because as Wooldridge (2006) mentioned in his textbook, "Unlike in the case of OLS, the R-squared from IV estimation can be negative because SSR for IV can be larger than SST. Although it does not really hurt to report the R-squared for IV estimation, it is not very useful, either" (p. 521). Therefore, we use Root MSE, AIC, and BIC.

The RMSD represents the sample standard deviation of the differences between predicted values and observed values. The RMSD serves to aggregate the magnitudes of the errors in predictions for various times into a single measure of predictive power. RMSD is a measure of accuracy, to compare forecasting errors of different models for a particular data and not between datasets, as it is scale-dependent.

Being a measure of predictive power, Root MSE (mean squared error) represents the sample standard deviation of the differences between predicted and observed values. It aggregates the magnitudes of the prediction errors into a single measure of accuracy. Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) are the two other statistics that can help us choose the better model. They select the model which best fits the data and penalize those that overfit it, thus providing a standardized way to balance sensitivity and specificity. The AIC prefers the models with minimized mean squared errors while the BIC prefers more parsimonious models by penalizing models with more parameters more than AIC (Vrieze, 2012). Generally, the model with the lowest AIC and BIC is considered to be the right one among other candidate models. Sometimes, AIC and BIC may disagree on their model selection, which usually happens when AIC prefers a larger model than BIC (Kuha, 2004).

Based on these three criteria, Model 2 appears to be slightly better than other models. Thus, we tend to believe the estimates provided by this model. However, the results from the Table 1 may not bear any informative significance if the instrument is poorly defining the endogenous variable of the spot prices. To check the relevance of the instrument, we should examine the first stage results of the IV estimation model. We can use the F-statistic of the overall significance of the instrument and other variables to assess the relevance of the instrument and overall fit.

TABLE IV – FIRST STAGE RESULTS

Variable	(1) Log of prices	(2) Log of prices	(3) Log of prices
Reservoir Level	-0.006*** 0.001	-0.002*** 0.001	-0.001** 0.000
Rain (mm)	-0.001*** 0.000	-0.000*** 0.000	-0.000*** 0.000
Month	✓	✓	✓
Year		✓	
Full time			✓
F-test of excluded instruments:	F (1,1202) = 69.63 Prob > F = 0.0000	F (1,1200) = 18.46 Prob > F = 0.0000	F (1, 1185) = 4.31 Prob > F = 0.0381
Number of ID	45	45	45

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

The F-test results from the Table IV show that the first and the second models are better specified compared to the third model. However, all the three have less than 5% probability that F-statistic is lower than its critical value. This suggests that the instrument defines the spot prices quite well in all three models and we can consider the second stage estimation results to be credible. The relationship also looks logical: higher reservoir levels are associated with lower spot prices, because the larger capacity to produce electricity increases the supply and, according to the conventional economic theory, reduces the prices. The rain variable is associated with lower spot prices in a similar way.

Usually, any type of econometric analysis may suffer from a number of technical problems. These problems may lead to consequences ranging from wrong standard errors to biased estimates. Therefore, we have conducted a few tests to ensure the accuracy of our results and to choose the better model out of three presented.

The first test is for multicollinearity. It is when one or more variables in the model are highly correlated with each other. Severe multicollinearity problem may lead to increased variance of the coefficient estimates and any minor changes in the model may result in large changes in the estimates. Estimates become hard to interpret as they become unstable and switch signs. This makes specifying the right model very difficult (Wooldridge, 2006).

Variance inflation factors (VIF) are used to reveal multicollinearity problems. Table 5 in the appendix shows the VIF statistics of all three models. The general rule of thumb is if VIF is more than 10, there is a significant problem of multicollinearity. We have suspected the temperature to be responsible for high correlation because the variable for temperature turns out to be the one causing high correlation. Therefore, we have excluded the temperature variable from the main estimation models. Even after removing the temperature variable, models 2 and 3 still suffer from multicollinearity problems, most probably caused by time dummies. Including yearly and full-time binary variables pick up much of the variation resulting from the development of electricity market environment. Since we cannot directly control for such developments, we have used more extensive time variables. This works as a double-edged sword: it removes all the bad variation that we do not need, but at the same time it may remove the good variation, that could explain the relationship more accurately.

