CRISTIAN ȘTEȚ

(In)flexibility in Power Markets with Supply from Variable Renewable Sources

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(In)flexibiliteit in energiemarkten tegenover het aanbod van variabele hernieuwbare bronnen

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Foreword

Back in 2017 I embarked myself in a beautiful PhD journey which led to the creation of this dissertation in Energy Finance. I already had some knowledge on power markets. However, I understood very fast that there is a lot more to learn and research in this fast changing field. Power markets are going through a major transition towards sustainability and this raises many questions that need to be answered. I am proud to be part of this field and also of the work performed together with my co-authors over the past four years, work that is presented throughout this dissertation. I hope that while reading my thesis you will get inspired and become curious about these complex markets which became indispensable to our daily lives.

The creation of the present dissertation would not have been possible without the contribution of many exceptional people. Among the many people that helped me with this process, there is one person that definitely stands out. Therefore, the only way in which I can continue this foreword letter goes with a big: Thank you Ronald! Ever since I started my PhD track, his guidance was priceless. I was and still am very lucky to have Ronald beside me, as a supervisor and friend, at each step of this long but beautiful journey. With every discussion we had, I learned from his professionalism and from his way of critically dissecting each subject. These lessons helped build upon my knowledge and improve the pieces of research I worked on. It is also along Ronald's side that I had my first experiences as a lecturer. These experiences taught me about the importance of guiding the next generation into finding their intrinsic motivation and becoming curious about learning more. From Ronald I also learned about the beauty of combining academia with industry. For example, our trip to Romania thought me a great deal about the current situation of the Romanian energy markets.

A special thanks goes to Han too, as without his support I will not have arrived to this step. Among others, what I learned from him is that it is important to dream big and to strive for excellency in each activity I do. In our discussions we never focused on details but rather on the bigger picture, on the societal impact that a paper can have. This will stay with me for the years to follow. I express my gratitude also to all the members of the doctoral committee, who took time scrutinize my dissertation and provide me with invaluable feedback on how and where I can improve it. Furthermore, I have special appreciation for the entire Finance Department at Erasmus School of Economics and for my colleagues at Erasmus Research Institute of Management who provided me with great companionship and help. In there I met exceptional professionals who turned out to be great friends too.

I want to thank also my fellow PhD colleagues who definitely made my time at Erasmus University Rotterdam unforgettable. Among many others, Annelot, Antti, Amar, Derck, Dyaran, Eric, Evan, Gianluca, Gloria, Jeroen, Joaquim, Megan, Merel, Nienke, Paniz, Qi, Sai, Sam, Shara and Taavi are an endless source of inspiration, compassion, motivation and fun. Having them all as PhD fellows made this process a lot more fun.

Last but not least, a huge *mulţumesc*, *merci* and *grazie* goes to my family for their unconditional support. They were the first in line to support me whenever needed and also the first with whom I could share each bit of my progress and success. I thank my dear wife, Clarisse, my parents, Maria and Vasile, my sisters, Ana, Ema and Ela and my "adoptive" Italian family, Riccardo, Elisabetta, Elena and Eugenio, for their continuous support in everything I do. You are my daily reminder that I am an extremely lucky person to have you all in my life. Last but not least, as I recently became the father of a beautiful baby boy, Paul, I can only end this note by thanking him for making me dream even more about the future. He is my motivation for working hard in order to prepare a better world for the generations to follow.

August 2021, Rotterdam, The Netherlands
Cristian Ştefţ

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Chapter 1

Introduction [1]

1.1 (In)flexibility in power markets

Since the first time it was commercialized, electricity as a commodity moved from being a luxury good to a basic need for the major part of the world's population. Over the past few decades, the importance of this commodity in our lives has grown exponentially and, with the foreseen electrification and decarbonisation of various industries, this tendency will likely continue in the years to come. The push towards a decarbonised society and the reliance of our economies on electricity, or power as it is hereafter referred to in this dissertation, introduces important changes in power systems. The power industry is going through a profound transition in which conventional power producing technologies, such as for example coal or gas fired power plants, are replaced by the relatively more environmentally friendly renewable alternatives. In particular, wind and solar photovoltaic technologies have gotten good traction over the past decade due to a sharp fall in investment costs and favourable subsidy schemes in various geographies.

We should encourage policies which target to reduce the carbon intensity of power markets. However, we have to be careful in tailoring them. We have to acknowledge the

[1] Parts of this chapter appear in the following publication:
Ştet̨, C. Oil prices in negative territory? In power markets frequent negative prices could become the norm. *IAEE Energy Forum, Special Covid-19 Edition 2020, 17-19.*

fact that power supply from wind and solar photovoltaic power plants introduces new issues into power systems. The main problem of variable renewable sources, hereafter referred to as VRES, lays within their output variability. Their weather dependency poses at times threats to the flexibility of power systems or, in other words, to the power system's ability to swiftly adapt to changes in supply and / or demand in order to always keep the grid in balance. In a world with VRES supply, power market players face increasing uncertainties related to the power grid's counterbalancing needs.

The pieces of research presented throughout this dissertation aim to improve our understanding on how supply from VRES impacts the flexibility needs of power markets. This goal is achieved through four studies, which provide a detailed picture on the relation between VRES supply and prices in power markets. Before further elaborating upon the contributions of this present dissertation, it is important to properly understand what the (in)flexibility in power markets means. The continuation of this section of the introductory chapter provides a description of this concept.

To explain how VRES supply puts pressure on the flexibility of today's power markets we can take a look at how power markets functioned in the past. Throughout the twentieth century, the norm within power markets was to have a centralized, often state owned, monolith organisation which serviced the entire power market, from production to transmission and distribution. Demand was to a large extent inflexible, meaning that consumers generally didn't adapt their consumption levels in function of changes in price. In the same time, power storage was economically unavailable at large scale[2]. In this model, conventional suppliers have to ramp up or down their production output in order to service the variation in demand. Coming back to the twenty first century, demand inflexibility and unavailability of utility scale storage facilities is still present in most places around the world. Yet, changes have taken place and in several countries the markets have been liberalized. These markets work on a merit order principle in which the cheapest power producers have priority for dispatch. In this context, VRES supply, as it has a close to zero marginal cost, takes conventional supply out of the dispatchable part of the merit order curve. Since the

[2]With the exception of areas where it was feasible to indirectly store power through underlying fuels (i.e. storing power in the form of water in hydro pumped dams).

output from VRES is weather dependent, nowadays conventional suppliers have to rebalance not only changes in demand but also variations in VRES supply.

The constant need of rebalancing both a relatively inflexible demand and the supply from VRES, combined with the limited availability of storage or demand response applications[3], makes power markets unique among the existing financial markets. Because of these peculiarities, power prices have an unusual behaviour which exhibits extreme volatility and frequent mean reversion patterns. The extreme power price volatility is closely linked to the flexibility needs of power markets as frequent extreme power prices point towards the inflexibility of a power market. Moreover, the inflexibility of power markets leads at times to periods with negative power prices.

An example from the oil industry can help us understand why inflexibility induced negative prices can occur in power markets. This example comes from the time of the first COVID-19 wave in Europe, in the spring of 2020. In this period, the lock-down restrictions put in place around the world led to unprecedented sudden low oil demand levels. As oil refineries operated at lower than usual capacities, producers had to find new ways to place the excess oil produced, creating an imbalance in the demand-supply equation. Through a spiralling of events, the setting of the oil market brought market participants to a situation where they were trapped with positions that they could not physically comply with. As a result, prices for WTI crude oil futures for delivery in May 2020 traded for a brief period in negative territory. Why this situation occurred? The answer to this question represents a story of flexibility and storage. A first solution to rebalance the demand-supply equation would have been to store the excess supply. However, as the stored oil volumes increased rapidly, their levels were headed towards reaching the maximal storage capacity in certain areas around the globe. Considering that storage expansion is both costly and time consuming, this lack of storage made oil prices behave temporarily like prices of non-storable commodities, such as power, where demand or supply shocks induce extreme price changes. The other obvious alternative for stabilizing the market would have been to reduce supply. Leaving

[3]Demand response applications are designed to shift power demand from moments of under-supply to moments with over-supply of power. The operators of such applications aim to take advantage of the differences in power prices between moments with under- and over-supply of power.

aside the geopolitical and strategic thinking hurdles that affect the supply reduction equation, a major reason for which oil companies were not willing to significantly cut production is that such a process can be extremely costly. In some cases, closing a well could permanently damage it. Thus, such an action could have led to losses far greater than the loss incurred by temporarily selling the produced oil output at a price below the marginal cost or even at a negative price. What this example shows is that some oil producers are inflexible as they do not have the technical ability or economic incentive to quickly ramp up or down production when needed. Moreover, the example tells us that as long as storage capacity is limited or extremely costly, supply and / or demand is relatively inflexible and oversupply is temporarily present, there are chances for negative prices to reappear in the oil market as well as in any other market.

How does this relate to power markets? Price patterns that we see in oil markets over a time-frame of decades can be spotted within only one day in power markets. Power is a commodity that is often traded in an environment similar to the one of oil markets in moments with extreme demand-supply frictions. As explained above, power demand is still inflexible and direct power storage is still in early phases, as economically feasible utility scale batteries are out of reach in most places. In addition to the inflexibility of demand, same as for the oil market, some conventional power producers are not flexible enough to be able to expand or contract their production in a fast and economically efficient way when a sharp change in demand or VRES supply occurs. In several geographies such inflexible power producers represent a significant share of the power generation mix. In those power markets, a high sudden demand decrease (increase) and / or VRES supply increase (decrease) often leads to oversupply (undersupply) as the inflexible suppliers are not able to act fast enough to restore the supply-demand balance. These moments create a favourable climate for extreme and often negative prices to frequently occur in power markets.

What made the oil and power markets comparable in the spring of 2020 was the fact that in both markets storage and flexibility offering options were limited. In normal market conditions, among others, what differentiates oil markets from most power markets is the availability of sufficient storage capacities. Most of the times, in oil markets storage is able to provide a relatively cost-efficient solution to short term changes in the balance between demand and supply. The storage availability makes it easier for the oil market to smooth prices and to avoid extremes. Thus, while negative oil prices might appear again in extreme market conditions, it is unlikely to observe frequent negative oil prices. On the contrary, in power markets such extreme prices do not seem to go away any soon as for years we observe an increase in their frequency. This signals an increasing inflexibility of power markets.

While the blame for the inflexibility of the power markets is often attributed to certain conventional producers such as coal or nuclear generators which have technical difficulties to quickly ramp up or down production, this is only part of the story. The other main reason for the increased inflexibility of power markets is embedded in the business model of VRES suppliers. As briefly mentioned above, VRES supply is one of the cheapest power supply in terms of marginal cost and often comes the first in line for dispatch. Moreover, subsidy schemes such as feed-in tariffs or green certificates lead VRES supply to profitability even when power prices are negative. Thus, there is a strong incentive for VRES producers to generate the maximum output possible even when prices are extremely low. In this way, in inflexible power markets, VRES supply favorises the occurrence of extreme low prices. Moreover, the variability of supply from VRES puts pressure on conventional suppliers to ramp up fast their supply whenever the wind is not blowing or the sun is not shining. Because of this, if a market has limited ramp up flexibility, there will be moments when the lack of supply from VRES will create a favourable environment for extreme high prices to occur.

The dependency of wind and solar photovoltaic power output on weather conditions is investigated throughout the second and third chapters of this dissertation proving that VRES supply can impact the occurrence and magnitude of extreme power prices. The variability of VRES power output creates supply shocks in power markets on a daily basis. As a consequence, with the integration of a higher share of supply from VRES in a power market, as the average level of power prices gets lowered, the supply-demand imbalances will more often lead to extreme low and less often to extreme high power prices. The second chapter of this dissertation demonstrates for the German day-ahead power market that higher levels of VRES supply lead to less frequent extreme high power prices and more frequent extreme low power prices. Furthermore, the third chapter shows that the more the flexibility of a power system is challenged, the stronger is the price reducing impact of VRES supply on power prices.

As in most power markets the share of VRES supply is set to increase, if there is not enough flexibility to quickly ramp up or down production or consumption when needed, extreme, and sometimes negative, power prices will appear with an increasing frequency. Besides learning this from the following chapters of this dissertation, the same lesson can be drawn also from the situation created by COVID-19 restrictions imposed in Europe in the spring of 2020. Same as in oil markets, with the temporary closure of businesses, demand for power decreased in that period, in some geographies by even more than 20%. At the same time, wind and solar operational capacity remained unchanged. Because of this, power markets were suddenly operating in an environment with a much higher share of VRES supply. What we had in front of our eyes was a unique experiment on how power markets could behave in the future if the only thing we do is to add more VRES.

The results? In the German power market, while for the period 23rd March - 22nd April 2019 the average share of VRES output in the power generation mix was 30%, for the same time-frame in 2020, the average share of VRES output grew to 44%, with some moments exhibiting VRES share values of over 60%. While a small part of this wind and solar share increase is due to more installations that became operational in 2019, the main factors that increased the share of VRES supply temporarily in the German power market are the lower demand and the favourable weather conditions. With a much higher share of VRES supply, we could observe various moments when the German day-ahead prices fell lower than or close to -80 EUR/MWh. While it is not the first time when such extreme negative prices appear on this market, the frequency of the negative prices increased with the share of VRES supply. In total, for the period between 23rd March - 22nd April 2020, the German day-ahead power price settled in negative territory in 49 hourly occasions. Over the same period in 2019 only 10 hours traded with negative prices, and, on average, the monthly number of negative prices in 2019 was under 18 hours/month. Similar increases in the numbers of hours with negative settled power prices could be observed across most European markets in that period period. In some markets, the negative power prices appeared as a result of an increased share in VRES supply output. In other markets, negative prices were propagated through cross border transactions. This means that in an interconnected European power grid, VRES supply changes power prices not only in the country of origin, but also in the adjacent countries. One example of cross border propagation of negative power prices can be found in the Swedish and Finish power markets which recorded negative prices for the first time in their history in 2020. Another example comes from the Hungarian day-ahead power market where, over the selected month period in 2020, 9 hours traded in negative territory, compared to only 1 such observation for the entire year of 2019. A similar situation occurred in The Netherlands with 37 hours being settled with negative power prices in the selected month interval for 2020 as opposed to only 5 such observations for the entire year of 2019. The list can go on, but the message is clear: in a world of subsidised and prioritised VRES supply, without adequate supply of flexibility in place, we will have to get used with more frequent negative prices and with increased power flexibility needs. Even if the examples above do not have statistical power, the change in the frequency of occurrence of negative prices in such a short period of time is striking.

The formation of power prices does not depend only on supply from VRES. Cleared power prices, and implicitly flexibility of power markets, are formed based on a multitude of fundamentals. However, we know from academic literature and practice that wind and solar output changes patterns in power prices. The way power markets behave in moments when they are challenged the most tell us that, while striving to integrate more VRES supply, we should also make sure that power markets are flexible enough to cope with it. The events exemplified in the previous paragraphs indicate that a high share of supply from VRES increases the flexibility needs of power markets. Furthermore, this can lead to changes in the relation between the power prices on power markets with different maturities (forward, day-ahead, intraday or imbalance power markets). The fourth and fifth chapters of the dissertation examine this aspect in detail. The present dissertation, through the four studies performed, provides more clarity on how VRES supply challenges the flexibility needs of power markets. The importance and opportunity to research this topic is further elaborated in the next section of this chapter.

1.2 Relevance

The previous section introduced the flexibility issues present in today's power markets and how this dissertation helps to better understand them. As a natural continuation, this section comes to complete the rationale for creating this dissertation by presenting the ways in which the research performed adds value to the academic world, policy makers, managers and also to the society as a whole.

We are facing an increasingly pressing problem in our society: climate change. To limit its effects, we must find ways to decarbonise our economies. Power industry has been and it still is in some parts of the world one of the most carbon intensive industries. Finding ways to change this represents a crucial step in the move towards a low carbon society. Therefore, we need to better understand what are the possible ways in which we can transition towards a low carbon intensity power grid. This present dissertation helps in this respect by improving our understanding on the flexibility needs of power systems which contain VRES supply. As it is further detailed throughout the pieces of research performed, the solution of solely installing more VRES supply is not sufficient to transition to a sustainable and stable power system.

More specifically, this dissertation suggests that besides encouraging the installation of more VRES capacity, policy makers should also make sure that the power systems that they supervise are flexible enough to efficiently incorporate a high share of VRES supply. If a power system has in its generation mix a significant share of inflexible supply, this will pose flexibility challenges when trying to incorporate a high share of VRES supply. Thus, policy makers should also encourage the deployment of flexibility offering assets such as storage facilities or demand shifting applications, and of low carbon footprint flexible supply. In addition to that, regulators could also reconsider the way in which we operate wind and solar power plants, and decide if the current subsidy schemes, which served their purpose in the past, are still a viable solution for the future. As the following chapters of the dissertation suggest, while prioritising VRES supply for dispatch is desirable from an environmental point of view, we should also consider to what extent the costs of temporarily and locally curtailing the production of VRES outweigh the potential flexibility gains. Ultimately, extreme prices are not desirable for a functional market. Even if from a consumer perspective low or negative power prices are appealing, if power prices fall too low, they will affect not only the conventional polluting producers but also the investments in new capacities of renewable supply as the economics for such investments will deteriorate. Therefore, without further technological developments or a change in policy, on long term, the transition to a carbon free power market will continue to be tied up to public financial aid.

This brings us to the managerial and practical importance of this dissertation. Understanding the flexibility challenges that power markets face and the changes that VRES supply impose on power prices is essential for power market players. Power market inflexibility can lead to extreme prices. Such prices can severely affect the profitability of both producers and retails present in power markets. The second and third chapter of the dissertation present ways of how to signal moments when power prices are expected to be extreme. These indications can help market players adjust their bidding strategies such that they are well positioned in front of a potential occurrence of a temporarily extreme low or high power price. Moreover, the fourth and fifth chapters increase our understanding on the interaction between power prices on different power markets. These chapters provide information on how VRES supply influences the forward power price premium. This information is useful for power traders as it indicates the type of moments when it is beneficial to sell or buy more power on the forward market as compared to the spot market.

Besides, the information presented throughout the following chapters is also useful to owners of flexibility offering assets, such as storage facilities or demand response applications. The value of those assets increases with the inflexibility of a power market as in an inflexible environment power prices get more extreme and volatile. Some of the methodological techniques used in this dissertation present ways in which inflexible power markets can be identified. Moreover, they also suggest what factors are important to be included when forecasting the likelihood of occurrence and the magnitude of extreme power prices. The ability to better forecast the moments when the extreme power prices will occur is crucial for operators of flexibility offering assets as their business model depends on these extreme prices. An enhanced understanding of the behaviour of extreme power prices improves the business case of flexibility offering assets. As a consequence, the prospects of a more rapid deployment of additional supply of flexibility into inflexible power markets also increases.

The works presented in the following chapters also enrich the growing energy finance literature. For the reasons elaborated above, flexibility in power markets is, and will be for the years to come, one of the central points of discussion in this field. This dissertation builds upon the pre-existing literature by showing how VRES supply impacts power prices and the flexibility of power markets. While academic literature already provides important answers on how VRES supply influences the flexibility of power markets, there are still many unknowns. We know that with the introduction of VRES supply in a power market, power prices decrease and that their volatility is affected. Yet, we don't know to what extent such an event changes the flexibility of a power market. The present dissertation comes to fill this literature gap and provides clarity on how VRES supply changes the probability distribution function of power prices in a relatively inflexible power market such as the German one. The pre-existing literature also does not tell us if a change in the share of VRES supply leads to the same power price drop at all moments in time or if at times the power price drop is more accentuated. The first two studies of this dissertation, presented in chapters two and three, shade light on those topics by providing empirical evidence on how the flexibility of a power market is challenged by VRES supply. Moreover, energy finance literature does not provide a common view on how the power price forward premium behaves in a world with VRES supply. The fourth and fifth chapters of this dissertation provide such a view. The fourth chapter, using simulated data, demonstrates that with the introduction of VRES supply into a power market, the power price forward premium decreases. The fifth chapter introduces a theoretical design which proposes a fundamentals based view on what explains the forward premium behaviour in prices of non-storable commodities, such as power. The results of this chapter show that in a power market with VRES supply, depending on the flexibility constraints of that market, the varying differences between forward and realised spot power prices are only in part explained by risk premiums and that a yield, similar to the convenience yield, plays a role too. These results represent only some of the main takeaways of this dissertation. All the tests performed and results obtained are presented in greater detail throughout the rest of the dissertation.

1.3 Dissertation overview

Chapter 1 serves as an introductory part for the research performed in the chapters 2 to 5. To give a better insight into the research displayed throughout the present dissertation this section summarizes the abstracts of the pieces of research performed, abstracts which lay the foundations of the following chapters. The sixth and final chapter concludes the dissertation by revisiting the main takeaways from the studies performed.

Chapter 2 abstract:

The large-scale integration of variable renewable energy sources requires flexibility from power markets in the sense that the latter should quickly counterbalance the variable renewable supply variation driven by weather conditions. Most power markets cannot (yet) provide this flexibility effectively as they suffer from inelastic demand and insufficient flexible storage capacity or flexible conventional supply.

Research accordingly shows that the volume of renewable energy in the supply system affects the mean and volatility of power prices. We extend this view and show that the level of wind and solar energy supply affects the tails of the power price distributions function as well and that it does so asymmetrically. The higher the supply from wind and solar energy sources, the fatter the left tail of the price distribution and the thinner the right tail.

This implies that one cannot rely on symmetric price distributions for risk management and for valuation of (flexible) power assets. The evidence in this chapter suggests that we have to rethink the methods of subsidizing variable renewable supply such that they take into consideration also the flexibility needs of power markets.

Chapter 3 abstract:
Understanding power prices dynamics is crucial for valuing real option assets that accommodate fluctuations in power supply from variable renewables. Real option owners, such as storage or flexible consumption facility owners, need to know how extreme power prices can become in order to optimally manage (dis)charging or adjusting consumption volumes. We examine how to predict those high and low prices, being the different quantiles of the power price probability distribution function, and question how supply from variable renewables affect different quantile prices.

The first contribution of this chapter is that we apply quantile regressions in a panel data framework. This methodology acknowledges that day-ahead power markets' data is structured as cross-sectional data and, as opposed to previous quantile regression techniques introduced in power markets, allows for simultaneous predictions for all hours during a delivery day. Day-ahead power prices for all 24 hours in the next day are determined at the same moment, one day before delivery. The hourly data is therefore not a time-series, but a cross section. The second contribution is that we examine the interaction between demand and supply from variable renewables, instead of linear dependencies only.

We find that lower and higher quantile prices are more heavily affected by variations in supply from variable renewables than center quantile prices. This enables real option asset owners to better manage their assets in anticipation of excess or scarce supply from renewables. By doing so, they increase the flexibility of power systems that face increasing installed capacity of variable renewable energy sources.

Chapter 4 abstract:
With the ongoing increase of variable renewable energy sources (VRES), such as wind or solar power, weather dependent production profiles induce uncertainty on the supply side and drastically change operations in power markets. In this paper, we study how an increasing market share of VRES affects spot power price dynamics and the forward price premium. Using data from simulated power markets, we analyse the forward premium in three identical power markets with a varying market share of VRES supplied to the system. We demonstrate that markets with a high share of supply from VRES yield a significantly lower forward premium than markets with a low market share of wind or solar supply. Where our results confirm that, regardless of the market share of supply from VRES, forward power prices contain information about future spot power prices, the study also provides evidence for a shift in the sign of the forward premium, from positive in a market with no VRES to negative when the share of VRES is high. These insights generate important implications for producers, retailers and other market participants exposed to wholesale price risk.

Chapter 5 abstract:
There is a vast finance literature on the forward premium in prices of non-storable commodities such as power. Nevertheless, there is no consensus on what explains the differences between forward and realised spot prices in those markets. The divergent literature results make it hard to develop practical expectations about the forward premium in the price of non-storable commodities. To overcome this situation, the present chapter proposes and empirically tests a theoretical framework which explains the formation of forward premiums in prices of non-storable commodities through two comprehensive fundamental factors: reserve margins and balancing needs present in the market.

The framework proposed illustrates that risk premiums alone cannot always fully explain the occurrence of forward premiums in prices of non-storable commodities. Using an example from power markets, we demonstrate theoretically and empirically that there are moments when convenience yields are present too in such markets. As those convenience yields are forecastable, non-storable commodity market players can use this theoretical framework in building their bidding strategies. These strategies are closely linked with real options theory, and we show that there are moments in time when the value of the option to increase production is higher than the value of the option to decrease production, and vice-versa. Moreover, for policy makers the presence of frequent convenience yields in the markets they supervise signals inflexibility. Such a situation suggests that in the respective power markets more flexibility offering capacity is needed at certain moments in times.

1.4 Declaration of contribution

Chapter 1: The author of this present dissertation developed independently the introductory chapter.

Chapter 2: This chapter is created based on a paper written in collaboration Dr. Huisman, Ronald and Dr. Kyritsis, Evangelos. The author of this dissertation did the majority of the analytical data work and writing part. Together with the co-authors, the author of this dissertation developed the conceptual framework. The co-authors of this chapter contributed significantly with ideas and comments. This chapter is based upon a paper which is forthcoming in The Energy Journal.

Chapter 3: The piece of research presented in this chapter is written based on a paper elaborated in collaboration Dr. Huisman, Ronald. The author of this dissertation did the majority of the analytical data work and writing part. Together with the co-author, the author of this dissertation developed the conceptual framework. The co-author of this chapter contributed significantly with ideas and comments. This chapter is based upon an article that is currently under review at a top economics journal.

Chapter 4: This chapter is developed based on a paper written in collaboration Dr. Huisman, Ronald and Dr. Koolen, Derck. The author of this dissertation did the majority of the analytical data work and writing part. Together with the co-authors, the author of this dissertation developed the conceptual framework. The co-authors of this chapter contributed significantly with data collection, ideas and comments. This chapter is based upon a paper which is accepted for publication in Renewable Energy.

Chapter 5: This chapter is elaborated based on a paper developed in collaboration Dr. Huisman, Ronald. The author of this dissertation did the majority of the analytical work, data collection, writing part and design of the empirical tests. Together with the co-author, the author of this dissertation developed the theoretical framework. The co-author of this chapter contributed significantly with ideas and comments. The paper resulted from the piece of research presented in this chapter will be submitted to a top finance journal.

Chapter 6: The concluding chapter was developed alone by the author of this present dissertation.

Chapter 2

Fat tails due to variable renewables and insufficient flexibility. Evidence from Germany [1]

[1]Parts of this chapter appear in the following peer reviewed conference proceedings:
Huisman, R., Kyritsis, E., and Şteţ, C. (2018). Renewables intermittency versus power (in)flexibility: new insights from tail index estimates. *2018 International Conference on Energy Finance.* Beijing, China (14-15 April 2018);
Huisman, R., Kyritsis, E., and Şteţ, C. (2018). Renewables intermittency versus power (in)flexibility: new insights from tail index estimates. *3rd HAEE Annual Conference.* Athens, Greece (3-5 May 2018);
Huisman, R., Şteţ, C., and Kyritsis, E. (2018). Impact of intermittent supply on tail fatness of electricity prices. *41st International IAEE Conference.* Groningen, The Netherlands (10-13 June 2018);
Kyritsis, E., Şteţ, C., and Huisman, R. (2018). Renewables intermittency versus power system (in)flexibility: new insights from tail-index estimates. *12th CFE International Conference.* Pisa, Italy (14-16 December 2018);
Huisman, R., Şteţ, C., and Kyritsis, E. (2019). Renewables intermittency versus power (in)flexibility: new insights from tail-index estimates. 4^{th} *IAFOR Independence and Interdependence Conference, Clean and Affordable Energy Session.* Honolulu, United States of America (3-5 January 2019);
Huisman, R., Kyritsis, E., Şteţ, C., (2019). Renewables intermittency versus power system (in)flexibility: beyond the mean and variance. 7^{th} *ELAEE Conference, Decarbonization, Efficiency and Affordability: New Energy Markets in Latin America*, Buenos Aires, Argentina (10-12 March 2019).

