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More flexibility in store?

A study of the development of volatility and extreme prices in the Dutch electricity markets between 2010 and 2020, and the potential role of energy storage

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Abstract

In order to limit the amount of emissions from electricity production the Netherlands is integrating increasing amounts of renewable energy sources into the electricity grid. These changes to the electricity mix bring about effects on the flexibility of the electricity system, because renewable energy sources are less predictable and less flexible than conventional sources. Noticeable signs of increasing inflexibility of electricity systems are more price volatility and the occurrence of more extreme price spikes. Increasing inflexibility and its effects can have a negative impact on most electricity market actors. A solution to bring more flexibility into the electricity grid is energy storage. Operators of such facilities can profit from the volatility and extreme prices by arbitraging the electricity market. This thesis studies whether the Dutch day-ahead and imbalance market have become more volatile and have seen more extreme prices in the period between 2016 and 2020 compared to the period from 2010 to 2015. In the latter half of the decennium the growth of renewable energy sources has been stronger compared to the first half. Furthermore, additional analyses are performed to determine the drivers of the price movements in the Netherlands, with a different dataset ranging from 2015 until 2020. This thesis finds findings contrary to most of the literature concerned with electricity price dynamics, namely that the volatility has decreased in recent years in the day-ahead market. In the imbalance market no significant change in the last 5 years was found. From the findings of this thesis, it can be concluded that despite the growth of inflexible renewable sources the Dutch electricity markets have not become more volatile in recent years. Implying that the possibilities for energy storage facilities to profit from more volatility and more extreme prices has not increased due to higher revenue potential.

JEL classification

C12, C20, C21, Q41, Q42

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1 Introduction

In order to keep global warming below a 2 degrees Celsius rise, the emittance of greenhouse gases must be decreased (RES, 2019). Because electricity generation causes approximately 20 percent of greenhouse emittance in the Netherlands (Rooijers & Naber, 2019). To limit the emittance of greenhouse gases a major shift in the way electricity is produced is necessary. Therefore, the Netherlands is transitioning towards renewable forms of electricity production. The introduction of renewable energy requires more flexibility from the electricity system, because it must adapt to the intermittency and weather dependency of renewable sources. Providing sufficient flexibility is difficult for most electricity markets. There are multiple reasons for this: the inelasticity of electricity demand, the underdevelopment of sufficient (carbon neutral) flexibility sources such as energy storage and a decreasing desirability for conventional peak power due to its high greenhouse gas emissions (Huisman, Kyritsis, & Stet, 2020). Hence, due to the shift towards more renewables and fewer conventional power sources in the Dutch electricity mix, the electricity supply is becoming less flexible. Inflexibility in electricity markets shows through increased volatility of prices (Rai & Nunn, 2020) and, through the occurrence of extremer prices when supply and demand are in mismatch (Huisman et al., 2020). This poses problems for generators of electricity as well as buyers of electricity such as utility companies for their operations in the market. It also leads to problems for grid operators and the government who try to make the market more flexible and let it operate as efficiently as possible.

Inflexibility is not only a problem for the Dutch government but also for most other parties involved in the Dutch electricity market (Van Hout, Koutstaal, Ozdemir, & Seebregts, 2014). Increasing inflexibility can also create opportunities for real options that can provide this missing flexibility. Of such flexibility options energy storage is theoretically the best option (Naseri, Ghiassi-Farokhfal, & Collins, 2020), as it can both supply and demand electricity from the grid (Cebulla, Haas, Eichman, Nowak, & Mancarella, 2018). Because the costs of storage options are decreasing fast, it is getting near to be on parity with other flexibility sources (Comello & Reichelstein, 2019; Henze, 2019; Schmidt, Melchior, Hawkes, & Staffell, 2019). In California, Germany and Australia there are already increasing amounts of energy storage, that are not pumped hydro, added to the electricity grids (Mejia & Kajikawa, 2020). In the Netherlands the roll out of energy storage facilities has been modest so far. Some parties call for subsidies to speed up the introduction of more energy storage in the Netherlands (Wiebes, 2020). Especially because in some countries this already takes place to great effect (Figgener et al., 2020; Varghese & Sioshansi, 2020). Before policies to support flexibility, options may be instituted, it is important to determine how the inflexibility of the electricity market in the Netherlands has been developing (Hoogland, Smit, Moerenhout, & Bolscher, 2019; Huisman et al., 2020). Those developments will determine the value of real options and subsequently will indicate whether policy changes are warranted.

1.1 Problem statement

This thesis aims to find out whether the Dutch electricity markets, balancing and wholesale, have becoming less flexible. Inflexibility results in higher volatility of prices and more price spikes according to researchers (Dong et al., 2019; Ketterer, 2014; Rintamäki, Siddiqui, & Salo, 2017). These effects can be turned to profit by providers of flexibility such as energy storage operators. By studying electricity price characteristics in the Dutch electricity market from 2010 until September 2020 it can be analyzed whether Dutch electricity markets have become less flexible. It is investigated whether inflexibility increased faster in the latter half of the decennium. The choice to split the period of eleven years in half is motivated by the fact that from 2016 the largest quantities of renewable wind and solar energy were added to the Dutch electricity grid. So, this thesis will be centered around answering the following thesis statement:

Dutch electricity markets have become less flexible in the last decennium especially since 2016, noticeable through increasing price volatility and more extreme prices, those effects cause problems for the functioning of the Dutch electricity markets.

This thesis aims to clarify the fundamentals of the Dutch energy market and the development of its price characteristics. Therewith, it complements the established literature on changing electricity prices and the occurrence of spikes. Furthermore, the findings of this thesis can provide more insight into price fundamentals of the different Dutch electricity markets. Storage facility owners can use these insights to make improved forecasts for the determination of their trading and operation strategies. It can also be of help to investors and the government in the decision-making process concerning investments in new flexibility options. This will help the energy transition in meeting the objective of zero emissions from electricity production.

1.2 Scientific relevance

This thesis will focus on the combination of volatility and extreme prices inducing effects and storage related issues of renewable energy. Currently, this combination is not researched which makes this specific set up a novel approach. Although most economic studies on the price effects of renewable energy mention their implications for storage, they do not have it as their main focus point (Rintamäki et al., 2017). Furthermore, empirical research studying energy storage and its economics is limited (Azhgaliyeva, 2019). Most studies concerning energy storage focus on the viability of storage are based on simulations and optimizations of storage facilities using limited amounts of historical data and are overall more application focused. The focus on the opportunities for a storage application with a focus on the Netherlands, based on the fundamental price effects of increasing renewable penetration, is novel to academic research. An added benefit of this is that such insights are rarely publicly available (Staffell & Rustomji, 2016). While historical patterns are not expected to hold into the future, this thesis and its analyses can help with a better understanding of the markets studied.

By focusing on the changing dynamics of prices in the past years this thesis aims to study whether electricity markets are becoming less flexible. By studying the fundamental developments of electricity prices, the possibilities for storage facilities can be investigated. To date the number of studies focusing on the price effects of renewables on Dutch electricity prices is limited. Mulder and Scholtens (2013) published an influential paper that focused on renewable penetration with a dataset ranging from 2006 until 2011. They did not study volatility as a separate variable. Although some studies focus on multiple countries (Erdogdu, 2016; Johnson & Oliver, 2019) include the Netherlands. There are few recent studies that specifically study electricity price volatility and extreme prices in the Netherlands. There are studies that focus on the optimization of energy storage systems in the Dutch electricity market, but these studies have a more technical and engineering focus than this thesis (Terlouw, AlSkaif, Bauer, & van Sark, 2019; van Westering & Hellendoorn, 2020).

Besides, the addition to the recent studies on the price effects of renewable energy production could be useful to further improve the integration of larger shares of renewables. Despite the fact that analysis of past trends is by no means an explanation for future trends. It does serve as a way of understanding the current market conditions and could help to improve future market developments. With the application of more recent data and a proven relation in other markets, this thesis is an addition to the field. Because it investigates the price formation process and explores the potential further development possibilities of electrical storage facilities. Also, its relevancy is amplified by the current materialized interest that policymakers show in supporting storage as a source of flexibility (Abrell, Rausch, & Streitberger, 2019; Wiebes, 2020).

2 Theoretical framework

2.1 Electricity in the Netherlands

2.1.1 Energy transition

Currently the Netherlands is in the middle of a transition towards a less carbon intensive energy infrastructure. Concrete goals for this transition were first laid out in the Dutch climate agenda (‘Energie Akkoord' and ‘Klimaatagenda’) in 2013, which was later accompanied by the commitment to the Paris Climate agreement in 2015. Via these policies the Dutch government set out targets to drastically reduce the emittance of Greenhouse Gasses in order to limit global warming to a maximum rise of 2 degrees Celsius. This target will be achieved through reducing emissions to 49% of their 1990 level by 2030. With a further reduction of 95% of total emissions in 2050 (Wiebes, 2020). As a major contributor to emissions, the production and consumption of electricity is a key sector in which emissions can be reduced. Switching electricity production towards non-polluting, renewable production sources is one measure to meet the targets. Currently the two most important renewable energy production sources are wind power and solar PV. In 2020 the estimated share of renewable sources will be 15% of the total electricity production in the Netherlands. Dutch renewable energy targets for 2030 are the production of 35 TWh renewable production on land. It is estimated that 17.7 TWh will be produced by wind on land and 8.5 TWh by solar PV (RES, 2019). Still 9 TWh of electricity production has to be accounted for, in addition to the already installed capacity and the projects that are in development (Lampropoulos, van den Broek, van der Hoofd, Hommes, & van Sark, 2018). Despite this increase and the projected growth of renewable energy, the bulk of electricity in the Netherlands is still produced by natural gas and coal powered plants. A small percentage is produced by the only nuclear power plant in the Netherlands in Borssele. In figure 1 below, the changing production mix is noticeable, as is the dominant position of natural gas in the Netherlands (Tijdink & Muller, 2020). The energy production mix and its gradual shift towards more renewable energy can be seen in figure 1.

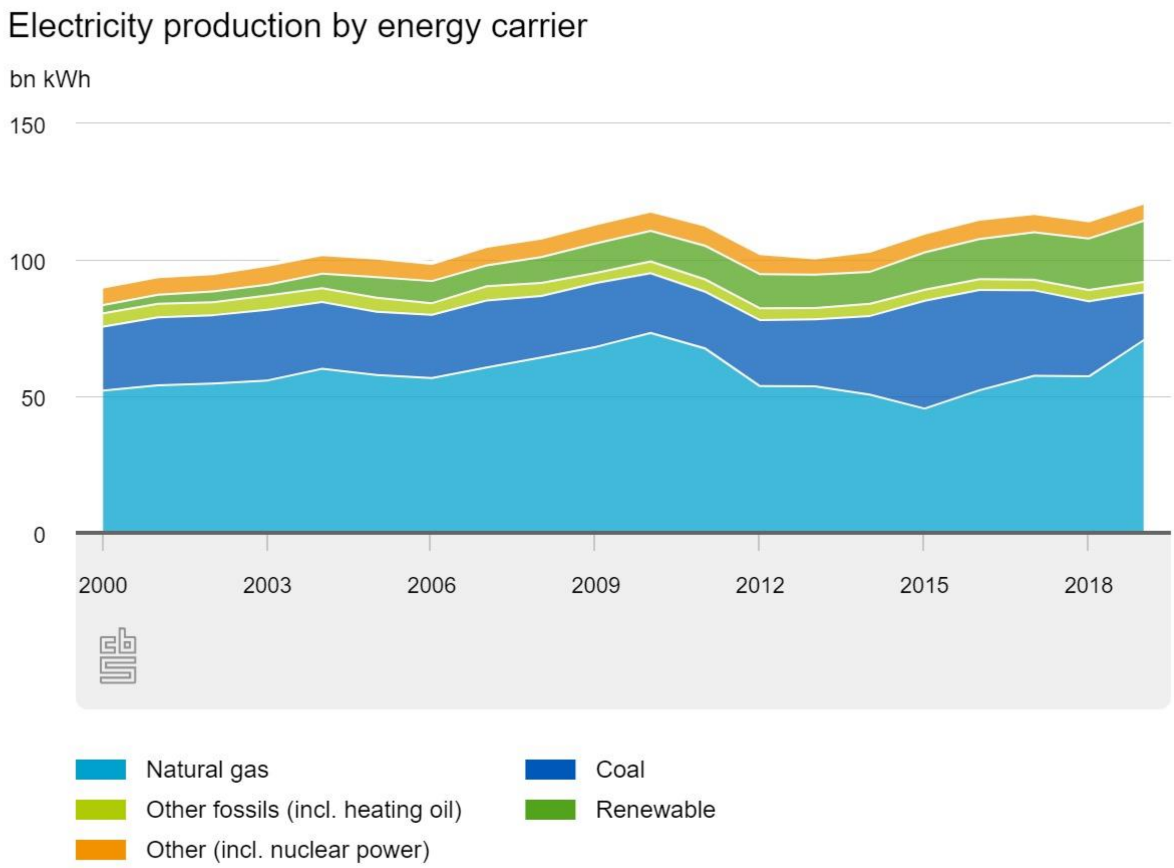

Figure 1 Electricity production Netherlands from 2000-2019, from CBS (2020a)

Driving this transition towards more renewables are subsidies and support mechanisms by the Dutch government. There have been several support schemes to stimulate the development of renewable energy production plants. Such as a subsidy scheme for renewable production sources and tax breaks for green innovations. Currently the subsidy system is called the SDE++ and it aims to stimulate renewable production and techniques to limit emissions (Hoogland et al., 2019). It guarantees operators of eligible facilities a guaranteed feed-in tariff for their electricity or the reduction of emissions. Since the introduction of this scheme the guaranteed tariffs have steadily decreased in line with the decreasing costs of generating renewable energy (Hoogland et al., 2019).

So far, the energy transition has led to several challenges and problems. Among these are decreasing wholesale prices of electricity due to the increased renewable production (Mulder & Scholtens, 2013). The intermittency of renewable sources also affects the fluctuation of prices throughout the day. In the spring of 2020 negative day-ahead electricity prices persisted for more than 6 consecutive hours resulting in curtailment of wind and solar plants (van Cleef, 2020). Both these effects on prices lead to higher costs for electricity producers and consumers (Van Hout et al., 2014). Other difficulties of the larger amounts of renewables in the electricity mix are increasingly frequent mismatches between supply and demand, instabilities of the grid and larger land-use requirements (Sinsel, Riemke, & Hoffmann, 2020). Also, reinforcing the electricity grid and developing more back-up capacity are expensive investments, but required to enable the growing share of renewable energy sources (Newbery, Pollitt, Ritz, & Strielkowski, 2018). These factors lead to higher system costs to enable the energy transition (Di Cosmo & Malaguzzi Valeri, 2018; Frontier Economics, 2015).

Despite these challenges the current transition towards more solar and wind energy is continuing. Most of the research done on the Dutch energy landscape sees the increasing importance of renewables as the main opportunity and challenge ahead. Especially since the adoption of renewable energy in the Netherlands has been lagging compared to other European Union countries (Killer, Farrokhseresht, & Paterakis, 2020; Mir Mohammadi Kooshknow & Davis, 2018). While the ambitions and targets of policy makers continue to become more ambitious. Making the continually increasing important role of renewable energy production in the future inevitable.

2.1.2 Power system flexibility

Electricity production must always match consumption. Otherwise, the frequency of the grid may shift from 50 Hertz per minute and that can cause blackouts (Slingerland et al., 2015). To prevent blackouts, system operators must ensure enough flexibility in the system to absorb and mitigate large swings in supply and or demand (Gaudard & Madani, 2019). Before renewables were a significant factor providing flexibility was already a challenging process, because electricity generation always fluctuates (Slingerland et al., 2015). Now that intermittent renewable sources, such as wind and solar, are becoming more important, balancing the supply and demand of electricity is becoming more challenging (Sinsel et al., 2020). Wind turbines need sufficiently strong wind speeds and photovoltaic panels do not supply when the sun is down, making them less reliable and predictable than conventional sources. Unlike other European countries, the Netherlands does not have the geographic features for large scale hydropower facilities that provide renewable and flexible electricity in other countries (Van Hout et al., 2014). These factors make researchers expect systems with larger shares of renewable energy production to face more issues with flexibility (Gaudard & Madani, 2019; Lampropoulos et al., 2018).

Mainly the Transmission Service Operator (TSO) and to a lesser extent the Distribution Service Operators (DSO) can address flexibility issues in roughly five ways (Papaefthymiou, Grave, & Dragoon, 2014). Energy generation can be reduced or stopped when there is excessive supply, examples are braking turbines or reducing the inflow of fuel into burners. Operators that receive feed-in tariffs, such as renewable sources, often lack the economic incentive to limit their production during negative-price events. Since 2015 subsidy policy states that when wholesale electricity prices are negative for six or more consecutive hours no subsidy is paid to renewable producers (RVO, 2020). This provides an incentive for subsidized renewable energy producers to limit excessive supply. The second option is using backup technologies, such as fast-responding natural gas fired peaker plants (Papaefthymiou et al., 2014). These can generate electricity quickly to ensure flexibility in making supply follow demand. Currently this is the dominant solution to ensure sufficient flexibility in the Dutch electricity system. Such plants are predominantly fueled by natural gas in the Netherlands (Slingerland et al., 2015; Virasjoki et al., 2020) and are expensive to operate (Mallapragada et al., 2020). A third option is demand-side management, an example of this is that large consumers of electricity regulate their consumption up or down. Also, through smart grids and ICT systems the demand for electricity could be managed (Terlouw et al., 2019). The interconnection of different countries' electricity is the fourth option to ensure system flexibility. Via these interconnections, countries can withdraw and supply flexibility to countries connected. Currently the Dutch grid has connections to and from Belgium, Denmark, Germany, Norway and the United Kingdom. More connections are being realized or will be created in the future (Tijdink & Muller, 2020). However, it is unlikely that this will be sufficient to provide all the required flexibility (Slingerland et al., 2015). Furthermore, interconnections are expensive and take a long time to be realized (Cebulla et al., 2018). The last option, which is the focus of this thesis, is employing energy storage technologies as a source of flexibility. Storage technologies can be charged during off- peak hours to release the stored energy during peak times (Gaudard & Madani, 2019). In this manner via arbitraging storage providers can earn revenues whilst providing flexibility to the grid. Other manners of employment of electricity storage will be discussed in section 2.4.1. Storage has the potential to be an essential part of flexibility sources in a future with more renewable energy (Newbery et al., 2018; Rai & Nunn, 2020).

2.2 Dutch electricity markets

Most of the flexibility in the Netherlands comes from trading in the different electricity markets in the Netherlands (Slingerland et al., 2015). Suppliers sell and consumers buy their electricity in several different markets that have different times of delivery. Ranging from years ahead of actual delivery to just several minutes before the actual delivery. Through these transactions in these different markets the necessary and continuous balance of supply and demand of electricity is maintained.

2.2.1 Forward market

Most electricity is traded on long term forward contracts which are in the Netherlands traded on the ENDEX exchange part of commodity market operator ICE (Slingerland et al., 2015; van der Welle, 2016). Contract terms range from several years to one week ahead of actual delivery. There is not much volatility in this market, and it is mainly used by suppliers and consumers of the electricity baseload. Closer to actual delivery there are some influences of weather variances, but these are limited and mitigated mostly in the day-ahead market. This thesis focuses on the flexibility issues in volatile short-term markets that could be mitigated by storage facilities. Therefore, the forward market with its long contracts and low volatility is not further studied in this thesis. Furthermore, the most suitable storage technologies for the Netherlands at the moment are not well suited for long term storage, rendering them unsuitable for operation in the forward markets (Mir Mohammadi Kooshknow & Davis, 2018).

2.2.2 Spot market

In the Netherlands the spot market is divided into two markets, respectively the day ahead market (DAM) and the intraday market. There are several operators that run these markets in the Netherlands, EPEX and Nord Pool operate the largest marketplaces (Tanrisever et al., 2015).

2.2.2.1 Day-ahead market

Most of the electricity that is not traded on the forward markets is traded on the day-ahead market. Trading volume in this market in 2019 was approximately 20% of the total electricity production in the Netherlands (CBS, 2020b; EEX, 2019). As the name implies, electricity is traded in this market a day ahead of delivery. Each midday at 12.00 o'clock the auction is closed, and the dispatch for the next day in hourly resolution is determined. This market is mainly used to adjust positions from the forward market of participants that change due to forecast errors. In this way the market can provide flexibility a day before the actual electricity is delivered and consumed (Van Hout et al., 2014). Bidding is anonymous and is done on the supply side by power generators and consumption comes from retail companies or big consumers of electricity. Every party bids the specific amount in MW that it is willing to sell or buy and for which price during a specific hour. All these bids are then ranked based price and amount of generation in an ascending order, resulting in the so-called merit order. Then the market is cleared by its operator and the traded volumes and market clearing prices are established (Tanrisever et al., 2015).

