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An Empirical Study of Electricity Price and Temperature

*Hedging against the Weather-Related Risks on the Nordic
Market*

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Abstract

Unfavorable weather raises cost of doing business around the world. According to the CME Group, around 30 percent of gross domestic product (GDP) of the United States (US) is affected by the weather. Only in the US total exposure to meteorological conditions accounts for nearly USD 5.3 billion. In order to address those risks, a market for weather derivatives emerged in 1996 which allows companies and individuals to use this financial instrument to hedge against losses associated with volatile weather.

In this thesis, I examine the impact of unanticipated fluctuations in air temperature on electricity prices to explore the relevance of weather derivatives for Norwegian companies. I conduct a time series analysis on historical observations for air temperatures in Oslo, Norway, along with the respective historical prices for electricity in the same area in order to either prove or dismiss the causality between the two variables. The data for electricity prices is from Nord Pool, while the series for air temperatures is from the Norwegian Meteorological Institute (MET Norway). In case the causal relation exists, it would provide local enterprises that are sensitive to air temperature fluctuations with a strong argument for using derivatives issued on temperature-based indices to mitigate their weather-related risks.

My study proves the causality between the two variables: air temperatures and electricity prices. In particular, it finds that warmer-than-expected winters cause the decline in electricity prices presumably due to their effect on demand for power. This adversely affects utilities which end up with selling less power.

In addition, there is the lack of academic works discussing the fast-growing market for weather derivatives. This is explained by the fact that this market is just recently developed. This thesis therefore aims at adding to the knowledge of weather-indexed instruments, and explicitly underlines the importance of further research on this topic.

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1. Introduction

“But who wants to be foretold the weather? It is bad enough when it comes, without our having the misery of knowing about it beforehand.”
– Jerome K. Jerome, *Three Men in a Boat*

1.1 Description of topic

In August 2005, hurricane Katrina has made landfall on the Gulf Coast of the United States and caused the economic damage that accounts for nearly USD 125 billion. In contrast with the quote by Mr. Jerome which my thesis begins with, the rapid growth of the financial market for weather during the last two decades implies that a great number of investors, which are represented by both individuals and companies, would rather mitigate their weather-related risks than not.

Weather derivatives are financial instruments that allow investors to hedge their exposure to unfavorable meteorological events. Straightforwardly, the side of the weather derivatives contract which issues the instrument, gets a premium and agrees to bear the risks if the unfavorable weather event, which the contract is written on, occurs.

The empirical research that underlies my thesis focuses on the impact of the air temperature fluctuations in Oslo on the power price in NO1 bidding area in Norway. NO1 bidding area covers Oslo region. The purpose of the study of temperature and electricity price is to prove the causal relationship between the two time series and argue that it creates opportunities for the development of the financial market for weather. If the causality is the case, this would suggest that Norwegian companies that suffer from unanticipated fluctuations in temperature may be interested in using weather derivatives for hedging purposes.

1.2 Background

People suffer from bad weather. In particular, extreme weather events increase cost of doing business and cause in turn financial losses. In order to decrease economic and financial impact of volatile weather, people have started to protect their assets initially by means of insurance. With the development of financial and energy markets, other types of financial instruments

appeared. The market of weather derivatives, for instance, has been experiencing a rapid growth since 1997.

It is not clear who made the first deal related to weather risk mitigation or what was the bargain about or when was the contract signed. Nevertheless, there will be no mistake to claim that the first transactions on financial markets that involved weather risk abatement were insurance contracts. Insurance for weather were widespread in 20th century all over the world. For example, it is acknowledged that ICICI Lombard, a private sector general insurance company in India, offered weather insurance for Indian farmers in the early 20th century. The product referred to the risks related to temperature and precipitation turmoil (Sivakumar Mannava, p. 410).

The integration of capital and insurance markets in 20th century gave birth to new financial instruments that allowed to hedge against extreme weather events. Catastrophe bonds and weather derivatives are cases in point (Taušer Josef, p. 309).

Industry experts agree on the fact that financial market for weather developed in 1990s after the deregulation of US electricity market. New market conditions of the second half of 20th century forced American government to modify energy legislation in favor of market competition. The reform focused on utility industry and presumed the switch from the government regulation of utility rates to the price formation by means of market mechanism (The Center for Responsive Politics (CRP)).

The cornerstone of new institutional environment of American power market was Energy Policy Act of 1992. The bill enabled electricity producers to sell their power to utilities (102nd Congress (1991-1992), 1992). This increased competition on the market and was supposed to push the prices for end consumers down.

Another key element of the electricity deregulation reform was Order #888 issued by the Federal Energy Regulatory Commission (FERC) in 1996. According to this directive, electric utilities had to provide all of players with free access to transmission lines. This shortened in turn the supply chain network of electric power (Federal Energy Regulatory Commission, 1996).

Free access to American transmission capacity along with new approach to pricing based on the laws of demand and supply created new opportunities for weather risk mitigation. Such

financial instruments as weather derivatives appeared. Targeting on weather forecasts, these became soon an efficient tool for hedging against extreme weather events.

In 1996, for instance, Consolidated Edison Company of New York (Con Edison) signed the contract on power supply with Aquila. The deal included weather risk abatement and prevented Con Edison from financial losses in case the August would be cold and people's demand on electricity for air conditioning would decline. Companies relied on the weather forecast supplied by New York City's Central Park weather station. According to the deal, Aquila had to provide Con Edison with the predetermined discount to the electricity price in case the number of cooling degree days prevailed the expectation by more than 10 percent (Bishnupriya Mishra, p. 17).

Another example dates back to 1997, when Willis Group Holdings, Koch Industries and Enron Corporation incorporated weather data to risk indices and conducted one of the first transactions that the one may describe as weather risk management by means of derivatives (The Weather Risk Management Association).

The El Niño oscillation in winter of 1997-1998 became a crucial driver of the development of the weather derivatives market. According to National Climatic Data Center, the event brought the second warmest winter since 1895 (National Climatic Data Center, p. 3). As a result, many companies suffered from serious financial losses owing to an uncharacteristic mild winter. At the same time, this was a trigger for investors who subsequently started to look for opportunities to hedge against the risk associated with the weather (Considine, p. 1).

The deal between Con Edison and Aquila along with Willis-Koch-Enron contract referred to the weather risk management on over-the-counter market (OTC). The rapid growth of OTC market for weather derivatives in 1990th was due to its unique features. Specifically, OTC contracts allow an investor to hedge weather-related risks for almost any location. The International Securities and Derivatives Association (ISDA) Master Agreement, however, decelerated the further growth of the OTC market because of the credit risk issues that OTC contracts include.

Organized market subsequently became major driver in trade of weather-related financial instruments. The boom refers to 1999 when Chicago Mercantile Exchange (CME) introduced standardized futures and options on weather indices. Initially, CME listed only temperature contracts. These were standard contracts of HDD and CDD. Both of them represented hedging

opportunities in only ten cities in the US at the initial launch (CME Group, p. 1). Nowadays, there is more weather related contracts traded on exchange than on OTC.

To sum up, the liberalization of commodity markets, which took place in the second half of the last century, resulted in new opportunities on financial markets. Hedging weather risk with the help of derivatives is a case in point. Since 1997, when El Niño increased the demand for the derivatives written on weather indices, both OTC and organized market for weather has grown remarkably. Nevertheless, the latter one has a greater potential for further development given the market legislation and credit risk constraints imposed on OTC market.

1.3 Relevance

The market for weather derivatives is completely new. The first trade dates back to 1996 and the first exchanged-traded derivatives appeared just in 1999. For that reason, there is a small amount of literature and research with the focus on weather derivatives. In case of Norway, the lack of interest of Norwegian academic community to the topic is also partially explained by absence of the market being considered. Simultaneously, Norway is one of the largest European countries with the seventh largest coastline in the world (Central Intelligence Agency). The country is exposed to various hurricanes that arrive from the Atlantic Ocean. Norwegian hydropower stations along with its ski resorts depend on the level of precipitation. Moreover, the country's second largest export good – fish – depends on water temperature (World's Richest Countries, 2016). All of these vulnerabilities can be reduced using weather derivatives. With this work, I hope therefore to enhance the knowledge about the market for weather derivatives.

In addition, I aim at finding the causal relationship between the air temperature in Oslo and the power price for the same region. If the causality is the case, then the temperature-based indices like Heating Degree Days (HDD) and Cooling Degree Days (CDD), which are calculated by CME Group, may be considered as the underlying for futures or forwards. The use of temperature-indexed contracts for hedging could help Norwegian enterprises to mitigate their exposure to unfavorable weather events. The exposure of energy companies like Statkraft to warmer-than-expected winters is a good case in point.

2. Nordic Electricity Market

As mentioned earlier, I examine the impact of air temperature fluctuations in Oslo on the electricity price in Oslo bidding area. Additionally, I control my model for both the electricity prices in neighboring bidding areas as well as the transmission capacities between the last-mentioned ones and Oslo bidding area. In order to understand the prospective impact of all of these variables on my model, it is necessary to explore Nordic power market at first. This is the market for electricity that combines trade in electricity as well as power generation, transmission and distribution in the Nordic and Baltic countries. In this paper, I usually use the terms power and electricity as synonyms. They have slightly different meanings in real world, though.

2.1 Electricity as commodity

With regard to physics, electricity is defined as the fact of accumulation and movement of electrons – elementary particles that hold electric charges (Suckling, 2015). In this paper, I use the economic interpretation of electricity. Specifically, I look at electricity as the commodity that includes both energy itself and its transportation to consumers. Unique qualities of electricity as commodity define the essence of power market. It is therefore necessary to discuss these qualities at first.

To start with, electricity is the commodity that should be supplied immediately. Unlike oil, crops, metals, or other typical commodities, the delivery period for electricity is zero. There is therefore no predetermined conditions for transportation and delivery such as the International Commercial Terms (Incoterms) or similar rules. By way of illustration, consider the consumer of electricity who is supposed to get his or her light as soon as he or she turns a switch on. Immediate consumption causes in turn immediate generation.

Immediate generation and consumption lead to another quality of electricity. The logistics of the power market is, in a nutshell, an electric circuit that contains a continuous flow of electricity. The continuous flow is a very important characteristic because it allows to provide consumers with electric power instantly – it stands with the immediate supply characteristic.

Moreover, electricity is intractable and intangible, meaning an individual cannot see electrical current as well as the one cannot grasp it. This implies for electricity consumers that they are

unaware of which generator have supplied to them precisely. Frankly, all of active power plants constantly supply electricity to a common transmission network, whereas consumers just take electricity from the network whenever they need it.

Although true, the process is in fact slightly more complicated than that. For the sake of clarity, I move to the other quality of electricity as commodity – a common grid. Transmission network of a country is defined by its grid. The one may think of the grid as a chain or, more accurately, a system of interconnected power lines and nodes that form the electric circuit with a continuous flow of electric current and transmit this current from producers to consumers. Electric current carries in turn some amount of electrical energy. This energy is partially wasted while being transmitted by means of power lines. The following relationship is true: the longer is the total length of lines used to transmit electricity from one location to the other one, the more energy is wasted in the process of transmission. This is why the existence of several competing grids is not optimal. This also describes the monopoly on the transmission market.

Additionally, electricity is a variable and unpredicted commodity in the sense that the quantity of electricity produced often depends on unpredicted factors such as the weather. Indeed, various hourly, daily, weekly, monthly, and seasonal discrepancies define the amount of electricity that enters the grid. In the power markets full of solar energy, for example, the amount of energy produced is highly sensitive to the amount of sun during days. The power markets with dominating hydro power, as another example, are affected by precipitation during either rainfall or snowfall seasons, or both. Norway is a good case in point. Furthermore, the weather has impact on the other side of the market too, meaning the weather influences the demand for electricity. In my empirical analysis in Section 4, for instance, I study how different is the impact of warmer and colder winters in Oslo, Norway, on both the demand and price for electricity.

Last but not least, electricity is not storable. This is probably the most important difference between electricity and crops, oil, metals, and other typical commodities. Here, I need to shed light on the issue. There exist batteries nowadays that can store electrical energy in actual fact. A good and contemporary example would be the famous Powerwall (Tesla Motors). This product of Tesla Motors is mainly for households, but there are larger and more powerful batteries as well which can even charge small factories for some short time interval. Nevertheless, there is currently just under 1 gigawatt (GW) of storage capacities in the form

of the batteries connected to the grids around the world. Although Bloomberg New Energy Finance (BNEF) forecasts the increase in market value of the world battery market to astonishing USD 250 billion by 2040, none of the today's battery technologies is capable of storing the amount of electrical energy that makes difference to national economies (Bloomberg New Energy Finance, 2016). There is even no battery technology that can provide an economic unit such as an aluminium smelter with electricity over some noticeable period.

For the reason stated above, I am eligible for saying that electricity is the commodity that cannot be stored directly. Electricity can be stored, however, if it has been changed into some other form of energy in advance. Bulk electricity storage which stores electrical energy in the form of water is the case in point. I will discuss this technology in Subsection 2.5 in detail.

2.2 Power market preliminaries

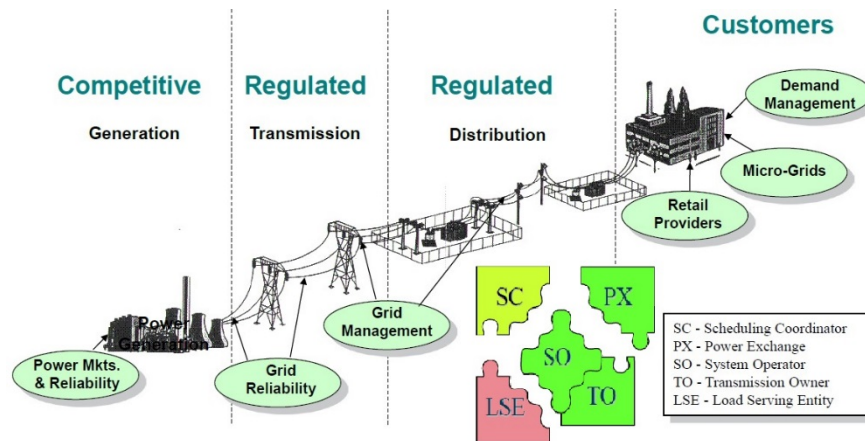
Norway has implemented a substantial reform of its power market in 1991. The reform presumed the transition from the traditional regulated market organization to the modern deregulated market of electricity. In the past, Norwegian power market was vertically integrated. This means basically that there existed a state monopoly on power generation, transmission and distribution. This was a very inefficient system that resulted in a number of issues. There was, for example, the discrepancy between domestic and foreign electricity prices. It was often difficult to logically explain high prices for electricity in Norway. Moreover, the market was characterized by overcapacity, so that there was potential for producing enough electricity with fewer generators.

The power market reform of 1991 has brought the number of changes in the market organisation. Firstly, the power market was deregulated and vertically disintegrated. Every generator got equal access to the grid. As a result, the state monopoly in power production was replaced by competition among generators. Transmission and distribution of power remained monopolistic, though. Secondly, the approach to pricing of electricity became different. Indeed, electricity price has been formed by competitive forces on the spot market since 1991.

With respect to a functional role, the one may split a typical power market into the following four dimensions: generation of power, transmission, distribution, and selling electricity to customers. *Figure 2.1* reflects the idea of four basic functional dimensions within the power

market. Now, let me discuss this classification in detail with focus on power market of Norway.

Figure 2.1 Market players of the power market of Norway



Source: S. Oren

To start with, I refer generation to electricity production. Production of electricity traditionally presumes either burning fossil fuels or nuclear fission process. However, power generation from renewable energy sources such as sun and wind has become common over the last decade. In Norway, above 96 percent of electricity is produced by hydropower plants. Table 2.1 includes the figures that show the amounts of electricity that were produced from different energy sources in 2013. The statistics is for Norway. Particularly, the hundreds of small and big hydropower plants located in the country produced in 2013 around 129 terawatt hours (TWh) of electricity and besides, the authorities estimate that there is the potential to produce additional 35 TWh of power from water flow (The Royal Norwegian Ministry of Petroleum and Energy, 2016).

Table 2.1 Electricity produced from different sources, 2013, Norway

Source	Amount (TWh)
Hydropower	129
Wind power	1.9
Thermal power	3.3
Total	134

Source: The Royal Norwegian Ministry of Petroleum and Energy

Statkraft is the largest electricity producer in Norway. It operates almost 150 hydropower production units in Norway and is also present in 19 other countries around the world. Statkraft's annual electricity production equals 56.3 TWh (Statkraft). The company is state-

owned. Another major electricity producer in the country is Norsk Hydro. Although its main focus is on aluminium production, Norsk Hydro owns 20 power plants that produce annually nearly 10 TWh of electricity. This makes the company the second biggest producer of hydroelectric power on the Norwegian power market (Norsk Hydro ASA). Lastly, Norwegian state-owned company Statoil, which is one of the world's largest oil and natural gas producers, has started to produce electricity from offshore wind in the North Sea. Statoil's offshore wind projects portfolio consists of five locations today. The company has declared its ambition to make use of its offshore experience and become eventually a substantial player on the power market (Statoil).

The second and third functional dimensions within the power market are respectively transmission and distribution of electricity. Here, it is crucial to identify the underlying differences between the two. In general, transmission stands for electrical energy transportation over long distances using high-voltage (HV) cables, whereas distribution captures both the conversion of HV electricity to electricity of low voltage (LV) and the delivery of the latter one to consumers. In contrast with transmission, distribution presumes electrical energy transportation over shorter spans (Bjørndal, ENE424 Design and operation of deregulated electricity markets. Lecture notes, p. 16).

The key characteristic of transmission to point out is the utilization of HV cables. In Norway, for example, the voltage in the transmission grid varies from 300 kilovolt (kV) to 420 kV. The reason for HV is Ohm's law in physics. It presupposes that the current in electric circuit such as the power grid is defined solely by voltage and resistance. The rule is the following:

$$I = \frac{V}{R},$$

where V stands for voltage in the line, R describes resistance, and I is electric current.