2.1 Introduction

Power markets have experienced radical structural changes over the past few decades. During this period of time, many countries liberalised their electricity sector and set the path to the creation of competitive power markets. Besides that, most of these markets experienced drastic reforms during the energy transition, with the most prominent being the increasing penetration of energy supply from renewable energy sources (VRES). The rapid and large-scale integration of intermittent VRES, however, induces significant impact on power prices and substantially increases the demand for power system flexibility, as intermittent energy supply comprises non-controllable variability and partial predictability (Perez-Arriaga and Batlle (2012) and Kyritsis et al. (2017)).

Partial predictability is predominantly driven by the fact that weather-dependent VRES do not perfectly adapt their output as a reaction to economic incentives, and therefore to the flexibility demand from the energy system. A better understanding of the impact that intermittent VRES have on electricity prices are of great concern to managers, who must take better long- and short-term decisions in the operating on electricity markets, but also to policy makers who endeavour to adjust the electricity market design in order to increase power system flexibility, and thereby accelerate the reduction of emissions in the power sector.

Focusing on the German electricity market, a prominent example of a market integrating variable energy supply from VRES, Kyritsis et al. (2017) show that both solar and wind power generation have an impact on the probability distribution function of electricity prices by decreasing the average price which is - in other words - the a merit-order effect. According to Kyritsis et al. (2017), electricity prices decline when the share of VRES in the power system increases. Würzburg et al. (2013) discuss several studies, of which nine focus on the German electricity market, and all provide evidence for the merit-order effect. More recent studies that yield the same conclusion are, among others, Tveten et al. (2013), Ketterer (2014), Paraschiv et al. (2014), and Dillig et al. (2016).

Tveten et al. (2013), Ketterer (2014), and Kyritsis et al. (2017) go one step further and examine how changes in intermittent renewable energy supply affect the volatility of electricity prices. In fact, Kyritsis et al. (2017) study both solar and wind power generation technologies and, considering the recent period of high renewable penetration, they show that solar and wind have a different impact on the volatility of electricity prices; while solar power generation reduces the volatility of electricity prices and the probability of electricity price spikes, wind power volatility increases electricity prices volatility and introduces electricity price spikes. The same relation between solar and the volatility of electricity prices manifests in Tveten et al. (2013) and between wind and electricity prices volatility in Ketterer (2014), during the first period of VRES integration. A more recent study by Johnson and Oliver (2019) analyzes wind and solar supply together and also find that VRES is increasing power price variance. Increased price variance induced by VRES calls for more knowledge about managing energy price risk and valuing real options such as the option to store power in batteries and alternative power storage systems and the option to flexibly adjust consumption and supply to respond to changes in VRES.

The view from the literature is that power prices decline (ceteris paribus) is a result of an increase in VRES and that the volatility of power prices changes (ceteris paribus) is a result of solar and wind energy supply variations. This view motivates us to further examine the impact of intermittent energy supply on the probability distribution of power prices. We question whether the increasing share of variable solar and wind power generation also affects the tails of power price distribution. The motivation for our research question becomes clear from Figure 2.1 which shows the development of the day-ahead average daily prices in EUR/MWh in Germany from January 2010 to June 2015. In this figure, the typical characteristics of day-ahead power prices, such as mean reversion and extremely high and low prices, become apparent. Kyritsis et al. (2017) focus on how power price variation (volatility), being the second moment of a probability distribution function, is affected by changes in VRES supply. As extreme prices, which are kurtosis events, influence the fourth moment of a probability distribution function, we think that these observations cannot be captured only by variation (or the second moment as it were). Therefore, the

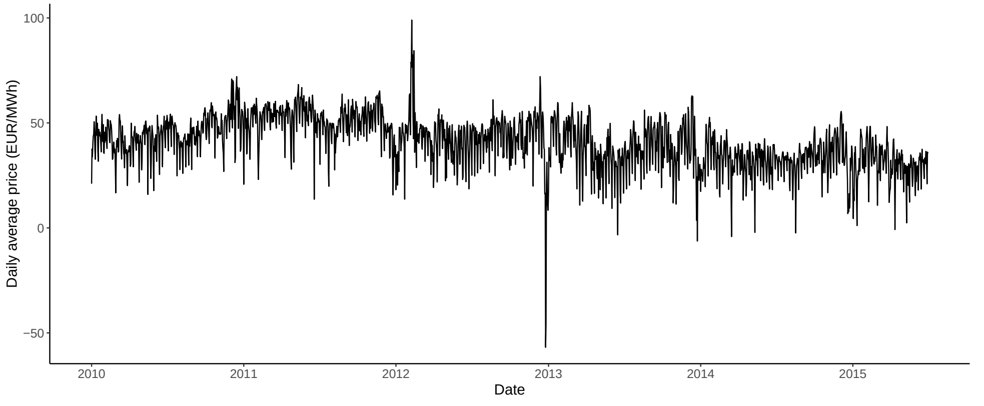


Figure 2.1: Average daily price on the German day-ahead market 2010-2015.

present study examines extreme power prices.[2]

The expansion of variable or intermittent VRES requires an increasing effort from the non-intermittent suppliers to counterbalance abrupt changes in production volumes. This may result in increased supply frictions, which become more prominent during periods of limited power system flexibility, in terms of adjusting the production volumes by the non-intermittent suppliers. Thus, the lower the flexibility of the power system, the higher the probability of extreme prices to occur. Hence, beyond the mean and variance of the electricity price distribution, the shape of the probability distribution in the tails is also driven by the penetration of VRES into the power system.

This reasoning relates the tail structure of electricity price distribution closely to power system flexibility, which is the key challenge towards the large-scale integration of VRES. However, there is not a consensus view in the literature on the relation between intermittent wind and solar energy supply and the tails of the power price probability distribution. Limited evidence comes from studies that marginally touch

[2]The day-ahead power price dataset exhibited in Figure 2.1 was checked for outliers, none being found present. For example, the most extreme prices that can be observed in Figure 2.1, the extreme high prices in February 2012 and the extreme low prices in December 2012, are formed based on the demand-supply fundamentals of the German day-ahead power market, thus, not representing outliers.

on the link between extreme electricity prices and intermittent supply. For instance, Paraschiv et al. (2014) do not find conclusive evidence for the case of solar supply, but their results show that upward price spikes occur mostly when wind energy supply is low. By comparing the tail fatness of the empirical power price distributions between emerging and developed economies, LeBaron and Samanta (2005) show that one of the factors influencing the distribution of electricity prices is the different penetration level of intermittent renewable generators. From a similar point of view, Lindstrom and Regland (2012) study six European electricity markets through the employment of a regime switching model, and find a positive relation between the frequency of extreme price events and the penetration of renewable energy sources in the power system; hence, they provide evidence of renewable energy supply increasing the tail fatness of the electricity price distribution. In contrast, Keles et al. (2016) apply an AR-GARCH model on EPEX day-ahead market data and indicate that the tail fatness of the power price distribution is reduced over the period from 2008 to 2014. Although the authors do not make a strong claim, they suggest that their results are possibly driven by the increasing share of VRES, and particularly wind, in the power generation mix.

Kyritsis et al. (2017) demonstrate the different impact of wind and solar energy supply on power price variation and provide some main distributional properties of electricity prices related to price spikes, for different solar and wind power penetration levels. Those price spikes (being both extreme high and low prices) are not studied in particular. Extreme Value Theory (EVT) is a field within statistics that focuses on the probability structure of extreme observations only. As extreme high and low prices occur due to unexpected changes in supply from VRES and the inflexibility of the power system to cope with these changes, prices behave different than when such changes do not occur. This motivates us to apply EVT as we believe that the probability distribution of extreme prices could not necessarily be caused by higher variance or volatility only. In this study, we therefore proceed a step further and investigate whether the results Kyritsis et al. (2017) found for volatility also hold with regard to the tail fatness of the power price distribution. Not only we look at the effect of solar and wind on the tails, but the main advantage is that we disentangle the effects of each of them on the left and right tail of the power price distribution. This chapter contributes to the literature by extending Kyritsis et al. (2017). Using their data and methodology, we examine the impact that the penetration of intermittent VRES in the German power supply mix has on both tails of the power price probability distribution, but also separately on the left and right tail.

The distribution of electricity prices can significantly deviate from the normal distribution, and one needs to incorporate information about the tails to correctly model the shape of the distribution. The tail fatness of the electricity price distribution has direct implications for risk management, energy policy making in the sense that supply from VRES in combination with insufficient flexible storage and / or production capacity and inelastic demand lead to extreme electricity prices, and for the real options valuation of flexible power suppliers for which price variation is a key-input variable.

The remainder of the chapter is structured as follows. Section 2.2 introduces our methodology. Section 2.3 discusses the data, and subsection 2.4 presents the empirical findings. Section 2.5 concludes the chapter and section 2.6 presents additional relevant figures and tables.

2.2 Methodology

Motivated by the aforementioned discussion, we investigate the impact of energy supply from VRES on the tail fatness of the empirical power price distribution. Due to price inelastic short-term demand and non-flexible storage and / or production capacity, power prices exhibit mean reversion, high volatility, and frequent upward and downward price spikes. As a consequence, the probability distribution of power prices is non-normal and exhibits fat tails. This has been recognized by, among others, Huisman and Huurman (2003), Byström (2005), Walls and Zhang (2005), Chan and Gray (2006), and Herrera and González (2014), who apply extreme value theory (EVT) to examine extremely high and low power prices.

None of the aforementioned studies focus on the relation between the probability and magnitude of extreme prices and the fundamentals of the electricity markets, such as generation mix, flexible storage capacity, expected demand, and available supply. We agree with Paraschiv et al. (2014) stating that stochastic models are often built on simplistic assumptions and that one should focus more on the role of fundamentals in the analysis of power prices. This motivates us to examine the relationship between the probability and magnitude of extreme power prices and wind and solar energy supply. In addition, we examine whether changes in intermittent supply from renewable supply sources have a different effect on the right side of the (empirical) power price distribution than on the left side, as previous studies found mixed evidence for this tail asymmetry. Frestad et al. (2010), for instance, do not find sufficient evidence for tail fatness asymmetry in the Nordic Electricity Swap Market. González-Pedraz et al. (2014), however, suggest that positive price spikes are more frequent in electricity prices than drops, thereby indicating tail asymmetry. We aim to contribute to this literature by examining the relation between the volume supplied by renewable power sources and extreme power prices.

To formulate our expectations about this relationship, we think of a power market with intermittent VRES, non-intermittent suppliers who can adjust production volumes, price inelastic consumers and, insufficient flexible storage and / or production capacity. With intermittent VRES we mean, for instance, wind and solar power producers who have limited capacity to adjust volumes; intermittent can also be called variable in that sense, and we shall use both terms interchangeably. In such a power market, non-intermittent suppliers have to increase or decrease production when supply from variable VRES decreases or increases so as to keep the system in balance.[3]

Now, consider a period in time when the energy market is in balance: the non-intermittent producers and VRES supply the customers' demand. We question what would happen with extreme power prices when supply from VRES increases or decreases, for instance due to a change in weather conditions. We distinguish between

[3] In most markets, non-intermittent output is predominantly generated using coal, nuclear, gas or hydro technologies and each of these technologies have different flexibility levels regarding ramping up and down production.

periods of high or low demand from customers and supply from VRES.

Increased demand for flexibility arises when supply from VRES changes. The non-intermittent producers are the only ones who can supply flexibility as they can adjust production. The prices that the non-intermittent suppliers charge for this flexibility depend on the merit order curve. When reserve margin, being ready to produce spare capacity, is low, demand for increasing production can be supplied only by a few non-intermittent producers, and this might result in very high prices. Demand for reducing production can be supplied by many producers and extremely low prices are not likely. Therefore, extremely high prices are more likely than extremely low prices when reserve margin is low. When reserve margin is high, only a few non-intermittent power plants produce. When a decrease in production is demanded, only a few producers can fulfil that demand and this might lead to extremely low prices. When an increase in production is demanded, many producers that are standing idle can increase production and extremely high prices are therefore less likely.

Reserve margins are, to a certain extent, correlated with demand levels. Thus, we argue that the discussion above holds for demand levels too. Summarising, extreme high (low) prices are more likely to occur than extreme low (high) prices when consumer demand is high (low). When examining power prices we expected that the probability distribution function of power prices has a fatter right (low) than low (high) tail, when demand is high (low). This is summarised as:

1. during periods of high demand, the right tail is fatter than the left tail;
2. during periods of low demand, left tail is fatter than the right tail.

So far, we have only looked at the relation between tail fatness and demand (or reserve margin). But the supply from VRES plays a crucial role as well. When demand is low and the share of VRES supply is high, less non-intermittent power plants produce than when the share of VRES is low. As a consequence, there are even less non-intermittent producers that can provide flexibility through decreasing production. Therefore, very low prices even become more likely when the share of VRES is high. When demand is high and the share of VRES supply is low, a decrease of supply from VRES can be met by only a few producers that have spare capacity left to increase production. Consequently, they might even charge higher prices than when the share of VRES supply is high. The combined effect can be summarised through our hypotheses below:

1. during periods of low VRES supply, the right tail is fatter than the left tail and the difference in fatness will be more pronounced when the demand is higher;
2. during periods of high VRES supply, the left tail is fatter than the right tail and the difference in fatness will be more pronounced when the demand is lower.

These statements summarise our expectations about the tails of the empirical power price probability distribution function. The statements directly relate tail fatness on one side and demand and VRES supply fundamentals on the other.

2.2.1 Measuring the fatness of the tails

To observe the fatness of the tails, we apply extreme value theory (EVT) and measure what is called the tail-index. The tail-index is a measure for tail fatness. The following discussion is based on Huisman et al. (2001) unless otherwise stated.

EVT investigates the distribution of tail observations. Fat-tailed distributions are probability distributions whose tails do not exhibit exponential decay such as the normal distribution. Instead they have fatter tails. In the limit, the tail shape follows a Pareto distribution or power law for a general class of fat-tailed distributions. This power law is $x^{-1/\gamma}$ when x becomes large. The parameter γ is the tail-index. The higher γ is, the fatter the tail becomes, i.e. the slower the probability density function decays to zero. This definition is good for the purpose of this chapter, but for a more general discussion we refer, for instance, to Huisman et al. (2001) and to Keles et al. (2016). The latter is more recent and applied this to power prices.

Hill (1975) proposed a maximum likelihood estimator for the tail-index of a conditional Pareto distribution. Consider a sample of n positive and independent observations drawn from some fat-tailed distribution. Let $x(i)$ be the ith-order statistic such that $x(i) > x(i-1)$ for $i = 2...n$. Hill (1975) proposed the following estimator for γ:

$$\gamma(\kappa) = \frac{1}{\kappa}\sum_{j=1}^{\kappa} ln(x(n-j+1)) - ln(x(n-\kappa)). \tag{2.1}$$

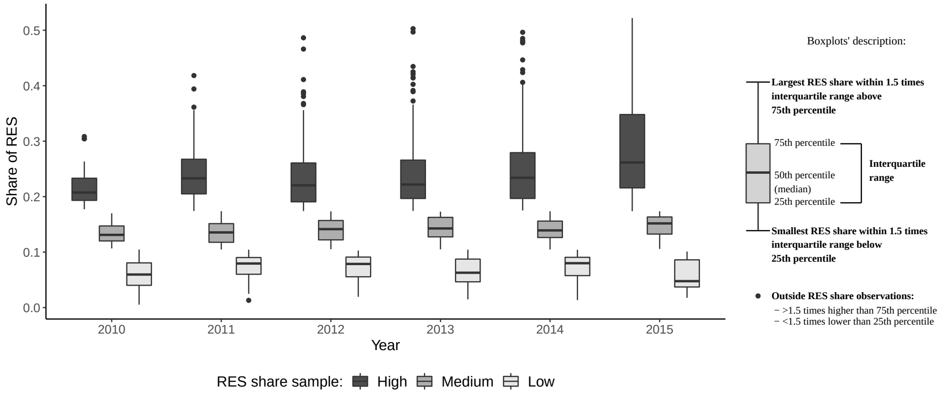
The idea behind the Hill (1975) estimator is that one selects to include the κ largest observations and that one starts at the threshold observation $x(n-\kappa)$ and that one measures the distance between the other tail observations and that threshold. This estimator is simple and frequently applied, but suffers from the problem that the researcher has to select κ, being the number of tail observations to include in the estimate.

Huisman et al. (2001) suggest a variation of the Hill estimator that reduces the impact of the choice for κ. They observe that the γ estimates from the Hill (1975) estimator increase almost linearly in κ for several fat-tailed distribution functions. They propose the following regression equation:

$$\gamma(k) = \beta_0 + \beta_1 \times k + \epsilon(k), \tag{2.2}$$

for $k = 1...\kappa$. The first reason for using this method is that the evaluation of equation (2.2) for k approaching zero yields that β_0 becomes an unbiased estimate of γ. We refer to Huisman et al. (2001) for the derivation, a weighted least squares variant, and the calculation of standard errors.

Huisman et al. (2001) argue that their approach, which is less dependent on a subjective choice for κ, provides more robust estimates even in smaller samples. We choose to adopt this methodology as we want to observe tail-index estimates from several smaller sub-samples of our date (left and right tails and periods with high / low demand). We chose not to consider others as we are not interested in the exact levels of the tail-index estimates. Following our hypotheses, we want to observe whether tail-index estimates increase or decrease as a result of the market share of VRES and demand and are therefore more interested in differences, in fact only higher or lower, and not so much in exact levels. This makes our results being less dependent on the



Individual boxplots comprise the daily share of VRES observations in either the Low, Medium or High share of VRES samples, categorized by year. Low, Medium and High VRES share samples each contain 669 observations, spread across the the five and a half years of data analyzed. All investigated years contain data points from each of the three VRES categories.

Figure 2.2: Share of VRES per selected subsample.

exact tail-index estimation method chosen.

Keles et al. (2016) offer an in-depth investigation on the thresholds κ to be used for German electricity prices. They show that the tail-index remains relatively stable between selecting the biggest/smallest 10% and 15% of the observations. We follow their result and select κ to be set at 10% and 15% thresholds and also include the 20% threshold for robustness reasons.

A last note on estimating the tail-index is that Hill (1975) assumes that the tail observations $x(i)$ are positive. Assuming that the mean of the distribution function under consideration is zero, this assumption implies that we can only measure the tail-index of the right tail. However, by using the absolute values of all $x(i)$'s, we can measure the tail-index for both tails simultaneously and by taking $-x(i)$, we can measure the tail-index for the left tail.

2.3 Data

We use the data from Kyritsis et al. (2017). Their sample consists of German day-ahead (Phelix) power prices, solar and wind power generation, and total electricity load from January 2010 to June 2015. We have three reasons why we chose to use their data. First, the time span is characterised by a rapid and large-scale integration of VRES. Second, this is a period for which we know that intermittent wind and solar supply explains variation in electricity price volatility. Third, the data enables us to test the relationship between the tails of the power price probability distribution and the share of renewable energy supply.

It is important however to note that our results obtained from the German power market do not necessarily hold in other markets, in particular for those with different market structure and different power generation mixes. Besides the power mix particularities, each power market has also different regulations in place. For the German market during the period investigated, as Patrick et al. (2019) explain, through Renewable Energy Sources Act (Erneuerbare-Energien-Gesetz – EEG) passed in 2000 and further strengthened by Energiewende in 2010, VRES output is prioritised for dispatch. These legislative measures led to a feed-in tariff system for the wind and solar supply, system that incentivises VRES producers to maximize their production, regardless of the impact on power prices. For German VRES producers, since they are subsidised at a fixed positive EUR/MWh rate, curtailment of supply is not beneficial even at negative day-ahead prices. This aspect, combined with the fact that there is no curtailment obligation imposed at day-ahead market level, leads to VRES supply being always placed first in the merit order curve on the German day-ahead market [4]. Another particularity of the German power markets is that negative prices are allowed to be bid in the market, and in this way, extreme negative low prices can appear in certain moments.

[4]As both Michael and Iain (2018) and Patrick et al. (2019) show, it is only by 2016 that curtailment regulation was implemented in the German power market and it affects only the real time markets. Through an amendment to the Renewable Energy Act, up to 3% of VRES installed capacity can be curtailed yearly in each Distribution System Operator area and only if such a measure is needed for maintaining grid stability.

As we want to examine the differences in tail fatness for high and low demand periods and observe how these differences alter when the share of VRES changes, we create different samples. To distinguish between high and low demand periods, we separate between average daily prices (average over 24 hours), average prices during off-peak hours (average over the prices for delivery during hours 21-8) - being low demand periods - and average prices during peak hours (average over the prices for delivery during hours 9-20) - being high demand periods.

To observe the tail fatness for different market shares of VRES, we follow the methodology of Kyritsis et al. (2017) and Nicolosi (2010) using actual power generation data for the total, wind and solar output. However, their sampling method creates too many categories and too small samples to draw conclusions. Therefore, we adjust their sampling method to create equally sized sub-samples, which are large enough to measure the tail-index estimates.[5] To differentiate between left and right tail of the distribution of electricity prices, we place the (absolute) values below the median into the left tail observations and the values above the median into the right tail observations. We are able to work with such a sampling strategy since our methodology treats data as a cross-section where the exact location in time of each data point not relevant.

Figure 2.2 illustrates a summary of the share of VRES in Germany for the period investigated in each of the three subsamples considered. The sub-sample “Low” contains prices from those days where the market share of supply from VRES is between 0.5% and 10.5%. The second sub-sample “Medium” contains those days with supply from VRES between 10.5% and 17.4%. The third sub-sample “High” contains the days with supply from VRES between 17.4% and 52.2% (the maximum observed market share from VRES). By construction, all sub-samples have equal size, and we use the same number of observations to estimate the left and right tail, as well as both tails simultaneously. Each of the three sub-samples contains 669 observations, of which and 334 are used to estimate the left-tail and 334 are used to estimate the right tail[6]. Each of the years comprised in the dataset includes days with “Low”, “Medium”

[5] Using initially the sampling method of Kyritsis et al. (2017), we obtained similar qualitative results as these that we discuss later.

[6] Since in each of the three subsamples we have an odd number of observations, the median data point is excluded from the tail index calculations.

and "High" share of VRES.

2.4 Empirical results

Table 2.1 presents tail-index estimates for various sub-samples assuming that 15% of the observations are tail observations (i.e. κ is 15%)[7]. The estimates for κ equal to 10% and 20% are also shown in Table 2.4. Since in our hypotheses we develop expectations only for the "Low" and "High" subsamples at the right and left tail of the power price distribution, we focus in this section on analysing these results. The tail-index estimates for the "Medium" samples are also available in Table 2.4. With these estimates, we want to test our two statements.

Table 2.1: Tail-index estimates for samples equally sized by RES supply. κ is 15%.

Share of RES supply	All hours Left	All hours Right	Peak hours Left	Peak hours Right	Off-peak hours Left	Off-peak hours Right
Low (0.5-10.5%)	0.16 (0.148)	0.36 (0.001)	0.19 (0.006)	0.31 (0.001)	0.19 (0.006)	0.19 (0.005)
	t=-1.37		*t=-19.21****		*t=0.03*	
High (17.4-52.2%)	0.39 (0.001)	0.06 (0.009)	0.31 (0.001)	0.08 (0.007)	0.53 (0.001)	0.11 (0.022)
	*t=37.19****		*t=33.03****		*t=19.04****	

*Significant at p***<0.01, p**<0.05, p*<0.1; standard errors in parentheses.*
t is the t-value of the difference between the estimates of the left and the right tail.

Our first statement is that during periods of low VRES supply, the right tail is fatter than the left tail and the difference in fatness will be more pronounced when the demand is higher. As demand during peak hours is higher than during off-peak hours, the peak hours represent the high demand observations. Let's focus on the first row with numbers. This row contains the tail-index estimates from the sample of power prices from days when the share of intermittent VRES supply is lowest. The column headed *peak hours* shows that the tail-index γ for the right tail is 0.31 and for the left tail is 0.19. The difference between the left and right tail-index is highly significant

[7] For t-statistics calculations in this chapter, in accordance with Huisman et al. (2001), we assume no correlation between the observations of the compared groups.

with a t-value equal to -19.21. The higher the tail-index, the fatter the tail is, and we can therefore safely conclude that the right tail is fatter than the left tail. This provides evidence of tail asymmetry, which is in line with our aforementioned expectations.

We also expected that the difference in fatness will be more pronounced when the share of demand is higher. This is what Table 2.1 shows as well. We see - as expected - that the right tail-index estimates becomes smaller and that the difference between the tail-indexes of the left and right tail is much smaller (and not significant) than in the "Low" VRES rows for the *off-peak hours*. The tail asymmetry appears to not be present in the *off-peak hours* for the "Low" VRES samples, as both left and right tail-index estimates are similar. From the results regarding our first statement, we observe that, on the German day-ahead market, when VRES supply is low, high price spikes are more likely to occur than low price spikes.

Our second statement is that *during periods of high VRES supply, the left tail is fatter than the right tail and the difference in fatness will be more pronounced when the demand is lower.*. When we move to the "High" tail index row, we see that the relation becomes the opposite: the left tail is now significantly fatter than the right tail. Apparently, in periods with high demand and high share of VRES supply, an increase in VRES supply, which yields a demand to ramp down supply from non-intermittent producers, leads more frequently to extremely low prices than when a decrease in VRES supply occurs. The energy market here is less flexible to deal with VRES supply increases than decreases, as only a few non-intermittent power plants produce and therefore can ramp down their supply. Those power plants are more likely to be inflexible producers for whom at certain moments in time ramping down production can be technically infeasible or economically not beneficial. Such a situation might lead to extremely low prices.

During off-peak hours demand is typically lower than during peak hours, and we'll use the samples with prices from off-peak hours as low demand observation. For the periods with an average lower demand, in the "High" sample, where the share of VRES supply is high, we clearly see that the left tail is fatter than the right tail, and that the difference between the two tail-indexes is highly significant with a t-value equal to 19.04. This finding confers additional robustness to our previous result on tail fatness asymmetry, which is in accordance with our expectations. Table 2.4 in the appendix shows the same estimates, but for different settings for κ, supporting that the previous conclusions are robust with respect to whether we set κ equal to 10%, 15%, or 20%.

The results that we found are all in line with our expectations. During periods of low share of VRES supply, the right tail is fatter than the left tail and the difference in fatness will be more pronounced when demand is higher. During periods of high share of VRES supply, left tail is fatter than the right tail and the difference in fatness will be more pronounced when demand is lower.

As mentioned earlier, Kyritsis et al. (2017) show that supply from VRES drives power price volatility and that wind and solar energy supply have a different impact. As energy supply from solar sources only occurs during day-time, it increases the reserve margin during peak hours. So far we have examined the impact of aggregate supply from VRES on the tails. We also examined the impact of energy supply from wind and solar separately, as in Kyritsis et al. (2017), to observe whether the two impact tails differently. To do so, we sample the data in groups with low and high supply from wind or solar sources. Tables 2.2 and 2.3 show how we constructed those samples for wind and solar, respectively. [8] Estimating the tail-index for each sample, and following these two tables, enables us to observe whether wind or solar affects our results differently, as what was observed for volatility by Kyritsis et al. (2017).