2.2.2.2 Intraday market

In recent years the traded volumes on the intraday market have been growing, although this amount is still small compared to traded volumes in the day ahead market (Tijdink & Muller, 2020). Especially the introduction of more renewable energy has sparked more interest in the intraday market. Since renewable power production is difficult to forecast ahead of time, suppliers of electricity can adjust their positions close to delivery in the intraday market (van der Welle, 2016). However, the data availability of this market is limited, and the market was not yet in operation in 2010. In combination with the fact that the trading volumes are still relatively small this market is not included in this thesis.

2.2.3 Balancing markets

If there are still mismatches in the supply and demand of electricity after corrections were made in the day-ahead and intraday market. TenneT (Dutch TSO) must activate one of its balancing mechanisms that are also known as ancillary services. These services are essential tools for the TSO to ensure the stability of power flow and therefore the health of the grid. Roughly there are three types of reserves classified as the primary reserve (Frequency Containment Reserve, FCR), secondary reserve (automatic Frequency Restoration Reserve, aFRR) and tertiary reserve (manual Frequency Regulation Reserve, mFRR). Other ancillary services are black start capacity and reactive power to maintain the voltage level of the grid (TenneT, 2020a), but these will not be addressed further in this thesis.

2.2.3.1 Primary reserve

In the Netherlands the primary reserve is known as Frequency Containment Reserve, it is automatically activated after several seconds of imbalance in the electricity grid. In order to keep the frequency of the electricity constant at 50 Hertz per minute. Market participants are required to place bids of a minimum size of 1 MW. When their bid is accepted, the reserve must be able to respond within 30 seconds and the capacity has to be available for at least 15 minutes. The FCR is a shared capacity market in which currently six countries participate (Austria, Belgium, France, Germany, the Netherlands and Switzerland). More countries will join in the near future with the addition of Denmark and Slovenia (Tijdink & Muller, 2020). All participating countries and their TSO's have to contract a predetermined amount of FCR capacity. TenneT in the Netherlands had to procure 111 MW in 2019, of which at least one third had to be procured from Dutch sources (TenneT, 2020a).

Since July 2019 there have been two changes to the procurement period of this capacity reserve. Firstly, on July first 2019 this period was shortened to one day instead of one week. Then, secondly in July 2020 the contract period was further reduced to 4 hours per day. Meaning that TenneT procures the reserve six times a day. These changes were implemented to bring the procurement of the reserve closer to real-time and make the provision of the reserve more appealing and accessible to new flexibility providers (TenneT, 2020c). Even before these changes the provision of FCR has been and remains a major source of revenue for energy storage facilities in the Netherlands (Mir Mohammadi Kooshknow & Davis, 2018). Even though it is an important source of revenue for storage operators at the moment, this market is small and does not offer much room for new entrants (Figgener et al., 2020; Killer et al., 2020). Furthermore, this thesis focuses on the major electricity markets in order to study flexibility. The FCR is more of an auction than a market and is therefore outside of the scope of this thesis.

2.2.3.2 Secondary reserve

The secondary reserve in the Netherlands is the automatic Frequency Restoration Reserve (aFFR). TenneT has two ways of procuring this reserve: Firstly, it obligates suppliers to bid for this service through contracts. Secondly, other market parties can also place bids for the provision of the service (TenneT, 2020b). Both contracted parties and other market participants must place bids for which price the can provide the required amount of aFRR. Within 15 minutes, the contracted power has to be operational after activation. TenneT uses aFRR to provide flexibility in two directions. Meaning that, it requires bids that enable more supply in cases of shortage and more demand in case of a surplus. The eventual price of the imbalance is determined after the imbalance has been resolved and is established via marginal cost pricing (TenneT, 2020b). It is important to note that the balance and therefore the price is not set by TenneT, but it is set by the bids that have been submitted via the parties operating this market. The earlier mentioned obligation to bid, is applicable to producers with more than 60 MW of production, in order to guarantee sufficient liquidity in this market.

This is a key market for the provision of flexibility to the electricity grid, due to this function and the fact that prices are not known upfront, the prices are often very volatile. This is enhanced evermore as it serves the purpose to mitigate periods of excessive supply and demand, which are already moments for prices to peak, the extreme prices in this market are higher than in other markets (Tanrisever et al., 2015). This makes it an interesting addition to this thesis as an intraday market. Because the prices and its movements that are closest to real-time can be studied.

2.2.3.3 Tertiary reserve

Finally, the third or tertiary reserve in the Netherlands is the manual Frequency Restoration Reserve. There are two variants, namely the directly activated and the scheduled activated. TenneT classifies mFRRda as the emergency reserve and mFFRsa reserve capacity for balancing operations. These reserves require large amounts of electricity and it are not as easily monitored as the other reserves (TenneT, 2020a). Moreover, the provision of this reserve is currently not possible for storage facilities. Lastly, these reserves are not often activated and concern a small volume of energy or power are therefore not as interesting for daily flexibility providers (Gaudard & Madani, 2019). Therefore, these services and their prices will not be covered in this thesis.

2.3 Electricity price dynamics

Electricity is unlike other commodities due to the fact that it must be consumed instantaneously, because storage costs are too high. Making it a very volatile and spikey priced commodity. Now that the cost of storage options are decreasing fast. The dynamics of electricity prices will be affected and that can enable energy storage and the provision of flexibility. Combined with the changing energy mix and the subsequent effect on electricity prices, it makes for an interesting subject of research.

2.3.1 Elasticity of supply and demand

Since electricity has to be consumed instantaneously, both sides of the spectrum have an influence on keeping the system in balance. This flexibility of supply and demand is not uniform among participants in the electricity market. Some suppliers of electricity can ramp up or down their production to some extent when necessary, but renewable sources are not yet flexible in both directions (Soini et al, 2020). Provisioning flexibility is also influenced by strategic motivations of electricity producers, in order to maximize returns (Slingerland et al., 2015; Verzijlbergh et al., 2017). So, flexibility on the supply side is driven by marginal costs of production, the ability of the production source to be operated flexibly, stochastic fluctuations in production and lastly, strategic decisions on production schedules. While suppliers of electricity in some cases can alter their production, demand of electricity is mostly inelastic. Most end users of electricity cannot observe real-time prices and therefore are unable to react to those price changes (Lijesen, 2007). Furthermore, for most end users it is difficult to be change their consumption in the short run (Csereklyei, 2020).

2.3.2 Seasonality

Seasonality influences demand and supply of electricity, caused by differences in weather fluctuations (Maciejowska, 2020; Metz & Saraiva, 2018). Demand for electricity is higher during winter months when there is less daylight than in the summer months. Seasonality is mainly caused by differences in weather between the seasons that influence demand and supply of electricity. The supply of electricity is affected by differences in solar irradiance and wind speeds that fluctuate throughout the year (Hagfors et al., 2016). Furthermore, differences in demand and supply of electricity fluctuate throughout the day because of daylight and work hours. Therefore, researchers and energy markets divide the day between on-peak and off-peak hours. Roughly speaking, the hours between 8.00 in the morning and 19.00 in the evening on working days are considered on-peak hours and prices tend to be higher (Kyritsis, Andersson, & Serletis, 2017). Demand for electricity notably peaks at the start and end of these on-peak hours. In terms of supply the production of wind is higher in the evening and during the night (Hagfors et al., 2016). While solar production peaks around midday and is non-existent during hours that the sun does not shine. Accounting for seasonality is done in studies on electricity price volatility (Huisman et al., 2020; Kyritsis et al., 2017; Mulder & Scholtens, 2013). Seasonality effects are also an important determinant of the amount of flexibility that is demanded and can be supplied by the electricity grid.

2.3.3 Volatility

Volatility is the movement of prices, electricity prices are prone to show erratic and unpredictable price movements (Page et al., 2018). Determining what the effects of an increasing share of renewable energy on the prices and the volatility of prices are, is important knowledge for multiple parties in the electricity grid. The first parties with interest are the producers and consumers of electricity, because volatility affects their operating strategies and their hedging approaches (Bunn et al., 2016). The second parties that are impacted by price volatility are policy makers and grid operators since it can affect the functioning of the market that they control and monitor (Slingerland et al., 2015). Lastly, it is an opportunity for storage operators and potential investors. Since the profitability of applications depends on the electricity prices and its movement because the can profit from price movements by buying electricity when prices are low and selling the stored electricity when prices are high (Gaudard & Madani, 2019). There is a significant body of research on the volatility of electricity prices and the fundamental drivers of volatility. The available literature is inconclusive to some extent about the effects of the changing electricity mix on the volatility of electricity prices.

Research has shown that electricity prices and its volatility are strongly affected by renewable electricity (Kyritsis et al., 2017; Rai & Nunn, 2020). Mainly due to its intermittency and the subsequent volatility effects. Other influential factors are the indirect effects of feed-in tariffs, subsidies and market regulations (Ciarreta et al., 2020; Percebois & Pommeret, 2019). An interesting study that focuses on these institutional drivers of the development of volatility of electricity prices is from Ketterer (2014) that finds an initial positive effect of wind energy on electricity price volatility. This effect persisted until 2010, when a policy change was instituted that obligated renewable energy suppliers to provide day-ahead forecasts of their production. Other studies come to a similar conclusion regarding the effectiveness of regulation and policy to limit the volatility effects of renewable energy (Ciarreta et al., 2020; Ciarreta & Zarraga, 2016). Both studies focus on the Spanish electricity market and find that results are driven by the market structure, the market design and the regulation of renewable generation. Not just the effect of renewable energy intermittency influences fluctuations. Confirmation of the importance of market design is found by Knaut and Paschmann (2019). In their study they show that German quarter-hourly price volatility is mainly triggered by limited market participation and not only by the high volatility of renewable energy sources. A solution to limit the volatility of electricity prices can be found in coupling markets within countries and increasing to other countries as well (Knaut & Paschmann, 2019).

Pereira da Silva and Horta (2019) come to the same finding regarding coupling markets with their focus on the MIBEL price area (Portugal and Spain) and its connection to France. They find a decrease in the volatility of prices after the finalization of the interconnection between the two market areas. Another finding is that the increasing share of renewable energy in total supply goes hand in hand with increasing electricity price volatility. The remark that the effects of wind and solar energy on volatility are not similar. They find that more wind energy in the grid tends to drive up electricity price volatility. While mixed results are found regarding the impact of PV power penetration ratio on price volatility. More mixed results concerning the volatility effects of increased renewable penetration are found by Rintamäki et al. (2017). They focus on both Denmark and Germany and they find interesting and diverse effects. In Denmark wind power decreases the daily volatility of prices, but in Germany wind energy increases its volatility due to its strong effect in off-peak hours. Their analysis suggests that these differences are mainly attributable to access to flexible generation capacity and wind power seasonality.

Another finding of their study is that solar power decreases price volatility in Germany. It brings them to the conclusion that policy measures for the integration of renewable energy should focus on region-specific patterns (Rintamäki et al., 2017). Akin to these findings is the paper from Kyritsis et al. (2017). This paper also studies Germany and finds that solar power generation reduces the volatility of electricity prices by replacing the use of peak-load power plants. Furthermore, they conclude that wind energy raises the volatility of electricity prices by putting strain on electricity market flexibility providers. Paraschiv et al. (2014) also find that renewable energy sources increase volatility of prices and that makes hedging of price risk to secure flexibility more expensive. They find that especially since 2012 in Germany the coefficient of historic price volatility has increased. According to the researcher this is due to the tremendous increase of renewable energy in the German electricity grid since the 'Energiewende'. Dong et al. (2019) also find that electricity price movements are a result of the level of penetration of renewable energy. Another important finding from their study is that the amount of stabilizing energy sources has a strong impact on the overall volatility in electricity markets. In Denmark, that has a high share of wind power and fewer stable electricity sources, such as hydropower or conventional generation, the volatility of prices is much higher than in the other countries. Lastly, the study of Hartner and Permoser (2018) is interesting, because it studies the effects of solar energy on price volatility in Germany and Austria. The authors find that the effects of renewables on volatility strongly depend on the level of penetration in the electricity grid. With rising levels of penetration of renewables, the effects on volatility will increase. With these findings they confirm the hypothesis stated in the paper by Wozabal et al. (2016) that the effect of renewables on electricity price volatility depends mostly on the level of penetration of renewables.

While Frömmel et al. (2014) do not study the impact of other variables on price volatility, such as renewable energy or gas prices, they do analyze volatility in a different and interesting manner. By studying the intraday range of electricity price, they find better estimates of daily price movements compared to realized variance. Through studying the intraday along other of daily volatility Page et al. (2018) find that increases in wind energy decrease the daily volatility of electricity prices in Texas. Another measure of price volatility is studied by Maciejowska (2020). She focuses on the inter-quantile range (IQR) of electricity prices. Her study on the German electricity market, shows that wind and solar influence price volatility differently. When demand is low wind generation decreases the IQR and when it is high it increases the volatility, measured with the IQR. While the increase of solar energy stabilizes the price, volatility is demand is at a moderate level. This leads her to stress the importance of finding a regional balance between solar and wind power production.

While most mentioned studies focus on one country or on a couple, the study of Johnson & Oliver (2019) studies a panel of nineteen different countries. Another distinctive element of this study is that they study quarterly volatility instead of daily price volatility. They find that the intermittency effect of more renewable energy dominates the merit-order effect. Hence, that more wind and solar increase the volatility of electricity prices. Another panel study on volatility of electricity price is the study by Erdogdu (2016). By studying fourteen European countries he finds that the daily volatility of electricity prices has decreased since 2008. Furthermore, he finds that there is an impact of seasonality on prices, an explicit pattern could not be identified. Lastly, countries that have more conventional sources and are thus less impacted by intermittency are likely to experience less volatility than countries with more renewables.

2.3.4 Extreme prices

Not only is the overall movement of prices is affected by the changing energy mix, also the prices are becoming more extreme. Meaning that the occurrence of lower and higher prices is becoming more frequent because of the changes in the electricity markets. In 2020 there were more occasions of negative prices on the Dutch day-ahead market than in all other years combined (van Cleef, 2020). The study of the highest and lowest price spikes is relevant for market participants, because they base their trading strategies on these spikes. Especially because the spikes of the price also represent the moments when flexibility is most needed, so when the market is at its most inflexible points. Furthermore, for flexibility providers these spikes provide the potentially most lucrative trading opportunities (Wilson, et al., 2018).

Similarly, to the amount of research regarding volatility, studies on extreme prices and its drivers are becoming increasingly important. In recent years the application of quantile regressions to study the impact of fundamentals on electricity prices and their extremes has become popular. The merit of quantile regressions to study electricity prices and their drivers comes from Bunn et al. (2016). According to them quantile regressions yielded superior outcomes compared to other methods. Via a similar approach Hagfors et al. (2016) find that the formation of negative prices and positive price spikes is different. Positive spikes are linked to high demand, low supply and primarily take place during the morning and afternoon peak hours. Where negative prices happen mainly during the night and are mainly driven by low demand and higher levels of wind energy. Regarding the impact of renewable energy on price spikes, they find that renewables increase the probability of these. Especially wind energy has a strong influence on price extremes. Research by Do et al. (2019) also finds that extreme prices are mainly influenced by three factors: persistence of prices, the expected demand and forecasted production of wind turbines. Not only can quantile regression study the impact of fundamentals, but also the impact on volatility since these metrics are strongly related. An example of such a study that studies both kurtosis and volatility of the price is Maciejowska (2020). She finds that both types of renewable generation have a depressing effect on the prices of electricity in all quantiles. Indicating that the electricity prices in Germany between 2015 and 2018 decreased and showed less spikes with larger renewable input. While the findings of Huisman et al. (2020) also indicate that renewable energy has an impact on prices, this impact is asymmetrical according to them. Akin to Hagfors et al. (2016), they find that when there is more supply from wind and solar energy sources, the left tail of the price distribution becomes fatter, while it thins down the prices in the right tail of the distribution. According to the researchers this is an indication that there is not enough flexibility provision in the electricity system and that this should be a consideration for subsidization policy as well. Where the previously cited papers focus on the German electricity market, Mosquera-López et al. (2017) study the Nordic countries and their electricity market. Furthermore, instead of focusing on renewable energy production or other production related fundamentals this paper studies the impact on weather variables as well as market-related ones. Despite the different approaches they find similar effects compared to other papers. Furthermore, they attain extensive evidence in favor of quantile regression based on weather variables.

Besides the research on extreme prices through quantile regressions, other methods are used to study this topic. Among these studies are Aust and Horsch (2020) that use a multiple variable logit regression approach. According to their findings regarding Germany negative prices are becoming more common. Mainly, due to more renewable infeed, but economic policy has the biggest influence on price extremes. Another study focusing on the German electricity markets is from Mosquera-López and Nursimulu (2019). Through the analysis of structural breaks and threshold regressions they find that prices in spot markets are determined by renewable infeed and electricity demand, while in the futures market natural gas, coal and carbon prices have the largest effect on the prices. Lastly, the paper of Rai & Nunn (2020) finds that the South Australian electricity market, that has a very high penetration of renewables, is having extremely low prices that have become more frequent over time. While extremely high prices have become less frequent. Furthermore, not only in South Australia, but in Australia as a whole these effects are noticeable. They point out that it is caused by more investment in volatility-dampening, reliability-enhancing technologies such as storage and interconnectors. Also, the fact that more price-responsive demand has developed in the market and that there has been the emergence of extra ancillary service revenue possibilities in the Australian market. These findings lead them to the interesting finding that large inflows of renewable energy do not have to lead to more extreme prices in every situation.

2.4 Energy storage as a source of flexibility

Although there are multiple ways of addressing the problems and issues that the changes in the electricity mix brings about. This thesis focuses on the prospects that a higher demand for flexibility can bring for storage operators. Primarily, because storage is considered to become a key enabler of flexibility, in the near future already (Heuberger et al., 2017; Kelly & Leahy, 2020). Although it is likely that not just one technology or application will be able to solve the increasing need for flexibility (Risanger, 2018), storage is an important factor and therefore a popular research topic. In recent years the amount of published work, both from academic and industry sources, has been growing fast. The increasing popularity of energy storage is shown by Mejia & Kajikawa (2020). They analyzed more than 100,000 academic articles and patents concerning energy storage from the period between 2000 and 2018. With a steady increase in research in recent years. According to them this great interest in the topic is a sign of the importance of energy storage in developing a reliable production of electricity.

2.4.1 Storage as a real option

Already in the beginning of this century before the energy transition had fully begun, researchers pointed out that storage could become a necessary part of the electricity mix (Ummels et al., 2008; van der Linden, 2006). As mentioned earlier storage is currently studied extensively as a key technology in the transition towards less emissions from electricity production (Mejia & Kajikawa, 2020). Energy storage is recognized as an essential part of the (future) energy mix because of its various benefits. Mainly because it can enhance grid stability and help the expansion of renewable energy resources (de Sisternes et al., 2016; Kelly & Leahy, 2020; Kyriakopoulos & Arabatzis, 2016; Lazkano et al., 2017; Pierpoint, 2016; Ziegler et al., 2019). According to these authors, energy storage is essential in providing more flexibility to the electricity grid and this need for flexibility will even increase in the coming years. Furthermore, energy storage can improve the efficiency of energy systems, cut down the usage of fossil energy resources (Cruz et al., 2018) and reduce the overall environmental impact of energy generation (Aneke & Wang, 2016). It can also help with load-shifting, improving electricity system operation and frequency regulation (Cruz et al., 2018). Even though curtailment of renewables is not happening on a large scale in the Netherlands yet, it could become necessary with increasing renewable electricity production (Sijm et al., 2017). Arbabzadeh et al. (2019) find that energy storage can strongly reduce the need for curtailment. Empirical evidence shows that energy storage and higher levels of renewable energy go hand in hand comes from Azhgaliyeva (2019). From her empirical work she finds that countries that have greater levels of renewable energy sources in the electricity grid have invested more in energy storage in recent years.

A higher share of wind energy requires more transmission capacity, while increasing share of solar require more storage according to Cebulla et al. (2018). Furthermore, they argue that transmission capacity upgrades are often viewed optimistically, because delays and social opposition are neglected. While storage can provide flexibility that is can be used in charging from the grid or a power source, but if storage is charged it can also function as an electricity production source. Spodniak et al. (2018) see the importance of storage as well, but argue that it will not be profitable to operate as long as the flexibility, reliability and capacity that storage facilities offer are not rewarded the same way energy supply is. Johnson and Oliver (2019) argue that without energy storage the increased price risk resulting from wind and solar intermittency can ultimately lead to under-investment in these sources. In their paper López Prol et al. (2020) reach a similar conclusion regarding the necessity for storage with increasing amounts of renewable energy. They argue that renewable energy sources without flexibility support from energy storage can start cannibalizing its own profits when penetration reaches certain levels. Despite the increasing necessity and a growth in research regarding storage Mir Mohammadi

Kooshknow and Davis (2018) observe a lack of implementation of electricity storage systems in the Netherlands. Due to technical, institutional, and economical challenges facing this flexibility option.