The second test is for serial correlation, arising when the error terms from the one-time period, in a model involving time series data, are correlated with the error terms of a subsequent period. This can lead to a range of problems. Ordinary Least Square (OLS) estimates and any form of forecast based on them may be inefficient. It is not a critical problem if the sample size is very large but with smaller samples it may lead to wrong conclusions. Serial correlation can exaggerate goodness of fit and report too small standard errors when the independent variable grows over time, and the serial correlation is positive. Models with serial correlation can report a regression coefficient that is statistically significant even if it is not.

We have used Cumby-Huizinga test for autocorrelation. The results of the test are reported in Table 6 in the appendix. We have tested two models: model 1 and 3. Test statistics for both models reveal significant serial correlation issues. This suggests that we should be cautious when interpreting the significance and efficiency of the estimation results.

FORWARD-LOOKING CONSUMER THEORY

In theory, electricity consumers may act as forward-looking agents, deciding upon their actions in current period based on the expectation of the future circumstances. In our case, we hypothesize that electricity consumers in Norway are not forward-looking, and they may switch the electricity retailers roughly after one month since the spot prices have changed. We have tested this hypothesis using a model with lagged spot prices. Model 1 reveals a

significant coefficient suggesting that switching rates increase by about 0.006 percentage points in response to one percent increase in the spot prices one month earlier. Although the coefficient is statistically significant, its magnitude is economically insignificant, and therefore we conclude that the electricity spot prices and the switching rates in Norway are independent of each other.

TABLE V – LAGGED PRICES REGRESSION MODEL

Variable	(1) Share of switches	(2) Share of switches	(3) Share of switches
Log of prices	0.006** (0.003)	0.007 (0.008)	0.054 (0.042)
Rain (mm)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
Month	✓	✓	✓
Year		✓	
Full time			✓
Observations	1,260	1,260	1,260
Root MSE	0.003736	0.003738	0.005149
Number of id	45	45	45

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

The results of the first stage of this 2SLS estimation support the relevance of the instrument and are reported in the appendix.

7. CONCLUSION

The purpose of the research was to examine relationship between fluctuations in electricity spot prices and the rate of consumer switching to a different provider in the electricity market in Norway. Although a relatively well-functioning, the Norwegian electricity market is far from perfect in terms of switching behavior. Also, spot price contracts largely dominate among Norwegian consumers. Since these two phenomena largely shape the market in Norway, and since the question we have tried to answer in this paper has never been addressed before, we decided to exclusively focus on it in our research.

To answer the research question, we used Nord Pool monthly spot price data in 5 bidding regions in Norway as well as monthly switching rates in those regions, with the latter being a dependent variable. First, we used Fixed Effects method for estimation, yet a method that would remove an impact of unobserved omitted variables was needed. With this in mind, we proceeded to use Instrumental Variables regression method, with reservoir level as an instrument. Using those two methods, we created three model specifications: with control variables for seasonality effects, annual switching trend and binary variables for variations in the dataset respectively. Having used F-test for specification, Variance inflation factors (VIF) for multicollinearity check and Cumby-Huizinga test for identification of correlation issues, we found out that the first model was the only statistically significant one; however, its magnitude was insignificant economically – it suggested only 0.006 percentage points. This proved both our hypotheses wrong: electricity spot prices and switching rates in Norway are independent of each other, and Norwegian electricity consumers are not forward-looking.

There were several limitations to our research. First, we used aggregate data, while using household level data could allow us to conduct a more detailed analysis. Secondly, having data spread over longer period could reveal a more accurate picture. Last but not least, options of a good instrumental variable offered were limited.

Potential further research would include studying the relationship between spot prices and switching rates in other countries, especially those where electricity bill constitutes larger spending compared to that in Norway.