The power companies that install and serve transmission lines favor slim cables made of aluminum and copper. The choice of slim cables simply saves money to these companies. The price for it, however, is the increased resistance. Indeed, one of the numerous laws in physics implies that there is the inverse relationship between electric resistance and the cross-sectional area of the cable the electrical energy runs through, so that lower cross-sectional area corresponds to higher resistance (The Physics Classroom). In agreement with Ohm's law

represented by the equation above, slimmer cables adversely affect the level of the current I in the system. The transmitted electric power may be expressed as follows:

$$P = VI,$$

where V is voltage, I is electric current, and P is electric power.

According to the equation above, lower level of the electric current owing to slimmer transmission cables has to be neutralized by higher voltage in the system in order to get the same amount of electricity transmitted. This explains the utilization of HV cables for electricity transmission over long distances (Narbel, Hansen, & Lien, p. 9).

Regarding the distribution power network, it uses LV cables. In case of Norway, the country's distribution power network may be split into two parts. These are the so-called regional and distribution networks. The voltages of 66 kV and 132 kV characterize the former one, while the voltage of 22 kV is typical for the latter one. The distribution grid provides final consumers with electricity. Simultaneously, the regional grid connects the distribution network with the country's transmission network.

Furthermore, transmission of electricity and distribution of electricity are also different in terms of a number of companies operating at every stage. There is the only company that controls and serves the transmission grid in Norway, for instance. As to distribution of electricity, many small companies, which are mostly owned by local governments, control countywide distribution grids around Norway. These companies have exclusive rights to deliver electricity to consumers in particular areas (Bartes & Wasenden, p. 3).

As to power consumption, the dimension is represented by two sectors: households and industry. The former one speaks on behalf of above 5.2 million citizens of Norway that consume electricity on the daily basis. The latter one stands for companies that create Norwegian GDP producing goods and services. *Appendix 1* shows the most electricity consuming industries in 2014 in Norway. The data are taken from the official statistics agency of Norway (Statistisk sentralbyrå, 2015). Pay attention to the basic metals. According to the data, this niche consumed above 31 terawatt hour (TWh) of electricity. The niche is represented first and foremost by Norwegian aluminium smelters. An interesting fact is that the industry representative, Norsk Hydro, is the largest aluminium producer in the Nordic countries and therefore of one of the largest electricity consumers. Simultaneously, it was

already mentioned that the company is one of the largest power producers in Norway (Ministry of Trade, Industry and Fisheries, 2001).

Last but not least, *Figure 2.1* corrects for five important power market players. These are the following five bodies that make the whole system of generation, transmission, distribution and marketing work:

- Transmission owner (TO). TO is simply the company that is in charge of transmission network. In case of Norway, the state-owned company Statnett owns the whole transmission network in the country, which, incidentally, includes above 10 thousand kilometres of HV cable lines (Statnett, 2014).
- System operator (SO). SO is in control of security of supply. The body deals with supply breaks and other system externalities that have a detrimental effect on power balance. In order to balance the power market, SO monitors capacity margins in the system. Moreover, the body keeps both voltage and frequency in the grid at an adequate level.

In addition, depending on how a particular market is designed, the functions of SO can be merged with functions of TO, so that the only body is established, call it transmission system operator (TSO), that owns the power grid and is responsible for security of supply simultaneously. This is the case in Norway and *Figure 2.1* represents the issue.

- Scheduling coordinator (SC). The one may think of a SC as of a broker on financial market that acts on behalf of its clients. To be precise, SC is an intermediary that links generators, consumers and the TSO. In Norway, SCs are also known as balance responsible entities, because they are responsible for providing the TSO with balanced schedules. The balanced schedule of a particular SC reflects the information about generation and consumption of its clients, as well as the SC's prediction about utilization of transmission lines by market participants. Condition on the market design, SC can also play the role of power exchange (Wangensteen, p. 85). The California Power Exchange (CalPX) was a good case in point.
- Power exchange (PX). PX is the spot market for electricity. It gets bids from power producers and fits them to bids obtained from power consumers. Market price is the

outcome of this process. Nord Pool is PX for the Nordic power market. I include more information about PX in my next subsection.

- Load serving entity (LSE). LSE is basically an electricity company that sells power to customers. LSE guarantees energy security, meaning every consumer gets the electricity it needs whenever it needs it.

2.3 The physical and financial market for electricity

The last functional dimension of the power market is selling electricity. This commonly suggests selling electricity to final customers. Overall, how it is happening, depends on the architecture of a particular market. There are two typical marketing systems subject to market architecture. The first one is called integrated system. It is typical for various local power markets in the United States of America (US). In brief, it presumes higher authority for system operators and pricing based on solving optimization problem. In the second system, on the other hand, both competition among generators and competition among consumers influence the spot price at every time. The name for it is unbundled system. This one is typical for the Nordic countries and Australia (Wilson, pp. 1299-1315). In this subsection I only focus on the unbundled system partially because the region of my interest is Norway. A comprehensive analysis of integrated systems is therefore beyond the scope of this paper.

Let me now examine the process of price settlement in the unbundled system in detail. Consider price settlement in the Nordic countries as an example. Here, the price is settled on Nord Pool, which is PX for Nordic countries. In brief, Nord Pool is a physical exchange for power. It was established by Norwegian TSO in 1993. The exchange covers seven Nordic and Baltic countries nowadays. These are Norway, Sweden, Denmark, Finland, Lithuania, Latvia, and Estonia. Nord Pool is owned by TSOs of these countries. I provide with the thorough ownership structure in *Appendix 2*.

I indicated earlier that pricing in unbundled system is based on competition. The correct term for this is in fact market clearing. Market clearing on the power market means that the spot price for electricity equates the demand for electricity to the electricity supply. On the Nordic power market, market clearing consists of two phases. In the first phase, Nord Pool collects bids for the entire market and aggregates them as follows. The bids collected from consumers are put together in the decreasing order, so that they form the aggregated demand curve.

Simultaneously, the bids collected from suppliers are arranged in the increasing order, so that they form the aggregated supply curve. The spot market price corresponds to the level of price for which the two aggregated curves meet. The trade of electricity based on the described procedure is called auction trading. The spot price calculated at auction is called system price. The system price is the same for every region and country.

The second phase is zonal pricing. The problem with the system price is that it does not control for transmission capacities between regions. Norway, for instance, consists of five pricing areas. With regard to transmission constraints, local TSO defines the size of pricing areas as well as the number of separate pricing areas in the country. These areas are officially named bidding areas.

Truly, the limited transmission capacities do not let to set electricity price completely on the market basis. Zonal pricing solves the problem in the following way. If the flow of electricity which is required to equalize the prices between two regions is higher than the transmission network is capable of holding, then the price in the bidding area with surplus of power is artificially reduced. At the same time, the electricity price in the bidding area which suffers from deficit of power is artificially raised. Both prices are changed to some preset optimum level. This intervention intensifies consumption in the surplus bidding area due to lower prices and simultaneously distracts electricity consumers in the deficit bidding area due to higher prices. As to power generation, it falls in the surplus bidding area, because it becomes unprofitable for generators to produce power. The power generation in the deficit bidding area increases at once, because it becomes more profitable to produce power. The overall effect of the manipulation with the prices is the decreased flow of power between the regions to the level when the transmission capacity constraints are not violated.

Figure 2.2 reflects the result of market clearing mechanism in the Nordic countries quite well. The system price is calculated for September 15th, 2014. It equals EUR 39.87 and is the same for all bidding areas. However, this is not the price people or industries pay for electricity. The real price is adjusted for every bidding area conditional on transmission capacities. The real electricity price in Oslo, for example, is lower than the system price and equals EUR 34.33 per megawatt hour (MWh). At the same time, the real price for electricity in Tromsø is higher than the system price and equals EUR 42.45 per MWh.

Figure 2.2 Bidding zones



Source: Statnett

As it was already mentioned, the physical trade of electricity in the Nordic countries occurs on the spot market managed by Nord Pool through auction trading. In actual fact, the spot market in question is the generalized term for the three sequential markets – two spot markets operated by Nord Pool with the addition of balancing power market. *Figure 2.3* below is a very decent representation of the matter.

Nord Pool includes Elspot and Elbas market. The former one is a day-ahead market. This means that electricity for the delivery the following day is traded on Elspot market. An hourly power delivery the following day is considered as underlying of contracts. The trade of contracts ceases at 12:00 every day. This allows the purchase of electricity from 12 to 36 hours before it is needed.

Elspot is regarded as the most liquid electricity market in Europe. Around 84 percent of the traded power in the Nordic countries is either bought or sold on the Nord Pool's day-ahead market. Even though, the trade on this market is not compulsory and there are other options to buy or sell electricity such as bilateral contracts.

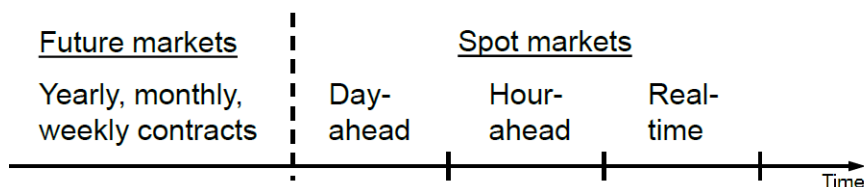
Elbas market is in turn an hour-ahead market. The power market participants trade on Elbas with the contracts for the same hours as they do on Elspot market. The difference is the actual time when this trade happens. Indeed, the trade for the hours starts as soon as the trade on Elspot ceases and lasts until one hour before the delivery. Elbas market allows in this way to adjust the amount of electricity bought and sold to the real needs of market participants.

The third market in the sequence is the balancing market. This one is a real-time market. It is considered as the last chance to reach power balance. Unlike Elspot and Elbas, which are managed by Nord Pool, the balancing power market is operated by local TSO, which is Statnett in case of Norway.

Although Elspot and Elbas deal with managing power balance quite well, it is sometimes impossible to avoid deviations in either real power production or real power consumption from the levels predetermined by contract obligations. One possible explanation for the deviations is new meteorological information which makes producers and consumers adjust their electricity needs in real time. TSO serves as balance keeper that keeps the transmission system working in the modified market conditions. The balancing market can be explained in the following way (Bjørndal, 2014).

Frequency in the grid is the indicator of the market which is in balance. As it was mentioned in the previous subsection, TSO is responsible for keeping frequency at the adequate level. With regard to the Norwegian standards, the “adequate level” corresponds to 50 hertz (Hz). If the real frequency in the system exceeds this level, this indicates overproduction of electricity. In this case, TSO orders producers to send less electricity to the grid and the power market becomes balanced again. The alternative scenario is overconsumption. Consider it is winter and air temperature outdoors is lower than it was forecasted by meteorologists. In this case Norwegians would consume more electricity in order to heat their houses. If the customers require more electricity than was contracted, the real frequency in the transmission system falls below the level of 50 Hz. In order to get frequency back to the adequate level, TSO orders producers to send more power to the grid. If it is not technically possible, TSO may order large power consumers to take less electricity from the grid.

Figure 2.3 Future and spot markets



Source: M. Bjørndal, Lecture notes

Apart from the physical market for electricity, there is also the financial market where electricity can be bought or sold using derivatives. As the one may see on *Figure 2.3*, financial market for power is represented by futures market which precedes the spot markets.

The financial market for power dates back to 1990 when Futures and Options Exchange in London (London FOX) has tried to organize the futures market for power. This was the first attempt in the history of the world financial markets to trade power. Unfortunately, London FOX has failed with the exchange-based trade for electricity. Nevertheless, Statnett Market established the forward market for electricity in 1992. This was the market for weekly contracts. Nowadays, the corporation NASDAQ OMX Group has gained control over the financial market for power trade in the Nordic countries.

With regard to the time interval, NASDAQ OMX Group offers a large variety of types of futures issued on power price for the Nordic countries (NASDAQ OMX Group). In particular, contracts for weeks, workdays, weekends, months, quarters and years are offered for trade. The system price, which was mentioned earlier, is taken from Nord Pool as reference price for futures contracts. Note that the Nord Pool's system price does not control for transmission capacity constraints. This means in turn that investors of such futures price do not care about the maximum electricity flow between bidding areas while investing in power futures. Furthermore, it is worth mentioning that the futures are settled financially. This means that no physical delivery is presumed.

Futures with power as the underlying are regarded as risk management instruments. These contracts allow to hedge against the risk that the power price is moving in unfavourable direction (Rud, 2014).

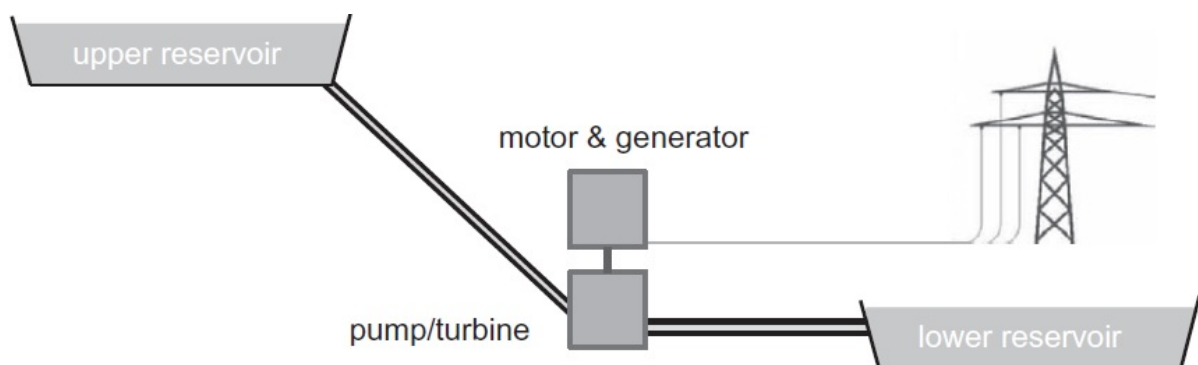
2.4 Bulk electricity storage

As it was already mentioned, there are around 150 operational hydropower plants in Norway. Moreover, the country possesses nearly 50 percent of the European reservoir capacities. For that reason, Norway is often regarded by power market analysts as the Europe's "green battery". In order to explain the meaning of this term, I refer to Subsection 2.1, where I mentioned that electricity can be stored in the form of water. In this subsection, I am discussing a bulk electricity storage technology and how it influences the power market. Be advised that I use here the term "bulk electricity storage" as the synonym for battery and vice versa.

To begin with, hydropower plants transform kinetic energy of water to electricity. The most ordinary type of hydropower plant is called impoundment. The basic working principle of an impoundment is straightforward: water is stored in reservoir. The reservoir may be artificially created when, for instance, a dam is constructed on the river. When there is a need to produce electricity, the sluice gates are opened and water flows from the upper reservoir through a turbine located downhill. The force of gravity makes this water spin the turbine. The electricity generator is attached to the turbine. It turns automatically when water gets to the turbine (Office of Energy Efficiency & Renewable Energy).

Since the energy is accumulated in the form of water in the upper reservoir, the power company which owns the impoundment can, in theory, release water whenever it is profitable. Nevertheless, the real energy storage is associated with another type of hydropower plant – pumped hydro storage (PHS). The basic working principle of PHS is very similar to the one of impoundment. It is shown on *Figure 2.4* below. The major difference in technology is the availability of a pump in PHS. The general idea is as follows: when electricity price is low, water is moved from the lower reservoir to the upper reservoir using the pump. When electricity price increases, the pumped water can be released. This process can be described as buying electricity at lower price and selling it at higher price. There is of course the cost of pumping which may even make the power plant a net consumer of electricity. Nevertheless, the power company would win from selling electricity at peak demand. Its profits will increase.

Figure 2.4 Pumped hydro storage



Source: M. Kloess & K. Zach

It has been proven by a number of researchers that the power market can benefit when PHS works together with such energy sources as wind energy (Kapsali & Kaldellis, 2010). PHS works as battery in this way. Truly, wind farms produce a lot of electricity, but at the time

when the demand is low. PHS can consume this electricity and pump the water uphill. The electricity will be stored in the form of kinetic energy of water. The energy will be released when the demand for electricity increases. It is estimated, that PHS accounts for around 99 percent of the world's total battery storage nowadays.

3. The Market for Weather Contracts

The one may consider weather derivatives as the combination of traditional insurance and financial instruments. The difference between insurance and weather derivatives is that the former one deals with mostly the events which are highly unlikely to happen, but with an enormous potential damage. The latter one, on the other hand, deals with the events which are likely to happen, but the risk of loss, however, is lower compared to the one covered by insurance. Furthermore, insurance provides with a fixed payoff only in case the predetermined event has happened. Weather derivatives, on the other hand, provide with a flexible payoff and it does not matter whether the predetermined event has actually happened.

3.1 Introduction to derivatives

It is necessary to get introduced to the basic terms that appear in the derivatives theory, before the one carries on with the discussion about the market for weather. In this subsection, I present the terminology that a derivative trader uses on the daily basis. In particular, I describe major instruments.

To begin with, derivatives are the instruments that transfer risk between the two sides of a contract. Derivatives are traded either on the organized market, or on OTC. The former one stands for the trade arranged by an exchange. Different instruments are offered for trade subject to the type of market. Futures, for example, are offered only by exchanges. Futures contracts are standardized contracts that include the bearer's obligations either to buy or to sell the underlying at a pre-agreed price during a pre-agreed future time interval. The word "standardized" means that the asset's volume, quality and terms of delivery are already predetermined by exchange and reflected in a futures contract.

Forward contracts, on the other hand, are solely offered on OTC. These are non-standardized contracts that include the bearer's obligations to buy or sell the underlying at a pre-agreed price during a pre-agreed future time interval. The advantage of a forward is that it is non-standardized. This means that the two sides of the contract can agree on the quantity, quality and terms of the delivery. The disadvantage of the contract is that there is the risk that the other side of the contract defaults. This risk is called credit risk. It is typical only for the forward market. In case of the futures market, the credit risk is neutralized by marking to market mechanism. This mechanism presupposes that every futures contract is revalued in the

end of a trading day in order to reflect the new price of the underlying that has changed over the day (Federal Reserve Bank of Chicago, pp. 3-5).