Table 2.2 shows the results for supply from wind sources. We observe the same pattern as what we found before: i) a fatter right than left tail during peak hours and low share of wind supply, and the opposite tail structure when the share of wind supply is at the highest level, and ii) a fatter left than right tail during off-peak hours with a high share of wind supply, which difference disappears when the share of wind supply is lower. The results from only wind supply are no different than the results observed from samples with aggregated energy supply, from both wind and solar

[8] Tables 2.5 and 2.6, similar as with 2.4 presented in the appendix of this manuscript, include the complete tail-index estimates set for the wind and solar subsamples.

sources.

Table 2.2: Tail-index estimates for samples equally sized by wind supply. κ is 15%.

Share of wind supply	All hours		Peak hours		Off-peak hours	
	Left	Right	Left	Right	Left	Right
Low (0.4-4.9%)	0.09 (0.042)	0.27 (0.002)	0.08 (0.013)	0.31 (0.001)	0.11 (0.012)	0.13 (0.024)
	*t=-4.25****		*t=-17.76****		*t=-0.95*	
High (11.2-50.6%)	0.37 (0.001)	0.02 (0.009)	0.26 (0.002)	0.09 (0.007)	0.53 (0.001)	0.05 (0.010)
	*t=36.82****		*t=26.12****		*t=46.06****	

*Significant at p***<0.01, p**<0.05, p*<0.1; standard errors in parentheses.*
t is the t-value of the difference between the estimates of the left and the right tail.

When we measure the tail-index for both tails of the electricity price distribution and thus do not disentangle the effect on the left and right tail, we clearly notice that the higher the share of wind supply, the fatter the tails of the power price probability distribution are. For instance, during all hours the tail-index estimate for low share of wind supply is 0.20 and for high share of wind supply is 0.29, which difference is statistically significant [9]. This finding confers additional robustness to our conclusions as it aligns with the findings of previous studies in the literature, for instance Ketterer (2014) and Kyritsis et al. (2017), who employ conditional heteroskedasticity models and find evidence of wind power generation increasing the volatility of electricity price in Germany, and thus the fatness of the tails.

Table 2.3 shows the tail-index estimates from groups sampled on the share of solar supply. For peak hours, we again observe the same pattern: a fatter right than left tail for low share of solar supply, which difference becomes not significant for higher shares of solar supply. For the "High" solar sample, we observe higher but not statistically significantly different left than right tail-index estimates. This result was drawn from a period when the penetration of solar supply in the German power market was relatively low. Comparing with the results from the wind supply samples, we would expect that for a higher penetration of solar supply to observe a significantly fatter left tail compared to the right one for the German day-ahead power prices during

[9] These results are displayed in Table 2.5 within the appendix of this manuscript.

peak hours. This consequence of high solar supply is closely linked with the "duck curve" phenomenon, where, in power markets with a high solar penetration rate, conventional producers are forced during the peak hours to ramp down significantly their production and ramp up again during the off-peak hours. High levels of solar supply generated during peak hours, put pressure on the flexibility of the power markets and in the same time they lower the prices, decreasing the probability of high spike occurrences. As opposed to tables 2.1 or 2.2, in table 2.3 we do not present the results for the off-peak hours and we choose to do this because of the date limitations that we face. The data used includes the level of solar supply as a total daily output without distinguishing between the hours when it was produced. As solar supply is generated in mostly during peak hours, and in many winter days exclusively during peak hours, we cannot draw expectations and conclusions based on the off-peak solar samples.

Both Tables 2.2 and 2.3 show the estimates in which we include 15% of the observations (κ) to estimate the tail-index. Tables 2.5 and 2.6 in the appendix also show the tail-index estimates from samples with different settings for κ.
When we measure the tail-index for both tails of the electricity price distribution and thus do not disentangle the effect on the left and right tail, we clearly notice that the higher the share of wind supply, the fatter the tails of the power price probability distribution are. For instance, during all hours the tail-index estimate for low share of wind supply is 0.20 and for high share of wind supply is 0.29, which difference is statistically significant [10]. This finding confers additional robustness to our conclusions.

Table 2.3 shows the tail-index estimates from groups sampled on the share of solar supply. For peak hours, we again observe the same pattern: a fatter right than left tail for low share of solar supply, which difference becomes not significant for higher shares of solar supply. For the "High" solar sample, we observe higher but not statistically significantly different left than right tail-index estimates. This result was drawn from a period when the penetration of solar supply in the German power market was relatively low. Comparing with the results from the wind supply samples, we would

[10] These results are displayed in Table 2.5 within the appendix of this manuscript.

expect that for a higher penetration of solar supply to observe a significantly fatter left tail compared to the right one for the German day-ahead power prices during peak hours. This consequence of high solar supply is closely linked with the "duck curve" phenomenon, where, in power markets with a high solar penetration rate, conventional producers are forced during the peak hours to ramp down significantly their production and ramp up again during the off-peak hours. High levels of solar supply generated during peak hours, put pressure on the flexibility of the power markets and in the same time they lower the prices, decreasing the probability of high spike occurrences. As opposed to tables 2.1 or 2.2, in table 2.3 we do not present the results for the off-peak hours and we choose to do this because of the date limitations that we face. The data used includes the level of solar supply as a total daily output without distinguishing between the hours when it was produced. As solar supply is generated in mostly during peak hours, and in many winter days exclusively during peak hours, we cannot draw expectations and conclusions based on the off-peak solar samples.

Both Tables 2.2 and 2.3 show the estimates in which we include 15% of the observations (κ) to estimate the tail-index. Tables 2.5 and 2.6 in the appendix also show the tail-index estimates from samples with different settings for κ.

Table 2.3: Tail-index estimates for samples equally sized by solar supply. κ is 15%.

Share of solar supply	All hours		Peak hours	
	Left	Right	Left	Right
Low (0.0-2.2%)	0.21 (0.004)	0.26 (0.002)	0.09 (0.012)	0.24 (0.002)
	*t=-11.63****		*t=-12.97****	
High (6.7-20.9%)	0.23 (0.002)	0.18 (0.013)	0.28 (0.001)	0.15 (0.185)
	*t=3.63****		*t=0.68*	

*Significant at p***<0.01, p**<0.05, p*<0.1; standard errors in parentheses.*
t is the t-value of the difference between the estimates of the left and the right tail.

Our results depend on the assumption that the energy market is not flexible enough to respond easily to changes in the supply of VRES, and therefore shed light on the value of electricity storage solutions. Fat tails represent one of the factors that makes the value of an option to store power, or an option to curtail production, higher than when tails are thin. For power storage facilities our results imply that one wants to have them charged when demand is high, and especially when the share of VRES is low. One wants them to be discharged, being ready to charge, when demand is low and the share of VRES is high. This charging strategy that follows from our results makes perfect sense, as it follows that the power storage facility is charged during periods when VRES supply is abundant (low demand and a high share of VRES) and discharged when VRES supply is relatively scarce (high demand and a low share of VRES).

2.5 Chapter's concluding remarks

VRES supply, being a variable and intermittent source of power production, poses challenges to power markets as they are often not flexible enough to counterbalance VRESs variation in production volumes, since power storage is insufficient and power demand is inelastic. Non-intermittent producers are the only ones that can provide this flexibility, and we argue that during times when the supply of flexibility is low they are technically constrained being not capable of supplying the needed flexibility. As a consequence, in such moments, extremely high or low prices are more likely to occur.

Using extreme value theory, we demonstrate that the tails of the power price probability distribution are fatter when the supply of flexibility is low. Such moments of low power flexibility occur when both the reserve margins of non-intermittent suppliers and VRES supply are either at low or at high levels. More specifically we find support for our claims that i) during periods of high share of VRES, the left tail is fatter than the right tail and the difference in fatness will be more pronounced when demand is lower, and ii) during periods of low share of VRES, right tail is fatter than the left tail and the difference in fatness will be more pronounced when the demand is higher. When we focus separately on the share of wind and solar supply, instead of aggregate supply from VRES, we find the same results for wind and for solar.[11]

Although it was already known that power prices are not normally distributed, this chapter shows that the amount of non-normality in the tails, i.e. the tail fatness, can be forecasted by demand and volume of VRES. For risk managers, this implies that risk models should be made conditional on those variables and one should use models in which the tail structure can be flexibly adjusted to the supply and demand conditions. This will also impact hedging decisions as one would like to hedge more for those periods when extreme losses may be expected. Another implication of this is that those who assess the value of storage facilities or determine storage strategies may want to include these conditional tail estimates in their models. By doing so, they will bring their charge / discharge decisions more in line with the demand for flexibility.

In order to achieve large-scale integration of VRES in the power system, policy makers and market participants should have a clear understanding of the requirements for power system flexibility. This study provides insights into when, and to what extent, extreme prices occur depending on the electricity demand and VRES supply, and thereby the demand for flexibility to adjust electricity supply through non-intermittent producers. This will directly affect the value of power storage facilities or, options to curtail production from VRES, during periods of time when the power system cannot provide sufficient flexibility to adjust production while VRES supply increases. Considering that with the increasing share of VRES we will have more variability in the power system and more frequent extreme low prices, policy makers should focus on the flexibility of the energy system when designing policies to increase installed renewable energy capacity.

We call for additional VRES search based on higher frequency data and on a much wider variety of countries with varying level of flexible power generation and intermittent renewable energy sources. The latter would provide a more accurate picture of the impact of intermittent VRES on the power system. Another path that

[11] Although, to be more precise, not for solar during off-peak hours. This is, however, a result that we do not consider relevant, as the sun does not shine during night time and the observation most likely cannot be attributed to solar supply.

is worth investigating is looking at how the integrated assessment models can be improved based on the information that VRES supply is changing the probability of low and high price spike occurrence.

2.6 Additional tables

Table 2.4: Tail-index estimates for samples equally sized by RES supply

Share of RES supply	Selected threshold	All hours Left	All hours Both	All hours Right	Peak hours Left	Peak hours Both	Peak hours Right	Off-peak hours Left	Off-peak hours Both	Off-peak hours Right
	tail at 10%	0,17	0,27	0,35	0,19	0,32	0,39	0,14	0,17	0,20
	se at 10%	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)	(0,001)	(0,000)	(0,000)
	(t-statistic)		*t=-337****			*t=-460,17****			*t=-54,62****	
Low	tail at 15%	0,16	0,26	0,36	0,19	0,28	0,31	0,19	0,19	0,19
(0.5-10.5%)	se at 15%	(0,148)	(0,001)	(0,001)	(0,006)	(0,001)	(0,001)	(0,006)	(0,004)	(0,005)
	(t-statistic)		*t=-1,37*			*t=-19,21****			*t=0,03*	
	tail at 20%	0,17	0,25	0,34	0,16	0,25	0,34	0,18	0,19	0,18
	se at 20%	(0,026)	(0,008)	(0,003)	(0,016)	(0,008)	(0,003)	(0,040)	(0,007)	(0,027)
	(t-statistic)		*t=-6,4****			*t=-10,73****			*t=0,11*	
	tail at 10%	0,09	0,1	0,09	0,05	0,05	0,06	0,11	0,05	0,03
	se at 10%	(0,030)	(0,017)	(0,012)	(0,008)	(0,008)	(0,005)	(0,037)	(0,008)	(0,011)
	(t-statistic)		*t=-0,13*			*t=-1,59*			*t=1,95**	
Medium	tail at 15%	0,11	0,10	0,11	0,11	0,11	0,11	0,13	0,08	0,03
(10.5-17.4%)	se at 15%	(0,017)	(0,039)	(0,007)	(0,744)	(0,011)	(0,016)	(0,018)	(0,006)	(0,010)
	(t-statistic)		*t=0,29*			*t=0,01*			*t=4,82****	
	tail at 20%	0,13	0,1	0,11	0,12	0,12	0,12	0,13	0,09	0,07
	se at 20%	(0,007)	(0,103)	(0,216)	(0,055)	(0,018)	(0,030)	(0,022)	(0,015)	(0,010)
	(t-statistic)		*t=0,08*			*t=0,05*			*t=2,56***	
	tail at 10%	0,43	0,34	0,03	0,32	0,25	0,06	0,65	0,45	0,05
	se at 10%	(0,000)	(0,000)	(0,008)	(0,000)	(0,000)	(0,014)	(0,000)	(0,000)	(0,062)
	(t-statistic)		*t=48,01****			*t=18,58****			*t=9,63****	
High	tail at 15%	0,39	0,29	0,06	0,31	0,21	0,08	0,53	0,38	0,11
(17.4-52.2%)	se at 15%	(0,001)	(0,001)	(0,009)	(0,001)	(0,002)	(0,007)	(0,001)	(0,001)	(0,022)
	(t-statistic)		*t=37,19****			*t=33,03****			*t=19,04****	
	tail at 20%	0,37	0,25	0,07	0,25	0,18	0,09	0,48	0,34	0,11
	se at 20%	(0,003)	(0,008)	(0,010)	(0,014)	(0,019)	(0,008)	(0,002)	(0,002)	(0,007)
	(t-statistic)		*t=29,49****			*t=9,85****			*t=49,49****	

*Significant at p***<0,01, p**<0,05, p*<0,1; tail = tail-index estimate; se = standard errors.*
t is the t-value of the difference between the estimates of the left and the right tail.

Table 2.5: Tail-index estimates for samples equally sized by supply from wind sources

Share of wind	Selected threshold	All hours Left	All hours Both	All hours Right	Peak hours Left	Peak hours Both	Peak hours Right	Off-peak hours Left	Off-peak hours Both	Off-peak hours Right
Low (0.4-4.9%)	tail at 10%	0,08	0,13	0,29	0,04	0,15	0,29	0,06	0,11	0,12
	se at 10%	(0,010)	(0,001)	(0,000)	(0,011)	(0,000)	(0,000)	(0,006)	(0,016)	(0,003)
	(t-statistic)		*t=-20,67****			*t=-21,33****			*t=-10,1****	
	tail at 15%	0,09	0,2	0,27	0,08	0,17	0,31	0,11	0,14	0,13
	se at 15%	(0,042)	(0,003)	(0,002)	(0,013)	(0,008)	(0,001)	(0,012)	(0,018)	(0,024)
	(t-statistic)		*t=-4,25****			*t=-17,76****			*t=-0,95*	
	tail at 20%	0,15	0,22	0,27	0,12	0,18	0,29	0,14	0,14	0,11
	se at 20%	(0,008)	(0,059)	(0,008)	(0,036)	(0,023)	(0,006)	(0,016)	(0,010)	(0,014)
	(t-statistic)		*t=-10,29****			*t=-4,56****			*t=1,16*	
Medium (4.9-11.1%)	tail at 10%	0,13	0,23	0,32	0,13	0,22	0,35	0,11	0,15	0,21
	se at 10%	(0,002)	(0,000)	(0,000)	(0,002)	(0,000)	(0,000)	(0,008)	(0,001)	(0,000)
	(t-statistic)		*t=-114,35****			*t=-124,06****			*t=-12,29****	
	tail at 15%	0,13	0,18	0,26	0,08	0,19	0,35	0,11	0,14	0,16
	se at 15%	(0,021)	(0,006)	(0,002)	(0,007)	(0,004)	(0,001)	(0,046)	(0,038)	(0,041)
	(t-statistic)		*t=-5,99****			*t=-39,93****			*t=-0,73*	
	tail at 20%	0,11	0,17	0,25	0,08	0,19	0,33	0,14	0,12	0,15
	se at 20%	(0,007)	(0,022)	(0,012)	(0,010)	(0,014)	(0,004)	(0,019)	(0,242)	(0,037)
	(t-statistic)		*t=-10,83****			*t=-24,21****			*t=-0,41*	
High (11.2-50.6%)	tail at 10%	0,42	0,37	0,04	0,31	0,26	0,08	0,64	0,47	0,03
	se at 10%	(0,000)	(0,000)	(0,007)	(0,000)	(0,000)	(0,014)	(0,000)	(0,000)	(0,008)
	(t-statistic)		*t=53,54****			*t=15,79****			*t=77,16****	
	tail at 15%	0,37	0,29	0,02	0,26	0,22	0,09	0,53	0,36	0,05
	se at 15%	(0,001)	(0,001)	(0,009)	(0,002)	(0,002)	(0,007)	(0,001)	(0,001)	(0,010)
	(t-statistic)		*t=36,82****			*t=26,12****			*t=46,06****	
	tail at 20%	0,35	0,25	0,03	0,24	0,21	0,07	0,47	0,32	0,06
	se at 20%	(0,003)	(0,009)	(0,011)	(0,018)	(0,029)	(0,015)	(0,002)	(0,003)	(0,011)
	(t-statistic)		*t=28,34****			*t=7,1****			*t=35,49****	

*Significant at p***<0,01, p**<0,05, p*<0,1; tail = tail-index estimate; se = standard errors.*
t is the t-value of the difference between the estimates of the left and the right tail.

Table 2.6: Tail-index estimates for samples equally sized by supply from solar sources

Share of solar supply	Selected threshold	All hours Left	All hours Both	All hours Right	Peak hours Left	Peak hours Both	Peak hours Right	Off-peak hours Left	Off-peak hours Both	Off-peak hours Right
	tail at 10%	0,23	0,20	0,24	n.a.	0,10	0,19	0,38	0,32	0,20
	se at 10%	(0,000)	(0,000)	(0,000)	n.a.	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)
	(t-statistic)		*t=-31,62****			*n.a.*			*t=454,31****	
Low	tail at 15%	0,21	0,25	0,26	0,09	0,17	0,24	0,36	0,32	0,18
(0-2.2%)	se at 15%	(0,004)	(0,001)	(0,002)	(0,012)	(0,025)	(0,002)	(0,001)	(0,001)	(0,012)
	(t-statistic)		*t=-11,63****			*t=-12,97****			*t=14,56****	
	tail at 20%	0,25	0,26	0,24	0,17	0,22	0,26	0,32	0,31	0,17
	se at 20%	(0,015)	(0,006)	(0,022)	(0,022)	(0,022)	(0,010)	(0,004)	(0,003)	(0,028)
	(t-statistic)		*t=0,33*			*t=-3,49****			*t=5,19****	
	tail at 10%	0,27	0,30	0,31	0,08	0,22	0,33	0,44	0,34	0,17
	se at 10%	(0,000)	(0,000)	(0,000)	(0,050)	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)
	(t-statistic)		*t=-124,64****			*t=-5,16****			*t=482,25****	
Medium	tail at 15%	0,25	0,32	0,26	0,11	0,25	0,32	0,35	0,36	0,17
(2.2-6.7%)	se at 15%	(0,002)	(0,001)	(0,002)	(0,081)	(0,001)	(0,001)	(0,001)	(0,001)	(0,042)
	(t-statistic)		*t=-5,18****			*t=-2,56***			*t=4,28****	
	tail at 20%	0,28	0,32	0,22	0,15	0,24	0,29	0,34	0,36	0,14
	se at 20%	(0,006)	(0,003)	(0,080)	(0,019)	(0,011)	(0,006)	(0,003)	(0,002)	(0,028)
	(t-statistic)		*t=0,74*			*t=-6,8****			*t=7,45****	
	tail at 10%	0,24	0,19	0,10	0,33	0,23	0,12	0,11	0,08	0,04
	se at 10%	(0,000)	(0,000)	(0,080)	(0,000)	(0,000)	(0,004)	(0,008)	(0,011)	(0,010)
	(t-statistic)		*t=1,77**			*t=47,78****			*t=5,92****	
High	tail at 15%	0,23	0,20	0,18	0,28	0,22	0,15	0,14	0,11	0,10
(6.7-20.9%)	se at 15%	(0,002)	(0,002)	(0,013)	(0,001)	(0,002)	(0,185)	(0,040)	(0,006)	(0,018)
	(t-statistic)		*t=3,63****			*t=0,68*			*t=1,01*	
	tail at 20%	0,21	0,21	0,19	0,26	0,22	0,16	0,18	0,13	0,11
	se at 20%	(0,011)	(0,144)	(0,038)	(0,010)	(0,040)	(0,027)	(0,012)	(0,020)	(0,010)
	(t-statistic)		*t=0,66*			*t=3,39****			*t=4,87****	

*Significant at p***<0,01, p**<0,05, p*<0,1; tail = tail-index estimate; se = standard errors.*
t is the t-value of the difference between the estimates of the left and the right tail.

Chapter 3

How panel quantile regressions may help to better accommodate the varying supply from renewable energy sources[1]

3.1 Introduction

The inclusion of supply from variable renewables sources (VRES), challenges power systems. The volume supplied by these sources is variable as it depends on weather conditions, which are variable over time. These sources have limited capacity to adjust volumes as they can only curtail, not increase, production. Hence, such renewables

[1]Parts of this chapter appear in the following peer reviewed conference proceedings:
Huisman, R., and Şteţ, C. (2019). Varying impact of intermittent supply on hourly day-ahead electricity prices. *7th IAEE Asia-Oceania Conference.* Auckland, New Zealand, February 12-15, 2020;
Huisman, R., and Şteţ, C. (2020). Varying impact of intermittent supply on hourly day-ahead electricity prices. *1th IAEE Online International Conference.* June 7-9, 2021.

challenge the power system as their volume variability needs to be dealt with. Moreover, weather dependent supply from wind and solar does not match demand patterns. In such an environment, many current power systems are not flexible enough. This leads to frequent negative power prices due to an abundance of supply from VRES at times when there is no demand for it. Investments are needed to increase the flexibility of power systems in matching supply and demand.

One can think of power storage and more flexible consumption (demand response as some call it) as potential solutions. What these solutions have in common is that they are real options. A power storage facility provides the real option to charge when VRES supply is high and demand for it is low. The facility then has the option to discharge and deliver power when demand is high and supply from VRES is low. The same holds for flexible consumption. Having the option to scale up or down consumption in response to more or less supply from VRES makes the power system more flexible. Investments in such real option type of assets only take place when sufficient income can be generated from these assets. Income from real option assets depends on the variation of power prices as option theory tells us (Black and Scholes (1973)). When power prices are more volatile, the owner of a power storage facility can charge at lower prices and discharge at higher prices and yield more income than when prices are less volatile. This view of just volatility driving income of real option assets comes from financial markets but is too simplistic for power markets. There, frictions between supply and demand and often the lack of storage, make power prices behave more erratically than prices of financial assets. There is sufficient evidence for that claim put forward in the literature as it reveals that power prices tend to mean-revert and frequently jump to high and low (even negative) levels. Understanding these price dynamics is crucial for valuing real options assets in power markets, assets which represent an important source of flexibility and, thereby, enable the efficient inclusion of VRES.

To include VRES supply efficiently, we need those real options to respond to (expected) fluctuations in supply from renewables. Following the logic of supply and demand, the market price of power depends on supply from VRES. There is a consensus view on how a change in supply from VRES affects power prices since a change in the (expected) supply from VRES shifts the supply curve (or merit order as it is called in the energy world). Würzburg et al. (2013) summarises 20 studies and all find that an increase in supply from VRES decreases the market price of power. This result is intuitive since, by having almost zero marginal cost, VRES are highly competitive and are generally included in that part of the supply curve that is dispatched.

Other studies focus on the relation between supply from VRES and the volatility of the market price of power. Ketterer (2014), Kyritsis et al. (2017), and Rintamäki et al. (2017) show that an increase in the supply from wind producers increases the volatility of power prices as it challenges the flexibility of power markets especially during off-peak hours when demand is low and only a few power plants can curtail production. For supply from solar producers, Kyritsis et al. (2017) show that an increase in supply decreases price volatility as solar typically supplies during demand peak hours. Rintamäki et al. (2017) go one step further as they distinguish between periods with high and low prices. They show that supply from VRES lowers the volatility of power prices during periods with high prices and increases volatility when prices are low.

Beyond the mean and the variance of power prices, some papers, using either extreme value theory or regime switching models, show that VRES output influences also the likelihood of extremely high and low power prices. Lindstrom and Regland (2012), in a study on 6 European power markets, find a positive link between the two. Paraschiv et al. (2014) touches marginally on this aspect proving a connection between extreme negative prices and higher wind power output on the German EEX market. Benhmad and Percebois (2018) and Martin de Lagarde and Lantz (2018) show that a steep decrease in power prices was associated with an increase in wind power in-feed. In the second chapter of this thesis we argue that extreme high and low prices should be analysed separately as VRES output has a different impact on the left tail of the power price probability distribution (low prices) than on the right tail (high prices). For instance, an increase in supply from wind sources decreases the occurrence and magnitude of extremely high prices, while it increases the occurrence and magnitude of extremely low prices. A similar conclusion is also drawn by Hagfors et al. (2016b).

The summarising view is that an increase in supply from VRES decreases the day-ahead power price on average, changes the volatility of power prices and the frequency and magnitude of extremely high and low prices. Consequently, power prices will be low when supply from VRES is high and demand for power is low. Alternatively, one may expect power prices to be high when supply from VRES is low and demand for power is high. But, in order to maximise value, a power storage (real option asset) owner wants to make charging / discharging decisions based on expectations when market prices will be lowest / highest. She/he wants to profit from extreme prices, which occur when the flexibility of the power system is challenged most. The same, for someone who can adjust consumption volumes, she/he wants to reduce consumption when prices are highest and vice versa. The point is that real option assets owners want to profit from extreme price movements, and by doing so they will offer their flexibility at times when its most needed. In order to deliver this, they need to understand what drives those extreme prices. In power markets volatility by itself is not a sufficient parameter as input for real option valuation models. What we need is to understand how the interaction between supply from VRES and demand for power affects market prices.

Real option owners have to take decisions anticipating on power prices in the near future. Power storage owners want to have high / low inventory when they expect high / low prices. Therefore, understanding the range within which power prices behave in the near future is crucial for real option owners in order to maximise the value of such options. One could derive such a price range by estimating a confidence interval using the average price, standard deviation (volatility), and tail information (extreme prices) blended into a probability distribution function. More sensible is to estimate the boundaries of the confidence interval directly using a quantile regression. This enables the real option owner to predict what - for instance - the 1^{st} and 99^{th} quantiles of the power price probability distribution function are. This is what we do in this chapter, with a focus on the impact of VRES on power prices. We use a novel methodology and model for power markets, later detailed in the chapter, and we show that these power price boundaries depend on information about expected supply from VRES.

Bunn et al. (2016) summarise the benefits of the quantile regression technique (applied to power prices): it provides a semi-parametric formulation for predictive distributions, allows for inclusion of fundamental variables, permits for separating moments with differing patterns, and can offer an alternative to regime switching models (through the indirect incorporation of regimes at different quantile levels). Jónsson et al. (2014), Rodríguez et al. (2014), Hagfors et al. (2016a), Maciejowska et al. (2016), Chen and Lei (2018), Troster et al. (2018), Kyritsis and Andersson (2019) and Goodarzi et al. (2019) all use quantile regression models to study power prices, demonstrating that this research method is suited to study a wide range of research topics in power markets. More specific to wind and photovoltaic solar supply, Hagfors et al. (2016c) include supply from VRES in a quantile regression to predict power prices. They observe that during off-peak hours, where extreme low prices are more likely to occur, the effect of wind output on day-ahead prices is stronger than during peak hours. For solar, at higher price quantiles the effect on day-ahead prices appears to be stronger than for the center quantiles. Sapio (2019) and Maciejowska (2020) use quantile regression to predict price quantiles conditional on the share of VRES supply.