REFERENCES

- ACER. (2015). *Annual Report on the Results of Monitoring the Internal Electricity and Natural Gas Markets in 2014*, 1–274. Also available as <https://doi.org/10.2851/14037>
- Agva Kraft – Billig og fornybar strøm. (2018). *Alle strømavtaler -- Agva Kraft– Billig og fornybar strøm*. Retrieved April 30, 2018, from <https://www.agva.no/alle-stromavtaler/>
- Amundsen, E. S., & Bergman, L. (2006). *Why has the Nordic electricity market worked so well?* Utilities Policy. Utilities Policy, 14(3), pp.148-157.
- Andersen, K. (2017). *Variabel strømavtale eller spotpris? Forskjellen utgjør opptil 5000 kroner i året | Payr.no*. Payr.no. Retrieved April 15, 2018 from <https://payr.no/i/3793/spotpris-variabel/>
- Bansal, H. and Taylor, S. (1999). *The Service Provider Switching Model (SPSM)*. Journal of Service Research, 2(2), pp.200-218.
- Bye, T. & Hansen, P.V. (2008). *How do Spot prices affect aggregate electricity demand?* Discussion papers no. 527, Statistics Norway, Research Department. Also available as www.ssb.no/publikasjoner/pdf/dp527.pdf.
- Defeuilley, C. (2009). *Retail competition in electricity markets*. Energy Policy, 37(2), 377–386.
- Ek, K. & Soderholm, P. (2008). *Households' switching behavior between electricity suppliers in Sweden*. Utilities Policy, 16(4), 254-261.
- ERGEG. (2007). *Obstacles to supplier switching in the electricity retail market. Guidelines of Good Practice and Status Review*. Practice.
- Fjordkraft. (2017). *Fjordkraft Mobil*. Retrieved 13 November 2017, from <https://www.fjordkraftmobil.no/>
- Fjordkraft. (2018). *Velg strømavtale | Gode strømavtaler og mange fordeler | Fjordkraft*. Retrieved April 10, 2018 from <https://www.fjordkraft.no/privat/stromavtaler/>
- Flores, M. & Waddams Price, C. (2013). *Consumer behavior in the British retail electricity market*. Centre for Competition Policy, University of East Anglia, CCP Working Paper 13-10.
- Forbrukerrådet. (2017). *Strømpris.no*. Retrieved 13 November 2017, from <http://strompris.no/>
- Gamble, A., Juliusson, E. A., Gärling, T., et al. (2009). *Consumer attitudes towards switching supplier in three deregulated markets*. Journal of Socio-Economics, 38(5), 814–819.
- Giulietti, M., Price, C. and Waterson, M. (2005). *Consumer Choice and Competition Policy: a Study of UK Energy Markets*. The Economic Journal, 115(506), pp.949-968.