Unlike futures and forwards, options are offered for trade on both exchange and OTS. An option contract gives its bearer the right, but not obligation to buy or sell the underlying. The option to buy speaks about a call option, whereas the option to sell characterises a put option. For every option, there is the party which considers buying the underlying and the party that considers selling the underlying. The official market terminology defines that the former one takes a long position in a contract, while the latter one takes a short position in a contract.

In addition, options can be European, American and Asian. European options can be exercised solely when they expire, whereas American options can be exercised whenever it is optimal. An Asian option follows the average price of the underlying and pays the amount of money which is computed on the basis of this average (Hull, pp. 7-9).

3.2 Hedgers

Hedgers on the market for weather are the investors who trade in the weather-indexed contracts with the aim of reducing their volume risk. The last-mentioned term should be now explained. The point is that unfavourable weather events influence the volume of business. The price is in turn affected indirectly. Consider Norwegian energy company Statkraft. Norwegians commonly use electricity for heating. This means that warmer-than-expected winters would result in the decrease of demand, so that Norwegians would need to consume less electricity during the winter season than Statkraft may have predicted initially. In case of Statkraft, the decline in annual profits may follow.

Another illustration of hedgers I am using in my paper is the owners of Norwegian ski resorts in a particular area. This business is highly exposed to the level of snowfall in the same area. Indeed, both the length of the skiing season and the amount of incoming tourists depend on the snowfall. If there is less snow than was predicted, the owners of the ski resorts experience financial losses.

Overall, the revenues of the owners of Norwegian ski resorts may be hedged using the snowfall index similar to the one computed by CME Group, while the profits of Statkraft may be hedged using HDD indexed.

3.3 The Weather Risk Management Association

The Weather Risk Management Association (WRMA) is a non-profit organization that connects professionals of the weather risk management industry. It was founded 1999 by six companies which were pioneers of the market for weather contracts. These were such well-known companies as Aquila and Koch Industries, which I mentioned earlier in the context of the development of the market for weather, as well as Castlebridge Partners, Enron Capital and Trade Associates, Southern Company Energy Marketing, and Swiss RE New Markets. Nowadays, WRMA includes nearly 40 market participants representing 12 countries.

The association's professional ambition is to encourage the development of weather derivatives and help weather exposed businesses to mitigate their risk of unfavorable weather events. WRMA accomplishes this mission through informing the community about the market for weather contracts.

In addition, WRMA is involved in standardization of the market for weather indexed derivatives. For example, the association has created the preset format of ISDA confirmations for transactions with weather derivatives. Another example is the assistance of WRMA to the National Oceanic and Atmospheric Administration (NOAA) and the National Weather Service (NWS) in upgrading data reporting standards. The association educates also the public through organizing conferences and webinars (The Weather Risk Management Association).

3.4 Organized Market. CME Group

CME Group is a top-tier marketplace where trade of derivatives takes place. Its first quarter revenue reached a substantial figure of USD 934.2 million in 2016 (The Financial Times, 2016). The group is the world's largest futures exchange with the average daily exchange volume for May 2016, for instance, approximated to USD 14.9 million (CME Group, 2016). The Economist names it "the biggest financial exchange you have never heard of" (The Economist, 2013).

CME Group is headquartered in Chicago and owns a number of exchanges in the US and Europe, as well as financial indices such as Dow Jones Industrial Average. It brings together companies, institutions and individuals that want to mitigate their risks using the set of instruments CME Group provides.

The company takes its roots from grain, dairy, butter and egg merchants. Particularly, one of its ancestors is the Chicago Board of Trade which was founded as early as in 1848. Unlike competitors, CME has always linked its business to products, not clients. Furthermore, the group has always been at the forefront of technological progress. A successful transition to electronic trading is a good case in point (The Economist, 2013). All of this, along with the network effect from annual portfolio made up of 3 billion contracts, has resulted in a success story for the world's greatest derivatives exchange. In the same way, these advantages allowed CME Group to offer brand-new products time to time (CME Group). For example, CME was the first exchange that introduced standardized futures and options on weather indices. This dates back to 1999.

3.5 Temperature derivatives

The futures and options written on weather-based indices are considered as the most liquid instruments. Nowadays, the CME's portfolio of weather products consists of financial instruments that are written solely on three temperature based indexes for a number of American and European cities. Specifically, the company lists the indices of CME Heating-Degree-Days (HDD) and CME Cooling-Degree-Days (CDD) for the following American cities: Atlanta, Chicago, Cincinnati, Dallas, Las Vegas, Minneapolis, New York, and Sacramento. As to European cities, the exchange calculates and lists the index of Cumulative Average Temperature (CAT) for London and Amsterdam (CME Group).

CME Rulebook explores the approaches used to calculate these three indices. Take for example Chapter 403 that discusses both HDD and CDD index futures. It states that for every day t , HDD_t is either zero, or the difference between 65 and the daily average temperature – the highest value is taken into consideration. The formula is as follows:

$$HDD_t = \max \left\{ 65 - \frac{T_t^{max} - T_t^{min}}{2}; 0 \right\},$$

where T_t^{max} and T_t^{min} are respectively maximum and minimum day temperatures, $\frac{T_t^{max} - T_t^{min}}{2}$ represents arithmetic mean, and 65 is constant.

As to CDD_t , it is defined as the highest value out of the following two: zero or the difference between the daily average temperature and 65. It may be expressed in the following way:

$$CDD_t = \max \left\{ \frac{T_t^{max} - T_t^{min}}{2} - 65; 0 \right\},$$

where T_t^{max} and T_t^{min} are respectively maximum and minimum day temperatures, $\frac{T_t^{max} - T_t^{min}}{2}$ represents arithmetic mean, and 65 is constant.

The air temperature for every day t is taken from the predefined weather station. The weather station is in turn submitted to the city mentioned in the contract. The meaning of the constant term is compelling. The measure of 65 degrees Fahrenheit corresponds to 18 degrees Celsius. The one may refer to it as to the air temperature on the Fahrenheit temperature scale. It is the basis considered by utility companies when a population neither demands heating indoors, nor turns air conditioning on.

HDD and CDD indices for both a monthly contract and a seasonal contract are the cumulated values of HDD_t and CDD_t over the duration of the contract:

$$HDD = \sum_{t=1}^D HDD_t \text{ and } CDD = \sum_{t=1}^D CDD_t,$$

where D corresponds to the number of days in the month or season.

The underlying idea of the HDD and CDD indices is to estimate the time during which the ancillary demand for electricity was caused respectively by turned heating or air conditioning (Chicago Mercantile Exchange).

Chapter408 describes in turn the calculation of CAT. Here, the index at day t is simply the arithmetic mean of the maximum and minimum temperatures:

$$CAT_t = \frac{T_t^{max} - T_t^{min}}{2},$$

where T_t^{max} and T_t^{min} are respectively maximum and minimum day temperatures.

CAT index for both a monthly contract and a seasonal contract is the cumulated value of CAT_t over the duration of the contract:

$$CAT = \sum_{t=1}^D CAT_t,$$

where D stands for the number of days in the month or season (Chicago Mercantile Exchange).

Furthermore, it should be mentioned that CME measures days differently subject to the indices and cities in question. In case of HDD and CDD indices, for instance, the daily average temperature for day t is measured by weather stations during the interval $[00.00_t; 00.00_{t+1})$, or from midnight at day t to twenty three hours and fifty nine minutes after midnight of the same day. The same measurement interval is true for Amsterdam in case of CAT index. The exception is the measurement interval for London, where the weather station at Heathrow airport collects the data on temperature for day t from nine hours after midnight of day t to eight hours and fifty nine minutes after midnight of day $t+1$, so that the measurement interval is $[09.00_t; 09.00_{t+1})$.

According to CME's catalogue of products, the group offers its clients both futures and options on these three weather indices. The latter ones are explicitly European options (CME Group, 2016). The company's weather products summary is shown in *Appendix 3*. In addition, the clients can chose between monthly futures/options contracts and seasonal strip futures/options contracts. To explain the latter term, the one may consider futures strip as a series of sequential futures sold on an exchange as a separate and unique contract (Kumar, 2015). Similarly, options strip can be explained as a series of sequential options sold as a separate and unique transaction. In case of CME's catalogue of products, both futures strips and options strips are strictly bounded to the delivery periods mentioned in *Appendix A*.

One crucial thing to mention about the pricing of futures/options strips is the value additivity principle. This is the valuation principle that states that no profit can come from combining as well as dividing cash flows. This means in turn that the expected payoff from a seasonal strip contract has to equal the expected payoff from the number of corresponding monthly contracts (Bjerk Sund, 2016).

In general, the trade of temperature derivatives is very similar to the trade of other index products. HDD, CDD, and CAT indices explain the deviations from monthly or seasonal averages. The deviations are attached to some amount of money. Specifically, one index point deviation equals USD 20 for American cities, GBP 20 for London, and EUR 20 for Amsterdam. Minimum price fluctuation accounts for one index point. All of contracts are settled financially, which means open positions are marked to market (MTM) with respect to the settlement price on a daily basis.

3.6 Other weather derivatives offered by CME Group

In the past, CME offered its clients a large variety of instruments linked to weather instruments. Precipitation derivatives along with derivatives written on frost and hurricane indices are good cases in point. It is unfortunate that all of these were delisted on October 20, 2014. As the exchange explains in its notice SER-7216, the reason for this was the lack of open interest from market participants (The Chicago Mercantile Exchange Inc., 2014). With the development of the market for weather derivatives, the futures and options on rainfall, snowfall, frost and other indices have nevertheless potential for attracting investors' attention in future. For that reason, I want to describe them briefly in this subsection. Please be advised that I have replaced the exchange-based symbols with the abbreviations for the names of indices mentioned from now on.

To begin with, the constructions of rainfall and snowfall indices are very similar and the derivatives written on these two indices are therefore integrated into the common term "precipitation derivatives". Formerly, CME Group offered its clients both index futures on precipitation and options written on precipitation futures. In terms of time interval, there were two options: monthly futures and options and seasonal strip futures and options.

The precipitation derivatives traded by the exchange were issued on so called CME Snowfall Index (SI) and CME Rainfall Index (RI). The former one provided with the estimate of how much it snows over a certain time interval. Logically, the instruments written on this index were offered only for snowfall season, which corresponds to the period from November to April.

An interesting fact is that the first contracts linked to SI which the exchange started listing, were monthly futures contracts issued on just two locations: New York Central Park and General Edward Lawrence Logan International Airport in Boston. The listing started in 2006. The underlying idea of "snow" futures and options is to aid investors in mitigating their risk related to either insufficient snowing or excessive snowfalls (CME Group, 2006). For example, skiers are highly sensitive to the level of snowing. If there is no snow, ski resorts lose money. Therefore, it may be a good idea for the owners of the latter ones to hedge against warmer than expected winter. Alternatively, airports may be forced to stand idle in case of dramatic snowfalls. This means that SI contract may attract both operators of airports and airline companies in terms of hedging against excessive snowing during the winter season.

Regarding RI, the index measured the amount of rain fallen over a certain period. Furthermore, the instruments issued on this index were offered only for rainfall season, which relates to the time interval from March to October. Cabrera, Odening, and Ritter have conducted an explicit empirical study on pricing rainfall derivatives according to CME's approach (Cabrera, Odening, & Ritter, 2013).

Chapter 418 described the calculation procedure of SI, whereas Chapter 441 described the calculation rule for RI. The procedures are very similar to the calculation rule of CAT index. Really, the indices at day t were simply the total amounts of snow or rain on this day:

$$SI_t = S_t,$$

$$RI_t = R_t,$$

where S_t and R_t are respectively the amounts of snow and rain measured in inches that has fallen on the ground on day t .

SI and RI for both a monthly contract and a seasonal contract were respectively the cumulated values of SI_t and RI_t over the duration of the contract:

$$SI = \sum_{t=1}^D SI_t,$$

$$RI = \sum_{t=1}^D RI_t,$$

where D stands for the number of days in the month or season.

One last point about SI and RI is that one indexed futures contract, regardless of whether it is snowfall or rainfall indexed contract, was USD 500 times the index, meaning the investor who considered purchase of such a derivative for price F , would expect the payback equal to USD 500 times the value of the index at the expiration date. The contracts were settled financially and the practice of MTM was applied during the life of the contract. As to the options, these were European call and put options. Every option was issued on a single precipitation index futures contract – either snowfall index contract, or rainfall index contract (CME Group, 2014).

The key attribute of the frost index listed by CME was that the exchange designed it specifically for the airline industry. The correct name for it was Frost Index Amsterdam (FIA) because it was issued on the only city – Amsterdam. The idea was to allow air companies that

operate at the Schiphol airport to manage the risk related to the airport standing idle while the runway is covered with frost.

Frost is the weather event when the air temperature falls below zero and small crystals of ice cover surfaces such as trees, roads, and runways in airports (Oxford Dictionaries). Because of frost, the latter ones become slippery and aircrafts cannot safely land or take off. As a result, all flights cease and companies operating both airport and aircrafts lose money.

Futures contracts on FIA were USD 100 times the index. They were offered only for frost season, which is November to March. The contracts were settled financially and the practice of MTM was applied during the life of the contract. As to the basis of the index, the weather station at the Schiphol airport collected data on frost every day on weekdays (Barchart.com).

According to NOAA, a hurricane is the improbable weather event that is explained by a low pressure area formed in the tropical region. In terms of weather derivatives analysis, it is crucial to split the terms tropical depressions, tropical storms and hurricanes. Hurricanes are tropical cyclones with a maximum wind speed reaching 74 miles per hour (mph), which approximates 119 kilometers per hour (kph). Simultaneously, maximum wind speeds in case of tropical depressions and tropical storms are lower than that (The National Oceanic and Atmospheric Administration). This notation is important since CME had never counted for the tropical cyclones with the wind speeds lower than 74 mph while listing its hurricane indices.

Another defining characteristic of hurricanes is that they cause enormous economic harm. Take for example the famous hurricane Katrina that hit several states on the southern coast of the US in 2005 and resulted in multibillion damage. The NOAA's report includes the estimate of USD 125 billion of economic loss associated with this event (National Centers for Environmental Information). The hurricane that had such an adverse effect on households, companies, and US economy as a whole, aroused naturally the interest to new practices of hedging against hurricane risk exposure. CME Group, for instance, responded already in 2007, when it launched several hurricane-based indices and introduced a few new indexed instruments issued on these indices (CME Group, 2007).

The hurricane index was initially calculated by a reinsurance company and was named after it as the Carvill Hurricane Index. All of the indexed instruments were traded on CME, though.

In 2009, the exchange bought the rights to the index and renamed it to the CME Hurricane Index (CHI). CHI was computed according to the following formula:

$$CHI = \left(\frac{V}{V_0}\right)^3 + \frac{3}{2} \left(\frac{R}{R_0}\right) \left(\frac{V}{V_0}\right)^2,$$

where V represents the maximum level of wind velocity, R corresponds to the radius of storm, and respectively V_0 and R_0 stand for reference values of the wind speed and the radius.

The equation above shows that there are just two factors that determine the index value: wind speed and size of hurricane. This provides a certain level of transparency and simplicity. The latter fact allows in turn for computing the index soon after a hurricane is announced and modifying it in the process when the data on the maximum wind speed and radius arrive. Besides, the National Hurricane Center (NHC) collects the data on wind speed and radius of every tropical cyclone (CME Group, 2007).

The investors in CHI had the options that were very similar to the ones the investors in other weather-related indices had. CME traded both futures and options. However, the investors in CHI were not restricted with only two contract types, which were monthly contracts and seasonal strip contracts. In actual fact, they could choose between the following three alternatives:

- Futures and options issued on a single storm that was officially named by NHC;
- Futures and options issued on the number of officially named storms that landed on the Atlantic coast of the US;
- Futures and options written on the largest storm that landed on the Atlantic coast of the US.

Furthermore, CME has split both the Gulf Coast and the East Coast of the US into seven separate regions. The point in such a division is that every region out of the seven listed has a specific constant risk, or probability, that a tropical cyclone turns into hurricane and lands at the mainland. CHI indexed monthly futures and options contracts were issued on two regions. The first one combined all of locations in the Eastern US. This means that the futures and options contracts covered every hurricane making the landfall between Brownsville in Texas and Eastport in Maine. The second region listed as the underlying for futures corresponded to

the coastline which was clearly defined by the geographical coordinates of the following three vertices of a square:

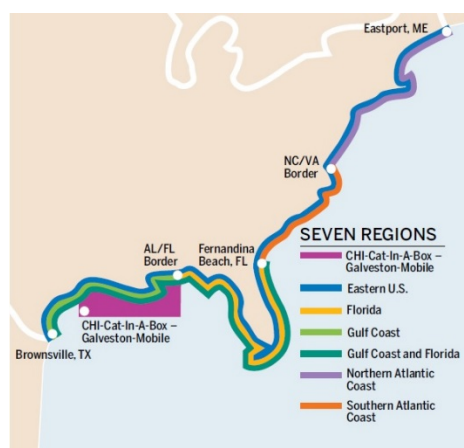
- 95°30'0"W to the west;
- 87°30'0"W to the east;
- 27°30'0"N to the south.

CME titled the hurricane region related to the coordinates above CHI-Cat-In-A-Box – Galveston-Mobile.

Futures and options issued on the number of officially named storms that landed on the Atlantic coast of the US could be regarded as seasonal futures and options contracts. In contrast with monthly contracts, these were written on six regions. These were Eastern US from Brownsville in Texas to Eastport in Maine, CHI-Cat-In-A-Box – Galveston-Mobile, as well as Gulf Coast, Florida, Southern Atlantic Coast and Northern Atlantic Coast.

Figure 3.1 shows the division of the US coastline into separate regions according to the CME's indexed risk of hurricanes with landfalls.