Predicting power price quantiles through quantile regression is not a new topic, but we contribute to the existing literature in two ways. First, we apply quantile regression in a panel framework for reasons that we point out below. Second, all papers specify linear quantile regression models, whereas we think that there is reason to believe that some interaction between variables might be expected. When power markets are not flexible enough to accommodate variation in supply from VRES, we would expect the impact of variation in supply from VRES to be different during periods with moderate demand or share of VRES than in periods with low (high) demand and high (low) share of VRES.

But why a panel framework? Huisman et al. (2007) argue that one should use a panel framework to study day-ahead power price data. The reason comes from the microstructure of most day-ahead markets that we know. In the day-ahead market one can trade contracts that involve the delivery of 1 MWh of power during a specific hour in the next day. For instance, one can trade a contract for delivery during hour 1 (starting at midnight) in the next day and/or for delivery during hour 18 (between 5pm and 6pm) in the next day. In fact, day-ahead contracts are futures contracts for delivery during a specific hour with maturity being the next day. The microstructure of such markets instructs traders to supply their bids and offers before a specific time (11am in the Netherlands for example) for all day-ahead contracts. The bids and offers for the hour 1 contract are submitted at the exact same time as the bids and offers for the hour 18 contract. After receiving those bids and offers, the market operator determines the market clearing price for all hour day-ahead contracts. This implies that the price of the hour 1 contract is determined at the exact same time as the price of the hour 18 contract. The information embedded in the price for the hour 1 contract is exactly the same information embedded in the price for hour 18 delivery. Therefore, those individual hourly prices are not formed based on information that evolves in a continuous time series manner. Identifying those contracts as hour 1 through hour 24 suggests a time-series but is misleading. This was observed by Huisman et al. (2007) and they therefore argue that day-ahead price data is in effect panel data; one should see day-ahead power prices as a time-series of a cross-section of 24 individual delivery hours. The papers that we mentioned above that use quantile regressions all use a time-series framework and not a panel framework. Off course, one can study the prices of hour 18 contracts in isolation, which is a time-series, or the average price during peak or off-peak hours. That is what the above studies did. But by doing so, they ignore (or don't need) the information embedded in the cross-section. Thus, when studying the prices of hour 1 and 18 in isolation, one does not observe the information that is embedded in both prices simultaneously as they were determined at the same market clearing time. Thinking about real options owners, such as power storage facilities, we think that focusing on average prices or hourly prices in isolation is an important limitation. For instance, when we expect a high price during hour 10, for instance because of low supply from renewables, we'd expect that the prices for the adjacent hours 9 and 11 could also be higher as solar radiation and wind supply does not have hourly boundaries. Huisman et al. (2007) show that such cross-sectional correlations are apparent. Correlations are close to one for adjacent hours and between all off-peak and peak hours. The correlations are lower between peak and off-peak hours.

Studying the time series of average prices or prices for one-hour contracts in isolation, in the way the papers cited above do, ignores this cross-sectional dependence among hourly prices and the information that is embedded in each hourly day-ahead price. Our contribution upon those previous studies is that we use a panel quantile regression approach. This avoids this information loss and provides a more realistic framework that matches the market microstructure of day-ahead markets which is attractive for market participants. Managers of storage facilities or demand response applications can use panel quantile regression techniques to predict how low or high power prices are expected to be at each hour for the next delivery day. In this way, they can foresee the moments in time when power prices are likely to become extremely low or high. This technique would then also indicate for how many hours power prices are expected to remain extreme. Hence, operators of real option flexibility offering assets could use such techniques in optimising their bidding strategies. To our knowledge, this piece of research is the first one to apply a panel quantile regression approach to day-ahead power markets.

There are various ways in which panel quantile regression models can be built and used. In this chapter we choose to use them focusing on the impact that VRES supply has on power prices. Getting back to day-ahead prices and their fundamentals, it makes sense that supply from VRES influences power prices much stronger at the higher and lower quantiles of the power price probability distribution function. To see this, keep the "hockey stick" shape of the supply curve in mind (see Borenstein (2002)). At high demand levels, when usually high prices occur, the supply curve is steeply upward curved, whereas it is almost flat at "normal" demand levels. This implies that the impact of a change in demand on prices is stronger at high demand levels than at normal demand levels. VRES supply will shift the supply curve to the right because VRES supply has zero marginal costs. At high demand levels, VRES supply will have a sharp price reducing impact on power markets as the upward sloped part of the supply curve shifts to the right. At normal demand levels, when moderate prices are expected to occur, the supply curve is almost flat and this remains the case when VRES supply moves the supply curve to the right. Consequently, during periods of high demand, the price impact of an increase in VRES supply will be stronger than during periods with normal demand. In other words, when prices are high due to high demand, an increase in VRES supply is expected to reduce that high price more than what the same level of VRES supply increase will reduce the price at normal demand level. This predicts that an increase of supply from VRES will have a bigger impact on the right side of the price probability distribution function than on the center part. We expect to observe the same effect also on the other side of the power price probability distribution function, on the very low prices, but for a different reason. In many countries, the cheaper non-VRES suppliers are relatively inflexible power producers (ie. coal and nuclear). For those producers, ramping up/down production is costly. Therefore, for short periods, for such inflexible producers, maintaining a stable level of production, even when the power prices are falling below their marginal costs, can be less costly than temporarily ramping down production. Such a situation can lead to extreme low prices during periods with low demand and high VRES supply. This predicts that an increase in VRES supply during moments when prices are already very low, should decrease much more the power price than the same increase in VRES supply would do during periods with moderate prices. These predictions suggest the following claim: An increase in supply from VRES reduces power prices more at extreme low and high quantiles than at the center part of the power price probability distribution function.

We test this claim in this chapter using quantile regressions in a panel framework. The knowledge that we can gain from this result may help market players to better predict power prices and especially the likelihood of occurrence and magnitude of extreme power prices. If the impact of wind and solar output on power prices has different magnitudes in different moments in time, this information adds value to participants in power markets. Consequently, market players should consider this information when constructing bidding strategies. More accurate price predictions can lead to less risky and hence more profitable strategies for storage facilities used in arbitraging in power markets. This can lead to an increase in investments in storage units and other real option assets in the power market and, thus, will then smoothen the path towards a more sustainable and flexible power market.

To test our claim, we chose to study day-ahead prices, being one day futures prices and not real-time imbalance prices. The reason for this choice comes from the fact that, in many countries, day-ahead markets are the platform on which most of the VRES supply is traded. Especially in European markets, feed-in tariffs are linked to the day-ahead prices. This policy makes it rational for VRES suppliers to sell their power output on the day-ahead markets. An alternative would have been to study intraday or imbalance markets, where, because of their weather dependency, VRES supply plays a big role. However, these markets are less liquid than day-ahead markets. Market participants use day-ahead markets already for many years and many of them refer to the day-ahead price as *the* power price. Therefore, we leave the exploration of the imbalance and more real-time markets for future studies. Let's proceed with the panel model we suggest to use.

3.2 Methodology

Quantile regression was introduced by Koenker and Bassett (1978) and build on the notion of estimating conditional quantile functions. In a quantile regression model one can locate the effect that independent variables have on the dependent variable for each quantile of the distribution function of the dependent variable. The model that we use is as follows. It's a linear model, similar to others used in different studies about power prices before.

$$p_{q,h,t} = \alpha_{q,h} + \beta_q \times mc_t + \gamma_q * D_{h,t} + \delta_q \times VRES_{h,t} + \epsilon_{q,h,t}. \tag{3.1}$$

The subscripts q, h, and t represent the specific quantile studied, the delivery hour, and time respectively. The dependent variable is $p_{q,h,t}$, which is the q^{th} quantile of the day-ahead price probability distribution function for delivery during hour h in day t. This linear model follows the rationale of Hagfors et al. (2016a) and Hagfors et al. (2016c) in the choice of factors that explain $p_{q,h,t}$. Let us discuss those factors in detail.

- $\alpha_{q,h}$. This is the fixed effect as it is called in the panel literature. It represents a constant term for each specific hour h.
- mc_t. This variable captures the local past median marginal cost of non-VRES supply at time t. One way to measure this is by using the prices of various underlying fuels. Because of the heterogeneity in the production technologies and also in the underlying fuels used, this would mean to include a series of variables like coal price, gas price, nuclear material price, CO_2 emission rights and to calibrate them depending on the supply mix of the power system in cause. Another approach that reduces complexity is to create a proxy variable which comprises all underlying fuel information into one variable. That proxy variable can be formed by making use of recent power prices. Due to the merit order construction in liberalised day-ahead power markets, these prices reflect the costs of the marginal producer. Therefore, it is sensible to use recent market clearing prices as a proxy for marginal cost. We use the median of hourly power prices over the past 4 weeks: 28 days * 24 hours/day = 672 observations [2]. The model attributes the same marginal cost value for all 24 hours in the day. Hence, the absence of the subscript h in $mc_{q,t}$. The logic behind this is that bidding in the day-ahead market happens in the same time for all the 24 hours of the day and, consequently, the bidding decision is based on the same level of underlying fuel prices for each hour within a day. The median value is preferred over the average value since the median value is less dependent on extreme power prices,

[2] The length of the past data was chosen in order to: i) include an equal number of weekdays and weekend days, eliminating in this way the within week seasonality concerns; ii) be short enough to avoid the inclusion of prices that are not anymore relevant to the local level of prices; iii) be long enough to allow the marginal cost variable to not be dependent on moments with a high concentration of extreme high or low prices. Shorter timeframes lead to much higher volatility for the calculated marginal cost variable and that is not in line with the volatility of the underlying fuel prices.

is less volatile and, therefore, it can better capture the local level of underlying fuel prices.

- $D_{h,t}$. This variable captures total demand for power during hour h in day t. It is measured from the hourly total system consumption.

- $VRES_{h,t}$. This variable is the share of total demand that is covered by wind (offshore and onshore) supply and by photovoltaic supply during hour h in day t. We do not separate between wind and solar output in this analysis as both technologies have close to zero marginal cost, both are dependent on weather and for each of them the literature proves that their supply is decreasing the wholesale power prices[3]. Percentages of VRES supply are preferred over the volumes of VRES supply since the share of VRES supply can better capture how dependent the power system is on the wind and solar output in a particular moment. Volumes are less accurate in capturing this since a certain volume of VRES output in a period with a low demand is challenging more the power system's flexibility than the same volume of VRES output in a period with a high demand.

- $\epsilon_{q,t} \approx (0, \Sigma)$. This is an independent and identically distributed error term with Σ being a (24x24) covariance matrix.

Having the mc_t, $D_{h,t}$ and $VRES_{h,t}$ present in the model eliminates the need for introducing seasonality control variables as the chosen variables capture the changes that each season brings into a power system. For the volumes of load and VRES supply, we had to make a decision between using actual / realised or expected / forecasted data. While both actual and expected data have their limitations (forecasted data is prone to player specific forecasted error; actual data is not available at the moment of day-ahead bidding), we follow Nicolosi (2010) and Kyritsis et al. (2017) by using actual volumes data. As Woo et al. (2015) explain, forecasted and actual data are highly correlated and, thus, the results not to differ much when changing from one

[3]The only economical difference between the wind power and the photovoltaics power products lays within the moments in time when they are set to produce. Solar supply is predominantly produced during peak hours and wind power can exhibit a high supply both in peak and off-peak hours.

approach to the other[4].

To estimate the parameters in equation 3.1 in a panel framework, we follow the methodology suggested in Baltagi (2013). Because of heteroskedasticity caused by the cross-sectional covariance matrix Σ, we cannot directly estimate the parameters. We do the following steps: i) we set-up a system of 24 seemingly unrelated regressions based on the model presented in equation 3.1; in fact 24 time-series for the 24 hourly contracts; ii) we then estimate the system of seemingly unrelated regressions using feasible generalised least squares approach and restricting that each of the coefficients is equal across the 24 regressions (except for the hourly fixed terms); iii) we estimate the covariance matrix Σ from the residuals; iv) we pre-multiply the original data with the Choleski decomposition of the inverse of the estimated Σ matrix and we obtained the transformed data; v) we estimate the parameters in equation 3.1 using quantile regression on the transformed data. The process used is not always efficient after the first transformation. Therefore, using the transformed data obtained in step iv), we redo the all the steps above until convergence of results of step v) is achieved. We define that convergence occurred when each δ_q estimated coefficient in equation 3.1 for each quantile level does not deviate by more than 1% from the estimated coefficient from the previous transformation panel quantile regression estimates.

Having these estimates, we then test our claim, that supply from VRES is having a stronger reducing impact on power prices at extreme quantile levels as compared to moderate quantile levels, by examining the estimates for the coefficients δ_q. These coefficients show the impact that the share of VRES supply has on day-ahead power prices at various quantile levels. Given our claim is correct, we expect to observe significantly lower coefficient estimates for the share of VRES supply on the lowest quantiles and on the highest quantiles compared to the quantiles in between.

[4]When performing robustness checks using forecasted data, the results are similar to the ones obtained using actual data.

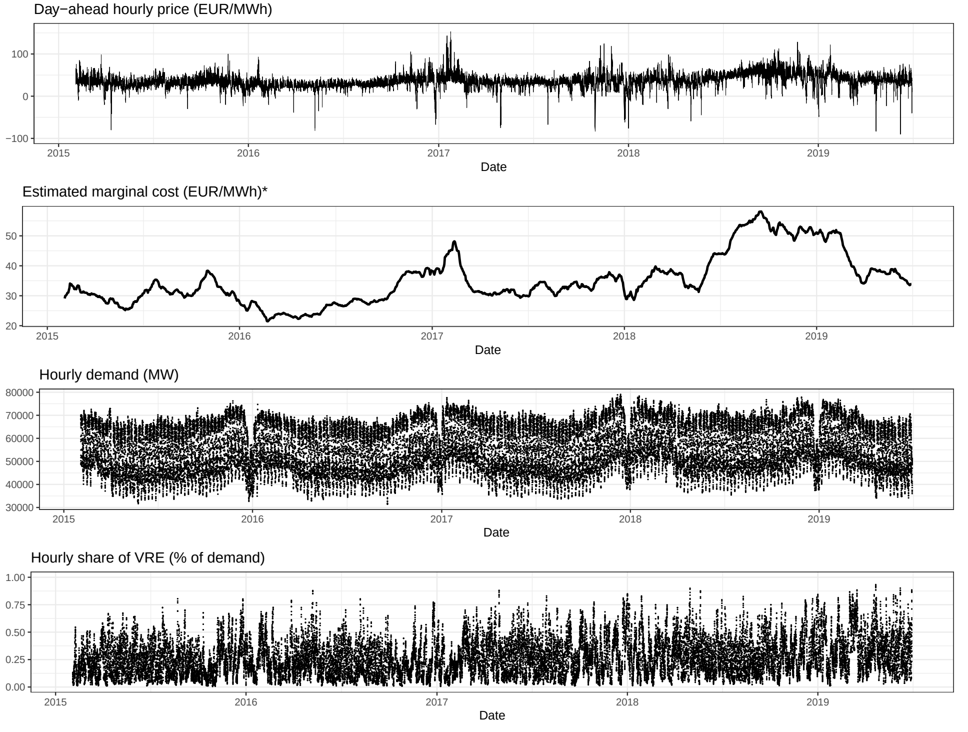
3.3 Data

The data that we use is comprised by hourly observations from the German day-ahead power market between 6th of January 2015 to 30th of June 2019, collected from Bundesnetzagentur — SMARD.de.[5]. The dataset contains information about German day-ahead power prices, demand level and share of VRES supply. The first 672 observations are used solely for estimating the initial marginal cost value of the power system, mc_t.

Figure 3.1 shows the data that we use from Germany. The first (top) graph shows the hourly day-ahead prices. It shows frequent extreme high and low values, ranging from below -100 EUR/MWh to over 163 EUR/MWh. The second graph shows the median lagged price variable which is our proxy for marginal costs mc_t. It's less volatile as it represents a moving average. Its values range from 21 EUR/MWh to 58 EUR/MWh. The third graph shows system's realised demand. The fourth (lower) figure shows the share of VRES supply and exhibits huge variability. The VRES share has hourly values from 0% to over 90%. To be noted that the variable constructed for the model represents the ratio between VRES supply and actual demand without considering the generation related to the export/import of power. Since in all of the months included in the analysis except for one, June 2019, Germany was a net exporter of power, we would observe on average lower values when we'd consider the share of VRES out of the total power generated in Germany.

To get an initial insight from the data, in table 3.1 we split the dataset into day-ahead price deciles followed by a further sub segmentation by the share of VRES supply. While not having any statistical power, already from this initial table we can observe that the share of VRES supply is putting a much higher pressure on the German day-ahead power market during the moments when prices are more extreme, the lowest and the highest price deciles. Table 3.1 shows that for price deciles 0.2-0.3 to 0.7-0.8, an average increase in the VRES share of 10% decreases prices only

[5] 23 days from the dataset were excluded due to unavailable data for certain hours. For 0.4% of the hourly observations, where only partial intra-hour (15 minutes blocks) information are available, adjustments (averaging based on available intra-hour data) had to be made in order to keep the dataset consistent.



**The estimated marginal cost is calculated as the lagged median day-ahead price for the previous 4 weeks of hourly observations.*

Figure 3.1: Overview of the German day-ahead market between January 2015 – June 2019.

marginally by 0.00-0.04 EUR/MWh. The same average increase in the share of VRES supply in the highest and the lowest price deciles decreases on average the day-ahead price with more than 2.8 EUR/MWh. Based on table 3.1, the price impact of a 10% increase in the share of VRES appears to be the highest, in absolute terms, in the two extreme cases: i) high VRES share in the lowest price decile and ii) low VRES share in the highest price decile. In the highest and the lowest price deciles, the price variation is also the highest, since in these moments the power system's flexibility is challenged more. The lack of flexibility in the highest and lowest price deciles, appears to lead to more abrupt price response when the VRES supply share changes.

Table 3.1: German day-ahead average price behavior by share of VRES supply and price decile

Day ahead price decile	Minimum day ahead price	Maximum day ahead price	Price interval (max-min)	Average day-ahead price by VRES share subsample 1 0-10%	2 10-20%	3 20-30%	4 30-40%	5 40-50%	6 50%+	Price change by 10% VRES share increase (2-1)	(3-2)	(4-3)	(5-4)	(6-5)	Avg
0.0-0.1	-100.1	18.0	118.1	16.5	15.5	14.8	13.9	12.3	2.3	-0.96	-0.71	-0.88	-1.64	-9.98	-2.84
0.1-0.2	18.1	24.3	6.3	22.3	21.9	21.8	21.6	21.7	21.1	-0.38	-0.12	-0.11	0.03	-0.53	-0.22
0.2-0.3	24.3	28.2	3.8	26.4	26.4	26.3	26.3	26.3	26.2	-0.01	-0.04	0.00	0.00	-0.15	-0.04
0.3-0.4	28.2	31.1	2.9	29.8	29.7	29.7	29.7	29.7	29.7	-0.07	-0.04	0.02	-0.04	-0.01	-0.03
0.4-0.5	31.1	34.4	3.3	32.7	32.8	32.8	32.7	32.7	32.5	0.04	0.02	-0.09	0.00	-0.17	-0.04
0.5-0.6	34.4	37.9	3.5	36.1	36.1	36.1	36.1	36.1	36.0	-0.04	-0.02	0.01	0.03	-0.12	-0.03
0.6-0.7	37.9	41.9	4.0	39.8	39.8	39.8	39.7	39.8	39.8	0.03	0.03	-0.15	0.11	-0.01	0.00
0.7-0.8	42.0	47.0	5.0	44.3	44.4	44.3	44.3	44.3	44.3	0.09	-0.07	-0.05	0.05	-0.06	-0.01
0.8-0.9	47.0	54.8	7.8	50.5	50.3	50.2	50.3	50.6	49.9	-0.23	-0.09	0.13	0.28	-0.73	-0.13
0.9-1.0	54.8	163.5	108.8	70.9	65.8	63.6	60.7	58.0	56.7	-5.11	-2.18	-2.87	-2.70	-1.35	-2.84

3.4 Results

The first result that we show is to demonstrate the validity of the panel framework. Table 3.2 shows the (24×24) correlation matrix obtained from the estimate of the cross-sectional covariance matrix Σ. The table clearly shows high correlations for adjacent hours. For example, the correlation between the residuals for the (seemingly unrelated) regressions for hours 10 and 11 is 0.94 and 0.92 for hours 11 and 12. The residuals for the regression on hour 11 have a much lower correlation, of 0.36, with the residuals of hour 23. A clear correlation (and covariance) pattern occurs indicating that information is thrown away when one considers the time-series of hour 11 separate from hours 10 and 12 for instance. Similar examples can be provided for each of the 24 hours within a day.

Table 3.2: Correlation of residuals matrix estimated using the SUR model

Hour	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
0	1	0.91	0.83	0.80	0.76	0.72	0.58	0.39	0.38	0.41	0.40	0.41	0.41	0.38	0.34	0.37	0.29	0.20	0.18	0.22	0.31	0.39	0.41	0.44
1	0.91	1	0.94	0.90	0.85	0.80	0.66	0.44	0.41	0.42	0.41	0.42	0.41	0.39	0.36	0.38	0.29	0.22	0.18	0.20	0.27	0.35	0.36	0.41
2	0.83	0.94	1	0.96	0.90	0.83	0.67	0.44	0.42	0.44	0.43	0.44	0.44	0.41	0.37	0.38	0.30	0.22	0.18	0.17	0.24	0.32	0.33	0.39
3	0.80	0.90	0.96	1	0.96	0.88	0.69	0.46	0.44	0.45	0.44	0.45	0.45	0.42	0.38	0.40	0.31	0.22	0.18	0.17	0.24	0.34	0.34	0.41
4	0.76	0.85	0.90	0.96	1	0.92	0.69	0.46	0.43	0.44	0.43	0.45	0.44	0.41	0.37	0.39	0.31	0.23	0.19	0.17	0.24	0.33	0.33	0.40
5	0.72	0.80	0.83	0.88	0.92	1	0.80	0.55	0.49	0.48	0.46	0.46	0.45	0.41	0.38	0.41	0.34	0.25	0.23	0.22	0.30	0.40	0.38	0.44
6	0.58	0.66	0.67	0.69	0.69	0.80	1	0.80	0.73	0.65	0.60	0.56	0.51	0.47	0.44	0.49	0.45	0.40	0.40	0.39	0.42	0.43	0.33	0.35
7	0.39	0.44	0.44	0.46	0.46	0.55	0.80	1	0.93	0.83	0.75	0.67	0.59	0.55	0.53	0.59	0.59	0.60	0.59	0.54	0.49	0.37	0.23	0.24
8	0.38	0.41	0.42	0.44	0.43	0.49	0.73	0.93	1	0.91	0.83	0.75	0.66	0.60	0.57	0.62	0.60	0.61	0.60	0.55	0.50	0.39	0.25	0.26
9	0.41	0.42	0.44	0.45	0.44	0.48	0.65	0.83	0.91	1	0.94	0.86	0.78	0.70	0.64	0.69	0.67	0.65	0.62	0.55	0.52	0.42	0.31	0.31
10	0.40	0.41	0.43	0.44	0.43	0.46	0.60	0.75	0.83	0.94	1	0.94	0.85	0.76	0.69	0.72	0.69	0.64	0.59	0.50	0.49	0.41	0.33	0.32
11	0.41	0.42	0.44	0.45	0.45	0.46	0.56	0.67	0.75	0.86	0.94	1	0.92	0.83	0.74	0.76	0.72	0.64	0.56	0.45	0.46	0.40	0.35	0.36
12	0.41	0.41	0.44	0.45	0.44	0.45	0.51	0.59	0.66	0.78	0.85	0.92	1	0.92	0.84	0.81	0.75	0.60	0.52	0.42	0.44	0.41	0.37	0.36
13	0.38	0.39	0.41	0.42	0.41	0.41	0.47	0.55	0.60	0.70	0.76	0.83	0.92	1	0.95	0.90	0.79	0.59	0.48	0.37	0.39	0.36	0.32	0.38
14	0.34	0.36	0.37	0.38	0.37	0.38	0.44	0.53	0.57	0.64	0.69	0.74	0.84	0.95	1	0.94	0.83	0.61	0.49	0.38	0.39	0.36	0.32	0.37
15	0.37	0.38	0.38	0.40	0.39	0.41	0.49	0.59	0.62	0.69	0.72	0.76	0.81	0.90	0.94	1	0.91	0.71	0.58	0.45	0.45	0.41	0.36	0.41
16	0.29	0.29	0.30	0.31	0.31	0.34	0.45	0.59	0.60	0.67	0.69	0.72	0.75	0.79	0.83	0.91	1	0.84	0.70	0.56	0.54	0.46	0.38	0.35
17	0.20	0.22	0.22	0.22	0.23	0.25	0.40	0.60	0.61	0.65	0.64	0.64	0.60	0.59	0.61	0.71	0.84	1	0.86	0.67	0.55	0.39	0.28	0.21
18	0.18	0.18	0.18	0.18	0.19	0.23	0.40	0.59	0.60	0.62	0.59	0.56	0.52	0.48	0.49	0.58	0.70	0.86	1	0.83	0.68	0.46	0.32	0.21
19	0.22	0.20	0.17	0.17	0.17	0.22	0.39	0.54	0.55	0.55	0.50	0.45	0.42	0.37	0.38	0.45	0.56	0.67	0.83	1	0.84	0.62	0.44	0.29
20	0.31	0.27	0.24	0.24	0.24	0.30	0.42	0.49	0.50	0.52	0.49	0.46	0.44	0.39	0.39	0.45	0.54	0.55	0.68	0.84	1	0.84	0.66	0.47
21	0.39	0.35	0.32	0.34	0.33	0.40	0.43	0.37	0.39	0.42	0.41	0.40	0.41	0.36	0.36	0.41	0.46	0.39	0.46	0.62	0.84	1	0.87	0.70
22	0.41	0.36	0.33	0.34	0.33	0.38	0.33	0.23	0.25	0.31	0.33	0.35	0.37	0.32	0.32	0.36	0.38	0.28	0.32	0.44	0.66	0.87	1	0.81
23	0.44	0.41	0.39	0.41	0.40	0.44	0.35	0.24	0.26	0.31	0.32	0.36	0.36	0.38	0.37	0.41	0.35	0.21	0.21	0.29	0.47	0.70	0.81	1

Model: $p_{q,h,t} = \alpha_{q,h} + \beta_q \times mc_t + \gamma_q * D_{h,t} + \delta_q \times VRE_{h,t} + \epsilon_{q,h,t}$
Data: German day-ahead prices

Table 3.3: Impact of share of VRES supply on selected day-ahead price quantile levels.