-
- Hortaçsu, A., Madanizadeh, S. and Puller, S. (2017). *Power to Choose? An Analysis of Consumer Inertia in the Residential Electricity Market*. *American Economic Journal: Economic Policy*, 9(4), pp.192-226.
- Johnsen, T. A. (2003). *Residential customers and competitive electricity markets: The case of Norway*. *Electricity Journal*, 16(1), 74–79. [https://doi.org/10.1016/S1040-6190\(02\)00418-9](https://doi.org/10.1016/S1040-6190(02)00418-9)
- Johnsen, T., & Olsen, O. (2008). *The relationship between wholesale and retail electricity price to households in the Nordic countries*. VaasaEMG, University of Vaasa, (173109), 10.
- Keaveney, S. M. (1995). *Customer Switching Behavior in Service Industries: An Exploratory Study*. *Journal of Marketing* 59 (2), 71-82
- Klemperer, P. (1987). *Markets with Consumer Switching Costs*. *The Quarterly Journal of Economics*, 102(2), p.375.
- Klemperer, P. (1995). *Competition when have Overview Switching with Consumers Costs: An Applications to Industrial Organization*. *The Review of Economic Studies*, 62(4), 515–539.
- Kuha, J. (2004). AIC and BIC: Comparisons of Assumptions and Performance. *Sociological Methods & Research*, 33(2), pp.188-229.
- Littlechild, C. (2000) *Why we need electricity retailers: A reply to Joskow on wholesale spot price pass-through*. DAE Working Paper 0008, Department of Applied Economics, University of Cambridge.
- Littlechild, S. (2005). *Smaller suppliers in the UK domestic electricity market: experience, concerns and policy recommendations*. OFGEM Report, London, (June), 1–74. Retrieved November 20, 2017 from <http://www.old.cambridgeprg.com/wp-content/uploads/2008/11/littlechildsuppliers.pdf>
- Littlechild, S. (2006). *Competition and contracts in the Nordic residential electricity markets*. *Utilities Policy*, 14(3), 135–147.
- National Audit Office, 2008. *Protecting Consumers. Removing Retail Price Controls*. The Stationery Office, London.
- NorgesEnergi. (2018). *Velg riktig strømavtale for deg - NorgesEnergi*. Retrieved April 30, 2018 from <https://www.norgesenergi.no/produkter/>
- NVE (2018). *Norges Vassgragt- og Energidirektorat*. Retrieved 10 May, 2018 from <http://nve.no>

-
- NVE. (2017). *Leverandørskifteundersøkelsen* — NVE. Retrieved 13 November 2017, from <https://www.nve.no/elmarkedstilsynet-marked-og-monopol/rapporter-og-analyser/leverandørskifteundersokelsen/>
- NVE. (2017). *Smarte strømmålere (AMS)* — NVE. Retrieved 13 November 2017, from <https://www.nve.no/stromkunde/smarte-strommalere-ams/>
- Olsen, O., Johnsen, T. and Lewis, P. (2006). A Mixed Nordic Experience: Implementing Competitive Retail Electricity Markets for Household Customers. *The Electricity Journal*, 19(9), pp.37-44.
- Pedersen, R. (2018). *Finn billigste spotprisavtale på strøm*. Smarte Penger. Retrieved April 30, 2018 from <https://www.smartepenger.no/markedsoversikter/1039-strompriser-spot>
- Peng, L. Y. & Wang, Q. (2006). *Impact of Relationship Marketing Tactics (RMTs) on Switchers and Stayers in a Competitive Service Industry*. *Journal of Marketing Management*, 22(1-2), 25-29.
- Samuelson, W., & Zeckhauser, R. (1988). *Status quo bias in decision making*. *Journal of Risk and Uncertainty*, 1(1), 7–59. Also available as <https://doi.org/10.1007/BF00055564>
- Shy, O. (2002). *A quick-and-easy method for estimating switching costs*. *International Journal of Industrial Organization*, 20(1), 71–87.
- Strøm.no. (2018). *Her er de 5 strømregionene vi har i Norge*. Retrieved April 15, 2018 from <https://xn--strm-ira.no/str%C3%B8mregioner-norge>
- Stock, J. H. & Watson, M. W. (2007). *Introduction to Econometrics*. Pearson, 2nd Edition.
- Sturluson, J. T. (2003). *Topics in the Industrial Organization of Electricity Markets*. Stockholm School of Economics, EFI, Economic Research Institute, Stockholm
- Strømpris. (2018). *Strømpris.no - Finn de billigste strømprisene der du bor*. Retrieved April 30, 2018 from <https://www.strompris.no/>
- Szymanski, D. M. & Henard, D. H. (2001) *Customer Satisfaction: A Meta-Analysis of the Empirical Evidence*. *Journal of the Academy of Marketing Science*, 29, 16-35.
- Telinet Energi. (2018). *Strøm til innkjøpspris | Teline Energi*. Retrieved April 30, 2018 from <https://www.telinet.no/stromavtaler/strom-til-innkjopspris/>
- Von der Fehr, N.-H. M., & Hansen, P. V. (2009). *Electricity retailing in Norway*. Department of Economics, University of Oslo.
- Vrieze, S. (2012). Model selection and psychological theory: A discussion of the differences between the Akaike information criterion (AIC) and the Bayesian information criterion (BIC). *Psychological Methods*, 17(2), pp.228-243.