Figure 3.1 The US coastline according to the CME's indexed risk of hurricanes with landfalls



Source: CME Group

It is crucial to remember that all of the storms should correspond to the category “hurricane”, meaning the wind speed should be 74 mph or higher. They should be officially named and have landfall in the mainland.

And lastly, futures contracts on CHI were USD 1000 times the index. The contracts were settled financially and the practice of MTM was applied during the life of the contract (CME Group, 2009).

3.7 Binary options

In addition to futures and options contracts on weather indices, CME Group also listed binary options contracts. These should be distinguished from ordinary options. Overall, binary call option is a call option that pays off either a fixed quantity of money, or nothing at all. The expected value of this contract at maturity is as follows:

$$\mathbb{E}[\max\{K, 0\}],$$

where K stands for the fixed quantity of money in future which both sides of the contract know today.

The payoff from ordinary call option, on the other hand, depends on the future price of the underlying. In case of weather derivatives, the underlying would be the respective index. This means that the holder of ordinary call option will get either the difference between the future spot price and the strike price, or nothing. In contrast with binary options, the sides of ordinary call options do not know the quantity of money the holders of calls will obtain in future, because this amount is not predetermined.

The advantages of binary call options compared to ordinary options are that binary options simplify hedging process, are easier to price, and may be used instead of call spreads. Binary options are also known as cash-or-nothing options.

With regard to weather derivatives, CME listed binary call options contracts for the number of weather indices. These were, in particular, all of snowfall-, rainfall-, and hurricane-based indices. In case of the latter ones, CME listed not only binary options related to single storm, storming season and the largest storm, but also binary options related to the second largest storm with landfall. Moreover, binary options were offered for all of the seven regions shown on *Figure 3.1*.

As to put options, CME did not list put binary options contracts because such options would result in the compensation for the weather event that does not happen (CME Group, 2009).

3.8 Weather derivatives offered by other exchanges

One of the most promising sources of energy, according to industry experts, is wind power. Indeed, a number of wind farms globally has been growing geometrically during the last decade. In general, this has a positive impact on the environment and results in lower electricity bills. The latter fact is due to the impact of wind power on the merit order curve. *Appendix 4* shows the merit order curve for Germany. Be advised that the blue line reflects marginal costs for electricity generated by wind farms. The graph suggests that the electricity generated by wind has the lowest marginal costs, which may be explained by the absence of fuel costs, and therefore enters the grid first causing lower average price for electricity (Ketterer, p. 26). Nevertheless, the increased input of wind in total electricity supply makes both producers and consumers highly dependent on the weather factor.

The owners of wind power capacities are highly exposed to weather risk associated with the availability of wind and its speed, as it happens. *Appendix 5* presents power curve of a typical turbine of a typical producer. Here, the model used is V90-3.0 MW made by a well-known company Vestas. The graph shows that the turbine starts producing only with the speed of wind equal to 3-5 meters per second (mps) and it is shut down at the wind speed of 25 mps. The wind speed which is lower than that interval just cannot make the turbine rotate. At the same time, when the speed is higher than the interval mentioned, there is the risk of damage and the wind mill cease to operate (Vestas).

Wind power producers usually do not know exactly how strong the wind next month will be, as well as they cannot be sure about how many days in the upcoming summer the whole farm will stand idle because of storm season. As a result, they face difficulties in forecasting future returns. Similarly, the company owner of a coal plant, which is used as backup to renewable energy, lacks reliable data on future wind speeds and fails to predict whether the backup will be necessary. The company's chair is unsure about future returns too. Moreover, if he or she decides to turn the plant on and the production from wind mills explodes, negative prices for electricity could follow. This may be true if it is costlier to pay consumers for buying electricity than to shut down the plant for a short time interval. This happened last month in the United Kingdom, for example, when local generators paid above GBP 30 MWh for their electricity to be taken off (Clark, 2016).

All of this describes the problem of wind speed volatility. This is the type of problem that generators face on everyday basis. In order to manage the risk related to wind speed volatility, U. S. Futures Exchange (USFE) introduced the set of instruments issued on the Nordix wind speed index (NI). These were futures and options contracts. The options were European puts and calls. Five wind sites in two American states, New York and Texas, underlay the contracts. The market for new indexed instruments lasted from 2007 to 2008, when the exchange ceased to exist (Cameron, 2008).

The index relied on the data collected in two zones. The first zone, which was located in New York, included three sites out of five traded on USFE. The second zone, which was in Texas, covered the rest of two. Along with daily averages of wind speed from these two zones, the exchange worked with historical daily means. The historical period of interest was 20 years. The formula for NI calculation for the interval from may be written as follows:

$$NI = 100 + \sum_{t=1}^D (W_t - w_t^{20}),$$

where $(W_t - w_t^{20})$ is the deviation of the average wind speed at day t from the respective historical daily mean, the factor W_t stands for the average wind speed at day t , the factor w_t^{20} corresponds to the 20-year historical mean for day t , D is the number of days in the month or season, and 100 is constant.

As the one may see, the index above cumulates the wind speed deviations from the normal over the interval of D days and is corrected for the indicator 100. Logically, the value of the index under the indicator 100 means that NI overestimated the wind speed of a specific site, so that less electricity than predicted by historical means is entering the grid. The index value above the indicator 100 means in turn that NI underestimated the wind speed of a specific site, so that more electricity than predicted by historical means is entering the network (Alexandridis & Zapranis, pp. 20-21).

Subject to the index value, the generator can either loose or win. If the generator's top management does not want to risk, it may secure the position by means of hedging.

3.9 OTC. Quantity-adjusted weather contracts

The problem of traditional indexed-based weather derivatives traded on exchange is that they deal with volume risk, but not price risk. This does not provide investors with all-inclusive hedge.

Compared to traditional weather products, quantity-adjusted options on energy markets, or simply energy quanto options, are brand-new instruments on the market for weather. These are hybrid options contracts that are available for trade over-the-counter and help investors to mitigate their exposure to the weather. Unlike traditional weather derivatives such as HDD/CDD indexed contracts, quantos help investors to manage both price and volume risk at the same time. For that reason quantos have become very popular recently.

It crucial to note that quanto options described in this paper are explicitly related to energy markets. The one should not compare energy quanto options with their mature “brothers” currency quantos. The latter ones hedge against the risk exposure to exchange rate fluctuations and have nothing in common with energy quantos.

A good and popular example of the application of energy quantos is the contracts for the supply of natural gas. Consider the wholesale natural gas market of Europe, where Norwegian gas supplied by Statoil is traded. Statoil sells its natural gas for the spot price settled on the basis of market equilibrium. Here, Norwegian company is exposed to two types of risk. Firstly, Statoil is sensitive to price changes caused by fluctuations in demand and supply at every particular point of time. Secondly, the company is exposed to volume risk. For example, if winter is warmer than expected, people in Europe use less natural gas for heating than predicted. This reduces in turn the demand for the fuel, which is literally the same as decline in the amount of gas sold. The price for natural gas eventually falls. Overall, the result is the decrease in the volume of gas sold as well as its price. Poor financial metrics of Statoil follows (Benth, Lange, & Myklebust, p. 3).

Standard weather indexed contracts such as the ones traded by CME cannot cover both types of risk, but energy quantos can. In order to show how it works, I briefly describe the things inside energy quanto options. Specifically, I use the example of Statoil on the wholesale natural gas market of Europe to describe the payoff from a typical quantity-adjusted energy option contract.

Unlike traditional weather indexed derivatives, energy quantos depend on two indices. One index represents commodity. The other is one of the weather index. Following my example, I consider natural gas as commodity of interest and HDD as the weather index. Although I am using the index listed on CME, the hedge is supposed to happen on OTC market. I assume that the period of interest is 90 days, which corresponds to three winter months. The prices of natural gas are daily means measured in EUR. Lastly, I assume today is the end of November 30th trading day.

I start the discussion with put quantos. The first step is to compute the values of indices. Referring the natural gas commodity index, I simply accumulate the values of natural gas spot prices over the period of interest and divide by the number of days D , which is 90. The equation may be expressed in the following way:

$$E = \frac{1}{D} \sum_{t=1}^D S_t,$$

where D stands for the duration of the period of interest and equals 90 in case of Statoil, S_t is the spot price for natural gas on the wholesale market in Europe at day t , t is the time index.

Note that Statoil starts counting at day $t=1$ in the equation above. This corresponds to the next day after November 30.

As to the weather index, I use the formula for HDD at day t shown in Subsection 3.7 of this paper:

$$HDD_t = \max \left\{ 18 - \frac{T_t^{max} - T_t^{min}}{2}; 0 \right\},$$

where T_t^{max} and T_t^{min} are respectively maximum and minimum day temperatures, $\frac{T_t^{max} - T_t^{min}}{2}$ represents arithmetic mean, and 18 stands for degrees Celsius and is constant.

HDD for winter season is then simply the cumulated value of HDD_t and over the duration of the contract:

$$HDD = \sum_{t=1}^D HDD_t,$$

where D corresponds to the number of days in the month or season.

The payoff from one put quanto option for energy at maturity T is the following:

$$P_T^{E,HDD} = \gamma \times \max\{(K^E - E); 0\} \times \max\{(K^{HDD} - HDD); 0\},$$

where γ stands for volume adjustment factor such as one million British thermal unit (MMBtu), E is the energy commodity index, HDD stands for Heating-Degree-Days index, T is maturity, $P_T^{E,HDD}$ is the payoff from one call quanto option for energy at maturity T , and respectively K^E and K^{HDD} are the strike prices of the energy commodity index and the HDD index.

The one may understand the equation above as the combination of two hedges: the first part of the equation, $\gamma \times \max\{(K^E - E); 0\}$, represents the price risk hedge, whereas the second part, $\max\{(K^{HDD} - HDD); 0\}$, reflects the volume risk hedge.

In case of Statoil, the company's financial metrics is highly sensitive to the demand for natural gas. Let me assume now that Statoil predicts the level of consumption of natural gas in Europe three months ahead and sets its production plan according to this estimate. The level of consumption in turn depends on air temperature outdoors. Indeed, natural gas is commonly used in Europe for heating purposes. The heating is usually turned on in winter only. The truth is that the demand for gas decreases if temperature goes up, because less natural gas is burned during warm winters compared to harsh winters. Suppliers cannot swiftly shut down their extraction, on the other hand. This leads to the decline in the market price. Hence, if the winter gets warm, the demand for Norwegian gas falls, along with the price for it. As a result, Statoil's three-month profit is lower than expected.

For Norwegian company, it may sound as a good idea to protect itself against loss on both volume of gas sold and price per unit using the weather derivatives contracts. CME HDD futures and options contracts, however, cover only the former one. For that reason, Statoil may consider energy quantos as a better option.

Regarding call quantity-adjusted options for energy, the form of their payoffs is very similar to the one of put quantos. One call energy quanto option at maturity T gives the following payoff:

$$C_T^{E,HDD} = \gamma \times \max\{(E - K^E); 0\} \times \max\{(HDD - K^{HDD}); 0\},$$

where γ stands for volume adjustment factor, E is the energy commodity index, HDD stands for Heating-Degree-Days index, T is maturity, $C_T^{E,HDD}$ is the payoff from one call quanto

option for energy at maturity T , and respectively K^E and K^{HDD} are the strike prices of the energy commodity index and the *HDD* index.

Major natural gas consumers like local authorities could find call energy quanto options very attractive. For instance, municipalities have to provide schools, universities and hospitals with heating during winter season. Similar to Statoil case, local governments make predictions about both the amount of natural gas they will need to buy during the winter season and the price per unit. These predictions are incorporated in local budgets. If the winter turns out to be colder than expected, the authorities would need to buy more gas. Furthermore, the aggregate demand for natural gas will increase the market price, as suppliers cannot respond to new market conditions fast enough. Higher price for energy together with greater volume that should be consumed for heating lead to financial loss of the local governments. Considering the above mentioned, the authorities could use the weather derivatives market to manage their weather-related exposure to volume and price of the fuel they consume.

4. Empirical Analysis

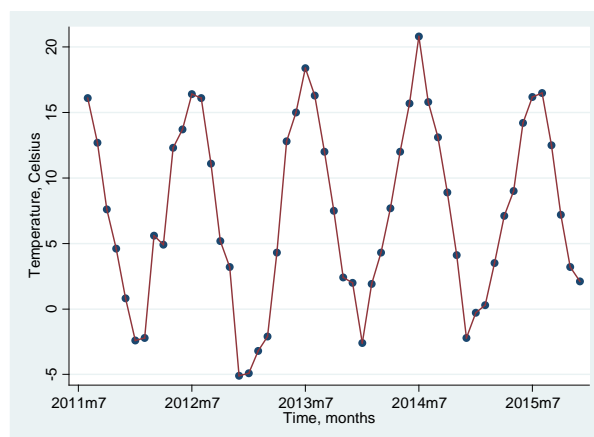
The goal of my empirical research is to investigate the causality between temperature variations and electricity prices. After the question of interest is posed, the database should be generated. The historical data for electricity prices in Oslo bidding area and air temperature in Norwegian capital are respectively my explained and explanatory variables. I work with monthly means. The time interval I take into consideration from August 2011 to December 2015. This gives me 53 observations. In addition, 54 other variables constitute my data set.

In Subsection 4.2 I pose the assumptions that underlie my empirical work. I describe methodology in Subsection 4.3. Model selection and regression analysis follow as soon as the database is complete and methodology is described. The final model and its interpretation are provided in the last subsection.

4.1 Data collection and data description

It should be mentioned that Norway is a very large European country – a total area of Norway is above 385 thousand square kilometers. Its population and industries are spread over the country, which means that electricity is consumed everywhere. For this reason, Norway is divided into several bidding areas (*Figure 4.1*). The term “bidding area” stems from Nord Pool definition of the specific geographical area within which producers and consumers can exchange electricity one with another without any transmission capacity constraints. Since the amount of electricity different zones can exchange with each other is limited by the bottlenecks in the system, the division into zones reflects local market conditions in the price. This means that prices in two different bidding areas in Norway may vary subject to transmission capacity constraints. In other words, market mechanism presupposes that electricity flows from the area with lower price of electricity to the area with higher price of electricity and bottlenecks in transmission system prevent the price in different regions from equalizing. Local transmission system operator defines a number of bidding areas within a country (Nord Pool, 2016).

Figure 4.2 Air temperatures in Oslo (monthly means)



Source: eKlima, NMI

The figure above shows that the series of air temperatures has the form of cosinusoid. It is difficult to suspect any trend in the series. With respect to a season, the air temperature in Oslo varies from -5.1 to 20.8 degrees Celsius.

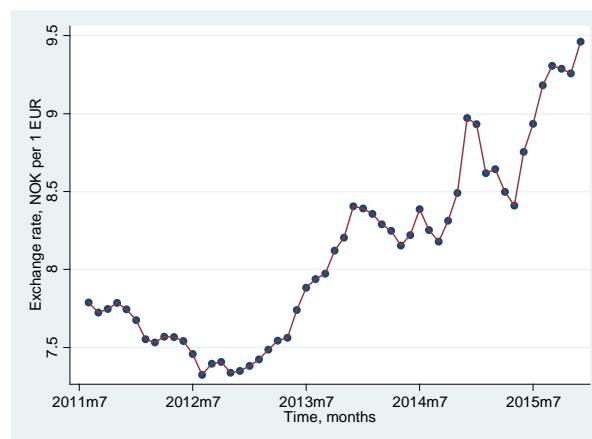
In order to reflect how people's financial security influences the demand for electricity and therefore its price, I wanted initially to control for either income or purchasing power of Norwegians. Unfortunately, there is no data showing monthly observations of either income or purchasing power. Official statistical services which are responsible for computing major indices for the well-being of economies, usually do not collect data for the measurements such as gross domestic product (GDP) per capita based on purchasing power parity (PPP) on a monthly basis. However, it is possible partially to capture the required effect by means of historical data for exchange rate. The one may think of the series of exchange rate as sort of instrumental variable (IV) for GDP per capita, PPP. This is not a very accurate term in terms of official statistical definition of IV, though.

Thus, my second independent variable refers to the exchange rate between NOK and EUR. Specifically, the variable shows how many NOK the one can get in exchange of one EUR at time t . The data is imported from Norges Bank, which is the central bank of Norway (Norges Bank, 2016). The reason for including the exchange rate in my model is straightforward. The change in the value of foreign currencies measured in domestic currency reflect the wellbeing of the people of the country where domestic currency functions. Economic theory presupposes that the price for imported goods increase when the exchange rate falls. As a result, people can buy less good for the same amount of money.

In case of electricity price, the idea is that the decrease in the exchange rate of NOK to EUR worsens welfare of the Norwegians. They try therefore to spend less on electricity. Lower demand makes in turn the prices for electricity fall. The research conducted by Longva, Olsen and Strøm, 1988, supports the relationship above. Truly, they have estimated electricity price elasticities of demand for Norwegian economy using a general equilibrium model. The result was the elasticities of -0.53 and -0.65 for the household and industry sectors respectively. These are rather high elasticities (Longva, Olsen, & Strøm, p. 305).

I plot the series of the exchange rates in *Figure 4.3*. Note that the decrease in the exchange rate of NOK to EUR means that the amount of NOK the one needs to get 1 EUR inflates.

Figure 4.3 The exchange rates (EUR/NOK)



Source: *Norges Bank*

According to the plot above, there is a reason to suspect an upward trend in the series. Truly, the value of EUR has been rising from 7.3239 NOK in August 2012 to 9.4626 NOK in December 2015. I can therefore think of the decline in purchasing power of Norwegians.

In my further analysis, I am exploring the relationship between the historical air temperatures in Oslo and the respective electricity prices for the Oslo bidding area. My initial guess is that lower temperatures outdoors correspond to higher electricity prices. The point is that Norwegians use solely electricity for heating purposes. In winter, the air temperature decreases and people start using extra amount of electricity for heating. This increases the demand, while the supply is stable. Transmission capacities between regions put some restrictions on how much of electricity Norway can import from its neighbors. As a result, the market price for electricity grows. The appropriate model for the relationship is as follows:

$$\ln(Oslo)_t = \widehat{\beta}_0 + \widehat{\beta}_1 Temperature_t + \widehat{\beta}_2 \ln(NOK1EUR)_t + \widehat{u}_t,$$

where index t is time and \widehat{u}_t stands for errors.