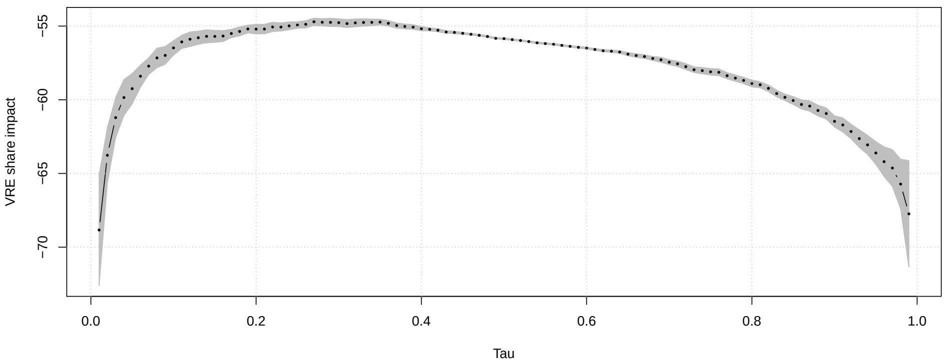
Quantile	1	2	3	...	50	...	97	98	99
δ_q	-68.84	-63.77	-61.21	...	-55.85	...	-64.63	-65.72	-67.74
$\delta_q - \delta_{50}$	-12.99	-7.92	-5.36	...	–	...	-8.78	-9.87	-11.89
s.e.	(2.30)	(1.14)	(0.83)	...	(0.03)	...	(0.76)	(1.02)	(2.20)

Model: $\hat{p}_{q,h,t} = \hat{\alpha}_{q,h} + \beta_q \times \widehat{mc}_t + \gamma_q * \hat{D}_{h,t} + \delta_q \times \widehat{VRE}_{h,t} + \epsilon_{q,h,t}$
Data: German day-ahead market data

We proceed with testing the claim that an increase in supply from VRES reduces power prices more at extreme low and high quantiles than at the center part of the power price probability distribution function. Table 3.4 in the appendix shows the parameter estimates for model 3.1 for different quantiles. To make it readable, we summarise the main findings in table 3.3. That table only shows the estimates for the parameter δ_q in model 3.1. That parameter can be interpreted as the ceteris paribus increase in the price of power as a result of a one unit increase in the share of demand supplied by VRES. Our hypothesis predicts that this parameter should be negative and more pronounced at extreme quantiles. This is exactly what we observe. For the extreme quantiles 1 and 99, the parameters are -68 and -67 respectively, whereas the parameter is -55 at the 50^{th} (median) quantile. The second row in table 3.3 shows the difference between the parameter for a quantile and for the median ($\delta_q - \delta_{50}$), and reveals that this difference is negative and significant (because of the low standard errors) at the extreme quantiles. Clearly, the estimates show support for the prediction that supply from VRES has a stronger impact on the extreme price quantiles than on the median price quantile.

Figure 3.2 provides the complete picture by showing the δ_q estimates for all the quantiles 1 through 99. This figure, while not being a focal point of our research[6], it illustrates two aspects which are worth mentioning. First, it's clear that δ_q is negative for all quantiles, supporting the existing view from the literature that an increase in VRES supply reduces power prices (because of its near zero marginal cost). Second, it shows that the impact is most negative at the higher and lower quantiles. When

[6] The model proposed in equation 3.1 is aimed at investigating the extreme ends of the probability distribution function of power prices and not the specific moderate price quantiles.



The black dots show the estimates for δ_q from the transformed equation 3.1. The grey shaded area show 95% confidence intervals for δ_q for quantiles 1 through 99

Figure 3.2: VRES share impact across the German day-ahead price quantiles (τ).

predicting power price ranges, one should keep in mind that supply from VRES has a different impact on power prices for different quantiles; the impact is relatively low when one is interested in predicting mean or median prices and more dramatic when one is interested in predicting high and low price ranges. This is what owners of real options are interested in since price ranges can help them optimize their bidding strategies. Because of this, we argue that is more important to use the model proposed in equation 3.1 for investigating the behaviour of extreme power prices rather than the one of moderate power prices.

Another takeaway from table 3.3 and figure 3.2 is that the coefficient δ_q has similar values at the lowest and highest price quantiles. This means that extreme low and high German day-ahead power prices are affected similarly by an increase in supply from VRES. While the values of the coefficients δ_q are similar at the lowest and highest day-ahead power price quantiles, the reasons for them occurring are different. We explain this as follows. High prices occur when demand is high and the share of VRES supply is low. During these moments, the higher marginal cost producers are the ones setting the power price. Many power plants produce to supply the high demand and there is competition to ramp down production when the VRES share increases. In this situation, an increase in share of VRES will reduce the power price fast as it will replace in the merit order curve the high marginal cost producers. On the other end of the power price distribution function, at extreme low prices, the fast decrease of power prices that comes with VRES share increases is due to less competition and inflexibility of base load power producers[7] to ramp down production. Competition to ramp down is low during low demand periods as only a few power plants operate. An increase in VRES supply puts higher pressure to ramp down production on the few base load producers that are still operating in such moments than the same increase in VRES supply when demand is moderate. If the base load producers are inflexible, in the sense that it is less costly for them to temporarily accept producing at price levels below their marginal cost rather than to ramp down and up their production level, the impact of a change in VRES share is getting bigger at extreme low power price quantile levels than at moderate power price quantile levels.

3.4.1 The impact of VRES share on quantile power prices conditional on demand level

Interpreting the difference between the estimates of δ_q in equation 3.1 is our means to examine the claim that VRES are having a varying impact on power prices. This model has similar variables as other models proposed in the literature that we discussed before. There is one aspect we want to discuss here. When we look in the table 3.4 in the appendix, we see that the demand coefficients, γ_q, have all positive values and are statistically different from 0. This means that, the higher the demand level is, the higher the power price[8] will be. At the same time, a part of that demand is catered by supply from VRES. Furthermore, as figure 3.2 shows, the VRES share coefficient δ_q is always significantly negative. We can then infer that an increase in demand will put upward pressure on power prices but, if that increase in demand is catered VRES supply, that upward pressure on prices will be diminished by VRES supply. We therefore expect that an interplay between demand and share of VRES should

[7] We refer to base load producers as conventional fuel producers that usually generate power at relatively constant levels for all hours of the day.

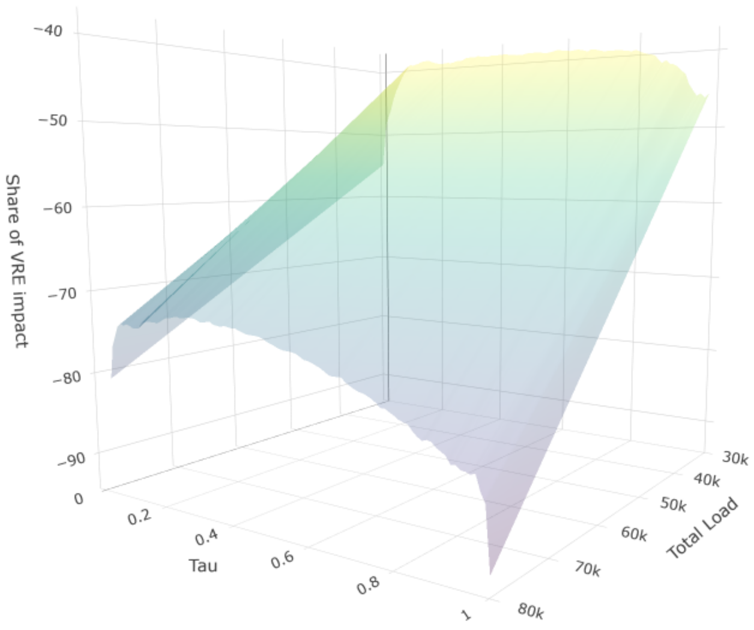
[8] While table 3.4 presents the γ_q coefficients only for a selection of price quantiles, for each analysed quantile, from the 1^{st} to the 99^{th}, the γ_q values are statistically significantly higher than 0

provide important information to better predict the impact of VRES share on power prices. We therefore suggest to use a revised model expressed in equation3.2:

$$p_{q,h,t} = \alpha_{q,h} + \beta_q \times mc_t + \gamma_q * D_{h,t} + \delta_q \times VRES_{h,t} + \zeta_q \times D_{h,t} \times VRES_{h,t} + \epsilon_{q,h,t}, \quad (3.2)$$

Compared with model 3.1, we include the interaction term $D_{h,t} \times VRES_{h,t}$. Note that the interaction term represents the actual supply of VRES. While it might appear counterintuitive to include in a model both the share and actual volume of VRES supply, this technique allows the model to control for the interplay between demand and share of VRES. Thus, the coefficient ζ_q, is aimed at capturing the effect of the interaction between demand and share of VRES on power prices. We estimate the parameters in equation 3.2 by following the same steps as we did for equation 3.1.

Using the revised model, we perform the same analysis as for the initial model in order to isolate the impact of VRES share on power prices conditional on a fixed demand level. To calculate this, we take the first order derivative of the estimated model 3.2 with respect to share of VRES. Thus, the impact of the share of VRES on power prices is: $\delta_q + \zeta_q \times D$. To be noted that in this estimation of the impact of share of VRES on power prices demand is exogenous to the estimation. This simplification is necessary for making it easier to exemplify the results of the second model, results that are shown in figure 3.3. Similar as for the first model, in the appendix table 3.5 we present the coefficients for all the variables included in the model estimated on equation 3.2 at selected extreme and at median price quantile levels.



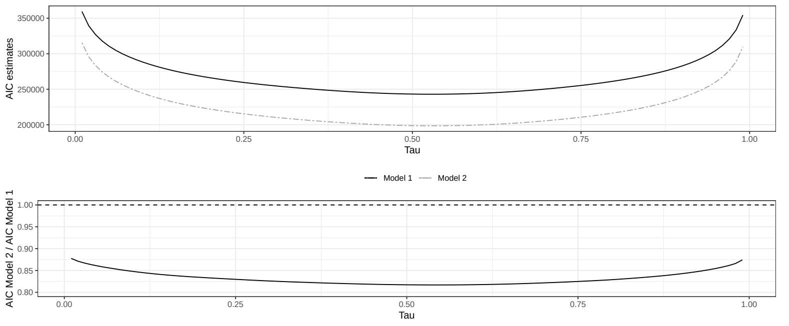
The shaded area indicates the impact of VRES share on the quantiles of German day-ahead prices conditional on demand level. Estimates are calculated using the first order derivative of the transformed equation 3.2 with respect to share of VRES.

Figure 3.3: VRES share impact on German day-ahead price quantiles, conditional on demand level.

Figure 3.3 shows the impact the share of supply from VRES has on quantile power prices conditional on the demand level. The demand level axis is formed by all the values comprised between the minimum and the maximum observed demand level in the German day-ahead power market. Conditional on a fixed demand level, results show similar patterns as for the first model. For any fixed demand level, in the lowest and highest price quantiles, the impact of VRES share on power prices is much more negative than for moderate quantiles. For example, let us consider a fixed moderate hourly demand of 50,000 MWh. Conditional on this demand level, all else equal, an increase in the share of supply from VRES leads to a higher power price decrease when power prices are very low (1^{st} quantile coefficient for share of VRES being -65) or very high (99^{th} quantile coefficient for share of VRES being -64) than when prices are moderate (50^{th} quantile coefficient for share of VRES being -53).

While for this chosen fixed demand level of 50,000 MWh the estimated share of VRES impact on power prices is similar to the one estimated in the first model, for other demand levels, the estimates differ. The differences come from the fact that in the second model, the share of VRES impact on power prices is conditional on a fixed selected demand level. When reading figure 3.3 and comparing it with 3.2 we have to keep in mind the fact that figure 3.2 presents the average impact of VRES share on power prices and that figure 3.3 separates the impact based on demand level. Furthermore, it is important to note that, while figure 3.3 presents an estimate for the share of VRES impact for each demand level at each quantile, the frequency of a certain pair of price quantile and demand level varies greatly. For example, it is unlikely that high prices appear on low demand levels or that low prices appear on high demand levels. Thus, the results in figure 3.3 should be read as an indication on what is the VRES share impact on power prices at specific power price quantile and demand level.

To compare the two models, figure 3.4 presents the AIC for both models. In the upper part of the figure, the AIC values for the two models are shown. The model estimated on equation 3.1 is represented with by the solid line and the model estimated on equation 3.2 is represented by the dashed line. For all the quantiles investigated, the second model has a lower AIC value, indicating a better performance of model 3.2. In the lower part of figure 3.4, the ratio between the AIC values of the model 3.2 and model 3.1 is illustrated, indicating that the second model (estimated on equation 3.2) has values between $0.14\% - 0.18\%$ lower than the first model (estimated on equation 3.1). From here, we can conclude that the interaction between demand and share of VRES is a factor that adds value to models aiming to predict German day-ahead power prices. This is another important finding that can help real option asset owners in Germany as it shows that, for this market, the interplay between demand and supply from VRES influences day-ahead power prices.



The lines in the upper part of the figure contain the AIC estimated for models 3.1 and 3.2 at each quantile (τ), from the 1^{st} to the 99^{th} quantile. The lower part of the figure shows the ratio between the AIC estimates for the model 3.2 and 3.1.

Figure 3.4: AIC comparison between the transformed models3.1 and 3.2 estimated on the German day-ahead market.

3.4.2 Challenge: the Spanish day-ahead market

The results presented so far provide a clear picture on how an alteration in output from VRES changes day-ahead power prices in Germany. Having a significant share of coal and nuclear supply in its power mix, the German power market is relatively inflexible. This fact reveals itself through the frequent price spikes that appear in the German day-ahead price. In this section, we challenge our findings and apply the same analysis to a more flexible power market which is not directly linked to the German power market: the Spanish power market. Spain has a relatively high share of VRES supply in its power mix, and compared to Germany, the Spanish power mix has a higher share of hydro, hydro pumped and gas supply and a lower share of coal supply. This is why we label the Spanish power market as more flexible than the German power market. Moreover, the policies of the Spanish power market do not allow for negative day-ahead power prices, limiting in this way the price reduction impact in periods with extreme low demand and high share of VRES.

To investigate the Spanish day-ahead power market, we use data collected from ENTSO-E Transparency platform and use a timeframe similar to the one for the German market: from 1st of January 2015 to 30th of June 2019[9]. A visual representation of the data used for this exercise is presented in the appendix figure 3.5. In the upper part of this figure, we can observe that the Spanish hourly day-ahead power prices are exhibiting, on the high end, less extreme high spikes as compared to the German day-ahead prices, and, on the low end, always positive prices.

In this additional analysis on the Spanish day-ahead market we use the same steps as for the German day-ahead market. The results for the impact of share of VRES on the Spanish day-ahead quantile power prices using the model detailed in equation 3.1 are presented in the appendix table 3.6 and appendix figure 3.6[10]. These results show that also for a more flexible power market, such as the Spanish one, the impact of the share of VRES supply on the day-ahead power prices is significantly stronger on the extreme low and extreme high day-ahead price quantiles than in the middle of the power price distribution function.

At the median price quantile level the share of VRES parameter value is -54. At the 1^{st} and at the 99^{th} price quantiles the parameters for the share of VRES are lower being -0.61 and, respectively, -0.59. The values for δ_q coefficients on the Spanish data at moderate price quantiles are similar to the ones obtained on the German data. At the extreme price quantiles, the Spanish δ_q coefficients are not as low as the German ones. This indicates that Spanish conventional producers can adapt faster their output level to changes in VRES supply than German conventional producers in moments when the power market is challenged the most. This confirms the fact that the Spanish day-ahead market is indeed more flexible than the German one. Thus, an increase in the share of VRES supply at the extreme low and high price quantiles does not induce in the Spanish power market a price shock as big as in the German power market. The comparison between the flexibility of the German and Spanish day-ahead markets is relevant at the extreme price quantile levels, since it is in those moments that the power markets are most challenged. When prices are moderate, most power markets

[9] 25 days from the Spanish data were excluded due to unavailable data for certain hours. The same as for the German market, the presented results are based on actual realised demand and share of VRES data

[10] For space limitations reasons the chapter presents only the coefficients for the VRES share impact. On request, the coefficients for all the other variables included in the model can be made available.

have enough conventional flexible supply available to shift their production levels in order to cater changes in VRES supply. This result suggests that, as compared to an inflexible power market, for a more flexible power market, the value of real options assets, such as storage facilities, is lower, since the occurrence of extreme prices is limited.

The results for the Spanish day-ahead market on the second model, the one estimated on equation 3.2, are similar with the ones presented in appendix figure 3.6 for the first model (3.1). Conditional on a fixed demand level, at extreme price quantiles VRES share is inducing a stronger negative impact on Spanish day-ahead power prices than at moderate price quantile levels[11].

Figure 3.7 compares the relative quality of the two models for the Spanish power market. In the upper part of the figure, the dashed line and the solid line represent the quantile specific AIC values for the second model 3.2 and, respectively for the first model 3.1. In the lower part of the figure, the per quantile ratio between the AIC for model 3.2 and model 3.1 is exhibited. As opposed to the results for the German day-ahead market, figure 3.7 shows that for the Spanish day-ahead market, the second model 3.2 does not perform better than the first model 3.1. For most quantile levels investigated model 3.1 has a lower AIC estimate than model 3.2. This indicates that for a flexible power markets, such as the Spanish day-ahead market, adding a term for the interaction between VRES share and demand level does not add explanatory value to a panel quantile regression model trying to explain power prices. While not expected, this result is not totally surprising. Having increased flexibility, the conventional producers in Spanish power market can more easily adapt their production levels to shifts in VRES share, regardless of demand level, as compared to conventional producers in an inflexible power market. Thus, the interplay between demand and VRES share becomes less relevant for a flexible power market, as opposed to an inflexible power market. For owners of real option assets this result suggest once again that it is in the inflexible power markets that their real options will be worth the most.

[11] There is one exception from this on the moments when the Spanish day-ahead market is in a situation of extreme high demand and extreme high prices

3.5 Chapter's concluding remarks

With increasing supply from wind and solar sources, the share of power demand supplied by variable renewable energy sources (VRES) becomes an important factor that influences power prices. We build upon the existing literature by presenting a panel quantile regression approach, showing that the share of demand supplied by VRES has a varying impact on power prices, with significantly higher impact when the power prices are in extreme low or high price quantiles ranges. This result proves that when the flexibility of a power market is challenged the most (in moments when extreme prices occur) the impact of an increase in VRES supply leads to much drastic downward adjustments in price than in periods when power markets are more flexible (when moderate prices occur). We observe this effect in both the German and Spanish day-ahead markets.

The chapter also proves that in periods when power prices are extremely low or high, in a more inflexible power market, such as the German day-ahead market, an increase in VRES share decreases the day-ahead power price more than the same increase in VRES share for a relatively more flexible power market, such as the Spanish day-ahead market. This means that the higher the flexibility and capacity of the conventional producers to adjust their production levels in function of VRES supply changes, the lower the variation in the impact that VRES supply has on power prices at extreme price quantile levels. When comparing the results for the two markets investigated, the chapter also indicates that for a relatively inflexible power market (the German day-ahead power market), the interaction between demand level and VRES share adds value in understanding day-ahead price movements. For the relatively more flexible Spanish day-ahead power market, the interaction between demand level and VRES share does not appear to add value in understanding day-ahead price movements. This means that in a flexible power market, conventional producers have enough flexibility in adjusting their production output to cater for changes in VRES supply such that the interplay between demand and VRES share becomes less relevant. The result suggests that policy makers should adjust their measures related to further integration of VRES supply based also on the pre-existing individual (in)flexibility conditions of each power market.

The results of this chapter are important for investments in assets that make the power markets more flexible in accommodating fluctuating supply from variable renewables. Power storage facilities or flexible consumption assets are such assets and, in effect, they are real options that give the right to charge / discharge or to adjust consumption levels. Those options are worth more when the range in which power prices behave in becomes wider. The results of this chapter show that the presence of a high share of supply from VRES in Germany leads to a power price distribution which enhances the value of these real options, as the pre-existing flexibility embedded in the German power market has now to cater more variability in supply. Our model demonstrates how one should incorporate (expected) output from renewables in predicting that price range through understanding the impact of VRES supply at different price quantile levels. Furthermore, the panel framework allows for simultaneous predictions for all hours during a delivery day, which is more in line with the microstructure of international power markets.

3.6 Additional tables and figures

Table 3.4: A selection of quantile regression coefficients estimated using the transformed equation 3.1.

Quantile level	1	2	3 ...	50 ...	97	98	99
Marginal cost (β_q)	0.82	0.73	0.70 ...	0.68 ...	0.56	0.51	0.56
	(0.09)	(0.05)	(0.03) ...	(0.001) ...	(0.03)	(0.04)	(0.09)
Demand (γ_q)	0.00067	0.00064	0.00062 ...	0.00057 ...	0.00064	0.00068	0.00078
	(0.00005)	(0.00002)	(0.00002) ...	(0.00000) ...	(0.00001)	(0.00002)	(0.00005)
VRE share (δ_q)	-68.84	-63.77	-61.21 ...	-55.85 ...	-64.63	-65.72	-67.74
	(2.30)	(1.14)	(0.83) ...	(0.03) ...	(0.76)	(1.02)	(2.20)
Hour 0 ($\alpha_{q,0}$)	-394.57	-282.23	-228.47 ...	-4.66 ...	190.88	233.14	328.68
	(19.07)	(10.81)	(9.45) ...	(0.24) ...	(6.89)	(9.51)	(18.64)
Hour 1 ($\alpha_{q,1}$)	-398.13	-285.14	-226.35 ...	-4.74 ...	191.53	234.69	330.47
	(19.97)	(12.78)	(8.31) ...	(0.24) ...	(6.97)	(9.62)	(19.06)
Hour 2 ($\alpha_{q,2}$)	-399.13	-288.86	-234.17 ...	-5.14 ...	192.63	237.17	335.55
	(21.40)	(11.10)	(8.64) ...	(0.25) ...	(7.04)	(10.17)	(21.35)
Hour 3 ($\alpha_{q,3}$)	-397.60	-284.39	-231.09 ...	-6.53 ...	190.00	232.39	328.42
	(19.26)	(10.69)	(9.49) ...	(0.24) ...	(6.79)	(9.51)	(18.89)
Hour 4 ($\alpha_{q,4}$)	-401.45	-288.03	-229.95 ...	-6.85 ...	190.77	233.58	329.92
	(19.84)	(12.85)	(8.31) ...	(0.24) ...	(6.85)	(9.59)	(19.24)
Hour 5 ($\alpha_{q,5}$)	-401.67	-291.81	-236.72 ...	-6.51 ...	191.72	236.49	334.45
	(21.23)	(11.25)	(8.63) ...	(0.25) ...	(7.07)	(10.15)	(21.51)
Hour 6 ($\alpha_{q,6}$)	-397.57	-283.31	-230.59 ...	-4.45 ...	191.96	233.81	328.93
	(19.13)	(10.62)	(9.44) ...	(0.25) ...	(6.91)	(9.24)	(18.78)
Hour 7 ($\alpha_{q,7}$)	-395.70	-283.03	-225.01 ...	-0.81 ...	196.07	238.66	334.38
	(19.65)	(12.84)	(8.40) ...	(0.24) ...	(6.71)	(9.79)	(19.19)
Hour 8 ($\alpha_{q,8}$)	-394.80	-284.45	-229.97 ...	1.25 ...	199.05	243.33	340.31
	(21.51)	(11.14)	(8.50) ...	(0.26) ...	(7.09)	(10.19)	(21.52)
Hour 9 ($\alpha_{q,9}$)	-391.56	-278.16	-225.33 ...	1.21 ...	198.28	239.67	333.27
	(19.33)	(10.73)	(9.50) ...	(0.25) ...	(6.95)	(9.36)	(18.86)
Hour 10 ($\alpha_{q,10}$)	-393.07	-280.93	-222.41 ...	0.89 ...	197.46	239.65	334.59
	(19.84)	(13.09)	(8.47) ...	(0.24) ...	(6.86)	(9.55)	(19.28)
Hour 11 ($\alpha_{q,11}$)	-393.77	-283.20	-228.63 ...	0.95 ...	198.83	243.50	340.23

Table 3.4 continued from previous page

	(21.76)	(11.14)	(8.60)	...	(0.27)	...	(7.09)	(10.22)	(21.87)
Hour 12 ($\alpha_{q,12}$)	-390.03	-277.80	-225.16	...	0.25	...	196.88	238.05	332.09
	(19.21)	(10.78)	(9.43)	...	(0.26)	...	(6.86)	(9.07)	(18.89)
Hour 13 ($\alpha_{q,13}$)	-390.96	-280.82	-222.81	...	-0.52	...	196.18	237.34	331.54
	(19.60)	(12.84)	(8.34)	...	(0.24)	...	(6.88)	(9.42)	(18.88)
Hour 14 ($\alpha_{q,14}$)	-393.08	-283.65	-229.66	...	-1.32	...	195.28	239.68	335.67
	(21.38)	(10.99)	(8.51)	...	(0.26)	...	(6.92)	(10.16)	(21.62)
Hour 15 ($\alpha_{q,15}$)	-388.57	-276.97	-224.68	...	-1.19	...	194.49	235.37	328.33
	(19.03)	(10.78)	(9.13)	...	(0.26)	...	(6.64)	(9.04)	(18.47)
Hour 16 ($\alpha_{q,16}$)	-390.31	-280.14	-222.27	...	-1.43	...	193.95	235.40	329.17
	(19.64)	(12.59)	(8.20)	...	(0.23)	...	(6.95)	(9.27)	(18.78)
Hour 17 ($\alpha_{q,17}$)	-389.92	-280.94	-227.13	...	-0.15	...	195.99	239.88	336.19
	(20.82)	(11.12)	(8.20)	...	(0.26)	...	(6.91)	(10.41)	(21.60)
Hour 18 ($\alpha_{q,18}$)	-386.03	-275.44	-222.16	...	0.77	...	195.58	236.65	329.20
	(18.60)	(10.61)	(9.27)	...	(0.26)	...	(6.74)	(9.19)	(18.39)
Hour 19 ($\alpha_{q,19}$)	-389.39	-278.83	-220.42	...	0.60	...	194.62	236.73	330.71
	(19.72)	(12.44)	(8.13)	...	(0.23)	...	(7.04)	(9.48)	(18.61)
Hour 20 ($\alpha_{q,20}$)	-393.84	-284.10	-229.82	...	-1.28	...	193.55	237.68	333.55
	(21.07)	(11.08)	(8.36)	...	(0.26)	...	(7.02)	(10.30)	(20.58)
Hour 21 ($\alpha_{q,21}$)	-392.47	-280.72	-226.65	...	-3.07	...	190.28	231.69	324.68
	(18.87)	(10.77)	(9.48)	...	(0.24)	...	(6.79)	(9.38)	(18.39)
Hour 22 ($\alpha_{q,22}$)	-396.05	-283.56	-224.54	...	-2.82	...	191.06	233.73	327.97
	(19.90)	(12.71)	(8.29)	...	(0.24)	...	(7.03)	(9.50)	(18.74)
Hour 23 ($\alpha_{q,23}$)	-399.07	-288.46	-233.65	...	-4.65	...	191.80	236.11	333.09
	(21.31)	(11.21)	(8.55)	...	(0.25)	...	(7.10)	(10.24)	(20.96)

Model: $\hat{p}_{q,h,t} = \hat{\alpha}_{q,h} + \beta_q \times \widehat{mc}_t + \gamma_q * \hat{D}_{h,t} + \delta_q \times \widehat{VRE}_{h,t} + \epsilon_{q,h,t}$

Note: Standard errors in parenthesis — German day-ahead market data used

Table 3.5: A selection of quantile regression coefficients estimated using the transformed equation 3.2.