-
- Waddams Price, C., Webster, C., & Zhu, M. (2013). *Searching and Switching: Empirical estimates of consumer behavior in regulated markets*. Centre for Competition Policy, University of East Anglia, CCP Working Paper 13-11.
- Waterson, M. (2003). *The role of consumers in competition and competition policy*. *International Journal of Industrial Organization*, 21(2), 129–150.
- Wieringa, J. E., & Verhoef, P. C. (2007). *Understanding customer switching behavior in a liberalizing Service market: An exploratory study*. *Journal of Service Research*, 10(2), 174-186.
- Wooldridge, J. (2006). *Introductory Econometrics*. Mason, Ohio: Cengage Learning; International Ed edition.
- YR (2018). *YR*. Retrieved 10 May, 2018 from <http://yr.no>
- Øksnes, K. (2016). *Det er nesten umulig å finne frem til den billigste strømvartalen*. *Abcnyheter.no*. Retrieved 20 December, 2017 from <https://www.abcnyheter.no/penger/privatokonomi/2016/12/07/195261545/det-er-nesten-umulig-finne-frem-til-den-billigste-stromavtalen>

APPENDIX

TABLE A I – FIRST STAGE

Variables	(1) Log of prices	(2) Log of prices	(3) Log of prices	(4) Log of prices
Reservoir level	-0.0029582*** (0.000261)	-0.0113306*** (0.0006328)	-0.0056242*** (0.0005082)	-0.0004558** (0.0002009)
Month		✓	✓	✓
Year			✓	
Full time				✓
F-test of excluded instruments:	F(1, 2270) = 128.47 Prob > F = 0.0000	F(1, 2259) = 320.61 Prob > F = 0.0000	F(1, 2255) = 122.47 Prob > F = 0.0000	F(1, 2218) = 5.15 Prob > F = 0.0234

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

TABLE A II – MAIN REGRESSION

Variables	(1) Share of switches	(2) Share of switches	(3) Share of switches	(4) Share of switches
Log of prices	-0.000832 (0.00129)	0.00394*** (0.00105)	0.00727*** (0.00225)	0.0682* (0.0397)
Month		✓	✓	✓
Year			✓	
Full time				✓
Observations	2,316	2,316	2,316	2,316
Root MSE	0.004874	0.004858	0.004929	0.006181
Number of id	45	45	45	45

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

TABLE A III – FIRST STAGE INCLUDING WEATHER VARIABLES

Variables	(1) Log of prices	(2) Log of prices	(3) Log of prices	(4) Log of prices
Reservoir level	0.0038506*** (0.0002018)	-0.0027114*** (0.0006214)	-0.0008181* (0.0004911)	-0.0001279 (0.0003688)
Temperature	-0.0102302*** (0.000613)	-0.0320491*** (0.002197)	-0.018769*** (0.0018236)	-0.0198212*** (0.0022086)
Rain (mm)	-0.000252*** (0.0000688)	-0.0003147*** (0.0000782)	-0.0002017*** (0.0000564)	-0.0000772* (0.0000404)
Month		✓	✓	✓
Year			✓	
Full time				✓
F-test of excluded instruments:	F(1,1093) = 364.15 Prob > F = 0.0000	F(1,1082) = 19.04 Prob > F = 0.0000	F(1, 1080) = 2.78 Prob > F = 0.0960	F(1, 1065) = 0.12 Prob > F = 0.7289