The slope parameters from the regression above are interpreted in two ways. In case of a log-level model with dependent variable in logs and independent variable in levels, I say that a one-unit change in independent variable changes dependent variable by $(100 \times \beta_j)$ percent. The index j refers to the specific explanatory variable. In case of log-log model with both dependent and independent variables in logs, the slope parameter stands for elasticity, so that a one percent change in explanatory variable changes explained variable by β_j percent.

In the model above, I also control for the development of the exchange rate between NOK and EUR. Moreover, I use the logs of the variables for historical electricity prices and exchange rate. I name the model above as *Model 1*.

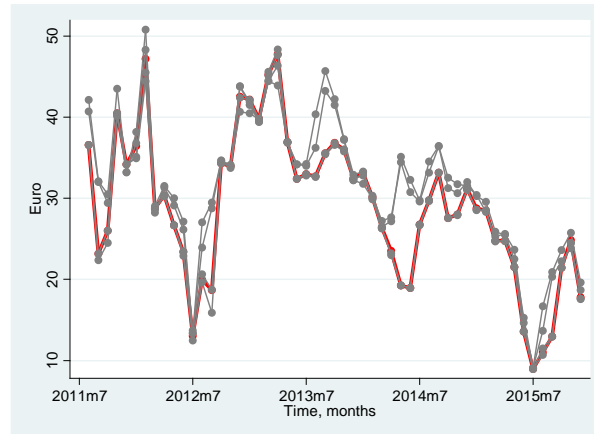
Furthermore, the database provides me with historical electricity prices for other bidding areas measured in EUR. The point is as follows. The availability of transmission lines between regions enables the flow of power from region to region. According to the laws of demand and supply, the electricity moves from low-priced zone to high-priced zone. Consequently, the domestic price of electricity in the former one increases due to the decrease in supply, whereas the declined domestic price of electricity in the latter region is ascribed to supplementary supply of power. I assume that transmitting power over long distances is not profitable, so I only control for bidding areas that are neighboring to Oslo. These are the following regions: Kristiansand, Trondheim and Bergen, and the bidding area SE3 in Sweden. The historical data of electricity prices in these regions constitute a set of secondary explanatory variables in my model.

As to Sweden, the country had the only bidding zone SE up to November 2011. Since November 2011, there exist four bidding areas in Sweden: SE1, SE2, SE3 and SE4. In my regression model, I control for SE3. The variable SE3 in my data set misses the initial three observations, because the division of SE into four pieces happened three months after the first observation in my time series. In order to fill the blank observations, I copied the last three observations from SE variable and pasted them as the first three observations in SE3.

The plot of historical prices for electricity for the period in question is shown on *Figure 4.4*. The red line on the plot stands for the time series of electricity prices in Oslo. The rest of power

prices of interest are represented by gray lines. It is possible to conclude that all of prices follow similar pattern. Moreover, electricity price in every region of interest has declined over the period of 53 months. Truly, the power price in Oslo has declined from EUR 36.58 in August 2011 to EUR 17.81 in December 2015. This suggests that a downward trend is common for all of series.

Figure 4.4 Electricity prices in Scandinavia



Source: Electricity prices in Scandinavia

In my empirical analysis, I modify *Model 1*, so that electricity prices of the neighboring regions are included in the regression. I call the modified equation *Model 2*. It looks as follows:

$$\ln(Oslo)_t = \widehat{\beta}_0 + \widehat{\beta}_1 Temperature_t + \widehat{\beta}_2 \ln(NOK1EUR)_t + \widehat{\beta}_3 \ln(Kristiansand)_t + \widehat{\beta}_4 \ln(Bergen)_t + \widehat{\beta}_5 \ln(Trondheim)_t + \widehat{\beta}_6 \ln(SE3)_t + \widehat{u}_t,$$

where index t stands for time, \widehat{u}_t refers to the error term, and regressors $\ln(Kristiansand)_t$, $\ln(Bergen)_t$, $\ln(Trondheim)_t$, and $\ln(SE3)_t$ represent natural logarithms of historical electricity prices in Kristiansand, Bergen, Trondheim, and SE3 respectively.

Another set of secondary explanatory variables refers to the evolution of maximum transmission capacities. I have mentioned previously, that transmission capacity constraints influence prices of electricity in various regions. *Figure 4.1* informs about the maximum transmission capacities in the Nordic countries. The values of the transmission capacity constraints are provided in megawatt (MW). I incorporate in my model the capacities related to the power transmission between the Oslo region and the neighboring regions, which are Kristiansand, Trondheim, Bergen and SE3 in Sweden. Moreover, I take the data on maximum transmission capacities for both directions, meaning I have separate variables for the

transmission capacity of import and export. I that my transmission capacities are not constant over time, because the construction of new transmission lines between two bidding areas increases the maximum transmission capacity between them. *Appendix 6* reflects the revision of maximum transmission capacities between the regions mentioned that happened several times during the period of interest (European Network of Transmission System Operators for Electricity, 2016).

I modify my *Model 1* and include the set of transmission capacities in the regression. There are eight transmission capacities in total. I call the modified equation *Model 3*. It may be expressed in the following way:

$$\ln(Oslo)_t = \widehat{\beta}_0 + \widehat{\beta}_1 Temperature_t + \widehat{\beta}_2 \ln(NOK1EUR)_t + \sum_{c=1}^8 TC_{t,c} + \widehat{u}_t,$$

where the index t stands for time, the index c identifies the order number of the capacity in question, TC corresponds to the transmission capacity representation in MW, and \widehat{u}_t refers to the error term.

Last but not least, I generate the logs of every variable representing power price, as well as the logs of the variable standing for the exchange rate of Norwegian krone. All of these are natural logarithms of the variables from my data set. As to my major variable of interest, which is $Temperature_t$, it is examined in levels. The point is that air temperature can be negative. There are actually nine negative observations in my data set. It is a known fact that the logarithm of negative number is undefined, so I cannot log transform $Temperature_t$ (Murray).

I have decided to work with explanatory variables in logs because of the number of reasons. Firstly, natural logarithms of the variables may help to get rid of heterogeneity problem, meaning there is a chance that the variance becomes stable due to log transformation (Nirian Martin, 2014). Secondly, logarithmic model is optimal in terms of forecasting by means of Box-Jenkins ARMA models, so the log transformation of the model may be useful for further research on weather derivatives. Finally, the economists like logarithmic models better as the causality may interpreted as elasticity.

Finally, I make the choice between levels and logs of the dependent variable based on the test procedure described in *Appendix 7*. This appendix contains my do-file from Stata with comments related to the test procedure I used.

4.2 Assumptions for asymptotic normality of ordinary least squares

Assumption 1: Linear in parameters, stationary and weakly dependent model

The model is linear in its parameters when the stochastic process $\{(x_t, y_t): t = 1, 2, \dots, n\}$ can be represented in the following way:

$$y_t = \beta_0 + \beta_1 X_{t,1} + \dots + \beta_k x_{t,k} + u_t,$$

where the sequence $\{u_t: t = 1, 2, \dots, n\}$ refers to disturbances or errors with n time periods. The sequence $\{x_{t,j}: t = 1, 2, \dots, n; j = 1, 2, \dots, k\}$ refers to j explanatory variables with n times. There are k explanatory variables in the model.

We say that the model is stationary if its mean and variance do not change as time passes (Li, p. 4). The time series $\{x_1, x_2, \dots, x_n\}$ is weakly dependent if

$$\text{Corr}(x_t, x_{t+h}) \rightarrow 0 \text{ as } h \rightarrow \infty.$$

This means that the correlation between x_t and its future values weakens as time passes.

Assumption 2: No perfect collinearity

This assumption states that the value of an independent variable cannot be computed based on the exact linear combination of the values of other independent variables. The assumption also means that independent variables in the model should not be constant over time.

Assumption 3: Zero conditional mean

The zero conditional mean assumption states that the expectation of the error term u_t , provided the independent variables $x_{t,j}$, equals zero for every time period t :

$$\mathbb{E}(u_t | x_{t,j}) = 0.$$

In the notation, the index t stands for time and the index j refers to the specific explanatory variable.

If the equation above holds, then the independent variables are contemporaneously exogenous. This means that the errors are uncorrelated with the independent variables at every time:

$$\text{Corr}(x_{t,j}, u_t) = 0, \forall j.$$

This assumption holds for every explanatory variable j and is critical for a causal interpretation of a model. If it holds, I can be sure that the slope coefficient indicates the causal relationship between the independent variable it precedes and the dependent variable (Balsvik, The simple regression model. The zero conditional mean assumption, 2015).

Assumption 4: Homoskedasticity

This assumption implies that variance of error terms, conditional on explanatory variables in the model in question, is constant over time. In other words, the disturbances in the model should be contemporaneously homoskedastic:

$$\text{Var}(u_t | x_{t,j}) = \sigma^2,$$

with index t corresponding to time and index j relating to particular explanatory variable.

Assumption 5: No serial correlation

Subject to explanatory variables, the disturbances u_t and u_s at two times t and s ($t \neq s$) should be uncorrelated (Taber, p. 9):

$$\mathbb{E}(u_t, u_s | x_t, x_s) = 0.$$

Taking assumptions 1 through 5 for granted provides me with the information about the accuracy of the OLS estimators. It does not inevitably allow me to conduct statistical inference. For the latter one, an additional assumption is necessary.

Assumption 6: Normality

In the population, the error terms $\{u_t: t = 1, 2, \dots, n\}$ are independent of the explanatory variables $\{x_{t,j}: t = 1, 2, \dots, n; j = 1, 2, \dots, k\}$. Moreover, I say that the errors are independently, identically, and normally distributed with mean zero and variance σ^2 :

$$u \sim \text{Normal}(0, \sigma^2).$$

This results in turn in normally distributed OLS estimators of the linear regression model:

$$\hat{\beta}_j \sim \text{Normal}(\beta_j, \text{Var}(\hat{\beta}_j)).$$

The normality assumption informs me about the exact shape of a probability density function. With this information, the one can calculate any area between the probability density function and the horizontal axis in a Cartesian coordinate system (Descartes, 1637). The horizontal axis represents in turn the values of estimators as well as population parameters. If the distribution is normal, it is possible to find the likelihood that an estimate is no less than a certain value. This is crucial for hypothesis tests.

In case the assumptions 1 through 6 hold, I say that the OLS estimators are asymptotically normally distributed. I can also say that the distributions of the OLS estimators are centered in the actual values of the population parameters. This means that the estimations of error terms, t statistic, and F statistic are well founded. Hence, I can use them in a regression analysis (Wooldridge, p. 376).

4.3 Methodology

Ordinary least squares (OLS)

The method of least squares or ordinary least squares (OLS) refers to the method of rough calculation of the parameters of a linear regression model. For the sake of argument, I describe the method based on a simple regression model with the only explanatory variable. Nevertheless, the same logic applies to multiple regression models with many regressors. In this paper, β_0 and β_1 represent intercept and slope parameter respectively. The goal of the OLS method is to minimize the sum of squared residuals (SSR). SSR measures how an estimated model deviates from the real-world dynamics, so that a low value of SSR represents a good fit of the model while a high value of SSR shows that the model in question poorly estimates the population:

$$SSR = \sum_{t=1}^n (y_t - \hat{y}_t)^2,$$

where \hat{y}_t stands for the fitted values of y_t and is derived from the following equation:

$$\hat{y}_t = \widehat{\beta}_0 + \widehat{\beta}_1 x_t.$$

Minimizing the sum of squared residuals presumes differentiating SSR, finding the first order conditions for intercept and slope parameter and setting them equal to zero (Lambert, 2013):

$$FOC_1 = \frac{\partial SSR}{\partial \beta_0} = 0,$$

$$FOC_2 = \frac{\partial SSR}{\partial \beta_1} = 0.$$

Based on the resulting system of two equations, I can find β_0 and β_1 :

$$\begin{cases} -2 \sum_{t=1}^n (y_t - \widehat{\beta}_0 - \widehat{\beta}_1 x_t) = 0 \\ -2 \sum_{t=1}^n x_t (y_t - \widehat{\beta}_0 - \widehat{\beta}_1 x_t) = 0 \end{cases} \Rightarrow$$

$$\widehat{\beta}_0 = \bar{y} - \beta_1 \bar{x},$$

$$\widehat{\beta}_1 = \frac{\sum_{t=1}^n (x_t - \bar{x})(y_t - \bar{y})}{(x_t - \bar{x})^2} = \frac{Cov(x_t, y_t)}{Var(x_t)}.$$

Inference with hypothesis test statistic

The major problem in econometrics modeling is that a researcher does not know the true population parameter. In order to make any conclusions regarding the causality between the regressors and the regressand, the one needs to hypothesize the value of the population parameter. I call this statement of the null hypothesis H_0 :

$$H_0: \beta_j = c, c = const.$$

Usually, researchers who conduct econometrics analysis tend to be conservative and state the null hypothesis about what they hope is not true. The null hypothesis is considered true until researchers get the evidence that claims otherwise. The null hypothesis is rejected when the estimate includes a small probability of rejecting a true H_0 , meaning the estimate is such that it is not likely to make the type I error (David M. Lane). In this paper, I refer to the significance level as the probability of the type I error. In particular, the modeling subsection further in the paper includes 5 percent significance level unless stated otherwise.

The normality assumption implies that the OLS estimators are normally distributed. I can use this assumption as the foundation for creating a test statistic with a known distribution by means of $\widehat{\beta}_j$ and H_0 . As soon as I have the test statistic, I can compare it with the critical value of the test statistic for the given significance level. In case the constructed test statistic is higher

than the critical value, I am entitled to reject the null hypothesis H_0 in favor of the alternative hypothesis H_1 stating that H_0 is not true:

$$H_1: \beta_j \neq c, c = \text{const.}$$

Subject to the number of restrictions, researchers work with two major types of test statistic: t -distributed and F -distributed. If the null hypothesis presumes the only restriction, the statistic is t -distributed. In case of several restrictions, I work with F -distributed test statistic.

The null hypothesis with the only restriction has two general cases: the population parameter is set to be equal to the constant term provided or a linear combination of two or more parameters is set to be equal to the constant term provided. For any occurrence, Student t -distributed statistic is an appropriate tool to test the null hypothesis. William Sealy Gosset developed it in 1908. The statistician used the pen name Student for his published works (Student, pp. 14-19). The formula for the calculation of t -statistic is the following:

$$t = \frac{\widehat{\beta}_j - \beta_j}{se(\widehat{\beta}_j)} \sim t_{n-k-1},$$

where n stands for the number of observations, k is the number of explanatory variables that are included in the model. In this paper, I often refer to $df = n - k - 1$ as to the degrees of freedom.

In the formula above, I replace β_j with the constant term in the null hypothesis H_0 . The term $\widehat{\beta}_j$ stands for the estimated population parameter. The standard error term $se(\widehat{\beta}_j) = \hat{\sigma} = \sqrt{\frac{SSR}{df}}$ is the unbiased estimator of standard deviation of the estimated population parameter.

After t_{n-k-1} is calculated, the interest of a researcher is to find the critical value t_c of the t -distribution with respect to the degrees of freedom provided and the significance level predetermined. The critical value t_c can be extracted from the t -distribution tables or it can be calculated with the help of statistical software such as homoskedasticity. The method requires from a researcher to reject the null hypothesis if the test statistic calculated is higher than the critical value t_c .

Alternatively, the researcher who is dealing with t -distributed test statistic may be interested in finding a p -Value while he or she is testing the null hypothesis. P -Value refers to the lowest level of significance that allows me to reject the null hypothesis. Hence, if the p -Value for a given test is lower than the chosen significance level, I reject the null hypothesis. Again, statistical software such as Stata provides with p -Values for every estimated value of population parameter right after the regression is run (Balsvik, 2015).

The case when the researcher wants to test whether a group of regressors has zero effect on the regressand is the test with several exclusion restrictions. F -test is an appropriate tool for such a hypothesis. It tells me whether several slope coefficients in the regression equal zero at the same time. If it is true, the researcher is entitled not to include the population parameters tested with F -test in the model. The F -test was developed by American statistician George Snedecor and named in honor of English statistician Ronald Fisher (Snedecor, 1938).

F -test presumes the comparison between SSR of the two models: the unrestricted model and the restricted one. The former one accounts for all of populations parameters, including the ones that are tested. The latter one excludes the population parameters to be tested, meaning the restricted model stands for the case when the group of explanatory variable has no effect on the explained variable. A low value of SSR represents a good fit of the model. If SSR for one model is lower than SSR for another one, it means that the former model explains larger part of the total variation in the dependent variable and for that reason the model with lower SSR fits population better.

The logic behind the testing is that adding explanatory variables to regression model increases the part of the total variation in explained variable that the model can explain. The unrestricted model includes more variables than the restricted one. It should therefore possess smaller SSR:

$$SSR_{restricted} > SSR_{unrestricted}.$$

The inference with F -distributed statistic includes several stages. First, the null hypothesis is stated that the correct model is the restricted one. Take for example the model with four parameters and two exclusive restrictions ($p = 4, q = 2$). The null hypothesis would be that two out of four regressors should not be included in the model, so that the corresponding population parameters are set to equal zero:

$$H_0: \beta_3 = 0, \beta_4 = 0.$$

The alternative hypothesis is that H_0 is not true, so that at least one population parameter does not equal zero and, in turn, at least one explanatory variable should be included in the model:

$$H_1: H_0 \text{ is not true.}$$

Secondly, the researcher rejects the null hypothesis if the unexplained variation of the dependent variable in the unrestricted model is sufficiently smaller than the unexplained variation in the restricted model. At this point, it is worth clarifying what the term “sufficiently smaller” means. The algebra behind the F -distributed statistics presumes the use of the following formula:

$$F = \frac{(SSR_{restricted} - SSR_{unrestricted})/q}{SSR_{unrestricted}/df} \sim F_{(q,df)},$$

where q stands for the number of exclusive restrictions and $df = n - k - 1$ corresponds to the degrees of freedom.