Quantile level	1	2	3 ...	50 ...	97	98	99
Marginal cost (β_q)	0.78	0.68	0.68 ...	0.65 ...	0.53	0.48	0.51
	(0.08)	(0.05)	(0.04) ...	(0.001) ...	(0.03)	(0.04)	(0.08)
Demand (γ_q)	0.00087	0.00081	0.00079 ...	0.00079 ...	0.00088	0.00093	0.00105
	(0.00007)	(0.00004)	(0.00003) ...	(0.00000) ...	(0.00003)	(0.00003)	(0.00007)
VRE share (δ_q)	-37.76	-31.24	-28.94 ...	-15.74 ...	-19.68	-19.97	-14.72
	(9.46)	(6.53)	(4.94) ...	(0.12) ...	(4.22)	(4.33)	(9.23)
Interaction (ζ_q)*	-0.00054	-0.00057	-0.00059 ...	-0.00074 ...	-0.00083	-0.00084	-0.00099
	(0.00019)	(0.00012)	(0.00009) ...	(0.00000) ...	(0.00008)	(0.00008)	(0.00017)
Hour 0 ($\alpha_{q,0}$)	-400.23	-297.38	-239.35 ...	-14.46 ...	177.16	220.89	309.59
	(20.98)	(11.25)	(8.67) ...	(0.26) ...	(7.30)	(7.49)	(18.36)
Hour 1 ($\alpha_{q,1}$)	-405.18	-292.27	-239.68 ...	-14.74 ...	179.05	220.45	300.47
	(21.12)	(12.34)	(8.41) ...	(0.26) ...	(7.38)	(8.88)	(19.39)
Hour 2 ($\alpha_{q,2}$)	-416.76	-303.95	-245.45 ...	-15.07 ...	178.68	229.98	311.17
	(19.30)	(12.25)	(9.63) ...	(0.23) ...	(6.90)	(9.77)	(20.49)
Hour 3 ($\alpha_{q,3}$)	-403.00	-299.55	-242.04 ...	-16.11 ...	176.40	220.55	310.21
	(20.99)	(11.17)	(8.60) ...	(0.27) ...	(7.29)	(7.54)	(18.32)
Hour 4 ($\alpha_{q,4}$)	-409.14	-295.57	-242.85 ...	-16.86 ...	178.50	219.94	300.97
	(20.95)	(12.46)	(8.32) ...	(0.26) ...	(7.38)	(9.03)	(19.38)
Hour 5 ($\alpha_{q,5}$)	-419.83	-306.86	-248.28 ...	-16.68 ...	178.61	229.92	311.54
	(18.92)	(12.25)	(9.66) ...	(0.23) ...	(6.82)	(9.90)	(20.49)
Hour 6 ($\alpha_{q,6}$)	-403.29	-299.56	-241.37 ...	-14.82 ...	178.01	222.02	310.97
	(20.91)	(11.38)	(8.46) ...	(0.28) ...	(7.38)	(7.45)	(17.75)
Hour 7 ($\alpha_{q,7}$)	-404.63	-291.62	-238.74 ...	-11.81 ...	182.75	224.05	304.69
	(20.62)	(12.30)	(8.27) ...	(0.25) ...	(7.46)	(9.25)	(19.51)
Hour 8 ($\alpha_{q,8}$)	-414.00	-300.27	-242.43 ...	-9.72 ...	184.74	236.09	316.47
	(19.18)	(12.32)	(9.65) ...	(0.24) ...	(6.95)	(9.91)	(20.52)
Hour 9 ($\alpha_{q,9}$)	-398.07	-294.73	-236.38 ...	-9.24 ...	183.99	227.15	315.50
	(21.10)	(11.37)	(8.62) ...	(0.28) ...	(7.40)	(7.58)	(18.13)
Hour 10 ($\alpha_{q,10}$)	-402.73	-289.27	-236.28 ...	-9.44 ...	184.79	225.46	305.39
	(20.90)	(12.25)	(8.43) ...	(0.25) ...	(7.35)	(9.30)	(19.89)
Hour 11 ($\alpha_{q,11}$)	-413.43	-298.52	-240.98 ...	-9.39 ...	185.63	236.33	316.28

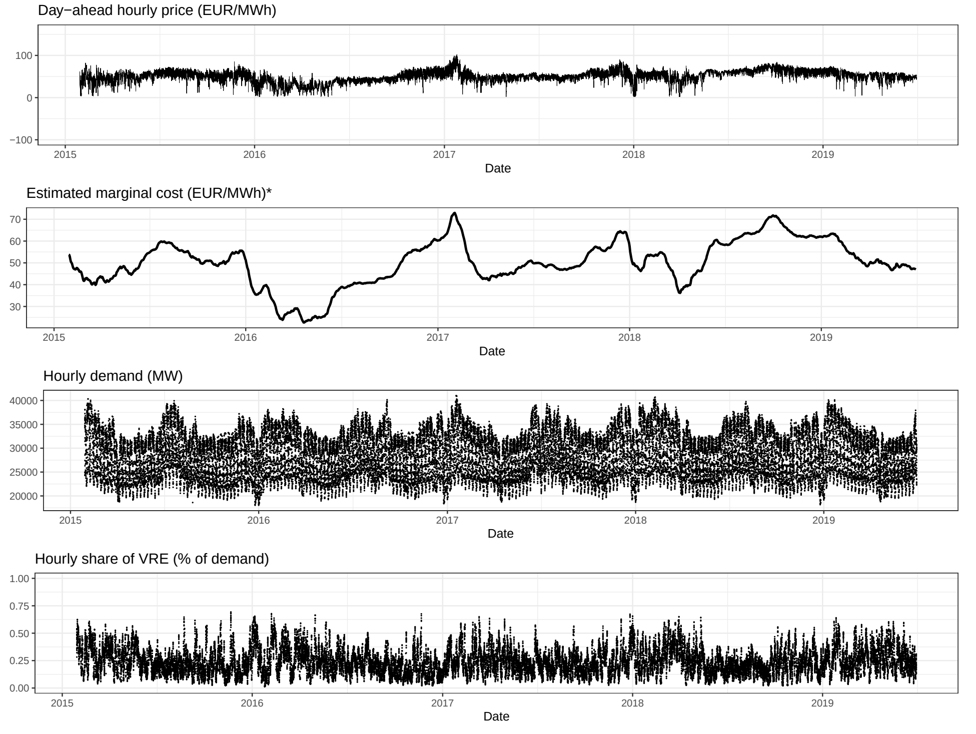
Table 3.5 continued from previous page

	(19.47)	(12.45)	(9.77)	...	(0.24)	...	(6.94)	(10.02)	(20.94)
Hour 12 ($\alpha_{q,12}$)	-397.40	-294.52	-235.92	...	-9.54	...	183.73	226.23	315.84
	(21.06)	(11.35)	(8.76)	...	(0.26)	...	(7.37)	(7.53)	(18.60)
Hour 13 ($\alpha_{q,13}$)	-400.92	-289.35	-236.62	...	-10.47	...	183.61	224.46	304.22
	(20.81)	(12.13)	(8.47)	...	(0.26)	...	(7.33)	(9.27)	(19.40)
Hour 14 ($\alpha_{q,14}$)	-413.59	-299.28	-242.02	...	-11.70	...	182.44	232.81	311.70
	(19.13)	(12.42)	(9.68)	...	(0.24)	...	(6.82)	(9.92)	(21.07)
Hour 15 ($\alpha_{q,15}$)	-395.99	-293.86	-236.21	...	-11.41	...	180.94	223.03	311.28
	(20.92)	(11.24)	(8.71)	...	(0.26)	...	(7.23)	(7.36)	(18.80)
Hour 16 ($\alpha_{q,16}$)	-399.48	-289.16	-236.42	...	-11.90	...	181.21	221.72	300.93
	(20.86)	(11.86)	(8.51)	...	(0.26)	...	(7.28)	(9.31)	(18.70)
Hour 17 ($\alpha_{q,17}$)	-409.98	-297.40	-239.82	...	-11.09	...	182.64	232.80	310.98
	(18.86)	(12.36)	(9.53)	...	(0.21)	...	(6.94)	(9.77)	(20.80)
Hour 18 ($\alpha_{q,18}$)	-393.71	-291.49	-234.10	...	-9.90	...	181.39	223.70	311.14
	(20.50)	(11.27)	(8.57)	...	(0.27)	...	(7.29)	(7.47)	(18.64)
Hour 19 ($\alpha_{q,19}$)	-398.23	-287.15	-234.85	...	-10.14	...	181.84	222.07	301.06
	(20.80)	(11.98)	(8.35)	...	(0.26)	...	(7.38)	(9.23)	(18.89)
Hour 20 ($\alpha_{q,20}$)	-412.93	-300.25	-242.45	...	-12.04	...	179.54	230.08	308.50
	(18.95)	(12.31)	(9.55)	...	(0.21)	...	(6.99)	(9.79)	(20.10)
Hour 21 ($\alpha_{q,21}$)	-399.43	-296.41	-238.27	...	-13.41	...	176.17	219.16	306.04
	(20.78)	(11.25)	(8.64)	...	(0.25)	...	(7.27)	(7.45)	(18.59)
Hour 22 ($\alpha_{q,22}$)	-403.75	-290.93	-238.28	...	-13.31	...	178.51	219.50	298.28
	(21.10)	(12.22)	(8.46)	...	(0.25)	...	(7.49)	(8.87)	(19.26)
Hour 23 ($\alpha_{q,23}$)	-417.21	-303.78	-245.28	...	-14.71	...	178.01	228.48	308.24
	(19.07)	(12.37)	(9.71)	...	(0.22)	...	(6.91)	(9.73)	(20.26)

Model: $\hat{p}_{q,h,t} = \hat{\alpha}_{q,h} + \beta_q \times \widehat{mc}_t + \gamma_q * \hat{D}_{h,t} + \delta_q \times \widehat{VRE}_{h,t} + \zeta_q \times \widehat{Interaction}_{h,t} + \epsilon_{q,h,t}$

Note: Standard errors in parenthesis — German day-ahead market data used

Note: Interaction variable* $= D_{q,h,t} \times VRE_{q,h,t}$



**The estimated marginal cost is calculated as the lagged median day-ahead price for the previous 4 weeks of hourly observations.*

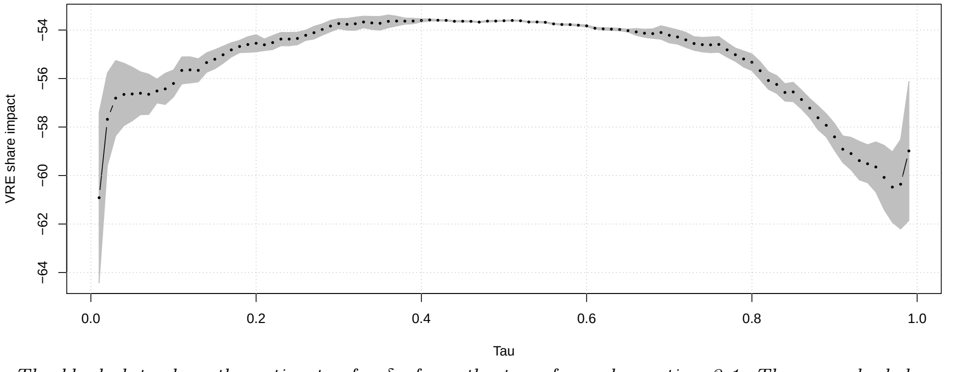
Figure 3.5: Overview of the Spanish day-ahead market between January 2015 – June 2019.

Table 3.6: Impact of share of VRES supply on selected day-ahead price quantile levels.

Quantile	1	2	3	...	50	...	97	98	99
δ_q	-60.91	-57.68	-56.81	...	-53.61	...	-60.48	-60.36	-58.98
$\delta_q - \delta_{50}$	-7.30	-4.07	-3.20	...	–	...	-6.87	-6.75	-5.37
s.e.	(2.13)	(1.16)	(0.94)	...	(0.01)	...	(0.88)	(1.12)	(1.74)

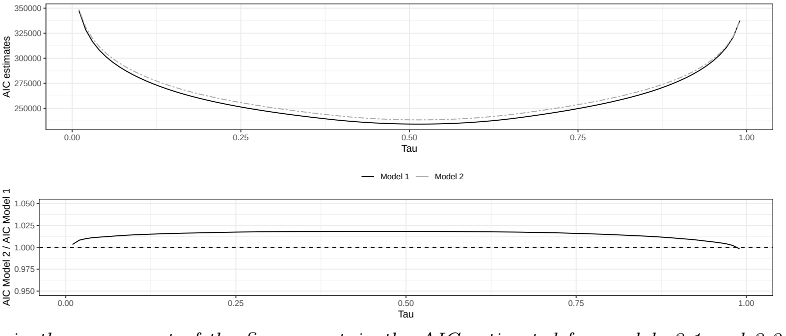
Model: $\hat{p}_{q,h,t} = \hat{\alpha}_{q,h} + \beta_q \times \widehat{mc}_t + \gamma_q * \hat{D}_{h,t} + \delta_q \times \widehat{VRE}_{h,t} + \epsilon_{q,h,t}$

Data: Spanish day-ahead market data



The black dots show the estimates for δ_q from the transformed equation 3.1. The grey shaded area show the 95% confidence intervals for δ_q for quantiles 1 through 99

Figure 3.6: VRES share impact across the Spanish day-ahead price quantiles (τ).



The lines in the upper part of the figure contain the AIC estimated for models 3.1 and 3.2 at each quantile (τ), from the 1^{st} to the 99^{th} quantile. The lower part of the figure shows the ratio between the AIC estimates for the model 3.2 and 3.1.

Figure 3.7: AIC comparison between models3.1 and 3.2 estimated on the Spanish day-ahead market.

Chapter 4

Simulating forward pricing in power markets with renewable energy

4.1 Introduction

This chapter is about how the share of supply from variable renewable energy sources (hereafter referred to as VRES), such as solar and wind, affects the premium priced in a forward contract for the delivery of power during a future period of time[1]. In their seminal work, Bessembinder and Lemmon (2002) provide a theoretical equilibrium model that relates forward prices in power markets to the expected variance and skewness of spot prices. Empirical validations of this framework have however led to mixed results, and Bunn and Chen (2013) point out that empirical studies exhibit a wide range of results in terms of the size and sign of the forward premium, as they tend to focus on the sign and size of forward premiums rather than on the underlying market fundamentals and production technologies. As such, we assess whether uncertainty coming from both the demand and supply side affects the above forward price dynamics. We assess this by focusing on the changes in the forward premium

[1] When we mention forward contracts in this chapter we refer to both forward and futures contracts.

under an increasing market share of VRES, which are variable and uncertain by nature.

Bessembinder and Lemmon (2002) derive the power forward premium as the difference between the forward price and the expected spot price of power. They consider wholesale forward and spot power markets where homogeneous producers sell power to retailers, who in turn purchase that power and sell it to final consumers at a fixed unit price. Demand from final consumers is uncertain and ramping flexibility of producers is unrestricted. In equilibrium, Bessembinder and Lemmon (2002) find that *the forward power price will generally be a biased forecast of the future spot price, with the forward premium decreased by the expected variance of wholesale spot prices and increased by the expected skewness of wholesale spot prices.* Otherwise stated, they show that:

$$F = E(S) - \kappa \times var(S) + \gamma \times skew(S), \tag{4.1}$$

where F is the forward price, S is the spot price, $E(S)$ is the expected spot price, $var(S)$ is the expected variance of spot prices, and $skew(S)$ is the expected skewness of spot prices and κ and γ being positive parameters. The rationale behind the negative effect of expected spot price variance on forward premiums relates to risk-averse producers mitigating price risk by engaging in forward contracts. A positive skewness on the other hand yields a high probability of large upward price spikes, resulting in risk-averse retailers to hedge against spot price risk. Risk-related hedging pressures of producers and retailers thus drive downward and upward pressure on forward prices in order to hedge against spot price uncertainty (Koolen et al. (2021)).

In this chapter, we study how the above forward market price dynamics are affected by an increasing market share of VRES. There is a growing stream of literature investigating the impact of VRES on the volatility of power prices in sequential markets. Goodarzi et al. (2019) find that high forecast errors from VRES yield higher trading volumes in spot markets. These increased volumes in turn affect the spot price, with possible spill-over effects in intra-day and day-ahead markets. Astaneh and Chen (2013) find that the volatility of forward prices increases with the share of VRES, as uncertainty on spot prices may indeed propagate into forward markets.

Looking at day-ahead markets, Kyritsis et al. (2017) and Rintamäki et al. (2017) show that the variance of power prices directly depends on the market share of VRES. Although mixed findings have been reported with regards to increasing solar supply, depending on the timing of production in relation to demand (Kyritsis et al. (2017), Reinhard et al. (2013)), increased supply from VRES thus typically increases (spot) price volatility. In this chapter, we relate the effect of VRES on forward pricing to the hedging needs of risk-averse producers described above, as anticipated forecast errors from VRES should decrease forward premiums. We thus expect an increasing market share of VRES to increase the variance of spot power prices and consequently, following (4.1), to impose a negative effect on the forward price premium.

Work on the effects of VRES on the (expected) skewness of power prices is relatively scarce. Gianfreda and Bunn (2018) find an effect of VRES on the skewness of spot prices, describing that in the German day-ahead market price skewness turns from positive to negative under the influence of VRES. The second chapter of this dissertation shows, in a similar market setting, that with the increase of VRES, the tail on the left side of the power price distribution function (low prices) becomes increasingly fatter and the tail on the right side of the power price distribution function (high prices) become increasingly thinner. The third chapter of this dissertation further shows that the lower and higher quantiles of empirical power price distributions depend directly on the market share of supply from VRES. Furthermore, forecast errors on VRES may asymmetrically impact market prices depending on the reserve margin[2] level and the relative market share of VRES. For example, when the market share of VRES is predicted to be high, VRES overproduction may lead to low or even negative skewness, whereas underproduction may impact the price much less due to the high reserve margin from non-variable power producers that can ramp up production to rebalance the system. The same logic holds vice versa. When supply from VRES is predicted to be low, VRES underproduction may lead to extremely high spot power prices, and thus to high skewness levels, whereas overproduction will have a smaller effect on spot prices due to the high number of non-variable power

[2]We refer to reserve margin as the idle capacity at a specific point in time of non-variable power producers. Non-variable power producers refer to market agents who generate power using conventional, mostly fuel based, non-weather dependent technologies, such as coal or gas fired power plants or nuclear power plants.

producers who can reduce production to rebalance the system. Indeed, Kiesel and Paraschiv (2017) document evidence on the asymmetric impact of VRES on intra-day and balancing market prices, finding proof for asymmetric effects from positive and negative forecast errors. It can thus be inferred that the introduction of VRES in spot markets[3] lowers the skewness of power prices by increasing the probability of low price spikes and decreasing the probability of high price spikes. Following (4.1), we expect risk-related hedging pressure of retailers therefore to decrease, resulting in a negative effect on the forward price premium.

The rest of this chapter is organized as follows. We describe the methodology in the following section, embedding our work in the forward pricing theory. In Section 4.3, we describe the market framework, using data from a simulated market environment. We next discuss the results of the analysis and conclude the chapter by considering implications for market participants in renewable power systems.

4.2 Methodology

Fama and French (1987) study the information embedded in the forward basis[4] in light of two alternative but not competing views: the theory of storage and expectations theory. In the first, traders can store and carry commodities until the delivery moment and the forward premium reflects storage, financing costs and a convenience yield for when traders expect frictions and prefer to have the physical asset instead of a contract. The other theory applies more directly to commodities for which storage is expensive or non-existing or for which quality depreciates over time. The forward basis then embeds information about an expected risk premium and expected change in the spot price between now and the delivery moment. Following the latter, let $F_{t,T}$ be the forward prices quoted at time t for delivery moment T. The forward basis is $F_{t,T} - S_t$, with S_t being the spot price of the commodity at time t. Let S_T be the

[3]The focus of the described papers concentrates on prices in day-ahead contracts, that involve the delivery of power during some period in the next day. In fact, a day-ahead contract is a one-day forward contract. However as the day-ahead market is widely regarded as the reference market for power pricing, it is reasonably to assume that the same relation holds for a spot market.

[4]We refer to the forward basis as the difference between the observed forward price for a contract that matures at a later date and the observed present spot price.

spot price at the delivery moment T. Fama and French (1987) propose two regression equations:

$$S_T - S_t = \alpha_1 + \beta_1 \times (F_{t,T} - S_t) + \epsilon_{1,t}, \tag{4.2}$$

$$F_{t,T} - S_T = \alpha_2 + \beta_2 \times (F_{t,T} - S_t) + \epsilon_{2,t}. \tag{4.3}$$

A positive β_1 signals that the forward basis contains information about the future change in the spot price, whereas a positive β_2 signals that the forward basis contains information about the to be realised risk premium. Note that by construction of equations (4.2) and (4.3), the summation of α_1 and α_2 is equal to zero and the summation of β_1 and β_2 is equal to one. The relation between β_1 and β_2 denotes that equations (4.2) and (4.3) will attribute the change in the forward basis to either the forecasting power of forward prices, to the expected change in spot prices or to a combination of both. Regarding the intercept of the equations proposed by Fama and French (1987), unless they are both equal to zero, α_1 and α_2 will have opposite signs.

Fama and French (1987) predict that in commodity markets with high storage costs, which is the case for power markets, forward prices are expected to contain information about future spot prices. We thus expect β_1 to be high, close to the value of one and, respectively, β_2 to be low, close to the value of zero. Huisman and Kilic (2012) provide a fundamental explanation for the relation between forward and spot power prices by testing equations 4.2 and 4.3 in Dutch and NordPool power markets. Their results show that forward contracts with maturities between 1- and 6-months exhibit forecasting power over the spot day-ahead power prices with β_1 varying between $0.6 - 0.8$ for the Dutch market and between $0.8 - 0.9$ for the NordPool market. The difference in β_1 is attributed to the power mix differences between the two markets and the relative capacity of indirectly storing power through the underlying fuels. The Dutch power market, dominated by gas power producers, has capacity to indirectly store power through storing gas, thus leading to a lower β_1 estimate. In contrast, NordPool is dominated by hydro power plants which are more weather dependent and have a lower capacity to indirectly store power, resulting in a β_1 value closer to one. The results of Huisman and Kilic (2012) thus confirm our view with regards to the value of β_1 in power markets that have no or limited (in)direct storage capacity.

Subtracting the current spot price from both sides of the equation (4.1) and using time subscripts, we obtain:

$$F_{t,T} - S_t = E(S_T) - S_t - \kappa \times var(S) + \gamma \times skew(S). \tag{4.4}$$

Equation (4.4) states that the forward basis embeds information about the expected change in the spot price and information about the variance and skewness of spot prices. Rewriting equation (4.4) in regression form gives us:

$$S_T - S_t = \alpha_3 + \beta_3 \times (F_{t,T} - S_t) + \epsilon_{3,t}, \tag{4.5}$$

where we expect that $\beta_3 = 1$ and that $\alpha_3 = \kappa \times var(S) - \gamma \times skew(S)$ contains information about the expected variance and skewness of spot prices. Recall that κ and γ in equation (4.1) are positive parameters. We use this regression to test our claim that the combined impact of variance and skewness in Bessembinder and Lemmon (2002) should lead to lower forward premiums in power systems with a higher share of VRES. We are thus interested to test whether α_3 is larger in a power market with a high share of VRES than in a power market without VRES.

An alternative way to test for the same hypothesis is by making use of equation (4.3) where, for power markets with no storage, we expect $\beta_2 = 0$. If we include this information in equation (4.3), we obtain:

$$F_{t,T} - S_T = \alpha_2 + 0 \times (F_{t,T} - S_t) + \epsilon_{2,t} = \alpha_2 + \epsilon_{2,t}. \tag{4.6}$$

Equation (4.6) is equivalent with equation (4.1). If in equation (4.1) we subtract on both sides $E(S_T)$, we obtain:

$$F_{t,T} - E(S_T) = -\kappa \times var(S) + \gamma \times skew(S), \tag{4.7}$$

where on the left side of the equation we have the forward premium, similar to equation (4.6). If we incorporate this information in equation (4.7), this finally renders the following equation:

$$F_{t,T} - S_T = \alpha_4 + \epsilon_{4,t}, \tag{4.8}$$

where $\alpha_4 = -\kappa \times var(S) + \gamma \times skew(S)$ is expected to be lower when the market share of VRES is high.

By estimating the parameters in equations (4.5) and (4.8) and analysing the patterns in α_3 and α_4 on markets with different levels of VRES in their power mixes, this work aims to provide evidence that an increasing market share of VRES decreases the forward premium in power markets. In other words, we test the hypothesis that α_3 increases and that α_4 decreases with the market share of VRES.

4.3 Market simulation environment and data

To examine whether an increase in the market share of VRES decreases the forward premium in power markets we examine forward and spot power prices in a simulated power market environment. We develop an experimental framework wherein human participants trade a specific good in a simulated market environment[5] and refer to such a market as the simulated market hereafter. The benefit of such an environment is that it allows us to isolate the effect of supply from VRES on the forward premiums from other factors such as changes in the power mix, marginal costs, and/or policies. We simulate three identical power markets, wherein the only difference between the markets is the share of supply from VRES, respectively 0%, 33%, and 67%. Each simulation run consists of two time periods. At time 1, agents trade forward contracts that involve the physical delivery of power at future time 2. At time 2, agents trade

[5]We like to think of such market environment as a commodity market platform, with the only difference that we know the exact environment wherein these prices were determined. The setting, framework and boundary conditions are thus not set to answer a specific question, rather resulting prices and volume can serve to answer a range of research topics. For example, Koolen et al. (2020) use the same dataset to examine the changes in the trading strategies of non-variable power producers when the supply from VRES increases in power systems.

in the spot market after which delivery takes place.

There are four types of agents participating in the market setting. The first two distinguish the two types of power producers. The first is a *non-variable power producer* that supplies power with a production capacity of 900 MW. It converts a storable fuel into power and can flexibly adjust the volume produced with unlimited flexibility or ramping capacity (i.e. production volumes can vary freely between 0 MW and 900 MW). The only variable costs are fuel and emission right costs which combined are 50 EUR/MWh and which are fixed throughout the experiment. Fixed costs are zero, representing a sunk cost that does not affect trading decisions in a competitive market. All non-variable power producers have the same technology. The second type represents a *VRES power producer* that supplies power from a variable renewable energy source such as wind mills or solar panels at time 2. The supply of VRES is variable and each producer faces uncertainty in that the realised production is drawn from a normal distribution function with mean 900 MWh and a standard deviation of 45 MWh. All VRES power producers operate independently in order to simulate an entire market rather than a specific region. Both types of producers submit bids and offers in the forward market at time 1, but only the non-variable power producers submit bids and offers in the spot markets as they have the flexibility to increase or decrease production.

During the simulation, the relative market share of VRES varies over three different market structures. The first market has 15 non-variable power producers and no VRES. We refer to this setting as the **N** market. The second is the **L** market with a low market share of supply from VRES: 5 VRES and 10 non-variable power producers. The third market is the **H** market with 10 VRES and 5 non-variable power producers. The number of VRES producers in the market is the treatment variable which enables us to examine forward premiums when the market share of VRES increases.

The third agent represents consumers by an automatised agent that demands a volume of power at time 2. The demand is uncertain at time 1, being drawn from a normal distribution function with mean demand of 11,500 MWh and standard deviation of 1,150 MWh. The demand is assumed to be price inelastic, which is common for power demand in the short run (Lijesen (2007)). Although modeled as a single agent, it may represent a group of power retail companies that deliver power to households and enterprises. The consumer purchases expected consumption in the forward market[6] and final deviations in demand are settled in the spot market. The fourth agent is the automatised market and system operator which is a price taker. It collects all bids and offers and determines the market clearing price as market operator. As system operator, it buys or sells the needed amount of power in the spot market in order to balance demand and supply. It is assumed that the system operator has a very good signal of actual demand and supply from VRES such that it knows what volumes to buy or sell with absolute certainty.