2.4.2 Forms of electricity storage

Electricity can be stored in different forms and mediums, basically any device that can store energy and return that energy at different points of time can be regarded as an electrical storage system (IRENA, 2017). The most used technologies of storage are (flow)batteries, flywheels, pumped hydro and compressed air energy storage systems (Koohi-Fayegh & Rosen, 2020). Each different technology has its benefits and drawbacks, furthermore they differ in applicability and capabilities (Verzijlbergh et al., 2017). Though other forms of storage are growing most of the storage capacity in the world still comes Pumped Hydro Storage installations (IRENA, 2017). Although other forms of storage are becoming more widespread, especially (flow)battery based facilities (BloombergNEF, 2019; Lazard, 2019). In order to construct pumped hydro storage facilities geographical features such as mountainous areas with large differences in height are necessary (Rehman, Al-Hadhrami, & Alam, 2015). Since the Netherlands lacks such geographical features PHS was and is not a feasible form of storage in the Netherlands in its current form (Ummels et al., 2008). So for the Netherlands more suitable storage technologies are other forms of storage that are also technological mature, such as compressed air energy storage and (flow)battery based storage (Mir Mohammadi Kooshknow & Davis, 2018).

Battery technology has been predominantly used, and is the most installed new technology for energy storage facilities worldwide (Schmidt et al., 2019). Similarly, to this global trend in the Netherlands, most new storage facilities are battery based, with lithium-ion as the most popular technology (EnergyStorageNL, 2019). Storage on large or utility scale in the Netherlands has yet to take off (Lomme & Kaat, 2020). Even though there have been several high-profile projects that have started operations or will start operation soon (EnergyStorageNL, 2019; Lomme & Kaat, 2020). The total storage capacity is low compared to other European countries such as Germany and the United Kingdom (Figgener et al., 2020; Gaudard & Madani, 2019; Killer et al., 2020). Partially because PHS is not an option in the Netherlands (Lampropoulos et al., 2018). Other major reasons for this are high costs of storage compared to the revenue possibilities and institutional challenges in the Netherlands (Mir Mohammadi Kooshknow & Davis, 2018). Besides these arguments, there are also other reasons for the meager deployment of storage facilities are according to Energy Storage NL (trade federation for energy storage providers in the Netherlands) due to the following: Double taxation of storage facilities, unclear regulation, exclusion of certain forms of storage for several ancillary services and a lack of support mechanisms (EnergyStorageNL, 2019).

2.4.3 Economics of energy storage

2.4.3.1 Costs

The costs of several storage techniques are and have been rapidly decreasing in the past decade, especially the cost of lithium-ion batteries. Firstly, due to the advancements of batteries for electric vehicles, and now for stationary applications as well (Henze, 2019). Now also because of increasing grid scale applications of lithium-ion (BloombergNEF, 2019). According to projections by Schmidt et al. (2019) lithium-ion will be the most cost-effective technology for nearly every storage application by 2030. Only for seasonal storage lithium-ion based facilities are not projected to the be the most cost-effective. Lithium performs best already according to Terlouw et al. (2019) in almost all applications. Currently most new storage projects are lithium based and other storage techniques are not as widespread.

In order to study the feasibility of electrical storage most studies focus on one storage technology or one application of storage. Furthermore, these studies are often technical, and the scope of these papers is the improvement of performance. In order to compare different forms of electricity generation a commonly used cost metric of Levelized Cost of Electricity (LCOE). However, this metric is regarded as unsuitable for electrical storage facilities since these produce no electricity. A more suitable metric therefore is the Levelized Cost of Storage (LCOS, other similar abbreviations are also used) metric. LCOS based valuations can be used to compare different types of storage in different markets (Belderbos et al., 2017; Comello & Reichelstein, 2019; Jülch, 2016; Lazard, 2019; Schmidt et al., 2019). With the LCOS it is also possible to compare the total lifetime power or electricity costs of a storage facility. That makes it an ideal metric to find out whether it is a viable investment that could break-even when it is compared to potential revenues (Elshurafa, 2020).

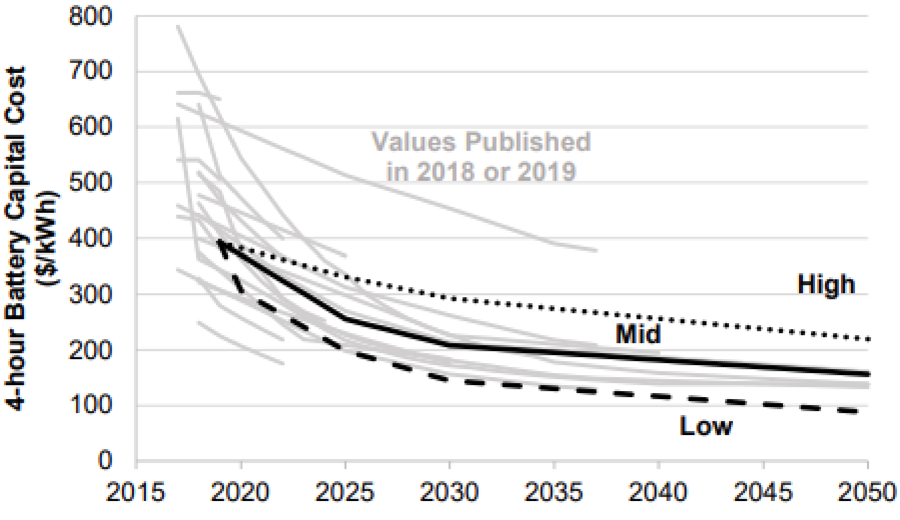

Figure 2 Battery Capital Cost from different studies aggregated, from Cole & Frazier (2020)

In figure 2 the LCOS values of battery storage estimations by several papers and reports are summarized (Cole & Frazier, 2020). From the latest report by Lazard (2020) on the levelized costs of energy storage, they consider batteries as the main technology, estimated costs for storage facilities focusing on energy arbitrage range between 132 $/MWh and 250 $/MWh.

2.4.3.2 Sources of revenue

There are multiple possible streams of revenue for energy storage (Battke et al., 2013; Lazard, 2019; Schmidt et al., 2019). According to Schmidt et al. (2019) these can be summarized in twelve different categories: Energy arbitrage, primary response, secondary response, tertiary response, peaker replacement, black start, seasonal storage, transmission & distribution investment deferral, congestion management, bill management, power quality and power reliability. The last three are most relevant as behind the meter solutions for energy consumers. Most applications are not yet profitable or feasible in the Netherlands (EnergyStorageNL, 2019; Mir Mohammadi Kooshknow & Davis, 2018). Although costs of battery storage systems have decreased in the past years, prices of these systems are often still too high for most commercial (standalone) applications (Lomme & Kaat, 2020; Naseri et al., 2020). As mentioned in chapter 2.2.3.1 almost all recently installed storage facilities in the Netherlands, as well in most other countries, derive most of their revenue from providing ancillary services (Figgener et al., 2020; Joos & Staffell, 2018). The provision of fast response services, such as the FCR service, are the most popular streams of revenue (Killer et al., 2020; Tijdink & Muller, 2020).

Gaudard and Madani (2019) note that the ancillary markets may be lucrative for now, but are too small to sustain the large-scale implementation of the required amount of storage into the electricity grid. This argument is supported by Figgener et al. (2020), who note that the ancillary markets in Germany are becoming saturated with participants (all new entrants are storage facilities) that cause decreasing prices already. The arbitrage of electricity is an important method of providing flexibility through time shifting. Although, it mostly is performed by pumped hydro storage facilities (Gaudard & Madani, 2019). This is changing soon and more and more modern energy storage facilities, such as batteries are performing energy arbitrage (Lazard, 2019; Zafirakis et al., 2016). According to Ward and Staffell (2018) energy arbitrage is the most studied revenue source for storage. Since its revenue can be quantified with the spread of electricity prices. Zafirakis, et al. (2016) extends this and argues that energy arbitrage will likely be the most profitable source of income for storage facilities in the future.

Revenues from energy storage with arbitrage are determined by the volatility of electricity prices (Metz & Saraiva, 2018; Wilson et al., 2018). In order to increase potential storage profits the volatility of electricity prices must increase. Another important determinant of arbitrage profits according to McConnell et al. (2015) are extreme prices. Making energy storage options similar to traditional peak generators in that respect. These studies, as well as other studies (Barbour, Wilson, Hall, & Radcliffe, 2014; Gaudard & Madani, 2019; Spodniak et al., 2018), show the importance of analyzing price fundamentals to study arbitrage profits for storage operators. Other factors that are also important for the profitability of arbitrage, like arbitraging opportunities between different markets (McPherson et al., 2020) and different times of day (Mallapragada et al., 2020).

It is expected in the near future that the profitability of provision of other flexibility services by battery storage will become commercially interesting as well (Rotman, 2020). Major changes are expected in 2025 for utility scale storage. The SDE++ subsidy will come to an end and that will likely result in bigger incentives to invest in energy storage (Peelen & Fleuren, 2019). For household storage to become more attractive the end of the net-metering scheme in 2023 is expected to be shifting moment (EnergyStorageNL, 2019; Londo et al., 2020). According to Arcos-Vargas, et al. (2020) an arbitrage only strategy of a battery storage facility could become profitable in the Spanish electricity market from 2024 onwards. They also argue that arbitrage alone currently is not attractive enough, but that by inclusion of the provision of ancillary services storage can be profitable faster.

According to researchers and operators of storage systems a solution to improve the business case for these systems is to provide several services, such as combining energy arbitrage and ancillary services (Arcos-Vargas et al., 2020; Lazard, 2019; Mallapragada et al., 2020; Staffell & Rustomji, 2016). This is known as revenue stacking and it is regarded to be of great importance in realizing the full potential of battery storage facilities (Newbery, 2018). Studying combined streams of revenue is mostly done by optimization methods (Elshurafa, 2020; Ward & Staffell, 2018) and it is therefore outside of the scope of this thesis. In this thesis the focus is exclusively on arbitrage and its potential revenues that are driven by electricity price movements.

2.4.4 Policies to stimulate energy storage

Governments and regulating bodies traditionally have a very large impact on the energy market. After the privatization of the energy market in most European markets their influence diminished somewhat. Still the effects of rules and regulations concerning the electricity market can have tremendous effects. Policies such as the feed-in tariffs for renewable energy sources in several countries have accelerated the introduction of these energy sources (Ciarreta et al., 2020; Hoogland et al., 2019). Besides the in earlier chapters mentioned direct economic benefits to the provider of the storage the addition of more flexibility sources to the grid can have social benefits as well (Gorman et al., 2020; Ji et al., 2019; Sidhu et al., 2018). More storage facilities can reduce the number of investments in transmission and distribution grid extensions in some cases (Child, et al., 2019; Lomme & Kaat, 2020). Moreover, the deployment of storage can enable faster deployment of renewable energy. However, these social benefits of other options are not considered by private investors, nor are they necessarily the main interest of grid operators (Cambini et al., 2016; Zwart, 2020). It is therefore that some parties call for subsidies to speed up the introduction of more energy storage in the Netherlands (EnergyStorageNL, 2019; Wiebes, 2020). Subsidies can be an effective way of stimulating storage to provide services that yield social benefits (Coester et al., 2020; Zafirakis, et al., 2013). Especially because in some countries this already takes place to great effect, such as in Germany (Figgener et al., 2020) and in California, USA (Varghese & Sioshansi, 2020).

3 Hypotheses

For providers of flexibility the price variation is a key-input variable in order to determine their operating strategies. The higher the volatility the more profit real options, that can provide flexibility, can make. Studies on the volatility of electricity prices in other countries found noticeable changes in the volatility of prices in the latter half of the past decennium (Ketterer, 2014; Kyritsis et al., 2017; Maciejowska, 2020; Rai & Nunn, 2020; Rintamäki et al., 2017). Research on the development of electricity prices in the Netherlands, such as (Mulder & Scholtens, 2013) is scarcer and does not cover recent data. Therefore, this paper will investigate the Dutch day-ahead market and its volatility development through the years will be done. The volatility of the day-ahead market is not only an interesting topic due to current research scarcity, but also in economic terms it is particularly interesting. In the Netherlands the market is, in terms of traded quantities, the largest electricity exchange. Thus, the following hypothesis focuses on the development of volatility in the Dutch day-ahead market and the implication for storage facilities.

Hypothesis 1

H0: Volatility in the Dutch day-ahead market between January 2016 and September 2020 was not more profitable for storage facilities than it was between January 2010 and December 2015.

HA: Volatility in the Dutch day-ahead market between January 2016 and September 2020 was more profitable for storage facilities than it was between January 2010 and December 2015.

However, volatility alone, as a measure of inflexibility, does not reveal information on the direction of the movement, i.e. whether they were positive and negative price spikes. Therefore, not only the development of volatility should be studied, but also the tails of the electricity price and their development throughout the years. The kurtosis is also relevant for flexibility providers. Since it provides more detailed information about the time of the price movements and its drivers. To study this the following hypothesis focuses on extreme price occurrence in the day-ahead market.

Hypothesis 2

H0: For storage facilities the occurrence of extreme prices in the Dutch day-ahead market between January 2016 and September 2020 was not more rewarding compared to the period between January 2010 and December 2015.

HA: For storage facilities the occurrence of extreme prices in the Dutch day-ahead market between January 2016 and September 2020 was more rewarding compared to the period between January 2010 and December 2015.

In the Dutch electricity market, power producers and users (suppliers and retailers) exchange most of the electricity at the wholesale level in the day-ahead market. However, in real time, it occurs that the amount of electricity effectively injected (or withdrawn) differs from the scheduled amount. Hence, an imbalance occurs, in the Netherlands these imbalances are corrected in the imbalance market. Which is operated by TSO TenneT and consists of two directions in which imbalance can be mitigated, electricity can withdraw or supplied by flexibility providers. Since this market is a fundamental part in the provision of flexibility in the Netherlands, studying its volatility development is useful in order to answer the research statement. Because TenneT controls both supply and demand, it states two different prices for feeding in electricity and withdrawing electricity when the system demands it. Since energy storage can both supply and withdraw electricity from the grid, both directions are studied. To determine the development of volatility of prices in the imbalance market the following hypothesis concerns this matter.

Hypothesis 3

H0: Volatility of the Dutch imbalance prices between January 2016 and September 2020 was not more profitable for storage facilities than between January 2010 and December 2015.

HA: Volatility of the Dutch imbalance prices between January 2016 and September 2020 was more profitable for storage facilities than between January 2010 and December 2015.

With the same rationale as for the extreme price occurrences in the day-ahead market, this hypothesis studies the kurtosis of the price distribution in order to provide a more detailed picture of high and low prices. Only now for the prices in the imbalance market.

Hypothesis 4

H0: For storage facilities the occurrence of extreme prices in the Dutch imbalance market between January 2016 and September 2020 was not more rewarding compared to the period between January 2010 and December 2015.

HA: For storage facilities the occurrence of extreme prices in the Dutch imbalance market between January 2016 and September 2020 was more rewarding compared to the period between January 2010 and December 2015.

As shown by (Mallapragada et al., 2020; Metz & Saraiva, 2018; Naseri et al., 2020) trading electricity between two different electricity markets can be more profitable than operating in just one market. By acting in more than one market, storage operators can benefit from price movements and opportunities in both markets. Therefore, studying whether the occurrence of extreme prices is correlated between the day-ahead market and the imbalance and whether these differences increased in the latter half of the decennium constitute the last hypothesis of this thesis.

Hypothesis 5

H0: Potential arbitrage revenues from trading on differences in volatility and extreme prices between the day-ahead market and the imbalance in the Netherlands were comparable between January 2016 and September 2020 when compared to the period between January 2010 and December 2015.

HA: Potential arbitrage revenues from trading on differences in volatility and extreme prices between the day-ahead market and the imbalance in the Netherlands were higher between January 2016 and September 2020 when compared to the period between January 2010 and December 2015.

4 Data

To test the hypotheses and to answer the research objectives of this thesis empirical methods on two datasets are performed. In order to investigate whether the circumstances for electricity storage owners have improved in the latter half of the last decennium a dataset ranging from January 2010 until September 2020 is studied. Then, to check the findings from this dataset and get a better understanding of what may drive changing market circumstances a shorter timespan ranging from January 2015 until September 2020 is studied as a form of robustness check. This second dataset contains data on a smaller granularity and more accurate variables than the main dataset. Making it a good addition to the research done on the first dataset. Both datasets will be discussed below in more detail. An important note is that for the creation of these datasets all the datapoints from the different sources were converted to the UTC time zone. In this way it is ensured that all measurements are from the exact same timeslot, so potential effects happen at the same moment.

A full description of all the studied variables is provided in the tables in part A of the appendix. In this table the sources of the data are also listed. Additionally in part B of the appendix all dependent variables that are studied are plotted as function of time. This visualization of the data shows the movements of the studied dependent variables throughout the years.

4.1 Main datasets: 2010 until 2020

For the first two hypotheses, the day ahead prices and its movements in the Netherlands between January 1st 2010 and September 30th 2020 are studied. These prices were downloaded from Datastream and are on an hourly level. This data is only available for weekdays, so regressions containing day-ahead based variables only account for weekdays. For the third and fourth hypotheses, the Dutch imbalance prices (aFRR prices), both the upward and downward regulation price, from the same period are from the website of Dutch grid operator TenneT. Unlike the day-ahead price data the imbalance price data also covers weekend days. In order to study the fifth hypothesis, prices from both markets are combined to study the potential benefits of operating on both markets.

Also, from Datastream comes the data regarding gas and emission prices that serve as control variables for the effects of conventional electricity production. The used gas price is the Title Transfer Facility and the emission prices os the European Union CO2 Emissions Allowance traded on the European Energy Exchange. Both these variables are daily variables, that are also only available for weekdays similar to the day-ahead price. In models were gas and emission prices are added as control variables, only the prices for weekdays are present. Another control variable is the hourly load, which is taken as a representation of total electricity demand per hour. The load data is retrieved from several different data repositories of ENTSO-E, the European grid operator association. Lastly, to account for the influence of renewable energy production, weather data is used as a proxy. Since there was no renewable production data on the same granularity of the other variables available the choice for wind speed and solar irradiance is made. Observations of these variables come from the Dutch meteorological institute, KNMI and consist of average values for wind speed and solar irradiance on an hourly level. For the wind speed observations from the stations Hoek van Holland (instead of station Valkenburg), De Kooy, Lelystad, Leeuwarden, Lauwersoog and Vlissingen (replacement for station Wilhelminadorp) are collected. The choice for these weather stations is similar to the selection used by (Mulder & Scholtens, 2013). However, some of the stations that they used do not publish data anymore, so the stations nearest to those stations were chosen as replacements. All stations of which the wind speed data is used are close to the areas were most wind turbines in the Netherlands are located (CBS, PBL, RIVM, & WUR, 2018). Similar to the approach of (Mulder & Scholtens, 2013) the cube of wind speed of this average wind speed is used in this thesis as well. By doing this a better approximation of actual wind energy production is created. To account for the potential effects of solar energy the data from the following selection of weather stations the following is used: De Bilt, Eindhoven, De Kooy, Lelystad, Lauwersoog, Leeuwarden, Maastricht, Twenthe and Vlissingen. From these stations the average hourly solar irradiance in the Netherlands per hour is calculated. This selection covers the whole country and allows for a representative average of solar irradiance per hour in the Netherlands. Contrary to the location of wind turbines and solar panels in the Netherlands are more dispersed over the country. Therefore, the selection of weather stations is larger and contains stations from all areas of the country. Both wind speed and solar irradiance data is averaged from the different stations to obtain an average hourly variable.

Tables 1 contains the descriptive statistics for this dataset and provides an overview for the daily variables. Hypotheses 1, 3 and 5 are studied with the above discussed variables on a daily level. While the other two hypotheses use the same variables, but on an hourly level, therefore in these models the prices of gas and emission prices are not included. Subsequent tables include the variable names and the descriptive statistics of the dataset.

Table 1
Daily descriptive statistics 2010 until 2020

	Count	Mean	SD	Minimum	Maximum
Log day-ahead volatility	2804	2.23	0.35	0.99	3.87
Log upward volatility	3926	3.79	0.54	1.55	5.47
Log downward volatility	3926	3.84	0.54	1.56	5.47
Log day-ahead intraday range	2804	6.93	0.77	4.71	10.65
Log downward intraday range	3926	5.75	0.51	3.59	7.00
Log upward intraday range	3926	5.74	0.52	3.59	7.00
Log load	3926	9.45	0.10	9.14	9.66
Log wind speed	3926	5.11	1.12	1.27	8.30
Log solar irradiance	3926	4.47	0.97	1.33	5.87
Log gas price	2804	2.89	0.38	1.13	4.33
Log emission price	2804	2.25	0.60	0.99	3.42
Log day-ahead and downward IIMR	2804	4.89	0.60	2.97	6.30
Log upward and day-ahead IIMR	2804	5.33	0.64	1.94	6.78
Log upward and downward IIMR	3926	5.74	0.52	3.59	7.00

Table 2 displays the descriptive statistics on an hourly level that are used to study the extreme prices. Hypotheses 2 and 4 are tested with this data.