From the equation above, I see that F -statistics depends on the relative change corrected for exclusive restrictions and degrees of freedom.

In order to reject H_0 , the researcher should compare the calculated $F_{(q,df)}$ with the critical value of F_c for the defined level of significance. I obtain the critical value F_c from the F -distribution tables. If $F_{(q,df)} > F_c$, the null hypothesis is rejected in favor of the alternative one.

Testing for autocorrelation in the errors

One of the most important assumptions in time series analysis is the assumption of no autocorrelation. This is Assumption 5 in the previous subsection. It states that the disturbances u_t and u_s at two times t and s ($t \neq s$) should be uncorrelated subject to explanatory variables (Taber, p. 9):

$$\mathbb{E}(u_t, u_s | x_t, x_s) = 0.$$

The violation of this assumption presumes the presence of autocorrelation. In general, autocorrelation, also known as serial correlation, is the relationship between two values of the same variable over time. In this paper, I study autocorrelation in the error term based on the

first-order autoregressive (AR(1)) model. In particular, I suspect the following structure of autocorrelation in the errors:

$$y_t = \beta_0 + \beta_1 x_t + u_t, t = 1, 2, 3, \dots, T$$

$$u_t = \rho u_{t-1} + e_t$$

$$\mathbb{E}(e_t e_s) = 0, \forall t \neq s$$

where ρ speaks about the relationship or correlation between a residual and its lagged value, indices t and s refer to time, and the term $e_t \sim N(0, \sigma_e^2)$.

Although the presence of autocorrelation still provides me with unbiased estimate $\widehat{\beta}_1$, so that $\mathbb{E}(\widehat{\beta}_1) = \beta_1$, the standard error of the estimate is not unbiased. This means that the OLS estimate $\widehat{\beta}_1$ is inefficient and I cannot rely on ordinary test statistic (Nilsen, Time-series analysis. Basics, pp. 20-23).

Before testing for the presence of autocorrelation, one point should be made straight away. Researchers often assume strict exogeneity in the regressors of the model. This means that the zero conditional mean assumption stated in Subsection 4.2 holds. One particular characteristic of strict exogeneity is that it rules out the possibility of lagged dependent variables in the model. The one usually prefers to the scenario with strictly exogenous explanatory variables because of its relative simplicity compared to the scenario when the zero conditional mean assumption fails. Nevertheless, the latter scenario is more common, and in the vast majority of cases, the explanatory variables are not strictly exogenous. Moreover, I want to examine the presence of lagged dependent variables in my model. Hence, while testing for autocorrelation, I use the tests that do not require strict exogeneity in the regressors.

In order to test for autocorrelation, I use the test based on AR(1) serial correlation model for the error terms. The test includes the following stages:

- Firstly, I run the regression of historical electricity prices on historical temperature data and exchange rate. Previously, I have controlled the price of electricity and exchange rate for time trend.
- Secondly, I find the OLS residuals from the regression that was just run.

- Thirdly, I run the regression of the residual \widehat{u}_t on its lagged value \widehat{u}_{t-1} . I also add the monthly temperature means and exchange rates as my second and third explanatory variables. The inclusion of these regressors allows me to avoid the problem of strictly exogenous explanatory variables.
- Finally, I test for the presence of autocorrelation using t statistic. My null hypothesis is that there is no autocorrelation in the original model. The alternative hypothesis is that AR(1) autocorrelation is present (Wooldridge, pp. 409-411).

In case the autocorrelation in the model is detected by the test described above, I correct for it by using Cochrane-Orcutt (CO) procedure (Donald Cochrane, 1949). The one may refer CO procedure to the feasible generalized least squares (FGLS) estimation method with the specific way to estimate the correlation ρ . FGLS estimation is the way to estimate the least squares when variance and autocorrelation pattern is not known and therefore the transformation of the initial model is required. One specific characteristic of the CO procedure is that it omits the first observation.

CO estimation has the following stages:

- I repeat the first three steps from the test based on AR(1) autocorrelation described above.
- From the regression of residuals on their lagged values and other regressors, I find an estimate of $\hat{\rho}$. This is the slope coefficient next to the lagged values of residuals.
- Next, I transform all of the variables from the original regression. The transformation procedure presumes the creation of so-called quasi-differenced data based on dependent and independent variables. The formulas for quasi-differencing are as follows:

$$y_t^* = y_t - \hat{\rho}y_{t-1},$$

$$x_t^* = x - \hat{\rho}x_{t-1},$$

$$c_0^* = 1 - \hat{\rho},$$

where y_t^* is the rule for quasi-differencing the dependent variable, x_t^* is the rule for quasi-differencing the independent variables, and c_0^* stands for the constant term.

- Following that, the original regression is run, but with transformed variables. The intercept, however, is not valid and has to be found separately based on the value of the constant term β_0^* and the estimate of $\hat{\rho}$. The formula is the following: $\beta_0^* = \frac{c_0^*}{(1-\hat{\rho})}$. This concludes the first iteration from CO procedure.
- I repeat then the last three steps several times until my correlation coefficient does not change much from iteration to iteration (Nilsen, Corchrane Orcutt Manually, 2015).

The CO procedure is a good way to correct for autocorrelation of unknown structure. If I have an idea about the autocorrelation structure, the other procedure may be useful. In other words, if I really believe that it is reasonable to correct for AR(1) autocorrelation specifically, I can apply the following mathematical procedure:

$$y_t = \beta_0 + \beta_1 x_{t,1} + \beta_2 x_{t,2} + u_t,$$

$$y_{t-1} = \beta_0 + \beta_1 x_{t-1,1} + \beta_2 x_{t-1,2} + u_{t-1} \mid \times \rho \Rightarrow$$

$$\Rightarrow \rho y_{t-1} = \rho \beta_0 + \rho \beta_1 x_{t-1,1} + \rho \beta_2 x_{t-1,2} + \rho u_{t-1},$$

where index t represents time, ρ speaks about the relationship or correlation, the variable y represents electricity prices, u relates to residuals, and variables x_1 and x_2 stand for temperature and exchange rate respectively.

Next, I find the first difference and rearrange the resulting equation:

$$(y_t - \rho y_{t-1}) = \beta_0(1 - \rho) + \beta_1(x_{t,1} - \rho x_{t-1,1}) + \beta_2(x_{t,2} - \rho x_{t-1,2}) + (u_t - \rho u_{t-1}),$$

$$y_t = \beta_0(1 - \rho) + \beta_1 x_{t,1} - \rho \beta_1 x_{t-1,1} + \beta_2 x_{t,2} - \rho \beta_2 x_{t-1,2} + \rho y_{t-1} + e_t,$$

where $e_t = u_t - \rho u_{t-1}$, and e_t is independently and identically distributed $e_t \sim iid(0, \sigma_e)$

The last equation is my restricted model. Now, I define the unrestricted one:

$$y_t = \theta_0 + \theta_1 x_{t,1} + \theta_2 x_{t-1,1} + \theta_3 x_{t,2} + \theta_4 x_{t-1,2} + \theta_5 y_{t-1} + e_t,$$

where $\theta_1 = \beta_1$, $\theta_2 = -\rho \beta_1$, $\theta_3 = \beta_2$, $\theta_4 = -\rho \beta_2$, and $\theta_5 = \rho$.

I start with the unrestricted model, run regression, and find the values for θ_1 through θ_5 . Subsequently, I work with my restricted model. In particular, I use the special command in Stata that does both conducts nonlinear estimation for the least squares and fits the values of regression coefficients, so that after several iterations SSR is minimized.

In the end, I compare the coefficients from the unrestricted model with those from the restricted one. If they are similar, this means that the linear model and the non-linear model provide with similar outcomes (Nilsen, Time-series analysis. Basics, pp. 38-39).

Heteroskedasticity

Researchers deal with heteroskedasticity in time series when the error term does not have constant variance subject to independent variables, meaning that the variance of disturbances is different for every time period. Clearly, heteroskedasticity is the problem when Assumption 4 about homoskedasticity fails (Wooldridge, pp. 420-425). The problem may be detailed in the following way:

$$\text{Var}(u_t | x_{t,j}) = \sigma_t^2,$$

where the subscript t suggests that the error terms are heteroskedastic.

Heteroskedasticity leads to wrong estimation of the variance of the error term. Even though heteroskedastic errors are not biased and both R^2 and *adjusted* R^2 have the same meaning as in case of homoskedasticity, the one cannot do any statistical inference before the problem of heteroskedastic errors is solved. The reason for this is that heteroskedasticity affects the variance, so that the usual formulas for the calculation of variance are no longer valid. This in turn damages the test statistic – researcher can reach a wrong conclusion about statistical significance of the coefficients (Balsvik, Heteroskedasticity. ECN 402 - Part 14, 2015).

In order to test for heteroskedasticity, I use the Breusch-Pagan (BP) test (Trevor Stanley Breusch, 1979). This one has the null hypothesis that the error terms in the model are homoscedastic:

$$H_0: \text{Var}(u_t | x_{t,j}) = \sigma^2.$$

If the zero conditional mean assumption holds, I may rewrite the null hypothesis in the following way:

$$H_0: \mathbb{E}(u_t | x_{t,j}) = \mathbb{E}(u_t^2 | x_{t,j}) = \mathbb{E}(u_t^2) = \sigma^2$$

The expression stated above means that in case of H_0 is a correct hypothesis, the squared errors should be uncorrelated with the independent variables from the model. The alternative hypothesis allows in turn heteroskedasticity.

In my regression analysis, I apply Stata in order to test for heteroskedasticity. This influences the expression, but not the logic, of my null hypothesis. Since the squared errors are unobserved, I am using the squared residuals \widehat{u}_t^2 instead. In case of heteroskedastic errors, the squared residuals are the function of the independent variables:

$$\widehat{u}_t^2 = \omega_0 + \omega_1 x_{t,1} + \omega_2 x_{t,2} + v_t,$$

where the index t corresponds to time, the index j relating to particular explanatory variable, and v_t stands for the error terms. In the equation above, \widehat{u}_t^2 is the linear function of two independent variables.

The null hypothesis of homoskedasticity in the error terms is now the following:

$$H_0: \omega_1 = \omega_2 = 0.$$

The alternative hypothesis is that at least one coefficient does not equal zero. In order to test H_0 , I use F -test for the joint significance (Yamano, p. 4).

In the end, if heteroskedasticity is detected, I correct for it by using heteroskedasticity robust standard errors after the model is estimated by means of FGLS.

Test for functional form

For the study of causality between temperature variations and electricity prices, it is also crucial to examine whether the zero conditional mean assumption holds. As I have put it earlier, the violation of this assumption leads to endogenous regressors. These ones correlate with the errors in the model:

$$\text{Corr}(x_{t,j}, u_t) \neq 0, \forall j.$$

The index t stands for the time and the index j refers to the specific explanatory variable.

The presence of endogenous regressors speaks about a specification problem. One reason why a model may be incorrectly specified is that some variables are omitted. In case the regressand is a function of the omitted regressors, I say that the problem is in functional form misspecification (Tastan, pp. 2-4).

In my econometric analysis, I want to check whether I have specified my model correctly. If I have not, the endogenous regressors in my model will result in biased and inconsistent OLS estimators. Hence, I want specifically to check whether the existing model is optimal in terms of the number of regressors, or it lacks some polynomials of the regressand. This requires the comparison of two nested models – there are two models to compare, and one model is identical to the other one with the exception of a few additional variables. Considering this, the Ramsey's regression specification error test (RESET) is the right thing to do in my analysis as it suggests comparing nested models (Ramsey, 1969).

Let me assume the following model:

$$y_t = \beta_0 + \beta_1 x_{t,1} + \beta_2 x_{t,2} + \delta_1 \widehat{y}_t^2 + \delta_2 \widehat{y}_t^3 + u_t,$$

where the index t represents time, \widehat{y}_t^2 and \widehat{y}_t^3 stand for the polynomials of the fitted values from the regression of y_t on $x_{t,1}$ and $x_{t,2}$, and δ_1 with δ_2 correspond to the slope coefficients in front of the polynomials.

Let me think of the model above as of the unrestricted model representing the relationship between temperature fluctuations and electricity prices. The model includes two regressors. The part $y_t = \beta_0 + \beta_1 x_{t,1} + \beta_2 x_{t,2} + u_t$ represents in turn the restricted model without any nonlinear combination of the regressors.

In the RESET, the null hypothesis is that the restricted model is correct. The alternative hypothesis is that the unrestricted model is preferred.

The RESET test includes the following sequence of actions:

- Firstly, I estimate the restricted model and obtain the fitted values of \widehat{y}_t .
- Secondly, I take the fitted values to the second and third power. This will give me the polynomials from the unrestricted model.

-
- Finally, I estimate the unrestricted model and test whether the estimates of the slope coefficients in front of the polynomials are significantly different from zero. Here, I use the F -test for joint significance.

If the F -test shows that the estimates of the slope coefficients in front of the polynomials are significantly different from zero, I reject the null hypothesis that there is no functional form misspecification in the initial model in favor of the alternative hypothesis that I should control the model for additional nonlinearities (Balsvik, Specification problems. ECN 402 - Part 15A, 2015).

4.4 Model selection and empirical results

In this subsection, I am trying to find the optimal model using statistical inference. I include mathematical expressions of the models tested. I also provide with the output of my empirical analysis in the form of tables produced with the help of data analysis and statistical software, Stata. The analysis is based on the methodology described in Subsection 4.3.

The purpose of this study is to find the causality between air temperatures in the specified geographical area and electricity prices in the same region. The region of interest is Oslo, Norway. The correlation coefficient between the variable describing temperature monthly means, denoted by $Temperature_t$, and the variable containing historical power prices in Oslo, denoted further by $Oslo$ equals -0.54. Further, the correlation coefficient between $Temperature_t$, and the variable containing natural logarithms of historical power prices in Oslo, denoted further by $ln(Oslo)$ equals -0.53. These correlation coefficients indicate the inverse relationship between the two variables, so that lower temperatures correspond to higher prices. The correlation coefficient speaks about dependence, but cannot characterize “cause and effect” relationships. In order to find out whether the decrease in temperature really causes the increase in electricity prices, I need the inference with hypothesis test statistic.

To begin with, the plots from the previous subsection allow me to assume that some variable contain a time trend. Therefore, I have to check the variables whether the time trend is really the case. If it is, I have to detrend the data. The whole procedure has several stages. First, I declare that my variable $Date$ is a time series data. The variable describes the period of interest. I use $tsset$ command in Stata.

Secondly, I run a regression of the variable of interest on *Date*:

$$y_t = \widehat{\beta}_0 + \widehat{\beta}_1 t + \widehat{u}_t,$$

where y_t is the variable of interest and t stands for time.

I check the p -Value. If it shows statistical significance, meaning it is not higher than 0.05, I conclude that the data contains the time trend. If the p -Value is higher than 0.05, I conclude that there is no time trend in the data.

Finally, I obtain the linear prediction \widehat{y}_t for the regression just run. Using this prediction, I generate the new variable by subtracting \widehat{y}_t from y_t . The variable generated is the detrended variable of interest. I repeat the procedure for every variable. $Temperature_t$, for instance, showed the absence of time trend in the data, whereas all of the variables related to electricity prices, along with the exchange rate variable $\ln(NOK1EUR)_t$, strongly suggested time trend and therefore had to be detrended.

After the trend is removed, I search for optimal candidate model. I start with *Model 1* from Subsection 4.1. The equation bellow incorporates the estimators from Stata output in the equation that represents *Model 1*:

$$\ln(Oslo)_t = 0.194 - 0.0262 \times Temperature_t - 2.235 \ln(NOK1EUR)_t + \widehat{u}_t,$$

where index t stands for time and \widehat{u}_t refers to the error term.

The output of this regression is in the second column of *Table 4.1*. Here, around 33.9 percent of the variation in $\ln(Oslo)_t$ is explained. Moreover, both slope coefficients are significantly different from zero. This indicates that *Model 1* is good enough so far. It shows that the growth in the air temperature in Oslo by 1 degree Celsius causes approximately 2.62 percent decline in electricity price in the region. This is in agreement with my initial assumption: people tend to consume less electricity for heating as it gets warmer outside.

Although *Model 1* is good, I would like to check whether the explanatory power of the model increases after controlling for the set of variables characterizing the historical electricity prices in Kristiansand, Bergen, Trondheim and SE3. This is Model 2 I described in Subsection 4.1. I incorporate the estimators from Stata output in the model. This gives me the following equation:

$$\ln(Oslo)_t = \widehat{\beta}_0 + \widehat{\beta}_1 Temperature_t + \widehat{\beta}_2 \ln(NOK1EUR)_t + \widehat{\beta}_3 \ln(Kristiansand)_t + \widehat{\beta}_4 \ln(Bergen)_t + \widehat{\beta}_5 \ln(Trondheim)_t + \widehat{\beta}_6 \ln(SE3)_t + \widehat{u}_t,$$

where index t stands for time, \widehat{u}_t refers to the error term, and regressors $\ln(Kristiansand)_t$, $\ln(Bergen)_t$, $\ln(Trondheim)_t$, and $\ln(SE3)_t$ represent natural logarithms of the historical electricity prices in Kristiansand, Bergen, Trondheim, and SE3 respectively.

The regression output is provided in the third column of *Table 4.1*. I put the p -Values in parentheses under the estimates. As *Table 4.1* shows, the second candidate model, *Model 2*, explains 99 percent of the variance in the electricity prices in Oslo. The one should be suspicious when the coefficient of determination is this high. Along with the fact that the values of the slope coefficients in front of $\ln(NOK1EUR)_t$, $\ln(Trondheim)_t$, and $\ln(SE3)_t$ are statistically insignificant, the value of adjusted R^2 close to unity may indicate the problem of perfect collinearity, so that the Assumption 2 in Subsection 4.2 is violated. The issue is that the values of electricity prices in Oslo in *Model 2* can be computed based on the linear combination of the values of electricity prices in neighboring regions.