Subjects were randomly allocated one of the first two agents in a counterbalanced order. Participants were recruited among graduate students that specialize in energy finance and received clear information on energy trading, power market design and financial decision making as part of the curriculum. In total 5 separate simulations were conducted. Each single simulation consisted of 3 sessions, one for each market structure. From each session data was collected on 25 rounds after controlling for learning rounds. While there are thus 125 observations available for each of the three market settings, only 120 observations can be used as the first rounds, for each of the 5 separate simulation sessions, do not have a previous observation from which we can obtain S_t. Table 4.1 summarizes the data collection within the framework of our sequential power market simulation.

Table 4.2 presents a summary of the collected data per market setting. We notice that with the introduction of VRES, as we move from the **N** market towards the **H** market, the average level of cleared prices decreases on both the forward and spot markets. This is in line with our expectation, as the literature on the direct effect of VRES on power prices stipulates that the merit-order effect leads to lower mean power price levels (Würzburg et al. (2013)). Looking at the mean volume, while on the forward market we do not observe a clear change from one market setting to

[6]Risk-averse retail companies hedge margin income by lowering the risk from highly variable spot prices. Furthermore, the spot market is less liquid than the forward market as only producers that can flexibly adjust their output can offer power for spot delivery.

Table 4.1: Summary of the market simulation setting

We use 5 identical simulalions organized as follows:

Market type	**N** market		**L** market		**H** market
Nb. of Rounds	25		25		25
Nb. of Producers:					
VRES	0		5		10
Non-variable	15		10		5
Nb. of bids / round:					
Forward market	15		15		15
Spot market[1]	30		20		10
Demand function in each round	$Mean = 11,500$ MWh	—	$St.Dev. = 1,500$ MWh		
Maximum capacity per non-variable producer[2]			900 MW		
Expected output per VRES producer[3]	$Mean = 900$ MWh	—	$St.Dev. = 45$ MWh		

Note 1: Only non-variable power producers can submit bids in the spot market. Each can submit 2 bids: 1 sell and 1 buy offer; — Note 2: Non-variable power producers can ramp up their production when needed; — Note 3: VRES output is subject to weather conditions.

another, on the spot market with the increase in share of supply from VRES there is an increase in the value of the absolute volume traded, suggesting increasing balancing needs as the market share of VRES increases.

We note two particularities that inherently follow from simulating power markets. First, the values of S_t represent a proxy for the value of the spot price at time 1 of each round. The equations introduced by Fama and French (1987) are meant to be applied on time series type of data. While in the collected experimental data the rounds follow each other in a sequential way, the simulation was not necessarily designed to be considered as a time series. Additionally, in an ideal setting, $F_{t,T}$ and S_t prices should be quoted and available for trading in the same time. In the setting used, S_t is quoted in the immediate period before quoting $F_{t,T}$ and not at the same time as $F_{t,T}$. The difficulties of getting spot price estimates were also incurred by Fama and French (1987), as they relied on forward prices of contracts close to maturity as proxy for spot prices. The values for S_t are used in the analysis to estimate equation (4.5).

Table 4.2: Summary statistics of the simulation data.

	N market	**L** market	**H** market
	Mean settled price (EUR/MWh)		
Forward market	78.0	68.8	61.8
Spot market	75.8	70.6	68.0
	Mean volume (MWh)		
Forward market	11,280	11,400	11,385
Spot market[1]	797	948	1,012

Note 1: Mean volume on spot market is calculated as the absolute cleared values on this market. The calculation includes both periods when the market found itself in a supply deficit and, respectively, surplus state.

S_t values are not used in equation (4.8) and hence this equation is not impacted by any potential bias in S_t. If the estimate used for past spot prices is a good proxy, we should be able to draw the same conclusions from either equation (4.5) or (4.8).

The second particularity is represented by the relative low number of observations in the original dataset. Power markets are known for exhibiting highly volatile prices. In such markets, one needs a high number of observations to draw significant conclusions. As the original dataset contains only 120 usable observations, using this dataset to estimate the coefficients α_3 and α_4 for the various market settings will likely lead to high standard errors in the estimated coefficients and, thus, to a situation where we cannot draw statistically significant conclusions. A solution to the matter of low number of observations is embedded in the experimental design. At time 2, once the forward market volume and price are cleared, each participant who acts as a non-variable power producer submits a sell and a buy spot market offer. This creates a merit order curve of 30, 20 and, 10 observations for respectively the **N**, **L** and, **H** markets. From these observations, based on the automised demand for the spot market, a spot price is cleared. Since this part is automised by the market and system operator, and bids are only reveled after final market closure, we argue that any of the bid offers in the spot merit order curve could have been the cleared spot price if the automised demand agent was required to select a different demand volume. We therefore argue that for each cleared forward price $F_{t,T}$, besides using the original values of cleared spot prices S_T, we can also use the entire merit order curve of S_T. By multiplying the number of 120 original cleared $F_{t,T}$ prices by the total number of spot merit order curve observations, the dataset used for estimating equations (4.5) and (4.8) grows to 3600, 2400 and 1200 observations for respectively the **N**, **L** and **H** markets[7]. From here onwards, we will refer to the dataset where we use the entire merit order curve of S_T as the *extended dataset*. The dataset where we use only the 120 cleared S_T observations, is referred to as the *original dataset*.

4.4 Results

We use data from the above described market simulation to validate our hypothesis that the increase of supply from VRES in forward and spot power markets lowers the forward power price premium through the combined impact of VRES on the variance and skewness of spot prices. We do so in 2 different ways. First, by analysing the estimated values of the parameters in equation (4.5), and secondly by estimating equation (4.8). These estimates are obtained through ordinary least squares regressions for each market setting on a pooled sample from the five experiments. For equation (4.5) we expect that β_3 to equal one and α_3 to be smallest for the **N** market, with zero supply from VRES, and highest for the **H** market, with the highest market share of supply from VRES. For equation (4.8) we expect α_4 to be highest for the **N** market and lowest for the **H** market.

The results obtained by estimating equation (4.5) are summarised in table 4.3, for the original dataset, and in table 4.4, for the extended dataset which uses the entire merit order curve of S_T. In both tables, the results confirm our expectation for both the estimates of α_3 and β_3. β_3 values are close to the value of one[8] for each of the market settings, regardless of both the amount of VRES in the power system and the type of dataset. This result proves that in power markets with little storage capacity,

[7] Although the minor downsides of this approach are i) the fact that in the extended newly created dataset each $F_{t,T}$ cleared price will be used for multiple S_T values, and ii) the fact that implied spot demand volume will no longer follow a normal distribution, we believe these do not affect our results.

[8] Note that for each setting investigated, the estimate of β_3 is not significantly different from the value of one.

Table 4.3: Results of estimating equation 4.5 on the different market structures using original dataset

Eq. 4.5 estimated:	$S_T - S_t = \alpha_3 + \beta_3 \times (F_{t,T} - S_t) + \epsilon_{3,t}$		
	N market	**L** market	**H** market
α_3	-0.758	2.574	5.730
	(4.265)	(4.522)	(6.672)
β_3	1.057	0.982	1.044
	(0.093)	(0.091)	(0.090)
Nb. observations	120	120	120
R^2	0.524	0.499	0.530
F Statistic	129.6	117.4	133.1
Note:		*Standard errors in parentheses.*	

Table 4.4: Results of estimating equation 4.5 on the different market structures using the extended dataset

Eq. 4.5 estimated:	$S_T - S_t = \alpha_3 + \beta_3 \times (F_{t,T} - S_t) + \epsilon_{3,t}$		
	N market	**L** market	**H** market
α_3	-6.891	0.219	5.823
	(0.974)	(1.252)	(2.197)
β_3	0.974	0.967	1.004
	(0.021)	(0.025)	(0.030)
Nb. observations	3600	2400	1200
R^2	0.385	0.382	0.487
F Statistic	2250	1485	1136
Note:		*Standard errors in parentheses.*	

as is the case in most power markets, the forward basis, $F_{t,T} - S_t$, has forecasting power over future spot prices, S_T.

Further, in line with our expectation, we observe an increasing trend in the estimated mean of α_3 moving from the **N** market to the **L** market and from the **L** market to the **H** market in both tables 4.3 and 4.4. We find evidence for the indicated result in both the original and the extended dataset. Nevertheless, only for the extended dataset, where we use the entire merit order curve of S_T, the estimates for the **N** market and **H** market are significantly different from each other. For the original dataset, the high standard errors make any comparison between the markets only indicative and less reliable due to the low number of observations. These results confirm the expectation that with the increase of VRES in power markets, forward premiums become lower. Moreover, note that $\alpha_3 = \kappa \times var(S) - \gamma \times skew(S)$, the opposite of the forward premium expressed as per equation (4.1). Looking at tables 4.3 and 4.4, this means that the forward premium estimated in our experimental framework is positive in the **N** market and becomes increasingly negative as we add a higher shares of VRES to the market. This result is statistically significant for the results on the extended dataset.

Table 4.5: Results of estimating equation 4.8 on the different market structures using original dataset

Eq. 4.8 estimated:	$F_{t,T} - S_T = \alpha_4 + \epsilon_{4,t}$		
	N market	**L** market	**H** market
α_4	0.633	-2.575	-5.500
	(4.249)	(4.504)	(6.634)
Nb. observations	120	120	120
Note:		*Standard errors in parentheses.*	

Table 4.6: Results of estimating equation 4.8 on the different market structures using the extended dataset

Eq. 4.8 estimated:	$F_{t,T} - S_T = \alpha_4 + \epsilon_{4,t}$		
	N market	**L** market	**H** market
α_4	6.949	-0.221	-5.801
	(0.942)	(1.252)	(2.190)
Nb. observations	3600	2400	1200
Note:		*Standard errors in parentheses.*	

Tables 4.5 and 4.6 present the results on the estimates for equation (4.8). Equation (4.8) does not require the use of the proxy estimate for past spot prices S_t. The results on estimating α_4 lead to the same conclusion regarding the relation between forward premiums in power markets and the share of VRES. In tables 4.5 and 4.6, we observe

in line with our expectation a decreasing pattern in the α_4 estimates. The same as for α_3 estimates, only in the extended dataset α_4 estimates for the **N** market and **H** market are significantly different one from another. Also, similar to estimates for α_3, we can deduce from the α_4 estimates that the forward premium in the **N** market is positive and that it becomes negative in the **H** market as the share of VRES increases, with the results from the extended dataset yielding for the **N** market and **H** market significantly different values.

We note that although the results on the impact of supply from VRES on forward premiums are robust for the different market settings in our study, one should take into account a number of considerations when extrapolating the insights to actual power markets, depending on individual market characteristics. For example, when a significant amount of direct or indirect, through the underlying fuel, storage is available in the market, it may reduce the variable nature of power prices induced by VRES and reduce the frequency of extreme low prices.

Finally, the behavior of the forward premium is affected when non-variable power producers experience significant ramping costs in adjusting output profiles close to real-time. Note that currently many power markets still have limited capacity to store power and demand is relatively price inelastic. This implies that any forecast errors need to be offset by non-intermittent producers with the capability to flexible adjust their power output close to real-time. Most of such market agents produce power using conventional, mostly fuel based, non-weather dependent technologies, such as coal or gas fired power plants. Although we believe that the main insights are robust to such extensions, underlying market fundamentals may impact the degree to which extent our results manifest itself.

4.5 Chapter's concluding remarks

We study the effects of an increasing market share of VRES on forward price dynamics in wholesale power markets. The introduction of VRES changes power market dynamics, as VRES typically bear lower marginal costs than traditional non-variable fuel-based power producers. Power output from VRES depends however on parameters that are uncertain by nature, like wind speed and solar radiation, and they have limited capacity to manage this variability, as curtailment is not preferred or incentivized in most power markets. This, in combination with the limited capacity of storing power and the variable inelastic demand, causes power price profiles for short-term delivery to vary drastically.

We study the above question in the framework of a simulated power market environment. This market set-up allows us to vary the share of VRES with a high degree of control and control for any other exogenous effects which may affect power price dynamics. We do so by analyzing simulated market data in three distinct market structures, ranging from a market with no VRES to a high VRES-supplied power system.

We study the effect of supply from VRES on power market prices in the scope of forward pricing. Forward markets help with the efficient allocation of resources for commodities that face uncertainty in price or quantity for a future time of delivery. Moreover, forward contracts are an important medium to allow market participants to deal with risk sharing over spot uncertainty close to real-time. Forward price premiums have been found to relate to spot price dynamics, most notably negatively to the variance and positively to the skewness of expected spot prices. In this chapter, we find evidence that the expected higher variance and lower skewness introduced by an increasing share of VRES leads to lower forward premiums. We further demonstrate that in power markets without storage capacities, the forward basis contains information about the future spot price. This result is consistent regardless of the amount of supply from VRES in the power system. It also implies that the forward basis does not contain information with regards to the realized risk premiums.

The present chapter indicates that with an increasing market share of VRES, there is an increasing need for storage and/or flexibility in power markets in order to reduce uncertainty and risks. The current limited capacity to store power and the largely inelastic demand imply that any imbalances caused by VRES output are offset by non-variable, mostly fuel based, power producers who provide the necessary flexibility needs to balance the system. In such systems, we find that higher shares of VRES in power markets may create a negative impact on the forward risk premium. In doing so, this work provides important insights for market participants, both producers and retailers, to effectively balance their portfolio in forward and spot markets as power systems become increasingly dependent on variable renewable energy sources.

Chapter 5

A (re)view on the forward premium in prices of non-storable commodities. Evidence from power markets

5.1 Introduction

Chapter 4 of this dissertation shows for a simulated power market that supply from variable renewable sources reduces the power price forward premium. Yet, this fundamental factor is not the only one affecting power price formation on forward and spot power markets. To further shed light on this topic, the present fifth chapter of the dissertation enlarges the discussion and aims to provide a comprehensive view on what explains the forward premium in non-storable commodity markets, markets exemplified in this chapter through power markets.

Expectations theory and theory of storage propose distinct but not mutually exclusive explanations for the price formation of forward contacts[1] in commodity markets. Expectations theory explains the level of forward prices through expected risk premiums and expected spot prices. Theory of storage explains the difference between forward and spot prices though interest rates, storage costs and convenience yields. Both theories can be applied to storable commodities. Yet, for non-economically storable commodities, such as power, it is still not clear in which way these theories apply and if both of them are relevant. The same as for storable commodities, non-storable commodities can be traded through forward and spot markets. However, forward positions of non-storable commodities cannot be economically hedged by buying the commodity before the delivery date and storing it until delivery. This aspect poses challenges when trying to apply the storage theory line of reasoning to such commodities. In this context, the question that arises is: What explains the forward premium in prices of non-storable commodity markets? We refer to the forward premium as the difference between the forward and the realized spot prices[2]. To answer this question, the present chapter introduces a fundamentals based theoretical framework which we later empirically test. To develop this framework we use power markets as an example of markets trading non-storable commodities.

Power markets are prominent among the non-storable commodity markets. For these markets there is already a vast empirical literature on how the power price forward premium behaves. Yet, the conclusions are still not clear. As most current power markets have limited access to large quantities of direct storage, the majority of studies in the energy finance literature attempt to explain the forward premium in power prices through risks premiums, thus, through expectations theory. Only a few studies try to link the forward premium in these prices to the theory of storage. They make this link through the rationale of indirect storage of power in the form of storage of underlying raw materials (ie. water, gas, coal etc.). This rich energy finance literature provides us with many clues about the relation between forward and spot power

[1] For readability reasons, throughout this chapter we refer to both forward and futures contracts as forward contracts. Similarly, we refer to both forward and futures markets as forward markets.

[2] While for readability we define the forward premium as a “premium”, we must point out that this difference can also be negative and, thus, it can be at times a “discount”. Additionally, forward premiums should not be confounded with “risk premiums”, which will be further discussed in this chapter.

prices. However, the lack of consensus among the various empirical results and the particularities of each power system diminish the practical utility of these clues. Thus, we claim that there is a need for revisiting our thinking on the forward premium in power prices and, implicitly, on the forward premium in prices of non-storable commodities. Before delving into the proposed theory, let us take a deeper look at what we already know from energy finance literature about the forward premium in power prices.

5.1.1 Forward premiums in power prices. What do we know?

Because of the lack of significant storage capacity in many power markets, most studies which analyse the forward premium in power prices use the expectations theory as starting point. The results of such studies, focusing on short-term power markets (forward contracts expiring next day), often attribute the occurrence and sign of the forward premium in power prices to risk premiums. Among others, Geman and Vasicek (2001), Longstaff and Wang (2004) and Hadsell (2011) choose to investigate the PJM[3] power market and find on average positive forward premiums. Yet, when the analysed data is split into various moments of the day, both positive and negative risk premiums appear to be present. Average positive differences between forward and spot power prices are found also by Saravia (2003) and Hadsell and Shawky (2007) for the New York power market. Karakatsani and Bunn (2005), using British data, and Viehmann (2011), using German data, find positive forward premiums in peak hours and negative forward premiums in off-peak hours. Haugom and Ullrich (2012) show that for the PJM market, risk premiums became smaller, close to zero, in the most recent part of their investigated data. Ronn and Wimschulte (2009), studying the German power market, find positive risk premiums on average. More recently, Valitov (2019), on the same German market, show that positive premiums have gotten smaller over time and suggest the introduction of negative prices as a factor contributing to this effect. On the Californian power market, Borenstein et al. (2001), later developed in Borenstein et al. (2008), document large and varying price differences between forward and spot power prices.

[3]Pennsylvania-New Jersey-Maryland Interconnection.

In the energy finance literature which focuses on forward contracts with longer maturities (expiration dates in weeks, months or years), NordPool power market received the most attention. Gjolberg and Johnsen (2001), Botterud et al. (2002), Lucia and Torró (2008), Weron (2008), Daskalakis and Markellos (2009), Capitán Herráiz and Rodríguez Monroy (2009), Redl et al. (2009), Botterud et al. (2010), Lucia and Torró (2011) and Weron and Zator (2014) find on average positive forward premiums[4] in NordPool power prices. The same as with the studies presented in the previous paragraph, most authors highlight the fact that the forward premiums do not stay constant over time. In fact, significant variation can be observed, and negative premiums are also documented (Marckhoff and Wimschulte (2009), Haugom et al. (2014) and Fleten et al. (2015)). Moving to the German power market, on one hand Bierbrauer et al. (2007) and Wilkens and Wimschulte (2007) document on average positive forward risk premiums with the mention that they are found to be highly volatile and that they change sign over time. On the other hand, Daskalakis and Markellos (2009) find the opposite, negative risk premiums. In other geographies, the results of Shawky et al. (2003), focusing on Californian power market, and Handika and Trueck (2013), focusing on Australian power markets, display positive premiums. A more recent paper, Ferreira and Sebastião (2018), documents negative risk premiums in the Spanish power prices. Another recent article, Bevin-McCrimmon et al. (2018), reports that the variability in risk premiums in New Zeeland's power prices leads to both positive and negative forward premiums. Bunn and Chen (2013), for the British power market, document large positive forward premiums in winter peak periods, small positive forward premiums in off-peak winter periods and small negative forward premiums in summer off-peak periods. Finally, Xiao et al. (2015), using a stochastic model for the PJM market, and Lucia and Schwartz (2002), for the Nordic Power Exchange, also find time varying seasonal risk premiums in power prices.

As the results of this long list of studies demonstrate, there is no consensus among empirical studies on how the forward premium behaves in power prices. Results of studies taking the expectations theory approach exhibit both positive and negative signs attributed to risk premiums in power prices. However, there is one aspect in

[4] In certain cases authors refer to them explicitly as risk premiums.

which a consensus emerges: the forward premium in power prices varies over time. Understanding why this is the case, is an important question to be addressed. In the articles mentioned above, the most common explanation for the power price forward premium variation is found in demand levels: seasonality, peak versus off-peak hours, sudden demand jumps etc. As in any other commodity market, demand proves to play a crucial role in the price formation process. Nevertheless, as we further explain, demand related factors are not the only ones to influence the forward premium in power prices.

Through a theoretical framework, Bessembinder and Lemmon (2002) prove that the forward premium in power prices depends on the skewness and variance of expected spot prices. Longstaff and Wang (2004) and Viehmann (2011) provide empirical support for this theory showing for the PJM market that the forward premium is affected positively by spot price skewness and negatively by spot price volatility. In a study on the Spanish power market, Furió and Meneu (2010) find partial support for the theory. Investigating the NordPool market, Lucia and Torró (2011) find both periods in time that comply with the view of Bessembinder and Lemmon (2002) and periods that do not support their view. In contrast, Bevin-McCrimmon et al. (2018) do not find support for this theory. We must keep in mind that the seminal paper of Bessembinder and Lemmon (2002) was developed at a time when in any power market supply from variable renewable sources (VRES) represented an insignificant share in the power mix. With the introduction of VRES capacity in power markets, price uncertainties do not come anymore just from demand side, but also from supply side. As presented in the fourth chapter of this dissertation, an increase in the installed VRES capacity in a power market can lead to a decrease in the power price forward premium and this can be explained through the skewness and variance of expected spot power prices.

With an increasing number of policies encouraging the deployment new VRES installations in power markets, the supply side of power systems has an increasing role in the power price forward premium formation. This happens because the weather dependent VRES supply increases the flexibility[5] needs of a power system by putting

[5]We refer to flexibility as the technical and / or economical ability of a certain producer or power system to adapt their production level in order to keep the power grid in balance at all times.

pressure on the ramping needs required from conventional suppliers. As conventional suppliers are generally the ones to provide flexibility to a power market, power generation mix is another factor that impacts the forward premium in power prices. Huisman and Kilic (2012) show that the power price forward premium has a different behaviour in the hydro dominated NordPool market than in the gas dominated Dutch power market. The authors attributed the variation in results to power mix differences. This finding is in line with Audet et al. (2004) who prove that water levels significantly influence forward power prices. Thus, particularities of each power system must be considered when one discusses about the forward premium in power prices.

From the discussion above it emerges the fact that both supply and demand factors influence the forward premium in prices of non-storable commodities such as power. To a certain extent, especially when approaching delivery time, we can forecast these fundamental factors. The question that arises then is: are forward premiums in power prices fully explained by risk premiums? The idea behind risk premiums is that market players are awarded a return in excess of the risk-free rate as a compensation for the uncertainty they have to face. Since the forward premium in power prices is influenced by factors that at times can be forecasted with a certain degree of accuracy, one can argue be that besides a risk premium, a yield, similar to the convenience yield, plays a role too in explaining the forward premium. This idea is also suggested by Gjolberg and Brattested (2011) who find it unlikely that the difference between forward and realised spot prices in the NordPool power market can be explained by risk premiums only.

This brings us to the applicability of theory of storage in power markets and in markets trading non-storable commodities. Power as a product is a conversion good. To produce power, a certain amount of underlying "fuel" (water, gas, coal, biomass etc.) is required. This means that power can be indirectly stored through an underlying fuel. Through indirect storage, market players can plan when to convert their underlying fuel into power and sell their output (when power prices are high) and when to save the fuel for later conversion (when power prices are low). From this perspective, convenience yields could be present in non-storable commodity markets.

In finance literature there are studies that acknowledge the importance of the underlying raw materials in power price formation. A change in gas prices will affect much more the Dutch power market, heavily reliant on gas power plants, than NordPool, a market heavily reliant on hydro power plants. Redl and Bunn (2013), acknowledge the fact that power is a conversion good and that fuel prices directly impact both spot and forward power prices. Taking a slightly different approach and extending the model of Bessembinder and Lemmon (2002), Douglas and Popova (2008), and later Bloys van Treslong and Huisman (2010), investigate the relationship between gas storage levels and power price forward premiums. They find that when stored gas levels are high, forward premiums tend to be low. This happens predominantly in days with high temperatures when demand for power is higher and demand for heating is lower. The results of these two papers indirectly suggest that, through gas storage levels, convenience yields play a role in the formation of the forward premium in power prices. Botterud et al. (2010) document the indirect presence of convenience yields in NordPool power market through the water volumes stored into the dam's reservoirs. They document both positive and negative convenience yields related to stored water levels. The results of these papers makes us believe that the forward premium in power prices cannot always be fully explained by risk premiums. In certain moments, convenience yields, depending on price movements and storage levels of the underlying fuels, are present in power markets and influence the forward premium.

It is worth mentioning also that risk aversion plays a role too in determining the power price forward premium. Anderson and Hu (2008), Benth et al. (2008), Buhler and Müller-Merbach (2012), Handika and Trueck (2013) and Redl and Bunn (2013) all consider the risk aversion as an explanatory variable for the forward premium in power prices. The relative risk aversion profiles of the power market suppliers and retailers at each moment in time can influence the forward premium. This can also provide a partial response to why both positive and negative risk premiums are documented in the energy finance literature. Furthermore, the uncertainties present across the lifetime of a forward contract are not constant. Diko et al. (2006), Benth et al. (2008), Marckhoff and Wimschulte (2009), Kolos and Ronn (2008), Pietz (2009) and Benth et al. (2014) all find evidence supporting the fact that forward power prices present a structural pattern. This pattern is represented by lower (often negative) forward premiums for the forward contracts having a long time to maturity and by positive forward premiums for the contracts having a short time until the delivery date. Diko et al. (2006), putting their findings into the light of the model proposed by Bessembinder and Lemmon (2002), claim that, as the time to maturity increases, risk premiums decrease because the skewness of spot prices becomes less relevant.

5.1.2 Forward premiums in power prices. What is missing?

As detailed above, energy finance literature provides many clues for understanding the forward premiums in power prices. We know that forward premiums are influenced by fundamental demand and supply factors such as seasonality, power mix, prices and storage levels of underlying fuels, demand levels, risk aversion and time to maturity of forward contracts. We also know that risk premiums are present in power prices and that they don't seem to always be able to explain by themselves the occurrence of forward premiums. In certain situations, convenience yields seem to have an impact too. What the energy finance literature does not provide us with is a consensus on how to understand and be able to forecast forward premiums in power prices. It is not clear when and how convenience yields can appear in those markets. Moreover, most papers focus on certain power markets and their particularities, making it hard to obtain a general view on the topic. An exception from this is found in Bessembinder and Lemmon (2002). However, this study was developed at a time when the share of supply from VRES in power systems was insignificant.

To build upon the actual status of the literature we propose a new approach, a thinking based on fundamentals. In the following section of this chapter we introduce a theoretical framework which aims to improve our understanding on the formation of forward premiums in prices of non-storable commodities such as power. The studies mentioned in this introductory section of this chapter all refer, directly or indirectly, to demand and supply factors that influence the forward premium in power prices.

Thinking further about each of these factors, they all relate to balancing needs[6] and ramping availability[7] of a power market. In the theoretical framework proposed, we show that by looking at these two factors we can better visualize how forward premiums are formed in power prices. In this way, the model that we propose can guide us in interpreting the empirical results of the existing literature on forward premiums in power prices. Furthermore, this chapter complements the work of Bessembinder and Lemmon (2002) by putting it in the context of actual power markets which incorporate a high share of VRES supply.

5.2 Theoretical framework

5.2.1 Power market design

Let us start presenting this framework by introducing a hypothetical non-storable commodity market, a power market, which contains in its supply mix significant shares of both VRES and non-VRES installed capacities. In this market, output from VRES varies with weather conditions. Non-VRES suppliers have the options to ramp up and down production. We further refer to these options as options to contract and to expand production. The extent to which non-VRES suppliers can expand or contract production in a specific moment in time depends on their flexibility levels. As with any market trading non-storable commodities, demand must equate supply at each moment in time and storage volumes are assumed to be negligible.