Table 2
Hourly descriptive statistics 2010 until 2020

	Count	Mean	SD	Minimum	Maximum
Day-head price	67296	45.17	14.84	-79.19	250.00
Upward price	94224	41.57	41.90	-434.20	735.37
Downward price	94224	46.60	44.12	-434.20	735.37
Load	94224	12808.67	2217.01	7490.00	18620.00
Wind speed	94224	300.36	453.27	0.13	9483.26
Solar irradiance	94224	125.94	195.32	0.00	903.40

4.2 Robustness analysis datasets: 2015 until 2020

Considering that the dataset from 2010 until 2020 has its limitations, especially with regards to the control variables for renewable electricity production. A second dataset that ranges from January 2015 until September 2020 is also used in this thesis. Primarily to further investigate the drivers for changes in volatility and extreme prices in more detail. Since this more detailed data is only available from 2015 onwards it could not be used to study the hypotheses directly. However, utilizing this extra dataset can help in studying the development and patterns of flexibility and electricity prices in the Netherlands better. The choice for this extension of the thesis with a second dataset has several reasons. For one it allows for the use of different variables that can represent effects volatility and flexibility better than the dataset that is used to test the hypotheses. Firstly, the second dataset allows for the weather data to be supplanted by forecasted production data from the ENTSO-E’s transparency website. All these variables are on a 15-minute scale, the exact variables are: total load, as well as production data from solar, wind onshore and offshore sources. Wind data is combined into one variable for wind production. All these variables are day-ahead forecasts. The actual production data on a 15-minute scale is also collected, but there are a lot of missing data points. So only the forecasted variables are used in the robustness checks. Also, from the ENTSO-E transparency website the day-ahead prices for all days of the week on an hourly scale were collected. This solves the lacune of the main dataset that only covers weekdays when day-ahead price variables are studied. Another benefit of using the ENTSO-E transparency data is that it allows to fully use the granularity of the imbalance price data from TenneT, that is on a 15-minute scale as well. Price data regarding the imbalance price is the same as the first dataset, but now it can be used in a smaller granularity. Gas and emission price data are also the same observations from the same source as they are in the first dataset. Unfortunately, that means that models containing these variables still only cover weekdays. In the tables 3 and 4 the descriptive statistics of this second dataset are presented.

Table 3
Daily descriptive statistics 2015 until 2020

	Count	Mean	SD	Minimum	Maximum
Log day-ahead volatility	2098	2.07	0.39	0.60	3.73
Log upward volatility	2100	3.82	0.51	1.36	5.47
Log downward volatility	2100	3.85	0.51	1.36	5.47
Log day-ahead intraday range	2098	3.32	0.41	1.96	5.15
Log downward intraday range	2100	5.75	0.44	3.14	7.00
Log upward intraday range	2100	5.75	0.44	3.14	7.00
Log forecasted load	2100	9.45	0.15	8.90	9.73
Log forecasted wind production	2099	6.69	0.87	3.53	8.36
Log forecasted solar production	2094	5.27	1.17	0.10	7.27
Log gas price	1500	2.72	0.40	1.13	4.33
Log emission price	1500	2.39	0.66	1.36	3.42
Log day-ahead and downward IIMR	2099	4.80	0.58	2.30	6.37
Log upward and day-ahead IIMR	2099	5.26	0.63	1.94	6.78
Log upward and downward IIMR	2100	5.73	0.44	3.14	7.00

Table 4
Hourly descriptive statistics 2015 until 2020

	Count	Mean	SD	Minimum	Maximum
Day-head price	50353	39.51221	14.45919	0	200.04
Forecasted wind production	50400	1109.771	930.4298	0	5118.25
Forecasted solar production	50256	330.656	621.7468	0	4160.75
Forecasted load	50400	12809.22	2498.518	4425	21475.75

15 minute descriptive statistics 2015 until 2020

	Count	Mean	SD	Minimum	Maximum
Upward price	201600	38.44175	60.54897	-561.17	936.12
Downward price	201600	42.13283	62.35727	-561.17	936.12
Forecasted wind production	201600	1109.771	930.9136	0	5230
Forecasted solar production	201024	330.656	623.7719	0	4240
Forecasted load	201600	12809.22	2507.327	4334	28270

5 Methodology

Studying volatility and extreme prices can be done with different types of models and with different kinds of variables. Especially volatility is measured in multiple ways in different studies. For this thesis a focus on measures that concern daily volatility of prices are studied. Because daily trading is the most probable operation strategy for storage owners and most studies studying energy arbitrage with storage facilities share this approach (Lazard, 2019; Schmidt et al., 2019; Spodniak et al., 2018; Wilson et al., 2018). Moreover, the increasing amount of renewable energy in the electricity grid is pushing energy trade towards moments closer to the delivery of electricity (Knaut & Paschmann, 2019). Which increases the relevance of daily volatility for energy trading parties. Lastly, because the electricity market is very volatile even during the day, studying it at a daily level is appropriate.

The most relevant measures of volatility are picked, through studying other papers that also examine the volatility of electricity prices (Erdogdu, 2016; Mauritzen, 2011; Pereira Da Silva & Horta, 2019; Rintamäki et al., 2017; Wilson et al., 2018). In accordance with these papers the daily standard deviation is selected as the first measure of volatility in the studied electricity markets. As a second measure of daily volatility for the different electricity markets guidance was found in the papers by Frömmel et al (2014) and Page et al. (2018). These papers use the intraday range (IR) that is the difference between the highest and lowest price on a given day. Even though this approach is not as common as the standard deviation to measure electricity price volatility. It does allow for a good display of potential daily arbitrage revenue. Studying both measures of volatility extends the validity of this thesis and provides a broader perspective on volatility. Lastly, a different measure of volatility is also studied, that is connected to the approach of this thesis to study extreme prices. This measure is the interquartile range between the 90^{th} and 10^{th} quantiles of the electricity prices. Interquartile range as a measure is akin to the studies of Maciejowska (2020) and Demir et al. (2020), that use it as well to measure volatility. Unlike the two other measures of volatility this measure does not gauge the daily volatility, but rather it measures volatility over the entire span of the data. Or in the case of this thesis the movements of prices in two periods, namely the first and the latter half of the studied eleven years.

Two types of statistical methods will be used to answer the hypotheses of this thesis. For the daily volatility measures Ordinary Least Squares regressions with robust standard errors will be used. A similar model was used by other research into the study of electricity prices and its volatility (Knaut & Paschmann, 2019; Mulder & Scholtens, 2013; Pereira Da Silva & Horta, 2019). While the hypotheses concerning the extreme prices will be tested with quantile regressions with a focus on the 5^{th} and the 95^{th} quantiles. This parametric approach to studying electricity prices is employed often in the literature (Bunn et al., 2016; Huisman et al., 2020; Maciejowska, 2020). All statistical analyses are implemented in the statistical software program Stata.

To not overly clutter this section of the thesis only a simple and general regression equation is presented underneath. A full list of the exact models can be found in the appendix in part C. The equation below is applied for all the regressions in this thesis. Also, for the regressions that check the robustness of the findings from the main dataset with the exemption of the period variable. This is shown in the results tables with the addition of the letter “a” to the equation number that is above each column of results in the tables displaying the found results.

$$dependent\ variable = \alpha_i + \beta_1 * Period_i + \beta_i * control\ variables_i + \varepsilon_i$$

Both the price itself and the daily volatility of the price are studied as dependent variables. With the control variables being the total load, proxy variables for renewable production (wind speed and solar irradiance) and prices of electricity production (prices for natural gas and emission allowances). The additional regressions use forecasted production of aggregated wind and solar sources instead of proxy variables. To control for possible day of week and monthly variables are included as dummy variables. Contrary to most studies that focus on volatility the models in this thesis do not account for yearly effects, because including them would cannibalize on the effect of the main variable of interest the dummy variable ‘period’. Except the dummy variable ‘period’ and the dummy variables to control for time effects all other variables in regressions that cover daily volatility measures as dependent variables have variables that are converted to natural logarithms to deal with outliers of the data. For the regressions that utilize quantile regressions no variables are on a logarithmic scale. Because these datasets contain observations that are negative or equal to zero and these variables are an essential part of the study. So, these variables cannot be expressed in logarithmic form, because that would result in many missing variables and that would negatively affect the statistical power of the results of these regressions.

6 Results

6.1 Main results

In order to test the hypotheses, the models, which can be found in the appendix part A, have all been performed on the data sets as described in the methodology chapter. The present chapter discusses the results and their implications for the hypotheses of this thesis. Each table has a brief description of its dependent variable(s), for a detailed description of the exact model refer to appendix part A. Firstly, the different measures of volatility that are relevant for hypotheses 1 and 3 are displayed beneath.

Table 5
Daily standard deviation and intraday range of day-ahead prices

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Period	-0.1904***	-0.2014***	-0.2023***	-0.0973***	-0.1057***	-0.4085***	-0.4247***	-0.4233***	-0.1995***	-0.2122***
	(0.0134)	(0.0128)	(0.0123)	(0.0152)	(0.0151)	(0.0291)	(0.0279)	(0.0266)	(0.0335)	(0.0324)
Log(Wind speed)		0.0003	0.0035	0.0009	0.0027		0.0271*	0.0309**	0.0282*	0.0292*
		(0.0058)	(0.0057)	(0.0056)	(0.0055)		(0.0122)	(0.0120)	(0.0119)	(0.0117)
Log(Solar irradiance)		-0.0371***	0.0359**	-0.0419***	0.0274*		-0.1053***	0.0728**	-0.1174***	0.0541*
		(0.0092)	(0.0128)	(0.0089)	(0.0120)		(0.0197)	(0.0280)	(0.0188)	(0.0265)
Log(Load)		1.2603***	1.3507***	0.7277***	0.7547***		2.3765***	2.3191***	1.2270***	1.0178**
		(0.1413)	(0.1532)	(0.1417)	(0.1613)		(0.2972)	(0.3183)	(0.2967)	(0.3329)
Log(Gas price)				0.3445***	0.3193***				0.7121***	0.6632***
				(0.0220)	(0.0226)				(0.0483)	(0.0487)
Log(Emission price)				0.1206***	0.1134***				0.2254***	0.2105***
				(0.0114)	(0.0108)				(0.0247)	(0.0236)
Constant	2.3157***	-9.4824***	-10.5115***	-5.7212***	-6.0164***	7.1058***	-15.1202***	-15.0348***	-6.8256*	-5.0397
	(0.0074)	(1.3711)	(1.4762)	(1.3594)	(1.5362)	(0.0166)	(2.8871)	(3.0672)	(2.8478)	(3.1691)
Month dummies	No	No	Yes	No	Yes	No	No	Yes	No	Yes
Weekday dummies	No	No	Yes	No	Yes	No	No	Yes	No	Yes
N	2804	2804	2804	2804	2804	2804	2804	2804	2804	2804
R^2	0.0714	0.1844	0.2524	0.2665	0.3212	0.0694	0.1831	0.2569	0.2537	0.3162
adj. R^2	0.0711	0.1833	0.2473	0.2650	0.3161	0.0690	0.1819	0.2518	0.2521	0.3110

Note: In between brackets are the standard errors. *, ** and *** refer to 10%, 5% and 1% significance levels, respectively

From table 5 a consistent pattern emerges, it shows that the daily volatility in the day-ahead market has decreased compared to the latter half of the period studied. Both volatility measures show a constant negative and significant relation with the period variable. Even though the introduction of control variables diminishes the effect that period has, it remains significant at 1% for all 10 models. Hence, the results in Table 5 reject the null hypothesis of the first hypothesis. However, the alternative formulation of this hypothesis as stated in the earlier chapter is also not correct. Since the alternative hypothesis stated that that the volatility between January 2016 and September 2020 ought to have increased. Which would mean that there would be more potential for profitable trade for a storage facility operating in the day-ahead market due to more fluctuations in the price. Based on the results above this is not the case and the amount of daily volatility in the day-ahead market has decreased in the latter part of the period studied.

Table 6
Daily standard deviation and intraday range of upward regulation prices

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Period	-0.0075	-0.0334*	-0.0258	-0.0115	-0.0238	-0.0060	-0.0370*	-0.0242	-0.0277	-0.0319
	(0.0172)	(0.0170)	(0.0172)	(0.0267)	(0.0266)	(0.0162)	(0.0159)	(0.0160)	(0.0248)	(0.0250)
Log(Wind speed)		0.0285***	0.0322***	0.0178*	0.0244**		0.0271***	0.0278***	0.0186*	0.0218**
		(0.0076)	(0.0076)	(0.0088)	(0.0089)		(0.0071)	(0.0071)	(0.0079)	(0.0080)
Log(Solar irradiance)		0.0124	-0.0332	-0.0401**	-0.0469*		0.0385***	0.0139	-0.0206	0.0009
		(0.0104)	(0.0189)	(0.0138)	(0.0220)		(0.0100)	(0.0177)	(0.0130)	(0.0197)
Log(Load)		1.3391***	1.1036***	0.6209**	0.9437***		1.4689***	0.9488***	0.6069**	0.6497**
		(0.0997)	(0.1773)	(0.1999)	(0.2176)		(0.0977)	(0.1717)	(0.1955)	(0.2230)
Log(Gas price)				0.0261	0.0017				0.0499	0.0398
				(0.0381)	(0.0378)				(0.0337)	(0.0339)
Log(Emission price)				-0.0980***	-0.1022***				-0.0998***	-0.1037***
				(0.0187)	(0.0185)				(0.0168)	(0.0167)
Constant	3.7978***	-9.0504***	-6.6400***	-1.7861	-4.6699*	5.7400***	-8.4425***	-3.3949*	0.1501	-0.1813
	(0.0118)	(0.9721)	(1.6858)	(1.9070)	(2.0673)	(0.0121)	(0.9528)	(1.6339)	(1.8698)	(2.1230)
Month dummies	No	No	Yes	No	Yes	No	No	Yes	No	Yes
Weekday dummies	No	No	Yes	No	Yes	No	No	Yes	No	Yes
N	3926	3926	3926	2804	2804	3926	3926	3926	2804	2804
R^2	0.0000	0.0615	0.0914	0.0457	0.0681	0.0000	0.0688	0.1017	0.0503	0.0654
adj. R^2	-0.0002	0.0606	0.0866	0.0436	0.0611	-0.0002	0.0679	0.0969	0.0483	0.0584

Note: In between brackets are the standard errors. *, ** and *** refer to 10%, 5% and 1% significance levels, respectively

In table 6 only model 2 and model 7 show a significant effect of period on the volatility of the upward regulation price. This is not strong enough evidence to reject the null hypothesis of the third hypothesis in terms of the upward regulation prices. Even though the sign of the effect of period on the volatility variables is consistently negative, the lack of significance in the effect of period in most of the models, means that the null hypothesis cannot be rejected. Thus, from the analyzed data it cannot be concluded whether there was a significant difference in the volatility between 2010 and 2015 than between 2016 and 2020.

Although there are more models in table 7 that show a significant effect of the period on the volatility measures. It is not the case for all models, especially the models that contain gas and emission price variables. These variables only have data for weekdays, so weekends are excluded when these variables are present in the model. Similarly, to the previous table, the findings in table 3 do not allow for an unequivocal rejection of the third hypothesis.

Table 7
Daily standard deviation and intraday range of downward regulation prices

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Period	-0.0346*	-0.0621***	-0.0518**	-0.0271	-0.0387	-0.0268	-0.0567***	-0.0401*	-0.0372	-0.0396
	(0.0174)	(0.0171)	(0.0172)	(0.0270)	(0.0268)	(0.0160)	(0.0157)	(0.0158)	(0.0247)	(0.0249)
Log(Wind speed)		0.0291***	0.0332***	0.0162	0.0234**		0.0337***	0.0344***	0.0233**	0.0268***
		(0.0076)	(0.0077)	(0.0088)	(0.0089)		(0.0069)	(0.0069)	(0.0078)	(0.0078)
Log(Solar irradiance)		0.0231*	-0.0283	-0.0349*	-0.0447*		0.0445***	0.0080	-0.0231	-0.0099
		(0.0105)	(0.0191)	(0.0137)	(0.0221)		(0.0098)	(0.0173)	(0.0126)	(0.0192)
Log(Load)		1.3666***	1.0280***	0.5160**	0.8145***		1.3952***	0.7255***	0.3539	0.3699
		(0.1006)	(0.1756)	(0.1994)	(0.2157)		(0.0971)	(0.1669)	(0.1908)	(0.2184)
Log(Gas price)				0.0238	-0.0012				0.0628	0.0546
				(0.0380)	(0.0375)				(0.0333)	(0.0336)
Log(Emission price)				-0.1198***	-0.1249***				-0.0988***	-0.1029***
				(0.0187)	(0.0184)				(0.0164)	(0.0163)
Constant	3.8508***	-9.3071***	-5.9227***	-0.6976	-3.3529	5.7635***	-7.7830***	-1.3092	2.5175	2.4381
	(0.0119)	(0.9797)	(1.6694)	(1.9007)	(2.0485)	(0.0119)	(0.9462)	(1.5871)	(1.8224)	(2.0764)
Month dummies	No	No	Yes	No	Yes	No	No	Yes	No	Yes
Weekday dummies	No	No	Yes	No	Yes	No	No	Yes	No	Yes
N	3926	3926	3926	2804	2804	3926	3926	3926	2804	2804
R^2	0.0010	0.0597	0.0925	0.0467	0.0709	0.0007	0.0641	0.1008	0.0489	0.0637
adj. R^2	0.0007	0.0588	0.0877	0.0447	0.0639	0.0004	0.0632	0.0960	0.0468	0.0566

Note: In between brackets are the standard errors. *, ** and *** refer to 10%, 5% and 1% significance levels, respectively

The following tables contain the results from the regressions with quantile regressions. Note that these tables do not report r-squared or adjusted r-squared values, but pseudo squared values for both quantiles that are studied.

Table 8
Interquartile range of hourly day-ahead, upward and downward regulation prices

	Day ahead			Upward			Downward		
	(11)	(12)	(13)	(11)	(12)	(13)	(11)	(12)	(13)
Period	3.2800***	5.4753***	5.3583***	5.6525***	4.2827***	3.7928***	2.2775*	1.0500	0.8280
	(0.3990)	(0.2220)	(0.2014)	(0.7461)	(0.7694)	(0.7288)	(0.9350)	(0.7984)	(0.7331)
Wind speed		0.0005*	0.0001		0.0047***	0.0059***		0.0039***	0.0059***
		(0.0002)	(0.0002)		(0.0011)	(0.0007)		(0.0010)	(0.0010)
Solar irradiance		-0.0005	-0.0014*		-0.0348***	-0.0373***		-0.0392***	-0.0418***
		(0.0005)	(0.0006)		(0.0017)	(0.0018)		(0.0014)	(0.0019)
Load		0.0016***	0.0016***		0.0039***	0.0033***		0.0049***	0.0045***
		(0.0000)	(0.0000)		(0.0002)	(0.0002)		(0.0002)	(0.0002)
Constant	33.3500***	1.7919**	0.2015	68.5850***	20.7670***	30.1772***	73.7850***	13.0569***	16.7356***
	(0.0796)	(0.5710)	(0.6744)	(0.4318)	(2.2116)	(2.6175)	(0.6828)	(2.2736)	(3.2884)
Month dummies	No	No	Yes	No	No	Yes	No	No	Yes
Weekday dummies	No	No	Yes	No	No	Yes	No	No	Yes
N	67296	67296	67296	94224	94224	94224	94224	94224	94224
pseudo R^2 90th	0.0054	0.2464	0.2614	0.0001	0.0457	0.0542	0.0005	0.0469	0.0562
pseudo R^2 10th	0.0467	0.2764	0.2889	0.0017	0.0376	0.0487	0.0053	0.0433	0.0534

Note: In between brackets are the standard errors. *, ** and *** refer to 10%, 5% and 1% significance levels, respectively

Effects of period on the last measure of volatility, the interquartile range between the 90th and 10th quantiles are interesting. In table 8 these are displayed and there is a positive and significant effect on the interquartile ranges of day-ahead and upward regulation prices from the period variable. Which is the opposite finding compared to the ones in tables 5 and 6. In the case of the results in table 1 the null hypothesis of the first hypothesis was rejected, which also can be done from the results in the table above. However, the implications of the results in table 7 are different, because these indicate a positive effect on price volatility in observations in the period between 2016 and 2020 compared to the first half of the period studied. These contradictory findings could be explained by the fact that the models presented in table 8 measure a different form of volatility than the earlier tables. In contrast to the daily standard deviation and the intraday range, which measure the daily volatility of electricity prices. The interquartile range measures the fluctuation of prices in the entire period. Furthermore, there are less control variables, because the control variables that are used for the daily models are only available on a daily level. In conclusion, based on the findings in table 4 the null statement of the first hypothesis can be rejected, but the sign of the effect of period is different from other volatility measures.