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

TABLE A IV – MAIN REGRESSION INCLUDING WEATHER VARIABLES

Variables	(1) Share of switches	(2) Share of switches	(3) Share of switches	(4) Share of switches
Log of prices	0.00200 (0.00131)	0.00871 (0.00603)	0.0190 (0.0227)	0.164 (0.483)
Temperature	-7.38e-05*** (2.11e-05)	0.000110 (0.000208)	0.000250 (0.000433)	0.00306 (0.00958)
Rain (mm)	1.40e-06 (1.49e-06)	2.34e-06 (2.46e-06)	4.76e-06 (4.76e-06)	1.33e-05 (3.60e-05)
Month		✓	✓	✓
Year			✓	
Full time				✓
Observations	1,141	1,141	1,141	1,141
Root MSE	0.00367	0.003677	0.003989	0.01123

Number of id	45	45	45	45
--------------	----	----	----	----

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

TABLE A V – MULTICOLLINEARITY AND SERIAL CORRELATION

	VIF					
	Model 1		Model 2		Model 3	
Pred. Prices	54.69	6.23	678.40	96.41	16484.74	1197.93
Temperature	136.11		439.56		9931.05	
Rain (mm)	2.76	2.63	7.60	3.57	22.64	7.98
Month	✓	✓	✓	✓	✓	✓
Year			✓	✓		
Full time					✓	✓

TABLE A VI – SERIAL CORRELATION TESTS

1. *ivreg2 switch_share (log_prices = res_level) rain_mm i.month i.id, robust*

Cumby-Huizinga test for autocorrelation

H0: variable is MA process up to order q

HA: serial correlation present at specified lags >q

H0: q=0 (serially uncorrelated) H0: q=specified lag-1

HA: s.c. present at range specified HA: s.c. present at lag specified

Lags	chi2	df	p-val	Lag	chi2	df	p-val
1 - 1	329.20	1	0.00	1	329.20	1	0.00

Test allows predetermined regressors/instruments

Test requires conditional homoscedasticity

2. *ivreg2 switch_share (log_prices = res_level) rain_mm i.month i.time i.id, robust*

Cumby-Huizinga test for autocorrelation

H0: variable is MA process up to order q

HA: serial correlation present at specified lags >q

H0: q=0 (serially uncorrelated) H0: q=specified lag-1

HA: s.c. present at range specified HA: s.c. present at lag specified

Lags	chi2	df	p-val	Lag	chi2	df	p-val
1 - 1	21.02	1	0.00	1	21.02	1	0.00

The test allows predetermined regressors/instruments

The test requires conditional homoscedasticity

TABLE A VII – FIRST STAGE WITH LAGGED RESERVOIR LEVEL VARIABLE

Variable	(1) Lagged log of prices	(2) Lagged log of prices	(3) Lagged log of prices
Lagged reservoir level	-.0062846*** .0007336	-.002295*** .0004909	-.0005839* .0003095
Rain (mm)	-.0003706*** .0000731	-.0000112 .000049	-.0000597* .0000355
Month	✓	✓	✓
Year		✓	
Full time			✓
F-test of excluded instruments:	F (1,1202) = 73.38 Prob > F = 0.0000	F (1,1200) = 21.86 Prob > F = 0.0000	F (1,1185) = 3.56 Prob > F = 0.0595
Number of id	45	45	45

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

TABLE A VIII – MAIN REGRESSION WITH LAGGED RESERVOIR LEVEL VARIABLE

Variable	(1) Share of switches	(3) Share of switches	(2) Share of switches	(4) Share of switches
Log of prices	0.00464* (0.00241)	0.00357 (0.00290)	0.00375 (0.00681)	0.00425 (0.00725)
Rain (mm)	1.43e-06 (2.24e-06)	1.69e-06 (2.15e-06)	1.85e-06 (2.59e-06)	1.09e-06 (2.10e-06)
Market	-0.212*** (0.0766)	-0.198** (0.0790)	-0.201** (0.0792)	-0.200** (0.0793)
Markup		-0.00386* (0.00230)		-0.0123 (0.0122)
Month	✓	✓	✓	✓
Year			✓	✓
Observations	1,260	1,260	1,260	1,260
Root MSE	0.003658	0.003641	0.003634	0.003636
Number of id	45	45	45	45

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1