I may conclude that my initial idea to control for the laws of demand and supply on the power market in the Nordic countries does not increase the explanatory power of $Temperature_t$ as expected. Rather, it invalidates the model. I therefore refuse from *Model 2*, and decide to stand with *Model 1* so far.

Although *Model 1* is good, I would like to check whether the explanatory power of the model increases after including transmission capacities to the regression. This is *Model 3* from Subsection 4.1. The output is in the fourth column of *Table 4.1*. It is now the case that the slope parameter next to $\ln(NOK1EUR)_t$ is insignificant. Furthermore, Stata drops most of the estimates of transmission capacities. The only estimates for transmission capacities left are the ones for *no2no1* and *no5no1*, which characterize the transmissions from Bergen to Oslo and from Kristiansand to Oslo respectively. However, these estimates are statistically insignificant. Consequently, there is no sense to represent *Model 3* in the form of equation. The regression result indicates the problem of perfect collinearity and in turn the violation of *Assumption 2* in Subsection 4.2. I suspect the issue is that the variables representing transmission capacities lack dynamics over time – only small amounts of changes happen over the period of interest. This does not allow me to rely on regression results from *Model 3*. Hence, *Model 1* is preferable - it becomes the candidate model for further analysis.

Table 4.1 Estimates from the regressions of electricity prices in Oslo on air temperatures and other regressors

	(1) Model 1	(2) Model 2	(3) Model 3
Temperature, Celsius	-0.0262*** (0.000)	-0.00113*** (0.000)	-0.0270*** (0.000)
detrn_ln_nok1eur	-2.235** (0.041)	0.0279 (0.578)	-1.794 (0.106)
detrn_ln_kristiansand		0.707*** (0.000)	
detrn_ln_bergen		0.259*** (0.000)	
detrn_ln_trondheim		0.0514 (0.239)	
detrn_ln_se3		-0.0125 (0.761)	
no1no2, MW			0 (.)
no2no1, MW			-0.000830* (0.069)
no1no3, MW			0 (.)
no3no1, MW			0 (.)
no1no5, MW			0 (.)
no5no1, MW			0.000123* (0.098)
se3no1, MW			0 (.)
no1se3, MW			0 (.)
Constant	0.194*** (0.001)	0.00836*** (0.002)	2.523** (0.049)
R^2	0.365	0.999	0.408
Observations	53	53	53

p-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

In addition to time trend, it is necessary to control for seasonality in the model of interest. The one may suspect that either monthly changes in electricity price have different magnitude over a year and this magnitude depends on air temperature outdoors, or electricity price changes its value rapidly when the weather changes season to season. The latter one may be a logical thing to assume since when winter comes, for example, and it becomes colder outside in a very short time interval, the demand for electricity grows rapidly, because households consume more electricity for heating purposes. Simultaneously, power suppliers cannot react fast enough to the increase in demand, and thus the price for electricity grows. Another example to consider is the increase of power consumption in summer – the price can grow, because it becomes hot outside and people start using air conditioning.

In order control for this type of weather changes, I use qualitative information in the form of dummy variables. The method is straightforward. I create a couple of binary variables with only two possible values: arbitrary zero and one. My first dummy variable equals one if the month is one of the three winter months: December, January, or February. The value is set to be zero otherwise. The second dummy variable is one if the month is one of the three summer months: June, July, or August. It is zero otherwise.

Seasonal dummy variables when added to regression model as separate variables influence its intercept. In the context of my research, this means that when the appropriate season comes, the prices for electricity change instantly by some amount. Apart from dummy that influences the intercept in my candidate model, I want to control for dummy that influences the slope parameter next to $Temperature_t$. If such a dummy were statistically significant, the interpretation would be as follows: air temperature effects power price differently conditional on the season of a year. In order to control for dummy that influences the slope parameter, I generate a couple of interaction variables multiplying ordinary dummies on the independent variable of interest, which is $Temperature_t$ (Balsvik, 2015).

Table 4.2 provides with the regression results for four cases. These four cases are as follows: candidate model plus dummy variable indicating summer, candidate model plus dummy variable indicating winter, candidate model plus interaction term for summer, and candidate model plus interaction term for winter. As the table shows, neither of the dummies and interaction terms is statistically significant. Furthermore, running regression on all of four additional variables and testing for the joint significance afterwards leads me to the result when

I cannot reject the null hypothesis that all of the four variables should be equal to zero. This states that seasonality is not the case in my model.

Table 4.2 Estimates from the regressions of electricity prices in Oslo on air temperatures, exchange rates and seasonal dummy variables

	(1) Seasonality: summer	(2) Seasonality: winter	(3) Seasonality: summer (interaction term)	(4) Seasonality: winter (interaction term)
Temperature	-0.0227*** (0.005)	-0.0276*** (0.001)	-0.0247*** (0.003)	-0.0275*** (0.000)
Exchange rate in logs	-2.259** (0.040)	-2.174* (0.054)	-2.244** (0.042)	-2.410** (0.038)
dummy for summer	-0.0761 (0.543)			
dummy for winter		-0.0311 (0.803)		
interaction term for summer			-0.00194 (0.803)	
interaction term for winter				0.0159 (0.631)
Constant	0.187*** (0.001)	0.211** (0.021)	0.191*** (0.001)	0.208*** (0.001)
R2	0.369	0.365	0.365	0.368
Observations	53	53	53	53

p-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

In fact, the absence of seasonality in my model does not correspond to my initial expectations. Before the model was run in Stata, I had suggested that the correction for summer season is not necessary. Norway is located up north in Europe and this fact has resulted in the maximum monthly mean of 20.8 degrees Celsius in my data set. This kind of temperature does not presume that Norwegians use a lot of air conditioning.

Nevertheless, I expected that the correction for winter season would be required. Norway uses solely electricity for heating. Heating is turned on when winter comes. It was therefore logical to assume that winter seasonality presents and I need to include it in my regression model.

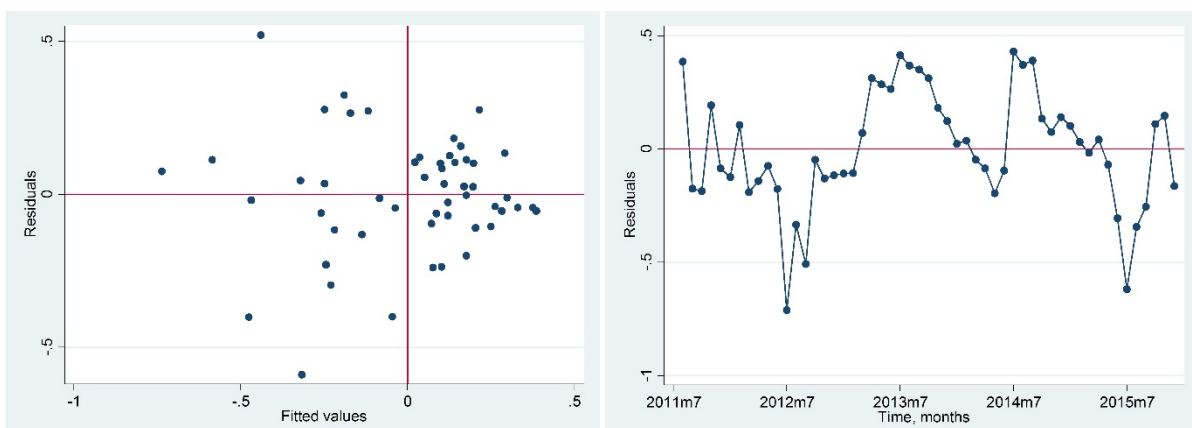
The latter point is eventually not the case, though. I can explain the result as follows. The corrections for seasons are odd, because $Temperature_t$ already includes seasonality in itself. *Figure 4.2* plots the series of air temperatures in Oslo – historical monthly means. The series plotted has the structure of cosinusoid, meaning it has two extremums per year: maximum and

minimum. These extremums repeat every year. Moreover, air temperature fluctuates during the year towards either maximum or minimum. In general, the whole series can be replaced by the comparable cosinusoid and still show similar impact on electricity prices. Hence, I do not really need to correct for seasonality, as $Temperature_t$ already includes such a correction.

As for now, I have proven that Assumption 2 in my candidate model, *Model 1*, is not violated. Next, I want to check whether the model violates other assumptions from Subsection 4.2. In particular, Assumption 3, 4 and 5 are crucial. These are the assumptions for zero conditional mean, homoskedasticity and no serial correlation respectively.

Referring to Assumption 5, I check for the presence of autocorrelation using the test based on AR(1) serial correlation model for the error terms. I run the regression of residuals from my candidate model on their lagged values and the independent variables. I find the value of the correlation coefficient $\hat{\rho}$ that equals 0.63. This one represents the correlation between the residuals from my candidate model and their lagged values. The coefficient is statistically significantly different from zero. This speaks about the presence of autocorrelation – I reject the hypothesis of no serial correlation. In addition, *Figure 4.5* (on the left) shows the plot of the residuals from *Model 1* against their lagged values. Specifically, the comparison is between the residuals at time t and the residuals at time $t-1$. Most of the observations are located either on the top right quarter, or on the bottom left quarter. This is typical for positive autocorrelation. Moreover, *Figure 4.6* (on the right) plots the residuals from *Model 1* as a function of time and it reflects autocorrelation too.

Figure 4.5-4.6 Residuals against the lagged values; residuals as a function of time



As serial correlation appears to be an issue in this particular case, it is important to correct for it in the regression model. In Subsection 4.3, I describe CO correction procedure. This is a

valid instrument if the structure of serial correlation is unknown. The procedure presumes the transformation of dependent and independent variables through generating quasi-differenced data. For CO correction, I rely on formulas I mentioned earlier in Subsection 4.3.

After quasi-differencing is done, I run the regression with the transformed variables. The output is free of serial correlation. *P*-Values are in parentheses. I provide it in *Table 4.3* below. According to the method, I calculate the intercept separately using the formula from Subsection 3.2. It is equal to 0.49. As to the values of the slope parameters, these are -0.0281 for $Temperature_t$ and -2.716 for $\ln(NOK1EUR)_t$. However, the coefficient next to the exchange rate delta is now statistically insignificant.

Table 4.3 Regression of the quasi-differenced data - CO procedure

	(1) Model 1 + correction for autocorrelation
Temperature	-0.0281*** (0.000)
Exchange rate in logs	-2.716 (0.105)
Constant	0.180** (0.046)
R^2	0.272
Observations	52

p-values in parentheses

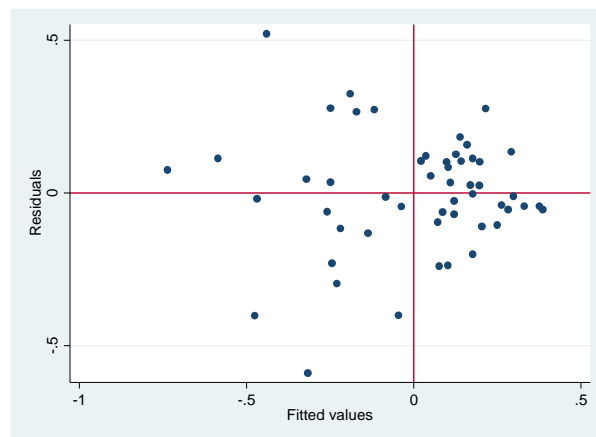
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

In Subsection 4.3, I have also mentioned an alternative procedure that may be used in order to correct for autocorrelation. That one is appropriate for the cases when the one is certain about autocorrelation structure in the model. The procedure presumes the comparison of coefficients from unrestricted and restricted model. Although I do not put much attention to the alternative procedure in this paper, I have done it in Stata with the only purpose to check my output from CO correction procedure. The result is that the coefficients in the restricted model are nearly the same as those in the unrestricted one, so that that the linear model and the non-linear model provide with similar outputs. This proves the output of CO correction procedure and supports the hypothesis that AR(1) autocorrelation structure is typical for my model (Nilsen, Corchrane Orcutt Manually, 2015).

After the problem of autocorrelation is solved, I focus on Assumption 4, which assumes homoskedasticity. To begin with, informal diagnostics may help to detect heteroskedasticity

in the model. I therefore produce a plot where I put the residuals from my candidate model against the fitted values. This is *Figure 4.7*. Based on the plot, it is difficult to conclude the presence of heteroskedastic errors, as it is hard to detect any particular pattern on the plot. Nevertheless, I am a bit suspicious about a higher concentration of observations when fitted values positive compared to when they are negative. Thus, I need to proceed with formal tests for heteroskedasticity.

Figure 4.7 The candidate model: residuals against fitted values



As described in Subsection 4.3, I apply BP test (Trevor Stanley Breusch, 1979). My null hypothesis is that the error terms in my candidate model are homoscedastic. The test command in Stata is *estat hettest*. It provides me with the test statistic that follows a chi-square distribution and equals 10.94, along with the *p*-Value of 0.0009. Because of the *p*-Value lower than 0.05, I reject the null hypothesis of homoskedasticity. I conclude that the variance in my candidate model is affected by heteroskedasticity. This means that I cannot calculate the variance applying the usual formulas.

I solve the problem of heteroskedasticity by means of heteroskedasticity robust standard errors. The regression output with heteroskedasticity robust standard errors (the errors are in parentheses) is shown in *Table 4.4* below.

Table 4.4 Correction for heteroskedasticity

	(1) Model 1 + correction for autocorrelation + correction for heteroskedasticity
Temperature	-0.0281*** (0.00678)
Exchange rate in logs	-2.716 (1.646)
Constant	0.180** (0.0879)
R^2	0.272
Observations	52

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

In contrast with *Table 4.3*, the standard errors in *Table 4.4* are larger. This does not change the values of the coefficients or their significance, though. Truly, the slope parameter for $Temperature_t$ is -2.0281 and it is statistically significantly different from zero. Simultaneously, the slope parameter for exchange rate is -2.716 and it is not statistically significantly different from zero.

Next, I turn my attention to Assumption 3, or zero conditional mean assumption. If the assumption holds, I can be sure that the slope coefficient represents the causal relationship between the independent variable it precedes and the dependent variable (Balsvik, The simple regression model. The zero conditional mean assumption, 2015). This is important, because my major goal in this empirical research is to examine the causality between weather and power prices.

The underlying idea is to check whether the candidate model is specified correctly. If it is not, the endogeneity problem caused by the violation of Assumption 3 results in biased and inconsistent OLS estimators. In this particular case, the term “correct specification” corresponds to the following dilemma: is the model optimal in terms of the number of regressors, or some polynomials of the dependent variable should be included? To answer this question, I conduct the RESET test (Ramsey, 1969). I have described the test procedure in Subsection 4.3 of this paper.

My null hypothesis is that the polynomials of the dependent variable equal zero, so that my current candidate model does not contain any misspecification of its functional form. The

2.81 percent decline in electricity price in the region. This result perfectly fits to what I expected at the time I started my research. The coefficient of determination, R^2 , equals 0.272. This means that the model describes nearly 27.2 percent of the total variation.

5. Conclusion

This empirical study of temperature and electricity price is to argue that the causality between the two variables exists, which is a prerequisite for the establishment of the weather derivatives market. My final model proves my initial assumptions that the causal relationship exists. Specifically, the regression of the time series for the power price in Oslo bidding area on the time series of the air temperature in the capital of Norway, shows that one degree Celsius growth in the air temperature in Oslo area causes 2.81 percent decrease in electricity price in the region, while controlling for the time series representing the exchange rate for EUR. This result suggests that Norwegian companies that are exposed to unanticipated fluctuations in air temperature could consider the weather-indexed derivatives as an attractive tool to mitigate their temperature-related risks.

The processes that underlie the variables of interest, electricity price and temperature, are very different. As I have mentioned in Subsections 2.2 and 2.3, the power price is settled overwhelmingly on the competitive basis in the Nordic countries. It depends on the three major factors: supply, demand, and transmission capacity. Regarding the process that underlies the series for air temperature, it may be described as cosinusoid-based. The observations of air temperature basically form the series of repeating cycles with the length equal to one year. The thesis has therefore the intention of showing how the two different processes can be examined by means of various econometric methods described in Subsection 4.3. An interesting finding of my work is that the model does not require controlling for seasonality, because the series of historical air temperature observations already includes seasonality in itself. I have found out that the whole series can be replaced by the comparable cosinusoid and still show similar impact on electricity prices.

In addition, I have managed to explain a good deal of the total variation in my model. The total variation explained accounts for just above 27 percent. Nevertheless, the model can be improved. Indeed, one particular way to improve my model would be to control for bulk electricity storage. In Subsection 2.4 of this paper, I have explained a crucial role of this technology as the battery which allows to store electricity produced by renewables at times when the demand is low and sell it in future at higher price when the demand is high. I have also mentioned that Norway is the country that could benefit from energy storage the most, since in controls nearly 50 percent of the European reservoir capacities. For this reason, controlling for energy storage is a logical thing to do.

Specifically, I recommend adding the explanatory variable that includes the time series for reservoir levels in Norway. The one should be careful with this variable, however. Although the time series for reservoir levels captures the idea of bulk energy storage well, there are several pitfalls that could complicate the study very much. Firstly, the reservoirs are spread across the country. Transmission capacity constraints among various bidding areas would in turn make the reservoirs located far from Oslo irrelevant. Secondly, the reservoirs in Norway are managed by different companies. Every energy company decides on how and when to either pump or release water by itself using its own optimization model.

All of this should be taken into account while controlling for bulk energy storage. The pitfalls associated with the reservoir levels as an explanatory variable is the reason why I have not included this variable in my model. The modified model which controls for energy storage should be the subject of a separate empirical research.