Findings regarding the imbalance price volatility are also different compared to earlier results. For these findings a similar explanation holds, as mentioned earlier, the interquartile range measures the volatility of prices on a different level. Besides, the sign changes from negative to positive from the effect of the period variable. More striking is the overall significance of the effect of the period on the interquartile range of the upward regulation price. For the downward regulation price only model 11 shows some significance of period, but this effect disappears in subsequent models. Hence, these findings lead to a rejection of the null statement of hypothesis 3, for upward regulation prices, but there is no rejection for the downward regulation price.

Table 9
Quantile regressions of hourly day-ahead, upward and downward regulation prices

	Day ahead			Upward			Downward		
	(14)	(15)	(16)	(14)	(15)	(16)	(14)	(15)	(16)
5th Quantile									
Period	-7.3100***	-9.0791***	-8.7588***	0.9075	-4.8228***	-4.7726***	-4.4925***	-8.4951***	-8.5310***
	(0.1659)	(0.1372)	(0.1552)	(0.7550)	(0.6213)	(0.6673)	(0.8160)	(0.6879)	(0.5709)
Wind speed		-0.0044***	-0.0035***		-0.0104***	-0.0065***		-0.0088***	-0.0057***
		(0.0002)	(0.0002)		(0.0010)	(0.0007)		(0.0011)	(0.0008)
Solar irradiance		-0.0044***	-0.0065***		0.0080***	-0.0048*		-0.0001	-0.0098***
		(0.0003)	(0.0004)		(0.0019)	(0.0019)		(0.0021)	(0.0015)
Load		0.0034***	0.0035***		0.0063***	0.0078***		0.0060***	0.0071***
		(0.0000)	(0.0000)		(0.0001)	(0.0002)		(0.0001)	(0.0002)
Constant	28.0100***	-9.6969***	-14.0507***	-8.2850***	-82.1198***	-112.3415***	1.3650*	-69.8577***	-95.8727***
	(0.0675)	(0.3762)	(0.5717)	(0.5349)	(1.9272)	(3.1479)	(0.5396)	(2.0880)	(2.7575)
95th Quantile									
Period	0.6800**	-1.1581***	-1.5551***	4.0925***	2.7760*	1.2148	-5.4775***	-6.7928***	-7.4622***
	(0.2369)	(0.3002)	(0.2239)	(1.2337)	(1.3672)	(1.2933)	(1.4650)	(1.2490)	(1.1896)
Wind speed		-0.0034***	-0.0031***		-0.0023	0.0038**		0.0002	0.0052**
		(0.0002)	(0.0002)		(0.0014)	(0.0014)		(0.0017)	(0.0020)
Solar irradiance		-0.0054***	-0.0078***		-0.0434***	-0.0524***		-0.0543***	-0.0613***
		(0.0006)	(0.0006)		(0.0025)	(0.0033)		(0.0033)	(0.0029)
Load		0.0055***	0.0057***		0.0107***	0.0112***		0.0112***	0.0112***
		(0.0001)	(0.0001)		(0.0003)	(0.0003)		(0.0004)	(0.0003)
Constant	69.3200***	-7.1492***	-13.8179***	108.9500***	-25.0698***	-43.1770***	125.3350***	-15.6024***	-34.1155***
	(0.1951)	(0.6246)	(0.8731)	(0.5361)	(3.2117)	(3.9928)	(1.0299)	(4.2269)	(5.0335)
Month dummies	No	No	Yes	No	No	Yes	No	No	Yes
Weekday dummies	No	No	Yes	No	No	Yes	No	No	Yes
N	67296	67296	67296	94224	94224	94224	94224	94224	94224
pseudo R^2 5th	0.0467	0.2705	0.2855	0.0000	0.0467	0.0594	0.0012	0.0546	0.0670
pseudo R^2 95th	0.0003	0.2416	0.2609	0.0003	0.0487	0.0584	0.0006	0.0464	0.0581

Note: In between brackets are the standard errors. *, ** and *** refer to 10%, 5% and 1% significance levels, respectively

Moving on from interquartile regressions, to the quantile regression results in table 9. These findings can shed light on the second and fourth hypotheses of this thesis. This table and hypotheses show the effect of being in the second part of the decennium when extreme prices occur. All models in table 9, except model 14 of the upward regulation price, show a negative effect of the period on the respective prices in the 5th quantile. Thus, from these findings, the second and fourth hypotheses their null statements regarding the prices in the 5th quantile remaining unchanged can be rejected. For the 95th quantiles only the models for the downward and day-ahead prices are constantly significant and therefore only for these prices the null statement of these hypotheses can be rejected. All in all, the findings in table 9 indicate that period leads to less extremely low prices for the day-ahead and both sides of the imbalance market. Being in the second part of the studied period, also leads to less extreme prices in the day-ahead and downward regulation prices.

Table 10
IIMR between highest day-ahead price and lowest downward price

	(17)	(18)	(19)	(20)	(21)
Period	-0.2240***	-0.2199***	-0.2166***	-0.0662*	-0.0415
	(0.0221)	(0.0220)	(0.0218)	(0.0275)	(0.0281)
Log(Wind speed)		0.0447***	0.0394***	0.0441***	0.0375***
		(0.0096)	(0.0097)	(0.0095)	(0.0095)
Log(Solar irradiance)		-0.0712***	0.0214	-0.0877***	0.0059
		(0.0155)	(0.0240)	(0.0154)	(0.0235)
Log(Load)		0.3935	-0.1628	-0.3792	-1.2313***
		(0.2037)	(0.2333)	(0.2184)	(0.2682)
Log(Gas price)				0.3254***	0.3659***
				(0.0402)	(0.0415)
Log(Emission price)				-0.0184	-0.0223
				(0.0198)	(0.0196)
Constant	4.9868***	1.3383	6.5071**	7.7836***	15.6763***
	(0.0154)	(1.9869)	(2.2532)	(2.0956)	(2.5435)
Month dummies	No	No	Yes	No	Yes
Weekday dummies	No	No	Yes	No	Yes
N	2804	2804	2804	2804	2804
R^2	0.0346	0.0694	0.0898	0.0946	0.1203
adj. R^2	0.0342	0.0681	0.0836	0.0926	0.1137

Note: In between brackets are the standard errors. *, ** and *** refer to 10%, 5% and 1% significance levels, respectively

Table 11
IIMR between highest upward price and lowest day-ahead price

	(17)	(18)	(19)	(20)	(21)
Period	0.0189	0.0015	-0.0027	-0.0016	-0.0263
	(0.0241)	(0.0244)	(0.0243)	(0.0335)	(0.0336)
Log(Wind speed)		0.0058	0.0151	0.0049	0.0150
		(0.0105)	(0.0105)	(0.0104)	(0.0105)
Log(Solar irradiance)		0.0100	-0.0087	0.0049	-0.0067
		(0.0177)	(0.0256)	(0.0181)	(0.0257)
Log(Load)		1.4130***	1.9004***	1.4363***	2.0511***
		(0.2518)	(0.2876)	(0.2839)	(0.3248)
Log(Gas price)				-0.1116**	-0.1625***
				(0.0432)	(0.0437)
Log(Emission price)				-0.1122***	-0.1180***
				(0.0234)	(0.0232)
Constant	5.3237***	-8.1594***	-12.7112***	-7.7771**	-13.4068***
	(0.0168)	(2.4533)	(2.7815)	(2.7230)	(3.0973)
Month dummies	No	No	Yes	No	Yes
Weekday dummies	No	No	Yes	No	Yes
N	2804	2804	2804	2804	2804
R^2	0.0002	0.0230	0.0443	0.0322	0.0556
adj. R^2	-0.0001	0.0216	0.0378	0.0301	0.0485

Note: In between brackets are the standard errors. *, ** and *** refer to 10%, 5% and 1% significance levels, respectively

Table 12
IIMR between highest upward and lowest downward price

	(17)	(18)	(19)	(20)	(21)
Period	0.0048	-0.0255	-0.0112	-0.0191	-0.0227
	(0.0162)	(0.0160)	(0.0161)	(0.0250)	(0.0252)
Log(Wind speed)		0.0301***	0.0309***	0.0208**	0.0241**
		(0.0071)	(0.0071)	(0.0080)	(0.0081)
Log(Solar irradiance)		0.0412***	0.0084	-0.0214	-0.0044
		(0.0100)	(0.0177)	(0.0131)	(0.0198)
Log(Load)		1.4263***	0.8512***	0.5558**	0.5917**
		(0.0979)	(0.1723)	(0.1958)	(0.2239)
Log(Gas price)				0.0387	0.0286
				(0.0339)	(0.0341)
Log(Emission price)				-0.0950***	-0.0992***
				(0.0170)	(0.0169)
Constant	5.7105***	-8.0969***	-2.5177	0.6195	0.3528
	(0.0121)	(0.9548)	(1.6397)	(1.8728)	(2.1312)
Month dummies	No	No	Yes	No	Yes
Weekday dummies	No	No	Yes	No	Yes
N	3926	3926	3926	2804	2804
R^2	0.0000	0.0643	0.0978	0.0431	0.0574
adj. R^2	-0.0002	0.0634	0.0930	0.0410	0.0503

Note: In between brackets are the standard errors. *, ** and *** refer to 10%, 5% and 1% significance levels, respectively

In order to test the fifth and final hypothesis of this thesis the daily differences between the day-ahead market and the imbalance market are studied. Table 10 shows a negative relationship between their respective dependent variables and the period variable. In table 10 this relationship is significant in most models. In table 11 a non-significant change of the sign of the effect of period on the respective IIMR. In conclusion, it can be stated that the alternative formulation of hypothesis 5 cannot be accepted. Thus, from the presented research methodology and data it cannot be concluded that the price movements between the day-ahead and imbalance market have become more profitable for storage facilities in the last years of the studied period compared to the first part of this period. Lastly table 12 displays the development of the intraday and intra market range with the highest upward and lowest downward regulation prices. That is arbitrage between both sides of the imbalance market. No persistent significant effects are found. In line with earlier findings regarding the other IIMR related. Thus, no rejection of the fifth hypothesis is possible from these findings.

6.2 Robustness check results

As mentioned in the data chapter of this thesis in order to get a clearer view on the factors that may influence the volatility of prices in the Dutch day-ahead and imbalance markets are more recent dataset is also studied in this research. All the following tables are similar to the earlier tables and the models that they display with the exemption of the period variable. This is the case because this dataset ranges from January 2015 until 30 September 2020. Furthermore, the variables wind and solar are no longer weather variables, but the forecasted production from wind and solar sources. These regressions are run to analyze the effects of volatility and extreme price with more precise data in order to find the drivers of price movements in the Netherlands.

Table 13
Check of daily standard deviation and intraday range of day-ahead prices

	(2a)	(3a)	(4a)	(5a)	(7a)	(8a)	(9a)	(10a)
Log(Wind prod)	0.0002	-0.0097	-0.0672***	-0.0654***	0.0241*	0.0115	-0.0445***	-0.0466***
	(0.0106)	(0.0099)	(0.0126)	(0.0111)	(0.0113)	(0.0107)	(0.0135)	(0.0122)
Log(Solar prod)	-0.0244**	0.0242**	-0.0411***	0.0297**	-0.0322***	0.0207*	-0.0430***	0.0229
	(0.0074)	(0.0092)	(0.0088)	(0.0109)	(0.0078)	(0.0099)	(0.0097)	(0.0123)
Log(Load)	0.6410***	0.3856***	0.5381***	0.3422***	0.5129***	0.3650***	0.4568***	0.2914**
	(0.0607)	(0.0683)	(0.0968)	(0.0988)	(0.0634)	(0.0727)	(0.1020)	(0.1075)
Log(Gas price)			0.3086***	0.3070***			0.3318***	0.3251***
			(0.0248)	(0.0250)			(0.0265)	(0.0271)
Log(Emission price)			0.2010***	0.1277***			0.2026***	0.1383***
			(0.0172)	(0.0180)			(0.0192)	(0.0203)
Constant	-3.8542***	-1.4858*	-3.6285***	-1.6870	-1.5156*	-0.1472	-1.8354	-0.1636
	(0.5868)	(0.6483)	(0.9041)	(0.9194)	(0.6139)	(0.6918)	(0.9565)	(1.0024)
Month dummies	No	Yes	No	Yes	No	Yes	No	Yes
Weekday dummies	No	Yes	No	Yes	No	Yes	No	Yes
N	2092	2092	1494	1494	2092	2092	1494	1494
R^2	0.0794	0.2137	0.2139	0.3176	0.0604	0.1768	0.1909	0.2850
adj. R^2	0.0781	0.2061	0.2113	0.3083	0.0591	0.1688	0.1882	0.2753

Note: In between brackets are the standard errors. *, ** and *** refer to 10%, 5% and 1% significance levels, respectively

From table 13 it becomes clear that the price of gas has a persistent positive effect on the volatility of day-ahead prices, that is significant. Considering that gas fired plants were the largest source of electricity production this is no surprise. Furthermore, the negative impact of wind energy on volatility in the more elaborate models that is significant at the 1% level is interesting and in line with the findings by (Ketterer, 2014; Rintamäki et al., 2017). Although these regressions do not contain as many observations due to the fact that gas and emission price data is only available for weekdays. For solar energy the findings are a mixed bag, and no clear relationship arises from the results in table 13.

Table 14
Check of daily standard deviation and intraday range of upward regulation prices

	(2a)	(3a)	(4a)	(5a)	(7a)	(8a)	(9a)	(10a)
Log(Wind prod)	0.0478***	0.0534***	0.0112	0.0167	0.0464***	0.0450***	0.0216	0.0215
	(0.0135)	(0.0132)	(0.0163)	(0.0159)	(0.0116)	(0.0114)	(0.0137)	(0.0135)
Log(Solar prod)	-0.0024	-0.0167	-0.0331*	-0.0206	0.0019	0.0024	-0.0310**	-0.0050
	(0.0105)	(0.0128)	(0.0139)	(0.0175)	(0.0091)	(0.0112)	(0.0113)	(0.0141)
Log(Load)	0.0904	-0.1937*	0.0724	0.0543	0.0892	-0.1830*	0.1086	0.0369
	(0.0804)	(0.0970)	(0.1356)	(0.1454)	(0.0715)	(0.0847)	(0.1127)	(0.1217)
Log(Gas price)			-0.0772*	-0.0901*			-0.0870**	-0.0955**
			(0.0383)	(0.0387)			(0.0318)	(0.0322)
Log(Emission price)			0.0657*	0.0468			0.0587**	0.0330
			(0.0261)	(0.0282)			(0.0210)	(0.0226)
Constant	2.6569***	5.3703***	3.3209**	3.6232**	4.5861***	7.1808***	4.8686***	5.6562***
	(0.7959)	(0.9287)	(1.2825)	(1.3564)	(0.7065)	(0.8091)	(1.0692)	(1.1377)
Month dummies	No	Yes	No	Yes	No	Yes	No	Yes
Weekday dummies	No	Yes	No	Yes	No	Yes	No	Yes
N	2094	2094	1494	1494	2094	2094	1494	1494
R^2	0.0076	0.0471	0.0112	0.0492	0.0094	0.0474	0.0174	0.0521
adj. R^2	0.0062	0.0379	0.0078	0.0363	0.0079	0.0382	0.0141	0.0392

Note: In between brackets are the standard errors. *, ** and *** refer to 10%, 5% and 1% significance levels, respectively

Results in table 14 are not conclusive, especially in terms of significance. A positive significant effect of wind energy is noticeable in the first two models of both measures of volatility is present. However, this effect disappears when control variables for natural gas and emission prices are added to the models. Another factor that is present in both this table as well as in the earlier discussed tables that display results from the imbalance in market prices, is the low R-squared values for these models. That indicates that the found effects are not strongly explained from the data.

Table 15
Check of daily standard deviation and intraday range of downward regulation prices

	(2a)	(3a)	(4a)	(5a)	(7a)	(8a)	(9a)	(10a)
Log(Wind prod)	0.0343*	0.0408**	0.0005	0.0057	0.0434***	0.0429***	0.0199	0.0191
	(0.0137)	(0.0133)	(0.0164)	(0.0161)	(0.0116)	(0.0115)	(0.0138)	(0.0137)
Log(Solar prod)	-0.0045	-0.0239	-0.0353*	-0.0254	0.0030	-0.0018	-0.0294**	-0.0064
	(0.0106)	(0.0130)	(0.0140)	(0.0178)	(0.0090)	(0.0112)	(0.0112)	(0.0141)
Log(Load)	0.1241	-0.1919*	0.0409	0.0202	0.1096	-0.1651	0.1047	0.0392
	(0.0809)	(0.0972)	(0.1342)	(0.1447)	(0.0711)	(0.0843)	(0.1088)	(0.1186)
Log(Gas price)			-0.0966*	-0.1127**			-0.1016**	-0.1118***
			(0.0379)	(0.0382)			(0.0320)	(0.0323)
Log(Emission price)			0.0408	0.0223			0.0422*	0.0187
			(0.0258)	(0.0279)			(0.0205)	(0.0220)
Constant	2.4672**	5.4703***	3.8481**	4.1716**	4.4095***	7.0254***	4.9916***	5.7040***
	(0.8016)	(0.9308)	(1.2690)	(1.3497)	(0.7007)	(0.8052)	(1.0307)	(1.1079)
Year dummies	No		No		No		No	
Month dummies	No	Yes	No	Yes	No	Yes	No	Yes
Weekday dummies	No	Yes	No	Yes	No	Yes	No	Yes
N	2094	2094	1494	1494	2094	2094	1494	1494
R^2	0.0053	0.0493	0.0087	0.0498	0.0086	0.0463	0.0150	0.0475
adj. R^2	0.0039	0.0401	0.0054	0.0369	0.0072	0.0371	0.0117	0.0346

Note: In between brackets are the standard errors. *, ** and *** refer to 10%, 5% and 1% significance levels, respectively

Similar results compared to the previous table in table 15, some significant positive effects on the volatility of downward price volatility of wind production. That disappears when emission and gas price effects are added. Other than there are no consistent effects on the volatility measures of the downward regulation price between 2015 and 2020.

Table 16
Check of interquartile range of hourly day-ahead, upward and downward regulation prices

	Day ahead		Upward		Downward	
	(12a)	(13a)	(12a)	(13a)	(12a)	(13a)
Wind prod	-0.0005***	0.0003**	0.0077***	0.0075***	0.0057***	0.0065***
	(0.0001)	(0.0001)	(0.0004)	(0.0003)	(0.0004)	(0.0004)
Solar prod	0.0028***	0.0018***	0.0018***	0.0016***	0.0009*	0.0010*
	(0.0002)	(0.0002)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Load	0.0015***	0.0020***	0.0040***	0.0037***	0.0058***	0.0053***
	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0002)	(0.0002)
Constant	10.0078***	5.5439***	-1.9247	14.7478***	-14.6311***	4.1826
	(0.6671)	(0.7820)	(1.3874)	(2.5165)	(2.1844)	(3.6157)
Month dummies	No	Yes	No	Yes	No	Yes
Weekday dummies	No	Yes	No	Yes	No	Yes
N	50209	50209	201024	201024	201024	201024
pseudo R^2 90th	0.1992	0.2331	0.0150	0.0200	0.0198	0.0259
pseudo R^2 10th	0.1584	0.2076	0.0181	0.0222	0.0159	0.0199

Note: In between brackets are the standard errors. *, ** and *** refer to 10%, 5% and 1% significance levels, respectively

As the final measure of volatility, the interquartile range is studied, the findings are in table 16. From these results it is remarkable how consistent and significant the effects of the control variables are. Only the effect of wind power on the IQR of the day-ahead prices is not constantly positive and in only one model significant. As with the previous IQR results, this measure of volatility is somewhat different to the daily models. From these results it can be concluded that solar energy has a small, but positive effect on the daily volatility of all prices. Wind power also has a small, positive and significant effect on the imbalance market price volatility.