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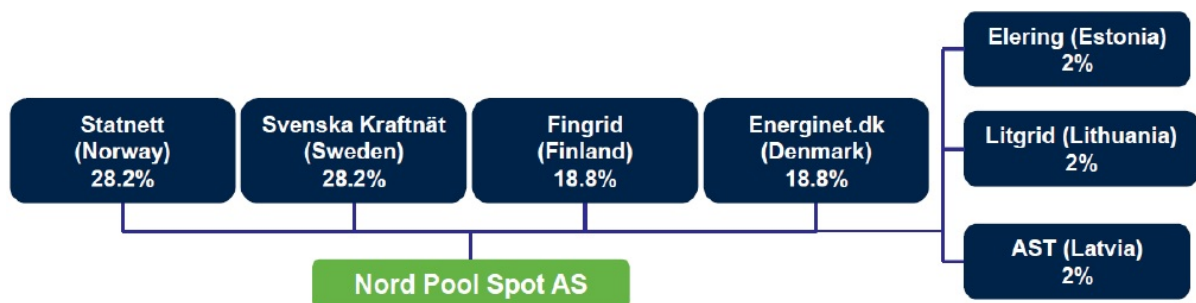
Appendices

Appendix 1. Energy consumption and costs for manufacturing, mining and quarrying

	Total energy consumption		Energy costs	
	GWh	Percent	NOK million	Percent
	2014	Δ	2014	Δ
Manufacturing, mining and quarrying	76983	-1.0	19 699	-2.2
Mining and quarrying	1 606	-7.5	909	-13.8
Manufacture	75 376	-0.9	18 790	-1.5
Manufacture of food products and beverages	4 795	7.8	2 389	2.6
Wood and wood products	1 683	-2.9	467	1.3
Paper and paper products	4 509	-26.4	1 179	-3.8
Refined petro., chemicals, pharmac.	25 128	0.5	4 082	-1.9
Rubber, plastic and mineral prod.	4 448	-8.1	1 442	-13.1
Basic metals	31 304	3.0	7 314	1.0
Manufacturing n.e.c.	3 509	-0.8	1 919	-4.2

Source: Statistisk sentralbyrå. Statistics Norway

Appendix 2. Ownership structure of Nord Pool



Source: Nord Pool company presentation

Appendix 3. CME – Weather products summary

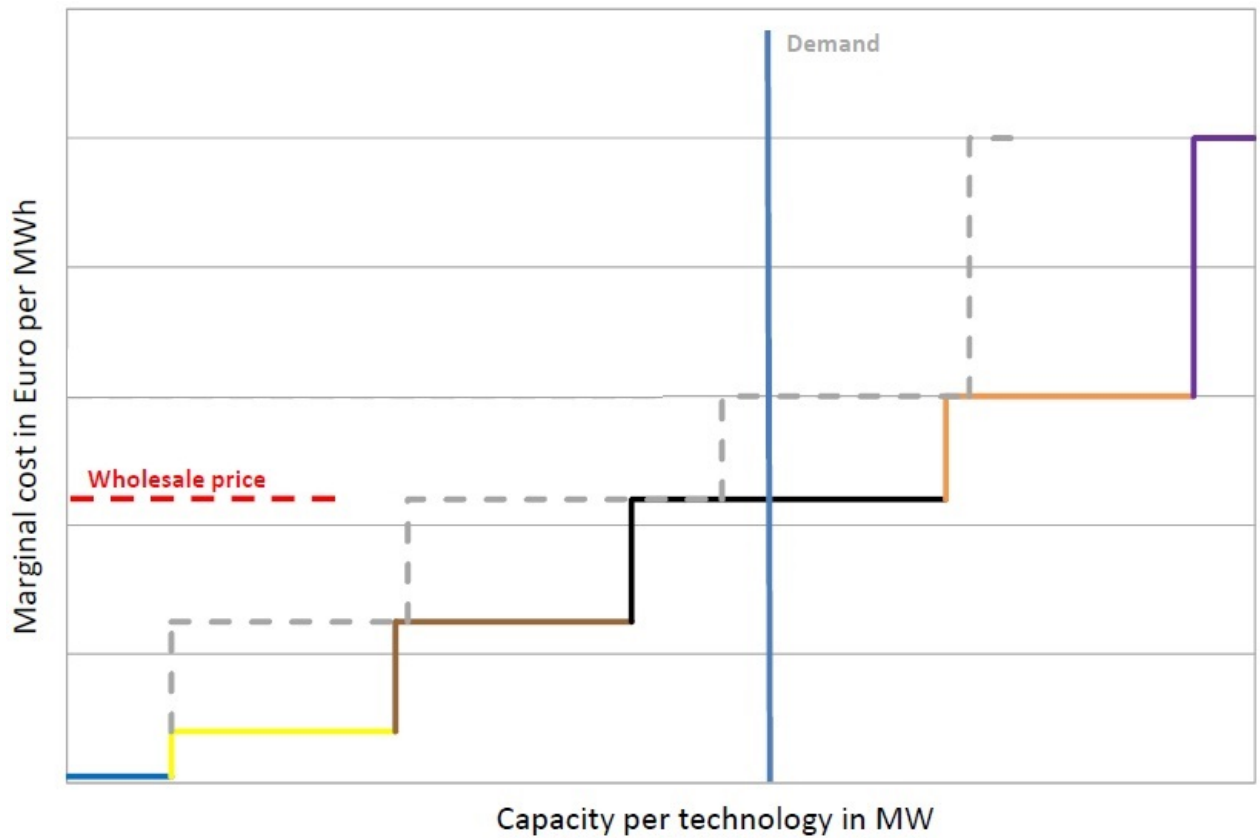
City	HDD CODE		CDD CODE		Monthly HDD		Monthly CDD (CAT for London & Amsterdam)		Monthly Futures		Seasonal HDD*		Seasonal CDD** (CAT for London & Amsterdam)	
	H4	H2	K4	K2	Yes	Yes	Yes	Yes	Yes	Yes	Nov-Mar / Dec-Feb	Nov-Mar / Dec-Feb	Jul-Aug / May-Sep	Jul-Aug / May-Sep
New York	H4	H2	K4	K2	Yes	Yes	Yes	Yes	Yes	Yes	Nov-Mar / Dec-Feb <td>Nov-Mar / Dec-Feb <td>Jul-Aug / May-Sep</td> <td>Jul-Aug / May-Sep</td> </td>	Nov-Mar / Dec-Feb <td>Jul-Aug / May-Sep</td> <td>Jul-Aug / May-Sep</td>	Jul-Aug / May-Sep	Jul-Aug / May-Sep
Chicago	H1	H3	K1	K3	Yes	Yes	Yes	Yes	Yes	Yes	Nov-Mar / Dec-Feb <td>Nov-Mar / Dec-Feb <td>Jul-Aug / May-Sep</td> <td>Jul-Aug / May-Sep</td> </td>	Nov-Mar / Dec-Feb <td>Jul-Aug / May-Sep</td> <td>Jul-Aug / May-Sep</td>	Jul-Aug / May-Sep	Jul-Aug / May-Sep
Atlanta	H5	H7	K5	K7	Yes	Yes	Yes	Yes	Yes	Yes	Nov-Mar / Dec-Feb <td>Nov-Mar / Dec-Feb <td>Jul-Aug / May-Sep</td> <td>Jul-Aug / May-Sep</td> </td>	Nov-Mar / Dec-Feb <td>Jul-Aug / May-Sep</td> <td>Jul-Aug / May-Sep</td>	Jul-Aug / May-Sep	Jul-Aug / May-Sep
Cincinnati	H0	H6	K0	K6	Yes	Yes	Yes	Yes	Yes	Yes	Nov-Mar / Dec-Feb <td>Nov-Mar / Dec-Feb <td>Jul-Aug / May-Sep</td> <td>Jul-Aug / May-Sep</td> </td>	Nov-Mar / Dec-Feb <td>Jul-Aug / May-Sep</td> <td>Jul-Aug / May-Sep</td>	Jul-Aug / May-Sep	Jul-Aug / May-Sep
Dallas	HQ	H8	KQ	K8	Yes	Yes	Yes	Yes	Yes	Yes	Nov-Mar / Dec-Feb <td>Nov-Mar / Dec-Feb <td>Jul-Aug / May-Sep</td> <td>Jul-Aug / May-Sep</td> </td>	Nov-Mar / Dec-Feb <td>Jul-Aug / May-Sep</td> <td>Jul-Aug / May-Sep</td>	Jul-Aug / May-Sep	Jul-Aug / May-Sep
Sacramento	D0	D6	G0	G6	Yes	Yes	Yes	Yes	Yes	Yes	Nov-Mar / Dec-Feb <td>Nov-Mar / Dec-Feb <td>Jul-Aug / May-Sep</td> <td>Jul-Aug / May-Sep</td> </td>	Nov-Mar / Dec-Feb <td>Jul-Aug / May-Sep</td> <td>Jul-Aug / May-Sep</td>	Jul-Aug / May-Sep	Jul-Aug / May-Sep
Las Vegas	D2	D8	G2	G8	Yes	Yes	Yes	Yes	Yes	Yes	Nov-Mar / Dec-Feb <td>Nov-Mar / Dec-Feb <td>Jul-Aug / May-Sep</td> <td>Jul-Aug / May-Sep</td> </td>	Nov-Mar / Dec-Feb <td>Jul-Aug / May-Sep</td> <td>Jul-Aug / May-Sep</td>	Jul-Aug / May-Sep	Jul-Aug / May-Sep
Minneapolis														
London														
Amsterdam														

City	HDD CODE		CDD CODE		Monthly HDD Option		Monthly CDD Option (CAT London & Amsterdam)		Monthly Strip Option		Seasonal HDD Option		Seasonal CDD Option** (CAT for London & Amsterdam)	
	H4	H2	K4	K2	Yes	Yes	Yes	Yes	Yes	Yes	Nov-Mar / Dec-Feb	Nov-Mar / Dec-Feb	Jul-Aug / May-Sep	Jul-Aug / May-Sep
New York	H4	H2	K4	K2	Yes	Yes	Yes	Yes	Yes	Yes	Nov-Mar / Dec-Feb <td>Nov-Mar / Dec-Feb <td>Jul-Aug / May-Sep</td> <td>Jul-Aug / May-Sep</td> </td>	Nov-Mar / Dec-Feb <td>Jul-Aug / May-Sep</td> <td>Jul-Aug / May-Sep</td>	Jul-Aug / May-Sep	Jul-Aug / May-Sep
Chicago	H1	H3	K1	K3	Yes	Yes	Yes	Yes	Yes	Yes	Nov-Mar / Dec-Feb <td>Nov-Mar / Dec-Feb <td>Jul-Aug / May-Sep</td> <td>Jul-Aug / May-Sep</td> </td>	Nov-Mar / Dec-Feb <td>Jul-Aug / May-Sep</td> <td>Jul-Aug / May-Sep</td>	Jul-Aug / May-Sep	Jul-Aug / May-Sep
Atlanta	H5	H7	K5	K7	Yes	Yes	Yes	Yes	Yes	Yes	Nov-Mar / Dec-Feb <td>Nov-Mar / Dec-Feb <td>Jul-Aug / May-Sep</td> <td>Jul-Aug / May-Sep</td> </td>	Nov-Mar / Dec-Feb <td>Jul-Aug / May-Sep</td> <td>Jul-Aug / May-Sep</td>	Jul-Aug / May-Sep	Jul-Aug / May-Sep
Cincinnati	H0	H6	K0	K6	Yes	Yes	Yes	Yes	Yes	Yes	Nov-Mar / Dec-Feb <td>Nov-Mar / Dec-Feb <td>Jul-Aug / May-Sep</td> <td>Jul-Aug / May-Sep</td> </td>	Nov-Mar / Dec-Feb <td>Jul-Aug / May-Sep</td> <td>Jul-Aug / May-Sep</td>	Jul-Aug / May-Sep	Jul-Aug / May-Sep
Dallas	HQ	H8	KQ	K8	Yes	Yes	Yes	Yes	Yes	Yes	Nov-Mar / Dec-Feb <td>Nov-Mar / Dec-Feb <td>Jul-Aug / May-Sep</td> <td>Jul-Aug / May-Sep</td> </td>	Nov-Mar / Dec-Feb <td>Jul-Aug / May-Sep</td> <td>Jul-Aug / May-Sep</td>	Jul-Aug / May-Sep	Jul-Aug / May-Sep
Sacramento	D0	D6	G0	G6	Yes	Yes	Yes	Yes	Yes	Yes	Nov-Mar / Dec-Feb <td>Nov-Mar / Dec-Feb <td>Jul-Aug / May-Sep</td> <td>Jul-Aug / May-Sep</td> </td>	Nov-Mar / Dec-Feb <td>Jul-Aug / May-Sep</td> <td>Jul-Aug / May-Sep</td>	Jul-Aug / May-Sep	Jul-Aug / May-Sep
Las Vegas	D2	D8	G2	G8	Yes	Yes	Yes	Yes	Yes	Yes	Nov-Mar / Dec-Feb <td>Nov-Mar / Dec-Feb <td>Jul-Aug / May-Sep</td> <td>Jul-Aug / May-Sep</td> </td>	Nov-Mar / Dec-Feb <td>Jul-Aug / May-Sep</td> <td>Jul-Aug / May-Sep</td>	Jul-Aug / May-Sep	Jul-Aug / May-Sep
Minneapolis														
London														
Amsterdam														

Please note that seasonal strips are limited to the specific terms described above. Customization of strips is no longer available. Cities remaining seasonal strips are limited to the specific terms of Nov-Mar & Dec-Feb for HDD and Jul-Aug & May-Sep for CDD/CAT

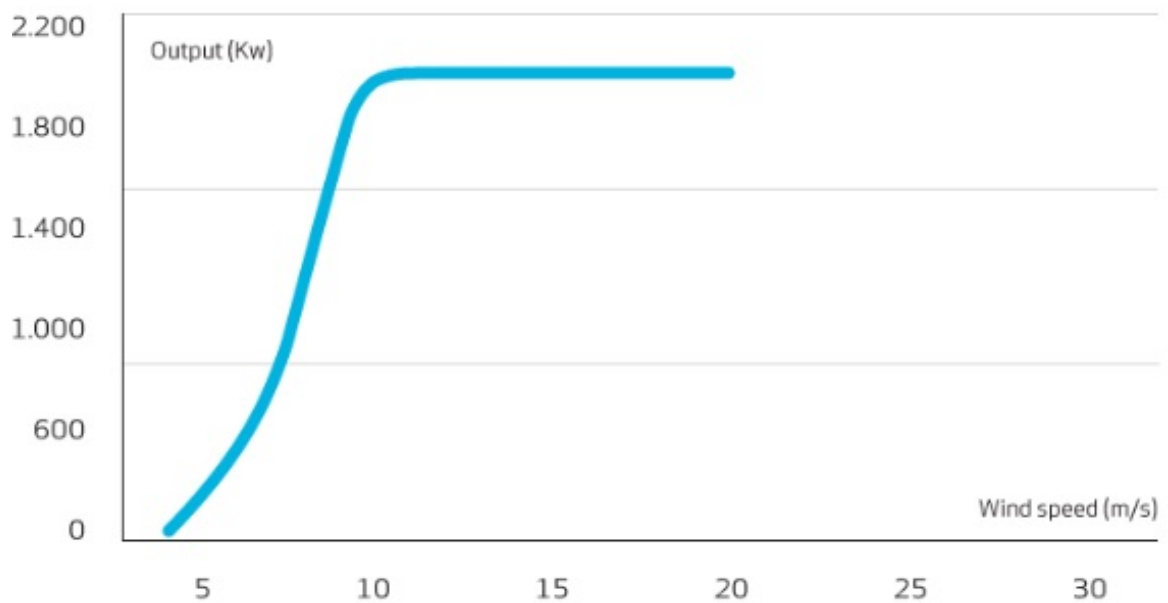
Source: CME Group (CME Group, 2016)

Appendix 4. German merit-order curve



Source: Ketterer (Ketterer, p. 26)

Appendix 5. Power curve of a typical wind turbine



Source: Vestas

Appendix 6. Organization of Nordic transmission system

<i>Time</i>	<i>Direction</i>	<i>From (MW)</i>	<i>To (MW)</i>	<i>Reason</i>
December 2013	Bergen-Oslo	700	3500	NA
December 2013	Oslo-Bergen	650	300	NA
December 2013	Kristiansand-Oslo	2900	3200	NA
December 2013	Oslo-Kristiansand	1700	2200	NA
December 2014	Bergen-Oslo	3500	3900	New system protection scheme
December 2014	Kristiansand-Oslo	3200	3500	Installation of new reactive components

Source: European Network of Transmission System Operators for Electricity (ENTSOE)

Appendix 7. Stata do file: the choice between y- and ln(y)-models

```

* Regressand in levels:  reg oslo temperaturemonthlymean ln_nok1eur

* Regressand in logs:   reg ln_oslo temperaturemonthlymean ln_nok1eur

* Step 1:
quietly reg ln_oslo temperaturemonthlymean ln_nok1eur
// Estimation of the log(y) model.
predict hat_logs // I am getting the fitted values here.

* Step 2:
gen hat_m=exp(hat_logs)
// Here, I am generating the following variable:
// m=exp(log(y)).

* Step 3:
quietly reg oslo hat_m, noc // I am regressing y on m. I am dropping the intercept.
predict tilde_oslo // I am saving the fitted values from the regression above.

* Step 4:
corr oslo tilde_oslo // I am looking for the correlation coefficient between
// the fitted values from the previous step and y

* Step 5:
display 0.7239^2 /
// I put the correlation coefficient to the power of two. Compare this with the adjusted R^2 from
// the regression where the dependent variable does not contain logarithm.
// Why not R^2? The difference between R^2 and adjusted R^2 is that the former one presumes
// that all of regressors have the explaining power in terms of the variation in the regressand.
// Adjusted R^2, alternatively, focuses only on the regressors that have the causal influence on
// the regressand.
// My final model includes two regressors with the only one which is statistically significant.

* Conclusion
// The model where the regressand in in logs is preferred: 0.52403121 > 0.5218

```