Table 17
Check of quantile regressions of hourly day-ahead, upward and downward prices

	Day ahead		Upward		Downward	
	(15a)	(16a)	(15a)	(16a)	(15a)	(16a)
5th Quantile						
Wind prod	-0.0027***	-0.0031***	-0.0156***	-0.0133***	-0.0126***	-0.0102***
	(0.0001)	(0.0001)	(0.0006)	(0.0007)	(0.0007)	(0.0005)
Solar prod	-0.0029***	-0.0020***	-0.0045***	-0.0038***	-0.0072***	-0.0061***
	(0.0002)	(0.0001)	(0.0007)	(0.0006)	(0.0008)	(0.0007)
Load	0.0024***	0.0020***	0.0037***	0.0031***	0.0030***	0.0026***
	(0.0000)	(0.0000)	(0.0002)	(0.0002)	(0.0001)	(0.0002)
Constant	-4.4250***	1.6784***	-44.5534***	-65.5542***	-30.0152***	-50.2479***
	(0.5037)	(0.4807)	(2.8654)	(4.9921)	(2.3252)	(3.7804)
95th Quantile						
Wind prod	-0.0022***	-0.0019***	-0.0024	0.0002	-0.0045**	0.0003
	(0.0001)	(0.0002)	(0.0012)	(0.0013)	(0.0014)	(0.0013)
Solar prod	0.0006**	0.0006*	-0.0049*	-0.0059**	-0.0115***	-0.0102***
	(0.0002)	(0.0002)	(0.0020)	(0.0019)	(0.0018)	(0.0020)
Load	0.0047***	0.0047***	0.0114***	0.0109***	0.0124***	0.0112***
	(0.0001)	(0.0001)	(0.0005)	(0.0005)	(0.0004)	(0.0005)
Constant	2.5718***	6.9660***	-4.1027	9.4826	4.5427	20.8692*
	(0.6795)	(0.9201)	(7.0071)	(7.5962)	(5.5733)	(8.1046)
Month dummies	No	Yes	No	Yes	No	Yes
Weekday dummies	No	Yes	No	Yes	No	Yes
N	50209	50209	201024	201024	201024	201024
pseudo R^2 5th	0.1863	0.2418	0.0243	0.0359	0.0239	0.0347
pseudo R^2 95th	0.2192	0.2615	0.0180	0.0294	0.0209	0.0329

Note: In between brackets are the standard errors. *, ** and *** refer to 10%, 5% and 1% significance levels, respectively

Table 17 displays the results in the study of the extreme prices between 2015 and 2020. Noticeable is the negative and significant effect of both solar and wind power on the low prices of all markets. Indicating that these variables have a negative impact on prices in the 5th quantile of the distribution. A less consistent situation on the other side of the distribution. Where the effects of wind on day-ahead prices in the 95th are significantly negative and the effects of solar are significantly positive. On the imbalance market prices the effects of solar in the 95th quantile is negative, albeit in the case of upward prices not on the same level of significance. In terms of wind power effects there are no consistent effects across the imbalance prices in the 95th quantile. Indicating that wind power does not significantly affect the high prices in this market.

Table 18
Check IIMR between highest day-ahead price and lowest downward price

	(18a)	(19a)	(20a)	(21a)
Log(Wind prod)	0.1065***	0.0974***	0.0750***	0.0675***
	(0.0149)	(0.0148)	(0.0178)	(0.0174)
Log(Solar prod)	-0.0302**	-0.0019	-0.0473***	0.0016
	(0.0112)	(0.0144)	(0.0137)	(0.0184)
Log(Load)	0.1840	0.2798*	0.2996	0.1722
	(0.0955)	(0.1153)	(0.1542)	(0.1656)
Log(Gas price)			0.1613***	0.1640***
			(0.0460)	(0.0464)
Log(Emission price)			0.0966***	0.0609*
			(0.0266)	(0.0299)
Constant	2.5112**	1.7599	1.0416	2.3150
	(0.9366)	(1.1042)	(1.4500)	(1.5408)
Month dummies	No	Yes	No	Yes
Weekday dummies	No	Yes	No	Yes
N	2093	2093	1494	1494
R^2	0.0366	0.0715	0.0623	0.0919
adj. R^2	0.0352	0.0625	0.0591	0.0796

Note: In between brackets are the standard errors. *, ** and *** refer to 10%, 5% and 1% significance levels, respectively

Table 19
Check IIMR between highest upward price and lowest day-ahead price

	(18a)	(19a)	(20a)	(21a)
Log(Wind prod)	0.0153	0.0148	-0.0124	-0.0090
	(0.0159)	(0.0156)	(0.0185)	(0.0183)
Log(Solar prod)	0.0122	0.0090	-0.0390*	-0.0060
	(0.0129)	(0.0153)	(0.0161)	(0.0194)
Log(Load)	0.1728	-0.3839**	0.1909	0.0881
	(0.1015)	(0.1212)	(0.1533)	(0.1714)
Log(Gas price)			-0.2254***	-0.2418***
			(0.0419)	(0.0426)
Log(Emission price)			0.0776*	0.0367
			(0.0307)	(0.0325)
Constant	3.4603***	8.6207***	4.2274**	5.3069***
	(1.0019)	(1.1617)	(1.4585)	(1.6080)
Month dummies	No	Yes	No	Yes
Weekday dummies	No	Yes	No	Yes
N	2093	2093	1494	1494
R^2	0.0018	0.0515	0.0232	0.0604
adj. R^2	0.0004	0.0424	0.0199	0.0477

Note: In between brackets are the standard errors. *, ** and *** refer to 10%, 5% and 1% significance levels, respectively

From tables 18 and 19, there is again a reminder of the importance of gas in the Dutch electricity market. Because it is the only variable that has a significant impact on all the dependent variables. Other noticeable effects are the effect of wind power in table 17, that is significant in most models and has a positive effect on the IIMR between the day-ahead and downward regulation market. The effect of solar on this variable is not consistent in its sign and not always significant. Besides these findings, no remarkable effects are present in these tables. Indicating that the impact of the variables studied is not significant on the IIMR.

Table 20
Check IIMR between highest upward and lowest downward price

	(18a)	(19a)	(20a)	(21a)
Log(Wind prod)	0.0486***	0.0480***	0.0248	0.0245
	(0.0117)	(0.0116)	(0.0140)	(0.0138)
Log(Solar prod)	0.0061	0.0029	-0.0284*	-0.0052
	(0.0092)	(0.0113)	(0.0113)	(0.0142)
Log(Load)	0.0975	-0.1789*	0.1325	0.0630
	(0.0719)	(0.0849)	(0.1125)	(0.1215)
Log(Gas price)			-0.1011**	-0.1101***
			(0.0323)	(0.0326)
Log(Emission price)			0.0569**	0.0328
			(0.0214)	(0.0228)
Constant	4.4509***	7.0845***	4.6312***	5.3894***
	(0.7091)	(0.8105)	(1.0684)	(1.1367)
Month dummies	No	Yes	No	Yes
Weekday dummies	No	Yes	No	Yes
N	2094	2094	1494	1494
R^2	0.0098	0.0472	0.0183	0.0499
adj. R^2	0.0083	0.0380	0.0150	0.0370

Note: In between brackets are the standard errors. *, ** and *** refer to 10%, 5% and 1% significance levels, respectively

Table 20 shows some significant relations between the IIMR in the imbalance market for wind power, but the significance disappears when gas and emission prices are added to the regression. Thus, there are no strong conclusions to be drawn from this table. Which is the case for most of the results concerning the imbalance market. This could indicate that the studied control variables do not explain much of the movements of the imbalance market independent variables in this thesis. This is a limitation of this thesis and it will be discussed in more detail in the next chapter.

7 Discussion

Despite the clear findings that add insights into Dutch electricity prices movements, this thesis also has some limitations. A critical analysis of this can aid further research and provide more context for the findings of this thesis.

7.1 Limitations

By focusing on pricing effects and the market this study has differentiated from the bulk of literature studying electrical storage. Where the focus is on simulation and optimization of storage facilities. This thesis is trying to complement these studies by not only focusing on the operation of a facility, but also determining the potential revenues for storage facilities. Furthermore, it is a more economic focused approach utilizing other tools, such as empirical methods to find the potential or future potential for storage arbitrage applications. So, it should be seen as such, an empirical inquiry into the storage research field that tries to shed light on some of the mechanisms that other research into energy storage does not cover. Given that there currently is a lack of empirical work concerning energy storage (Azhgaliyeva, 2019). While there is a

The narrow focus on only the Netherlands could be viewed as another limitation of this thesis. Although, the Netherlands is an interesting market due to its connections to surrounding countries and the central position in western Europe. Compared to its European peers the Netherlands is lagging in the integration of renewable energy sources. Even though the electricity transition and energy storage currently are popular research topics the amount of published research concerning these topics in the Netherlands has been limited to date. Especially compared to countries such as, Australia, Germany and parts of the United States of America. This lack of comparable sources helps to enhance the relevance and novelty of this thesis. On the other hand, it sometimes made it difficult to find sources to compare the findings of this thesis to, especially regarding the volatility of electricity prices. The findings of this thesis concerning the Netherlands could be applied to other countries in the world that are starting to transition towards more renewable energy sources.

Remarkably this thesis finds a different development of volatility than other studies have found. Namely that in the day-ahead market the volatility has decreased and extreme prices are also decreasing.

Furthermore, the effects of renewable energy sources that were studied via the second set of regressions on the 2015 to 2020 dataset, are that the effects of renewable sources are not as pronounced as in other countries. This could be due to the chosen methodology of this thesis. Though this seems unlikely, because the employed methodology is similar to other published papers as was shown in the methodology section of this thesis. More likely, is that variables and factors that are not covered in the analyses of this thesis have an influence on the levels of volatility and price movements in the Netherlands. This can also be derived from the relatively low r-squared and adjusted r-squared values of the found results. In particular, the results regarding the imbalance market have low r-squared values. Indicating that the studied independent variables do not explain the variations of the imbalance price volatility and extreme price variables much. There can be several reasons for this. For example, the design of market mechanisms or regulations may have a strong effect (Ciarreta et al., 2020; Kyritsis et al., 2017; Percebois & Pommeret, 2019). Another factor that could explain the findings of this thesis, is the relatively limited amount of renewable energy in the Dutch electricity grid. Especially in the earlier years of the studied period. Lastly, the very reliable and well-connected position of the Dutch electricity grid can have limited the fluctuations and spikes of electricity prices in the Netherlands. This fact coupled with the large amount of natural gas fired power plants and peaker plants in the Netherlands, could explain the slight decrease in daily price volatility and extreme prices in the studied period. Studying the impact of the reasons described would warrant a separate research in its own right.

Although the aim of this thesis was to describe the development of inflexibility in the form of extreme prices and volatility of the Dutch electricity market as complete as possible. Not all the flexibility markets are studied with the intraday market being the most important missing market. Intraday trading volumes increased with 51% from 2017 to 2018 and with a further 57% from 2018 to 2019 (Tijdink & Muller, 2020). This can be seen as a sign of a greater demand for flexibility (Slingerland et al., 2015). Obtaining data regarding this market was not possible due to the fact that price data from this market is not publicly available. Nor was it available through the data subscriptions of the Erasmus University. So, the studied volatility and extreme prices as signs of the flexibility of the Dutch electricity market only measure some part of flexibility trading taking place in the Netherlands. Thus, it might be that the volatility of intraday prices did increase in the period studied, while the prices in the studied markets became less volatile.

Another remark regarding the data used in this thesis is that the usage of weather data is not commonplace. But in order to study the chosen timespan it was necessary to resort to these variables. As shown in the methodology part of this thesis, other studies have resorted to this approach. Furthermore, the availability of reliable data regarding the Netherlands from before 2015 is lacking. So, the chosen approach seems appropriate, especially considering that the results are similar to the results from the regressions performed with production data. Even though the data that is used from ENTSO-E is not flawless (Hirth et al., 2018), there are no viable alternatives. This means that the chosen combination of weather data and production data allows for a study of electricity prices and its movements that are new and broad.

7.2 Further research

This thesis focuses on just one country and most other papers also focus on one or a few countries. While comparing multiple countries it can be interesting to examine the effects of differences in natural circumstances or electricity consumption. Furthermore, it could yield findings on the effects of having more or less renewable energy available and how countries deal with the changing energy mix. For such research to be possible, it is important that access to reliable and precise information is publicly available. Open-source data websites such as the ENTSO-E transparency platform, Open Power System Data and Renewables.ninja are essential sources for research currently. In order to enable further research, the development of these sources and the addition of other sources is crucial. For the further study of electricity markets and their development to be possible. In the Netherlands more information regarding the electricity markets has become available, but the amount and quality of the data could be improved to foster more better future research.

Not only a focus on other electricity markets abroad could be the topic of further research. As mentioned above, focusing on different Dutch markets such as the intraday market could yield interesting results. In terms of how these markets function such that policy makers can implement changes, but also for potential market participants investing in storage facilities and hybrid renewable energy sources. Studying the intraday market in conjunction with the existing markets in a similar fashion as this thesis has done, could also broaden the understanding of the flexibility requirements in the Netherlands. Such an approach is especially relevant now that intraday markets are becoming more important and are starting to see higher trading volumes in recent years (Tijdink & Muller, 2020).

This thesis has focused on an ex-post analysis of the dynamics of Dutch electricity prices. In order to avoid uncertain projections of the evolving market design and energy policies, as well as volatility projections, that are relevant for storage technologies. While historical patterns are not necessarily expected to hold into the future, this thesis analysis helps with better understanding the studied Dutch electricity markets. A next step could be to use the data studied to forecast future price movements via time-series models. In this way the findings of this thesis can help to provide forecasts and aid in developing trading strategies for storage operators. It could also be used to determine whether storage could be supported via subsidies or other policy measures and help to determine appropriate levels of such support.

In the future when more energy storage has been integrated into the Dutch electricity mix, it will be interesting to study the effects of these facilities on the electricity price. In some countries such research has been performed already (Blanco & Faaij, 2018; Gaudard & Madani, 2019; Nyamdash & Denny, 2013; Zamani-Dehkordi, Shafiee et al., 2017). For now, it is not yet relevant given the low amounts of storage in the Netherlands. In the future if the amount of storage does indeed grow, studying its effects can yield interesting findings. Another extension of such research could be to study multiple sources of revenue for storage. This revenue stacking is seen by many researchers to enhance the profitability storage facilities (Hiesl et al., 2020; Schmidt et al., 2019; Staffell & Rustomji, 2016). In the future with more actual experience and more knowledge about energy storage this could become a more concrete area of research.

8 Conclusion

This thesis focused on the changing electricity market in the Netherlands, more specifically on the developments of electricity prices and their movements from 2010 onwards. Therewith, investigating whether the increasing share of renewable energy in the electricity mix and decline of conventional sources leads to more inflexibility. Stark signs of inflexibility can be higher levels of volatility and more extreme prices in a market. High price volatility can be unappreciated as a risk, but it may impose high financial risk levels on electricity producers and end users alike. Although stronger fluctuating prices can be problematic for some electricity market participants, it can also be a form of revenue for other participants. Providers of electricity storage or demand response services can profit from it and therewith make the grid more resilient by providing the needed flexibility.

8.1 Main findings

Firstly, the findings regarding the first and second hypotheses (see chapter 3.2 for the full explanation regarding the hypotheses) of this thesis that concern the day-ahead market also show the prime results. From the findings it can be concluded that the null statements of the first and second are rejected. However, the alternative formulations of these hypotheses are not correct. Because the effect of the period between January 2016 and September 2020 on the daily volatility and extreme prices is negative. Which indicates that the circumstances for profitable trade for a storage facility operating in the day-ahead market have decreased in the last years of the studied periods. This is in stark contrast with most findings in the literature as discussed in chapter 2.3.3. As mentioned in the discussion chapter there could be several reasons for these findings, but that would be material for another thesis. The findings regarding daily volatility are contrasted by one measure of volatility also studied in this thesis. Namely, the interquartile range regressions. The results regarding this measure also lead to a rejection of the first hypothesis, but to an acceptance of the alternative statement. So, it indicates that the environment for storage operators did increase in the period between 2015 and 2020 compared to the period between 2010 and 2015. Note that it does measure a different form of volatility, which may be less relevant for actual trading strategies. That in the case of battery storage will most likely focus on daily arbitrage and are thus mostly focused on daily volatility (Gaudard & Madani, 2019; Lazard, 2019; Schmidt et al., 2019; Wilson et al., 2018). Still, it is remarkable considering its stark contrast to the earlier mentioned findings.

Where the findings of this thesis focusing on the day-ahead provide a strong basis to reject the null hypotheses, the findings regarding the imbalance market are less conclusive. From the analyzed data on daily volatility, it cannot be concluded that there was a significant difference in the Dutch imbalance market in both directions between 2010 and 2015 than between 2016 and 2020. Hence, the third hypothesis' null statement cannot be rejected for daily prices, but similar to the day-ahead prices the interquartile regression results provide a different view. Again, this measure has a different focus than the daily volatility measure. Nonetheless, the fact that these findings lead to a rejection of the null statement of hypothesis 3, for upward regulation prices is an interesting result. With regards to the fourth hypothesis of this thesis, the results point to clearer findings. Firstly, both for the upward and downward prices the effect of the period on the prices in the 5^{th} quantile is significant and negative. So being in the period between 2016 and 2020 leads to less extreme low prices. For the prices in the 95^{th} quantile only the downward results constantly show significance and a negative effect of the period. Hence, it can be concluded that the rejection of the fourth hypothesis only holds for downward price for the kurtosis, and for upward price only the 5^{th} quantile prices are affected by being in the later period.

Finally, the fifth hypothesis of this thesis relates to the daily differences between the day-ahead market and the imbalance market. Findings from the related regressions show mixed results. It can be concluded that the alternative formulation of hypothesis 5 cannot be accepted for the difference between the highest day-ahead prices and the lowest downward prices. Which is the most probable trading strategy. Thus, from the presented research methodology and data it cannot be concluded that the price movements between the day-ahead and imbalance market have become more profitable for storage facilities in the last five years compared to the first five when practicing this trading strategy. Other findings regarding the intraday and intra market volatility are not significant and thus do not warrant rejection of hypothesis statements.

When all the findings are combined the problem statement of this can be addressed. This statement is as follows: **Dutch electricity markets have become less flexible in the last decennium especially since 2015, exhibited through increasing price volatility and more extreme prices, that causes problems for producers, electricity users and market operators.** From the statistical results obtained in this study there is no clear indication that the volatility of Dutch electricity prices has significantly increased in the last five years of this decade. On the contrary there are indications that the overall volatility and the occurrence of extreme prices have decreased in the last five years. Especially in the day-ahead market, which makes it more understandable that to date there have not been major investments in storage facilities do focus on daily arbitrage. However, it may very well be that in the future when the influx of renewables will be larger and the trend of closing conventional power sources that rewards for flexibility in the form of arbitrage opportunities will arise. Coupled to the still decreasing costs of storage technologies, the predicted storage revolution may come in the future. For now, the banking on volatility and extreme prices is not yet rewarding to be pursued.

8.2 Findings of robustness checks

To further investigate the development of electricity prices and their volatility in the Netherlands a second dataset was researched in this thesis. Primarily, to find with more detailed and elaborate data how volatility has developed in the period from 2015 onwards. Secondly, to be able to compare this thesis to other studies focusing on the effects of renewable energy on extreme prices and volatility. Thirdly, the approach with the second dataset was done to be able to study whether the proxy variables wind speed and solar irradiance are useful to replace production data for wind and solar sources. Because this allows, as it has in this thesis, to study more price data on the effects of renewables in situations where there is no (renewable) production data available. Besides these arguments it allows enriched this thesis by performing additional research.

From the regressions on the 2015 until 2020 dataset the findings are less ubiquitous than the findings from the main dataset. However, some interesting results were obtained, especially regarding the day-ahead market. Analogous to the findings of (Ketterer, 2014; Rintamäki et al., 2017) a significant effect wind energy on the volatility of day-ahead prices is found although not in all studied models. While the effects of solar energy are not as clear cut. Another clear effect that is picked up by the regressions on day-ahead variables is that the price of gas has a persistent positive effect on the volatility of day-ahead prices. Which is a sign of the continued influence of gas-powered power plants on the Dutch electricity price.

Although the regressions on daily volatility measures in the day-ahead market yielded some robust results. The findings on the influencing parameters of Dutch imbalance prices are less distinct. Even though there are some significant influences in some models, none of these effects proves to be consistent in significance or sign. Therefore, no real conclusions regarding the daily volatility measures of imbalance prices can be drawn.

A different image arises from the interquartile regression results. From these results it is remarkable how consistent and significant the effects of several control variables are. Only the effect of wind power on the IQR of the day-ahead prices is not constantly positive and in only one model significant. As with the previous IQR results, this measure of volatility is somewhat different to the daily models. From these results it can be concluded that solar energy has a small, but positive effect on the daily volatility of all prices. Once more the results from the interquartile regressions show different findings than the other volatility measures. Which can be seen an interesting benefit of including this measure into research regarding volatility.

Noticeable findings from the checks on extreme prices between 2015 and 2020 are the negative and significant effect of both solar and wind power on the low prices of all markets. Indicating that these variables have a negative impact on prices in the 5^{th} quantile of the distribution. A less consistent situation on the other side of the distribution. Where the effects of wind on day-ahead prices in the 95^{th}

are significantly negative and the effects of solar are significantly positive. On the imbalance market prices the effects of solar in the 95th quantile is negative, albeit in the case of upward prices not on the same level of significance. In terms of wind power effects there are no consistent effects across the imbalance prices in the 95th quantile. Indicating that wind power does not significantly affect the high prices in this market.

From the robustness checks of the intraday intra market regressions only the results of the models containing the difference between the highest day-ahead price and the lowest downward regulation price show some consistent significant results. Here there is a noticeable effect of wind power on the IIMR between the day-ahead and downward regulation market. Other models do not have any consistent significant effects across their different models.

8.3 Implications of findings

The findings from this thesis can be extrapolated to implications for different actors in the Dutch electricity markets. For storage facility operators the findings indicate that the possibilities to derive sufficient income from arbitrage on a daily basis in the day-ahead market and the imbalance has not improved in the period from 2016 to 2020 compared to the period 2010 to 2015. Arbitrage between these markets has not more become more lucrative either. Even though the prices of energy storage and in particular battery-based facilities have decreased and are still decreasing. Thus, it is understandable that to date no energy storage facility in the Netherlands has solely focused on energy arbitrage, but rather on the more lucrative FCR market. As discussed in the theoretical framework, this market will become saturated at some point. Either the prices have to become more volatile in the future or the prices of energy storage have to decrease further to make energy storage with batteries a viable operation strategy.

Policy makers and grid operators can conclude from the findings of this thesis that the Dutch electricity markets have not become more volatile. So far the effect of more renewable energy on price movements and price extremes has been moderate. In the future the increasing volatility due to increased renewable feed in may also happen in the Netherlands, as it has in other countries. For now policymakers that want to create business opportunities for flexibility providers could look into subsidizing energy storage facilities. Or wait until the market conditions become more favorable. Perhaps as suggested by Huisman et al. (2020) to change the subsidy conditions to stimulate more flexibility provision could be a good approach. From this thesis it can be found that the volatility and extreme prices have mostly remained unchanged in the studied period and that energy storage arbitrage is not yet a viable business strategy. Lastly, the findings that are relevant for Dutch policymakers is the confirmed influence of natural gas prices on the Dutch electricity market price movements. If the amount the electricity production from natural gas is decreased it may be that the Dutch electricity market may become more inflexible. That could provide opportunities for flexibility providers, such as energy storage.

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Appendix

Part A: Description of variables

Description of daily level dataset for the testing of hypothesis 1, 3 and 5
Except for period, all these variables are expressed in logarithmic form

Variable name	Description	Source
DA volatility	Daily standard deviation of hourly day-ahead prices in €'s	Datastream, own calculation
Up volatility	Daily standard deviation of 15 minute upward regulation prices in €'s	TenneT, own calculation
Down volatility	Daily standard deviation of 15 minute downward regulation prices in €'s	TenneT, own calculation
Day-ahead IR	Intraday range of day-ahead prices, which is the difference between the highest and lowest price, in €'s	Datastream, own calculation
Up IR	Intraday range of upward prices, which is the difference between the highest and lowest price, in €'s	TenneT, own calculation
Down IR	Intraday range of downward regulation prices, which is the difference between the highest and lowest price, in €'s	TenneT, own calculation
IIMR	Intraday and intra market range between highest and lowest prices from two different markets per day	Datastream and TenneT, own calculation
Period	Dummy variable that is equal to 1 for years from 2016 and onwards	-
Wind speed	Cube of average wind speed in meters per second, daily average from hourly data	KNMI, own calculation
Solar irradiance	Solar irradiance in watt per m^2, daily average from hourly data	KNMI, own calculation
Load	Total load, daily average from hourly data, in MWh	ENTSO-E, own calculation
Gas price	Daily price of natural gas at the TTF in €'s per MWh	Datastream
Emission price	Daily price of emission allowance in €'s per metric tonne	Datastream

Description of hourly level dataset for the testing of hypothesis 2 and 4

DA price	Day-ahead prices per hour in € per MWh	Datastream
Up price	Hourly average of upward regulation price in € per MWh, average from 15 minute data	TenneT, own calculation

Downward price	Hourly average of downward regulation price in € per MWh, average from 15 minute data	TenneT, own calculation
Day-ahead IQR	Interquartile range between 90th and 10th quantiles of hourly day-ahead prices, in € per MWh	Datastream, own calculation
Up IQR	Interquartile range between 90th and 10th quantiles of hourly prices that are averaged from 15 minute upward regulation prices, in in € per MWh	TenneT, own calculation
Down IQR	Interquartile range between 90th and 10th quantiles of hourly prices that are averaged from 15 minute downward regulation prices, in in € per MWh	TenneT, own calculation
Period	Dummy variable that is equal to 1 for years from 2016 and onwards	-
Wind speed	Cube of average wind speed in meters per second	KNMI, own calculation
Solar irradiance	Solar irradiance in watt per m^2	KNMI, own calculation
Load	Total load per hour in MWh	ENTSO-E

Description of daily level dataset for robustness check
All these variables are expressed in logarithmic form

Variable name	Description	Source
DA volatility	Daily standard deviation of hourly day-ahead prices in €'s	ENTSO-E, own calculation
Up volatility	Daily standard deviation of 15 minute upward regulation prices in €'s	TenneT, own calculation
Down volatility	Daily standard deviation of 15 minute downward regulation prices in €'s	TenneT, own calculation
Day-ahead IR	Intraday range of day-ahead prices, which is the difference between the highest and lowest price per day, in €'s	ENTSO-E, own calculation
Up IR	Intraday range of upward prices, which is the difference between the highest and lowest price per day, in €'s	TenneT, own calculation
Down IR	Intraday range of downward regulation prices, which is the difference between the highest and lowest price per day, in €'s	TenneT, own calculation
IIMR	Intraday and intra market range between highest and lowest prices from two different markets per day	ENTSO-E and TenneT, own calculation
Wind production	Total forecasted electricity production from wind turbines (onshore and offshore combined), daily average from 15 minute data, in MWh	ENTSO-E, own calculation
Solar production	Total forecasted electricity production from solar PV, daily average from 15 minute data, in MWh	ENTSO-E, own calculation
Load	Total forecasted load, daily average from 15 minute data, in MWh	ENTSO-E, own calculation
Gas price	Daily price of natural gas at the TTF in €'s per MWh	Datastream
Emission price	Daily price of emission allowance in €'s per metric ton	Datastream

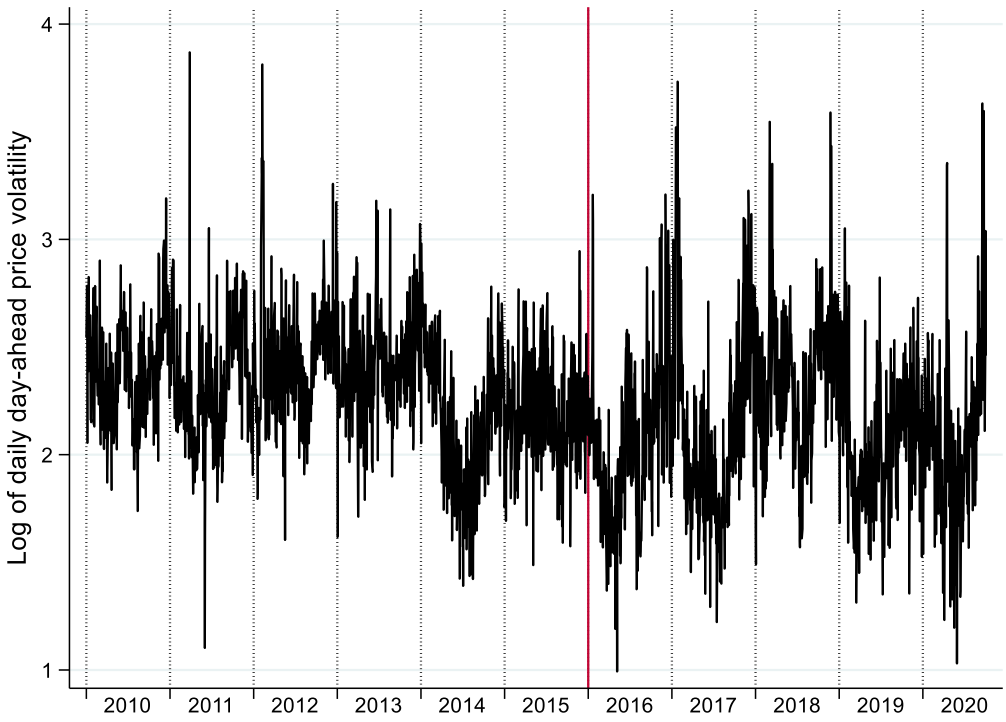
Description of hourly/15-minute level dataset for robustness check

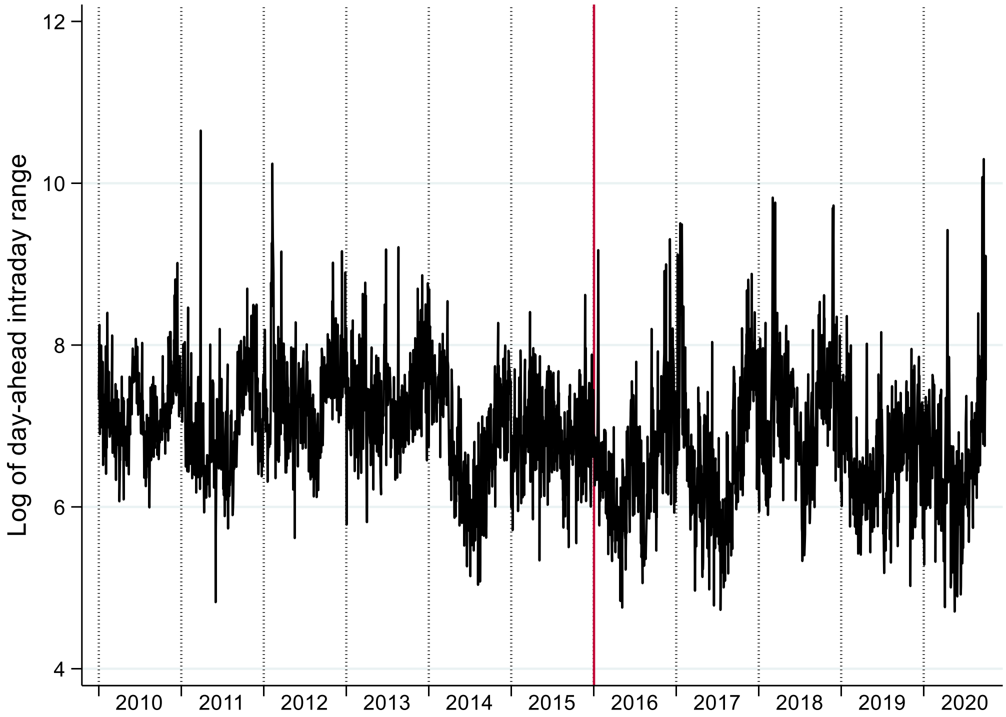
DA price	Day-ahead prices per hour in € per MWh	ENTSO-E
Up price	Upward regulation price per 15 minutes in € per MWh	TenneT
Downward price	Downward regulation price per 15 minutes in € per MWh	TenneT
Day-ahead IQR	Interquartile range between 90th and 10th quantiles of hourly day-ahead prices, in in € per MWh	ENTSO-E, own calculation
Up IQR	Interquartile range between 90th and 10th quantiles of 15 minute upward regulation prices, in in € per MWh	TenneT, own calculation
Down IQR	Interquartile range between 90th and 10th quantiles of 15 minute downward regulation prices, in in € per MWh	TenneT, own calculation
Wind production	Total forecasted electricity production from wind turbines (onshore and offshore combined), hourly average for day-ahead regressions, 15 minute data for imbalance regressions, in MWh	ENTSO-E, own calculation

Solar production	Total forecasted electricity production from solar PV sources, hourly average for day-ahead regressions, 15 minute data for imbalance regressions, in MWh	ENTSO-E, own calculation
Load	Total forecasted electricity load, hourly average for day-ahead regressions, 15 minute data for imbalance regressions, in MWh	ENTSO-E, own calculation

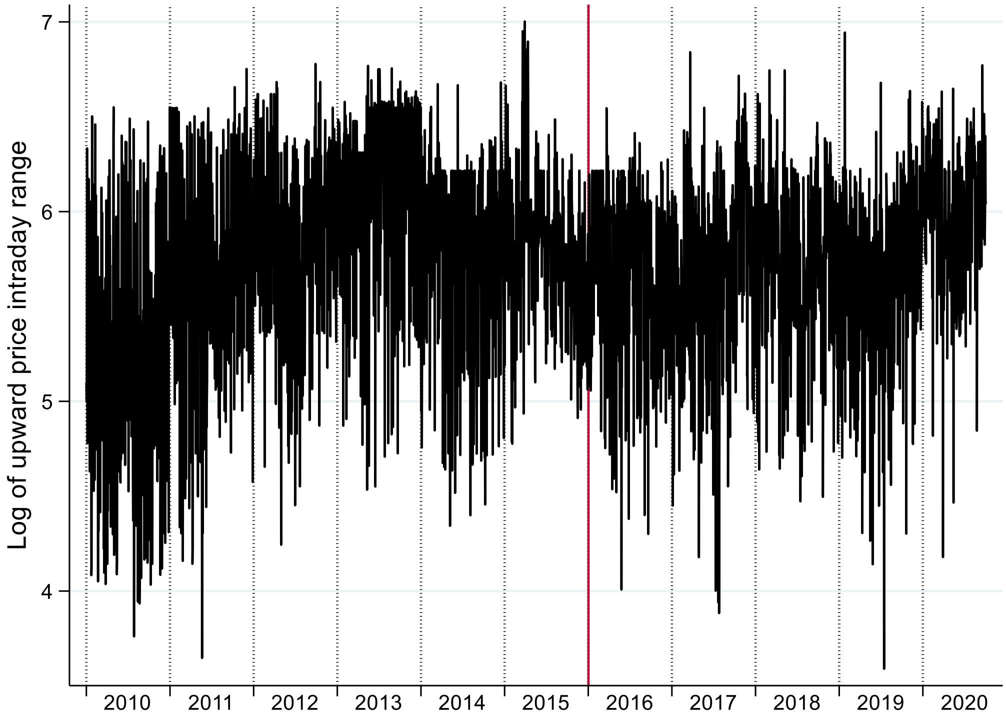
Part B: Graphs of dependent variables

All the studied dependent variables that are studied are plotted against time to show the movements of all the variables.

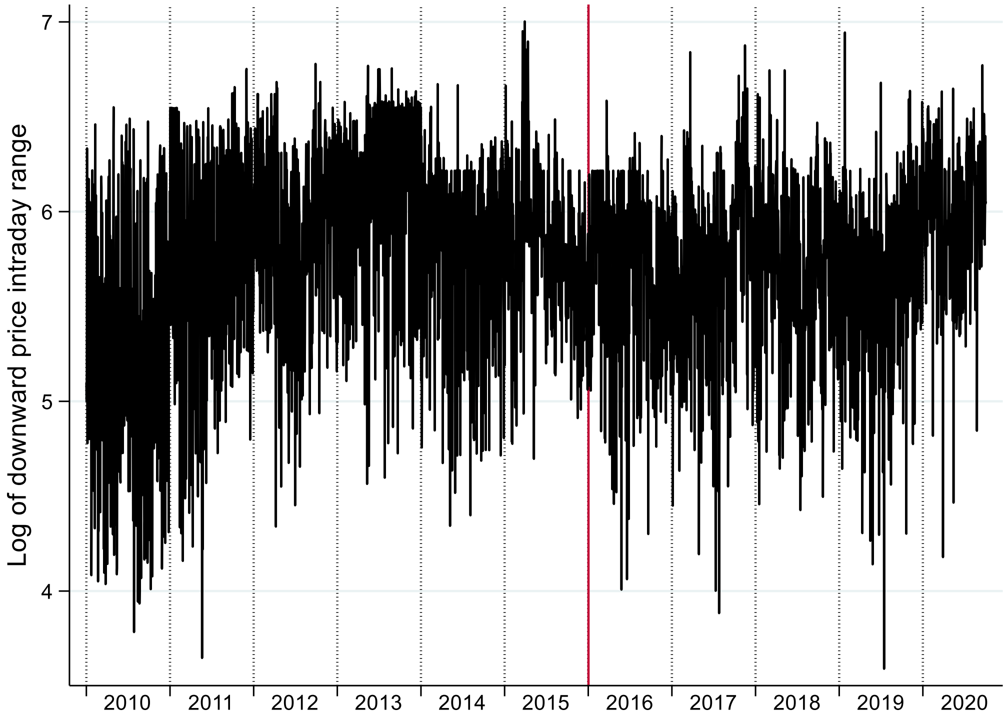


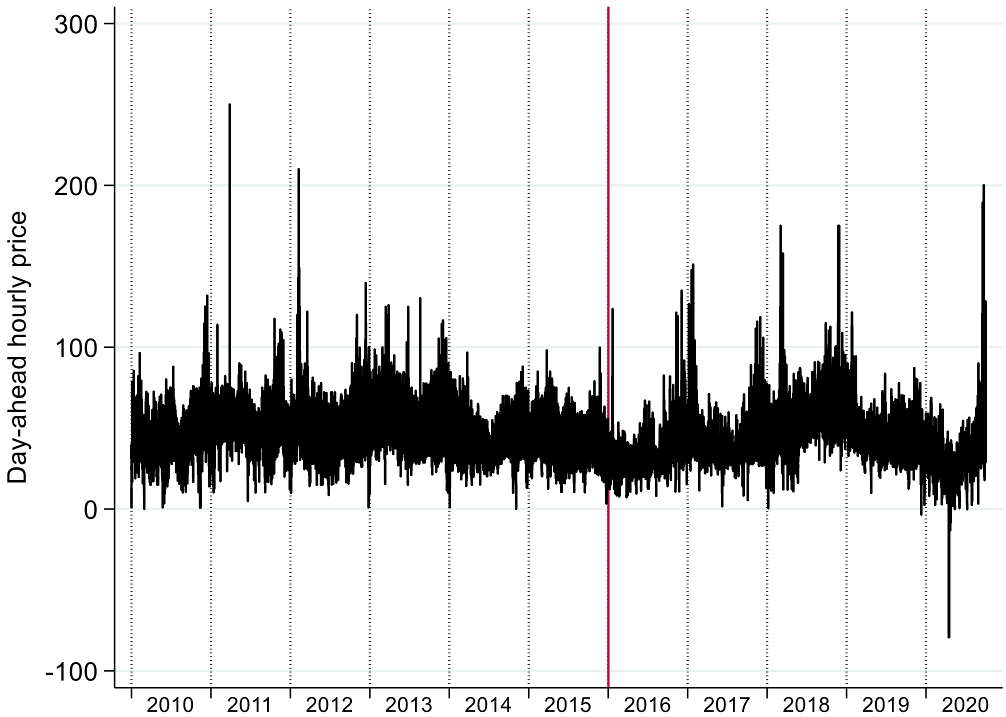

Log of day-ahead intraday range
12
10
8
6
4
2010
2011
2012
2013
2014
2015
2016
2017
2018
2019
2020

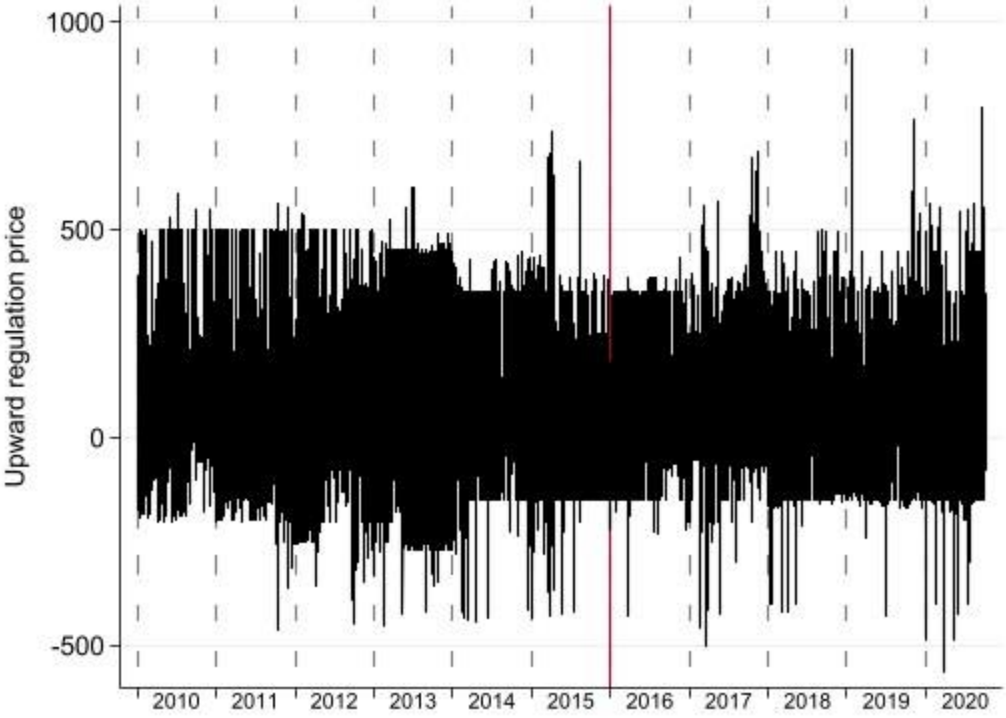

Log of daily upward price volatility
6
5
4
3
2
1
2010
2011
2012
2013
2014
2015
2016
2017
2018
2019
2020

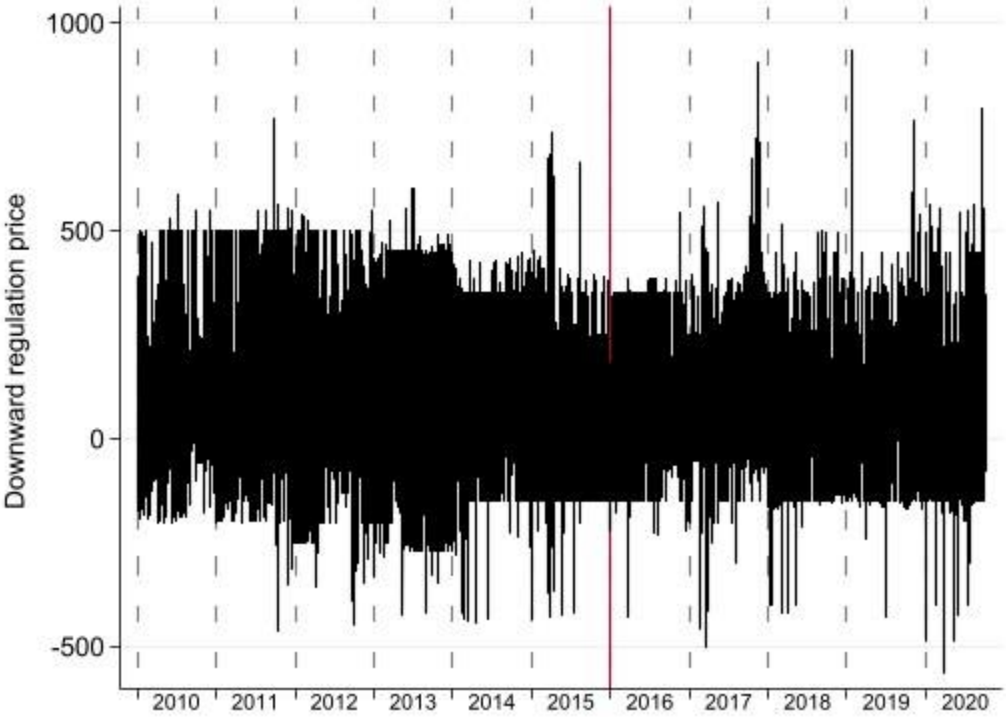

Log of upward price intraday range
7
6
5
4
2010
2011
2012
2013
2014
2015
2016
2017
2018
2019
2020

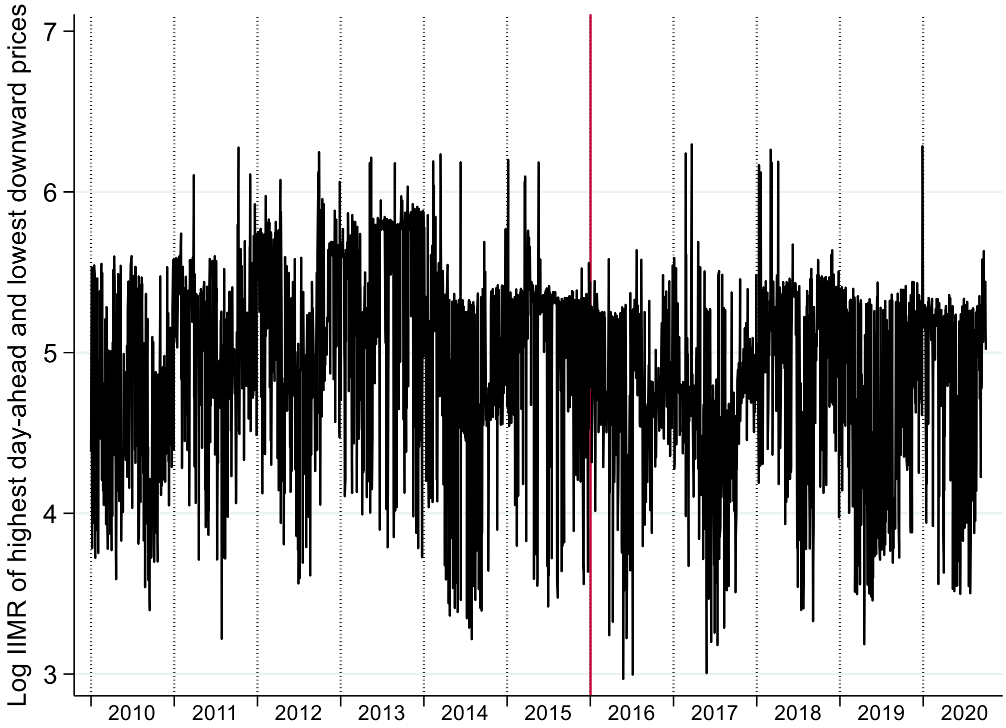

Log of daily downward price volatility
6
5
4
3
2
1
2010
2011
2012
2013
2014
2015
2016
2017
2018
2019
2020

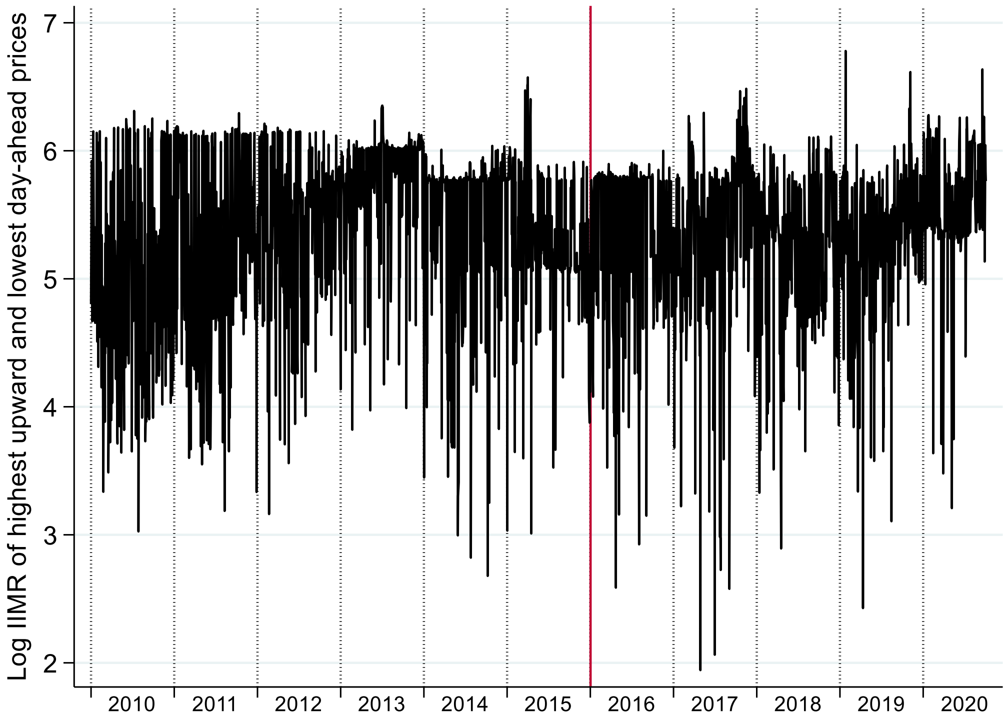

Log of downward price intraday range
7
6
5
4
2010
2011
2012
2013
2014
2015
2016
2017
2018
2019
2020

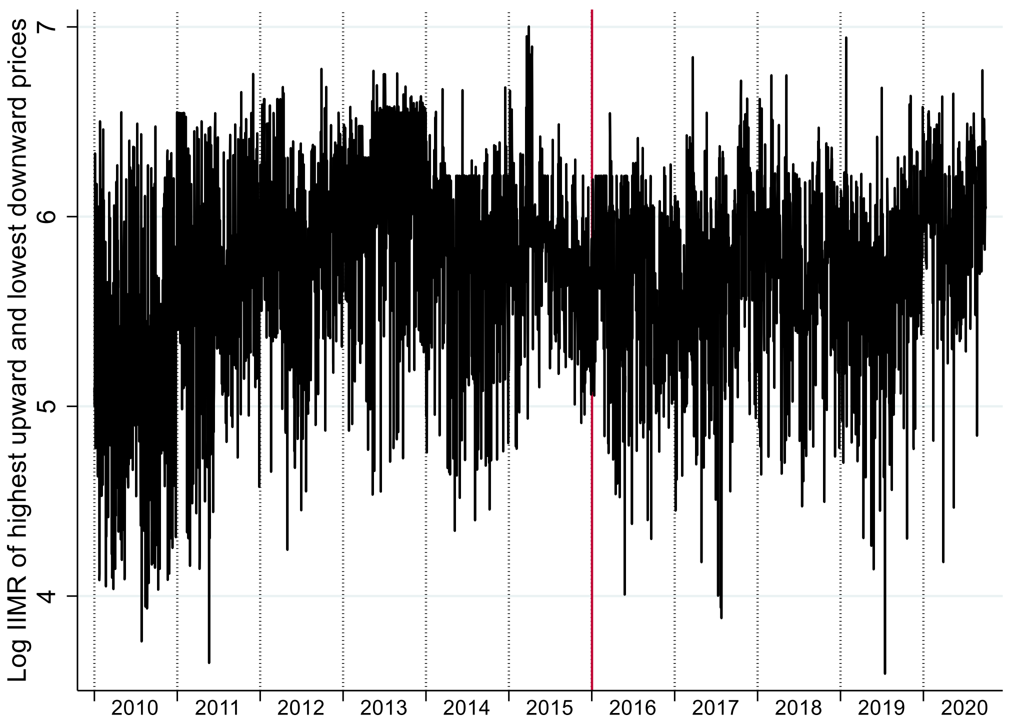

Day-ahead hourly price
300
200
100
0
-100
2010
2011
2012
2013
2014
2015
2016
2017
2018
2019
2020


Upward regulation price
1000
500
0
-500
2010
2011
2012
2013
2014
2015
2016
2017
2018
2019
2020


Downward regulation price
1000
500
0
-500
2010
2011
2012
2013
2014
2015
2016
2017
2018
2019
2020


Log IIMR of highest day-ahead and lowest downward prices
7
6
5
4
3
2010
2011
2012
2013
2014
2015
2016
2017
2018
2019
2020


Log IIMR of highest upward and lowest day-ahead prices
7
6
5
4
3
2
2010
2011
2012
2013
2014
2015
2016
2017
2018
2019
2020



Part C: Formula’s for all regressions models

In this section of the appendix all the equations that are used in the different regressions of this thesis. Each equation has a short summary of what variables are included in that specific formula and which number the model has. This number is referenced in the table where the model is used. In the tables that present the results from the regressions on the second dataset that ranges from 2015 until 2020 use the same model numbers with the addition of the letter “a”. This means that the regression uses the same formula without the variable period.

Model 1, uses as a measure of volatility the standard deviation of the hourly prices per day, as is done by (Pereira Da Silva & Horta, 2019; Rintamäki et al., 2017). This model does not include any control variables.

$$\ln \sigma_i \,(Price_i) = \alpha_i + \beta_1 * Period_i + \varepsilon_i$$

Model 2 is an extended version of model 1, with weather variables added to control for the potential effects of renewable energy production may have on the volatility of electricity prices. This is a similar approach as the research of (Mosquera-López et al., 2017; Mulder & Scholtens, 2013).

$$\ln \sigma_i \,(Price_i) = \alpha_i + \beta_1 * Period_i + \beta_2 * \ln Load_i + \beta_3 * \ln Wind\ Speed_i + \beta_4 * \ln Solar\ Irradiance_i + \beta_5 * \ln Gas\ Price_i + \varepsilon_i$$

$$\ln \sigma_i\,(Price_i) = \alpha_i + \beta_1 * Period_i + \beta_2 * \ln Load_i + \beta_3 * \ln Wind\ Speed_i + \beta_4 * \ln Solar\ Irradiance_i + \sum_{y=1}^{11} \varphi_y * month(y)_i + \sum_{z=1}^{4} \vartheta_z * weekday(z)_i + \varepsilon_i$$

Model 4, is based on a similar premise as the previous model, but with control variables to control for the effects of solar irradiance and wind speed, that serve as proxies for renewable production. Furthermore, the daily price of gas is also added. The variable load is added to control for total electricity demand. These control variables are similar to the ones used by (Mulder & Scholtens, 2013).

$$\ln \sigma_i\,(Price_i) = \alpha_i + \beta_1 * Period_i + \beta_2 * \ln Load_i + \beta_3 * \ln Wind\ Speed_i + \beta_4 * \ln Solar\ Irradiance_i + \beta_5 * \ln Gas\ Price_i + \beta_6 * \ln Emission\ Price_i + \varepsilon_i$$

Model 5, is a further expansion of the previous models, with control variables that account for time effects as well as the effects of weather, gas and emission controls on electricity price volatility.

$$\ln \sigma_i\,(Price_i) = \alpha_i + \beta_1 * Period_i + \beta_2 * \ln Load_i + \beta_3 * \ln Wind\ Speed_i + \beta_4 * \ln Solar\ Irradiance_i + \beta_5 * \ln Gas\ Price_i + \beta_6 * \ln Emission\ Price_i + \sum_{y=1}^{11} \varphi_y * month(y)_i + \sum_{z=1}^{4} \vartheta_z * weekday(z)_i + \varepsilon_i$$

Model 6, uses a different measure for volatility, namely the intraday range, similarly to (Frömmel et al., 2014). It is the difference between the highest and lowest daily prices. This model is run without any control variables.

$$\ln IR_i\,(Price_i) = \alpha_i + \beta_1 * Period_i + \varepsilon_i$$

Model 7, is an extension of model 7 with the inclusion of weather and load variables to control for those effects on the intraday range of electricity prices.

$$\ln IR_i\,(Price_i) = \alpha_i + \beta_1 * Period_i + \beta_2 * \ln Load_i + \beta_3 * \ln Wind\ Speed_i + \beta_4 * \ln Solar\ Irradiance_i + \varepsilon_i$$

Model 8, controls for load, wind speed and solar irradiance. Furthermore, the effects of month and day of the week are also included.

$$\ln IR_i\,(Price_i) = \alpha_i + \beta_1 * Period_i + \beta_2 * \ln Load_i + \beta_3 * \ln Wind\ Speed_i + \beta_4 * \ln Solar\ Irradiance_i + \sum_{y=1}^{11} \varphi_y month(y)_i + \sum_{z=1}^{4} \vartheta_z\, weekday(z)_i + \varepsilon_i$$

Model 9, also utilizes the intraday range as dependent variable, but now it is accompanied by the same control variables for the effect of weather, load, gas and emission on it.

$$\ln IR_i\,(Price_i) = \alpha_i + \beta_1 * Period_i + \beta_2 * \ln Load_i + \beta_3 * \ln Wind\ Speed_i + \beta_4 * \ln Solar\ Irradiance_i + \beta_5 * \ln Gas\ Price_i + \beta_6 * \ln Emission\ Price_i + \varepsilon_i$$

Model 10, controls for effects of gas price and emission price, as well as load and weather variables and it also accounts for monthly and daily effects.

$$\ln IR_i\,(Price_i) = \alpha_i + \beta_1 * Period_i + \beta_2 * \ln Load_i + \beta_3 * \ln Wind\ Speed_i + \beta_4 * \ln Solar\ Irradiance_i + \beta_5 * \ln Gas\ Price_i + \beta_6 * \ln Emission\ Price_i + \sum_{y=1}^{11} \varphi_y month(y)_i + \sum_{z=1}^{4} \vartheta_z\, weekday(z)_i + \varepsilon_i$$

Model 11, is the last measure for volatility of the Dutch electricity prices. By studying the interquartile range between the 90th and the 10th quartiles. This is a similar approach to that of (Maciejowska, 2020), in which the IQR is used to measure volatility in a non-parametric way. Given that this thesis also studies the extreme prices via quantile regression, this model is akin to that and therefore it is included as well. Model 7 is similar to models 1 and 4 in the sense that it is just concerned with the effect of the main independent variable period, that measures the differences between the period between 2010 and 2015 compared to the later part of the decennium between 2016 and 2020.

$$\ln IQR_i\,(Price_i) = \alpha_i + \beta_1 * Period_i + \varepsilon_i$$

Model 12, also studies the development of volatility through the IQR, with the inclusion of production related control variables.

$$\ln IQR_i\,(Price_i) = \alpha_i + \beta_1 * Period\ _i + \beta_2 * \ln Load_i + \beta_3 * \ln Wind\ Speed_i + \beta_4 * \ln Solar\ Irradiance_i + \varepsilon_i$$

Model 13, similar to model 8, with the addition of control variables that control for yearly, monthly and daily effects.

$$\ln IQR_i\,(Price_i) = \alpha_i + \beta_1 * Period_i + \beta_2 * \ln Load_i + \beta_3 * \ln Wind\ Speed_i + \beta_4 * \ln Solar\ Irradiance_i + \sum_{y=1}^{11} \varphi_y * month(y)_i + \sum_{z=1}^{4} \vartheta_z * weekday(z)_i + \varepsilon_i$$

In order to test the second and fourth hypotheses, concerning extreme prices, the next three models are all the equations for non-parametric quantile regressions. The quantiles of interest for this thesis are the 5th and 95th quantiles, similar to (Huisman et al., 2020).

Model 14, is similar to models 1, 4 and 7 in the sense that it is just the effect of dependent variable period on the quantiles of the studied electricity prices.

$$Q(Price_{i,t}) = \alpha_{i,t} + \beta_1 * Period_{i,t} + \varepsilon_{i,t}$$

Model 15, is similar to model 10, but with the inclusion of electricity production related control variables.

$$Q(Price_{i,t}) = \alpha_{i,t} + \beta_1 * Period_{i,t} + \beta_2 * Load_{\ i,t} + \beta_3 * \ Wind\ Speed_{i,t} + \beta_4 * \ Solar\ irradiance_{i,t} + \varepsilon_{i,t}$$

Model 16, also includes control variables for yearly and monthly effects. Contrary to previous models with time related control variables day of week effects are not included here, because these render statistical software program unable to converge and solve the model.

$$Q(Price_{i,t}) = \alpha_i + \beta_1 * \ Period_{i,t} + \beta_2 * Load_{i,t} + \beta_3 * Wind\ Speed_{i,t} + \beta_4 * Solar\ Irradiance_{i,t} + \sum_{y=1}^{11} \varphi_y * month(y)_{i,t} + \sum_{z=1}^{4} \vartheta_z * weekday(z)_i + \varepsilon_{i,t}$$

Model 17, uses a different a similar measure as the dependent variable from models 6 till 10, namely the intraday range, only now with the highest price for one market and the lowest from another. In this way it is possible to study the arbitrage opportunities that may arise when electricity is traded between two different markets, similar to the approach of (Mallapragada et al., 2020; Metz & Saraiva, 2018; Naseri et al., 2020). This model is run without any control variables. To differentiate these models from the models that study the intraday range, the dependent variable in these regressions is called the intraday and intra market range. The following models will be used to study hypothesis 5.

$$\ln IIMR_i\ (Price_i) = \alpha_i + \beta_1 * Period_i + \varepsilon_i$$

Model 18, is an extension of model 17 with the inclusion of weather and load variables to control for those effects on the intraday and intra market range of electricity prices.

$$\ln IIMR_i\ (Price_i) = \alpha_i + \beta_1 * Period_i + \beta_2 * \ln Load_i + \beta_3 * \ln Wind\ Speed_i + \beta_4 * \ln Solar\ Irradiance_i + \varepsilon_i$$

Model 19, controls for load, wind speed and solar irradiance. Furthermore, the effects of month and day of the week are also included.

$$\ln IIMR_i\,(Price_i) = \alpha_i + \beta_1 * Period_i + \beta_2 * \ln Load_i + \beta_3 * \ln Wind\,Speed_i + \beta_4 * \ln Solar\,Irradiance_i + \sum_{y=1}^{11} \varphi_y month(y)_i + \sum_{z=1}^{4} \vartheta_z\, weekday(z)_i + \varepsilon_i$$

Model 20, also utilizes the intraday and intra market range as dependent variable, but now it is accompanied by the same control variables for the effect of weather, load, gas and emission on it.

$$\ln IIMR_i\,(Price_i) = \alpha_i + \beta_1 * Period_i + \beta_2 * \ln Load_i + \beta_3 * \ln Wind\,Speed_i + \beta_4 * \ln Solar\,Irradiance_i + \beta_5 * \ln Gas\,Price_i + \beta_6 * \ln Emission\,Price_i + \varepsilon_i$$

Model 21, controls for effects of gas price and emission price, as well as load and weather variables and it also accounts for monthly and daily effects.

$$\ln IIMR_i\,(Price_i) = \alpha_i + \beta_1 * Period_i + \beta_2 * \ln Load_i + \beta_3 * \ln Wind\,Speed_i + \beta_4 * \ln Solar\,Irradiance_i + \beta_5 * \ln Gas\,Price_i + \beta_6 * \ln Emission\,Price_i + \sum_{y=1}^{11} \varphi_y month(y)_i + \sum_{z=1}^{4} \vartheta_z\, weekday(z)_i + \varepsilon_i$$