For this market, consider a period of time T. Let D_T be the demand for power during the period T. This demand is catered by both VRES (SV_T) and non-VRES (SNV_T) producers. We further define the part of demand that cannot be supplied at time T by VRES as net demand ($ND_T = D_T - SV_T$). As the grid has to be always in balance, the expected amount of power supplied by non-VRES producers equates the net demand ($SNV_T = ND_T$). Power suppliers cannot produce infinite amounts

[6] How much supply and / or demand is needed for rebalancing the power system at a certain moment.

[7] How much supply and / or demand is available for rebalancing the power system at a certain moment. Later on in the text we define the ramping availability of a power system in terms of reserve margins.

of power as their capacity is restricted by both their total capacity and flexibility levels. Let CV and CNV be the total installed capacity of VRES and, respectively, non-VRES suppliers. The values within which VRES and non-VRES production can vary is comprised between $0 \leq SV_T \leq CV$ and, respectively, $0 \leq SNV_T \leq CNV$. Moreover, non-VRES maximum and minimum capacity to be delivered at time T is influenced by their ramping capability to expand or contract production. Consequently, depending on the flexibility of non-VRES suppliers and on their expected output to be produced at delivery time T, the production boundaries for SNV_T can differ from 0 and CNV such that $0 \leq Min(CNV_T) \leq SNV_T \leq Max(CNV_T) \leq CNV$.

Power demand and supply from VRES are both uncertain variables. To cater the net demand and provide the power system's balancing needs, non-VRES power plants must anticipate their level of production at time T. This anticipation process is done at a period of time t before T, moment when non-VRES suppliers think about their production plan for the future delivery period T. Suppose that non-VRES power plants decide at time t to nominate / produce $N_{t,T}$ at the future time T. When non-VRES power plants nominate $N_{t,T} = 0$ at time t, they only have the option to expand production at time T. As opposed to that, when non-VRES power plants nominate $N_{t,T} = CNV$ at time t, they only have the option to contract production at time T. Depending on the level of $N_{t,T}$, the reserve margin of the system RM_t, which is the difference between the available non-VRES capacity and the expected net demand at a certain moment in time, changes ($RM_t = CNV - E(ND_T)$).

While, non-VRES producers have some liberty in choosing their $N_{t,T}$, they have to take into account the conditions of the market. As at time t the system has to foresee the balancing needs at time T, $N_{(t,T)}$ represents the expected net demand ($E(ND) = E(D_T) - E(SV_T)$). At the moment of delivery T the actual net demand might differ from the expected one by $B = (D_T - SV_T) - (E(D_T) - E(SV_T))$, where B is the demand for balancing power. Note that if at delivery time T $B > 0$, the power market finds itself in a deficit production state, meaning that suppliers must expand production in order to keep the power system in balance. Conversely, if at delivery time T $B < 0$, the power market finds itself in a surplus production state and suppliers must contract production to rebalance the power system.

In this environment of inflexible demand and lack of storage or demand response applications, only non-VRES power plants can supply balancing power[8], by either reducing or expanding at delivery time T their nominated volume $N_{t,T}$. As the capacity to contract or expand production lays within the limits mentioned above, it is exactly within these limits that the balancing needs of the power system can be supplied: $Min(CNV_T) - N_{t,T} \leq B \leq Max(CNV_T) - N_{t,T}$. We define $RM_c = N_{t,T} - (Min)CNV_T$ as the reserve margin to contract production and $RM_e = (Max)CNV_T - N_{t,T}$ as the reserve margin to expand production. In other words, the reserve margin to contract production is defined as the difference between the expected non-VRES output and the lowest limit to which non-VRES suppliers can contract their expected production at a certain moment in time. The reserve margin to expand production is defined as the difference between the highest limit to which non-VRES suppliers can expand their expected production and the expected non-VRES output at a certain moment in time.

5.2.2 Balancing needs, reserve margins and the forward premium in power prices

How do power prices behave in such a market setting? We can consider time t the moment when the forward prices are set and time T the moment when the spot prices are set. In the forward market, power prices are a decreasing function of the reserve margin RM_t. Thus, the lower RM_t is, the higher the forward market price of power is[9]. In the spot market, prices are dependent on both the power system's state at times t, the moment of forward price formation, and T, delivery time. The main uncertainties that exist at moment t with regards to the spot market are the ones surrounding the potential unexpected changes in the forecasted demand and /

[8] For ramp down balancing needs one might argue that also VRES supply can cater to a negative realised B through curtailment. While technically this is feasible, economically VRES suppliers have no incentives in doing so. VRES supply has usually the lowest marginal cost among power producers and, thus, comes first in line for dispatch and the last in line for reducing production.

[9] This explanations is derived from the merit order curve, which ranks for dispatch power producers from the cheapest to the most expensive in basis of their marginal cost.

or VRES supply[10]. At delivery time T, if the spot market finds itself in a situation of supply deficit ($B > 0$), spot power prices will be a decreasing function of RM_e. If instead supply surplus appears at delivery time T ($B < 0$), spot power prices represent an increasing function of RM_c. In other words, if the spot market is in supply deficit, the lower the system's capacity to expand non-VRES production and the higher the value of B, the higher the spot prices will be. In the other situation, if the spot market is in supply surplus, the lower the system's capacity to contract non-VRES supply and the lower the value of B, the lower the spot prices will be.

By building upon this reasoning, we can also explain the forward premium formation in power prices. If there are almost no imbalances at delivery time T, spot power prices should be approximately equal to the forward ones. If instead balancing demand appears, what we can conclude from the previous paragraph is that a positive B will lead to an expected average negative forward premium in power prices. Conversely, a negative B will lead to an expected average positive forward premium in power prices.

We can exemplify this as follows. At time t, based on the supply curve and expected demand, the cheapest available power supply is nominated for dispatched at delivery time T. At this moment t, the values for the reserve margins RM_t, RM_c and RM_e are formed. If deficit imbalance volume ($B > 0$) occurs at delivery time T, supply must be increased. Yet, only the available RM_e can provide the needed supply expansion service, meaning the non-VRES producers who still have spare capacity and who can fast enough increase their production level (flexible producers). Because of the merit order effect, those available flexible producers have a marginal cost equal to or higher than the forward price settled at time t. Therefore, when B is positive, the forward premium in power prices will tend to be on average negative (forward price < spot price).

The situation reverses when at delivery time T the market finds itself with surplus imbalance volume ($B < 0$). In such moments, supply must be decreased and only

[10]We assume that between the forward bidding time t and delivery time T no significant changes in installed VRES and non-VRES capacities occur. We also assume no changes in the pricing and storage level of underlying fuel assets between the two moments in time.

already operating flexible producers (RM_c) can offer supply contraction services. The producers are legally bound to provide the already contracted number of MWs ($N_{t,T}$) at time t at the forward power price. The only situation in which is attractive for such producers to reduce their supply level and fulfil their contractual obligations through buy contracts on the spot market is when the spot power price is lower than the forward one. Consequently, when B is negative, it is likely to observe an average positive forward premium in power prices (forward price > spot price).

The reasoning provided in the previous paragraphs explains theoretically the relationship between the realised demand for balancing and forward premiums in power prices. These paragraphs provide also an explanation for why the energy finance literature finds a varying pattern in the forward premium in power prices. Depending on the sign of B, the surplus or deficit state that the spot market finds itself in at delivery time, different incentives appear for flexibility offering non-VRES producers. As power demand and weather dependent VRES supply are highly volatile, it is not unusual to observe frequent changes in the sign of the forward premium in power prices.

Balancing demand B explains partly the forward premium behaviour in power prices. We say partly since reserve margins play a central role too. Forward power price formation depends on RM_t, which in turn directly impacts RM_c and RM_e. Spot power price formation is directly influenced by the reserve margins RM_c and RM_e. As the reserve margins volumes are known at time t, it results that expectations regarding forward and spot power prices can be formed already at this moment t. In other words, the observed levels of the reserve margins at forward bidding time t can provide clues about what will the forward premium be. The realised imbalance values B are not known at time t and its expected average value is 0. Therefore, at time t, the only information that non-VRES suppliers can rely upon when nominating their production to be sold forward ($N_{t,T}$) are the ones related to the reserve margins RM_t.

To explain how reserve margins can help forming expectations with regards to the forward premium in power prices let us analyse two distinct situations that can appear at forward market bidding time t: i) very high RM_t and ii) very low RM_t. The first situation appears when expected demand $E(D_T)$ is low and expected VRES output $E(SV_T)$ is high, close to its maximal capacity CV. In such moments $ND_{t,T}$ is low resulting in a very high RM_t. This in turns dictates for time T a very low capacity of the system to contract non-VRES supply (very low RM_c) and a very high capacity of the system to expand non-VRES supply (very high RM_e). A very high RM_t translates into a low forward price. However, the same high RM_t leads to an average expectation of even lower spot prices. We explain this as follows. As RM_c has a value close to 0, we know that if a moment of surplus occurs (negative B) there is limited non-VRES capacity in the system to reduce production. This leads to extremely low spot power prices, much lower than the already low forward prices. As the value of RM_e is very high, if at delivery time T deficit is present in spot market, there is a vast non-VRES idle capacity that can be put into operation. This will lead spot power prices to values just slightly higher than the low forward prices. At time t the probabilities of observing a negative or positive sign in B at time T are equal as B is expected to have the value of 0 MW. Therefore, when a power market is confronted with a very high RM_t the forward premium is expected to be positive on average. In the second situation, when RM_t is very low, the situation reverses. Following a similar line of reasoning, when RM_t is very low, we would expect to see on average negative forward premiums. Situations with very low RM_t occur in moments with high expected demand $E(D_T)$ and low expected VRES supply $E(SV_T)$.

Balancing needs (B) and reserve margins (RM_t, RM_c and RM_e) provide a simple and clear way of understanding the mechanisms surrounding the forward premium formation in power prices. Moreover, this perspective also provides an important clarification with regards to which theories explain the forward premium in such non-storable commodity prices: storage theory and / or expectations theory. We detail this aspect in the following subsection.

5.2.3 Forward premiums in power prices: Risk premiums or yields?

The impact of balancing needs and reserve margins on the forward premium in power prices can be split as follows: i) the unforecastable part attributed to balancing needs and ii) the forecastable part attributed to reserve margins. B cannot be forecasted at time t, as it represents unexpected changes in demand and / or VRES supply. Thus, this factor represents a risk that players in power markets bear. We attribute this part of the forward premium formation in power prices to risk premiums. The theoretical framework that we propose indicates that those risk premiums cannot fully explain by themselves the forward premium behaviour in power prices. Reserve margins play a role too. Due to their forecastable nature, reserve margins can be used to predict moments when it is likely to observe on average negative / positive forward premiums in power prices. In this way, they represent a yield, similar to the convenience yield presented in storage theory. When optimising their bids, market players can take advantage of the information that reserve margins embed. Therefore, both expectations theory, through the balancing needs, and storage theory, through reserve margins, explain in part the forward premium formation in prices of non-storable commodities, such as power.

Other papers in the energy finance literature already hinted at the presence of convenience yields in power markets through the levels and prices of underlying fuels. Our theoretical framework comes to expand this view and confirm that, at times, convenience yields are indeed present in power markets. The levels of reserve margins present in a power system depend also on the level and prices of underlying fuels needed for power conversion. Therefore, our line of thinking on the formation of forward premiums in power prices complements and completes what previous literature suggests.

The theoretical framework introduced in this chapter can also be related to the theory of Bessembinder and Lemmon (2002). In that work, the two main factors that impact the forward premium in power prices are the variance and skewness of expected spot prices. We can explain the expected variance and skewness behaviour of spot power price through the balancing needs and reserve margin concepts detailed above. In moments when the reserve margin RM_t is high, the probability distribution function of expected spot prices will likely contain a few extreme low prices, a big majority of moderate-low observations and almost no extreme high prices. In this situation the probability distribution function of the expected spot prices is negatively skewed. In the reversed situation, when the reserve margin RM_t is low, the probability distribution function of expected spot prices will likely contain a few extreme high prices, a big majority of moderate-high observations and almost no extreme low prices. In this situation the distribution function of the expected spot prices is positively skewed. These skewness expectations are in line with both Bessembinder and Lemmon (2002) and with our proposed theoretical framework as we argue that a high RM_t will reduce and a low RM_t will increase the forward premium in power prices. Regarding the variance of expected spot prices, this part represents an uncertainty which can be attributed in part to the unknown values of balancing needs B and in part to reserve margins. The moments when there is not enough flexibility in a power system, moments with either very low or very high RM_t, are the moments when the power prices are more extreme. Thus, in such moments one can expect the variance of spot power prices to be higher than in periods when the market has sufficient flexibility (moderate levels of RM_t). The increased variance of expected spot prices in moments with very low or very high reserve margins RM_t should then reduce the power price forward premium.

Going back to storage and expectations theories, variance and skewness of expected spot prices appear to address each of them one of the two theories. To a certain extent, skewness of expected spot prices is forecastable in moments when power systems do not have enough reserve margin RM_c or RM_e. As a consequence, the impact that the skewness of expected spot power prices has on the forward premium in power prices can be explained through a convenience yield (thus, storage theory). The impact that the variance of expected the spot power prices has on the forward premium formation in power prices can preponderantly be explained through risk premiums (thus, expectations theory). For example higher uncertainty in expected spot prices increases the risks that power market players face. However, the variance of expected spot prices can also be linked to storage theory through the logic of reserve margins. Seen from this perspective, also the theory presented in Bessembinder and Lemmon (2002) supports the presence of both risk premiums and convenience yields in formation of power prices.

The theoretical framework drafted above, together with the insights taken from Bessembinder and Lemmon (2002), leads us to form a set of expectations regarding the forward premium formation in power prices. First, in moments with very low levels of RM_e we expect to observe negative average forward premiums in power prices. In those moments, the low capacity of the system to expand production if needed puts upward pressure on expected spot prices and downward pressure on forward premiums, part that can be explained through the low expected skewness. On top of that, the high variance of expected spot prices in such moments puts further downward pressure on forward premiums. Second, when the capacity of RM_c is very low, we expect to observe positive but close to 0 average forward premiums in power prices. In these moments, the very low capacity of the system to contract production if needed puts downward pressure on spot prices and upward pressure on forward premiums, fact explained by the high expected skewness of spot prices. Nevertheless, the high expected variance of spot prices in such moments decreases the magnitude of the positive forward premiums. To provide empirical support to our theoretical model, in the following section of this chapter we empirically test these expectations regarding the presence of convenience yields in the formation of forward premiums in power prices.

5.3 Empirical tests

5.3.1 Test design

The theoretical framework introduced in this chapter indicates that forward premiums in prices of non-storable commodities cannot be fully explained by risk premiums, and that, through the reserve margin levels present in these markets, convenience yields play an important role too. We acknowledge the fact that in such markets, because of lack of storage, unexpected changes in the demand and / or supply at delivery time alter spot prices and, thus, the forward premium. This situation induces the presence of risk premiums and makes it harder to form expectations regarding the forward premium. Yet, while precise expectations cannot be formed for each moment in time, we argue that the information embedded in the capacity of the non-storable commodity players to increase (RM_e) and / or decrease (RM_c) production at delivery time can be used in forming expectations regarding the mean forward premiums[11].

More specific, in markets trading non-storable commodities, we expected low levels in the reserve margin to expand production (RM_e) to lead to a low and significantly negative average forward premium. In such moments we would expect to observe on average high forward prices and even higher spot prices. On contrary, when the reserve margin to contract production (RM_c) of a non-storable commodity is low, we expect to see a significantly positive average forward premium driven by a number of extreme low spot prices, lower than the average already low forward prices. In other words, our theoretical framework suggests that when the reserve margin of the system (RM_t) is very low or very high, forward prices will be extreme and spot prices even more extreme. As the approximate reserve margin levels are known at forward bidding time, it results that mean forward premiums can be at times forecastable, hence the presence of the convenience yields.

To empirically test these claims, we turn again our attention towards power markets. In these markets, we can identify and isolate moments when the reserve margin to either expand or contract production is very low. Power market reserve margin RM_t and implicitly RM_e and RM_c depend directly on power demand and VRES supply level. As presented in the previous section, the higher the demand, the lower the reserve margin to expand power output, RM_e, and the higher the reserve margin to contract production, RM_c. The opposite holds for VRES supply. The higher the VRES supply, the higher the reserve margin to expand power output, RM_e, and the lower the reserve margin to contract output, RM_c.

[11] We do not propose a forecasting model of forward premiums in prices of non-storable commodities. What we claim is that there are moments in those markets when we should observe certain patterns appearing in the mean forward premium.

Following this logic, the moments when we expect to observe a negative mean forward premium in power prices due to low reserve margins RM_e are the ones when demand is high and VRES supply is low. Using the same logic, the moments when we expect to observe a positive mean forward premium in power prices due to low reserve margins RM_c are the ones when demand is low and VRES supply is high. Moreover, as explained in the previous section using the theory proposed by Bessembinder and Lemmon (2002), we expect the magnitude of the negative mean forward premium due to a low RM_e to be higher than the one of the positive mean forward premium due to a high RM_c. Therefore, to check if the theoretical framework proposed above holds, we need to identify and isolate moments in a power market when either demand is high and VRES supply is low or the opposite, and examine the behaviour of the mean forward premium in those moments.

To perform such a test, we split the delivery moments in a power market in moments with Low Demand, Moderate Demand and High Demand. The 25% of observations with the lowest demand values are regarded as Low Demand hours. The 25% of observations with the highest demand values are regarded as High Demand hours. The remainder of 50% of observations is included in the Moderate Demand category. Using the same criteria, a similar split is done with regards to VRES supply: Low VRES supply (25% of observations), Moderate VRES supply (50% of observations) and High VRES supply (25% of observations). Next, we form data subgroups based on the demand and VRES supply categories. Among the 9 data subgroups formed, we are particularly interested in the ones where a power system is challenged the most, the ones with either low RM_e (High Demand and Low VRES supply) or low RM_c (Low Demand and High VRES supply) levels[12]. After forming the subgroups, we proceed with investigating the mean forward premium, forward price and spot price in each of these subgroups. In the data subgroup with High Demand and Low VRES supply we expect to observe a significantly negative mean forward premium. In the data subgroup with Low Demand and High VRES supply we expect to observe

[12]The focus on these two subgroups is linked to the choice of a relatively high threshold (25% of observations) for moments considered with low / high demand or VRES supply. As moments with both high (low) demand and low (high) VRES supply are less frequent than moments with moderate demand and / or VRES supply, to allow a critical mass to be present in the subgroups of interest, a higher threshold is found appropriate. For robustness reasons, checks are performed at different smaller and higher thresholds levels.

a significantly positive mean forward premium. For this later subgroup, we expect the forward premium to have a positive value closer to 0 EUR/MWh as VRES supply is expected to increase the variance of spot prices and, thus, to put lowering pressure on the mean forward premium.

To further test the viability of the theoretical framework introduced in this chapter, we perform an additional test based on linear regressions. We perform three ordinary leased squares regressions based on the following three equations:

$$ForwardPrice_t = \alpha_{forward} + \beta_{forward} \times Demand_T + \gamma_{forward} \times VRES_T + \epsilon_{forward}, \tag{5.1}$$

$$Spot\ Price_T = \alpha_{spot} + \beta_{spot} \times Demand_T + \gamma_{spot} \times VRES_T + \epsilon_{spot}, \tag{5.2}$$

$$ForwardPremium_{t,T} = \alpha_{premium} + \beta_{premium} \times Demand_T + \gamma_{premium} \times VRES_T + \epsilon_{premium}. \tag{5.3}$$

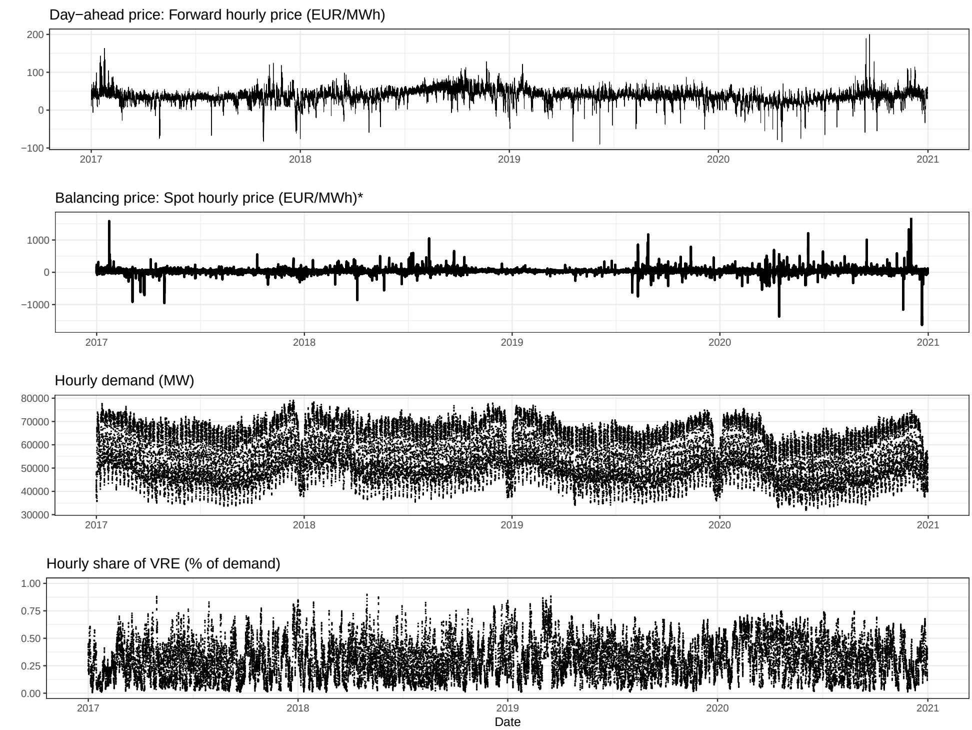
The aim of this set of simple equations is not to prove that they are good models for forecasting power prices or forward premiums in power prices, because they are not[13]. Instead, the goal of these equations is to investigate if the reserve margins, proxied by the levels of demand and VRES supply, do play a role in the forward premium formation in power prices.

Following the logic introduced in the previous paragraphs, in equations 5.1 and 5.2 we expect to see $\beta_{forward}$ significantly lower than β_{spot} and $\gamma_{forward}$ significantly higher than γ_{spot}. Moreover, we expect both $\beta_{forward}$ and β_{spot} to be significantly positive as power prices are expected to increase with demand. In the same way, we

[13]If one would want to develop reliable power price forecasting models for each moment in time, other relevant variables must be included too. For example, in forecasting forward and spot power prices, the price and storage levels of underlying fuels are important determinants. Moreover for spot prices, as explained in the previous section on this chapter, a major explanatory variable of their behaviour is the balancing need at delivery time.

expect both $\gamma_{forward}$ and γ_{spot} to be significantly negative as literature predicts that power prices decrease with VRES output. In other words, with this exercise we aim to prove in another way that a high decrease in the level of either RM_e or RM_c will lead to extreme forward prices and even more extreme spot prices. As a result, in equation 5.3, we expect to observe a significantly negative coefficient for $\beta_{premium}$ and a significantly positive coefficient for $\gamma_{premium}$.

5.3.2 Data



**For readability reasons, the values comprised in the spot price chart was limited to ± 1,700 EUR/MWh. As a consequence, 4 observations above the value of 1,700 EUR/MWh do not appear in the chart.*

Figure 5.1: Overview of the German day-ahead and imbalance power markets in the years 2017 to 2020.

The empirical tests are performed using four years of hourly prices from the German day-ahead and imbalance power markets collected for the years 2017 – 2020. Day-ahead power contracts are essentially hourly forward contracts for delivery next day, and we used them as proxy for forward prices. The imbalance market is operated at delivery time and, thus, we use imbalance prices as proxy for spot prices. The reason of choosing to use short-term power market data is that in those markets, between forward and spot bidding time, the fundamentals of the market remain relatively stable. The approximate demand and expected available VRES and non-VRES supply are known at forward bidding time. Furthermore, prices and storage levels of underlying fuels stay relatively constant between day-ahead and imbalance market bidding times. This stable environment makes it easier to identify and isolate the moments with low reserve margin levels RM_e and RM_c.

Besides price information, to perform the empirical tests we need hourly demand and VRES supply data. The need of including VRES supply data explains our choice of performing the tests on the German power markets. This power market contains a high share of VRES supply in its power mix, making it a prime candidate for our study. Following the rationale proposed by Nicolosi (2010) and Kyritsis et al. (2017), we choose to use actual values rather than forecasted ones for both demand and VRES supply, as forecasted values are prone to errors and as with approaching delivery time estimates get very close to actual values. Another choice we make is to follow the rationale proposed in the third chapter of this dissertation and use the values for the share of VRES supply out of the total demand rather than absolute VRES supply values. Figure 5.1 summarises the data used[14].

Further, table 5.1 presents an overview of the number of observations which fall in each data subgroup. As this table shows, the majority of the observations fall within the categories of either moderate demand, moderate share of VRES supply or both. Within the subgroups of interest, we have 1,644 hourly observations for moments with low reserve margin to expand production (low RM_e, High Demand

[14]Hourly day-ahead price data, together with demand and VRES supply data are collected from www.smard.de. For German imbalance settlement prices (reBAP) we rely on quarter-hourly data collected from www.amprion.net. We use the simple average of the four 15 minutes imbalance prices for obtaining a proxy for the hourly spot power prices.

Table 5.1: Number of hourly observations by selected demand and VRES supply subgroups.

Number of hours	Low VRES	Moderate VRES	High VRES	All VRES
Low Demand	2,726	4,153	1,887 High RM_e Low RM_c	8,766
Moderate Demand	4,395	8,414 Moderate RM_e Moderate RM_c	4,720	17,529
High Demand	1,644 Low RM_e High RM_c	4,963	2,158	8,765
Total Demand	8,765	17,530	8,765	35,060

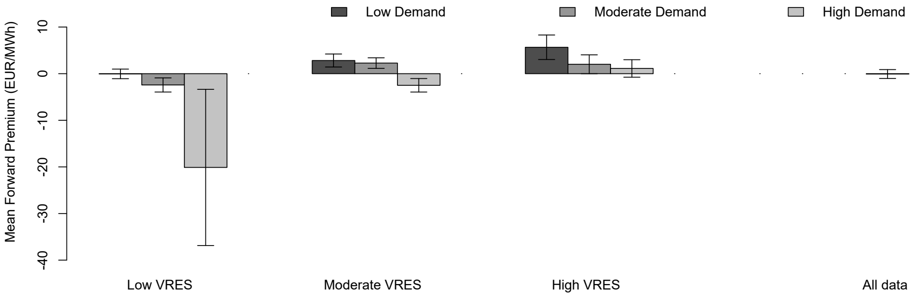
Data used: *German power market hourly observations between 2017–2020.*

and Low VRES) and 1,877 hourly observations for moments with low reserve margin to contract production (low RM_c, Low Demand and High VRES).

5.3.3 Results

The first set of results are exhibited in figure 5.2, which maps visually the mean forward premium and 95% confidence intervals around the mean for each data subgroup formed and for the entire dataset. In this figure we can see that while for the entire dataset the mean forward premium has a value very close to 0 EUR/MWh (mean of −0.1 EUR/MWh and a standard error of the mean of 0.5 EUR/MWh), when we look into the different data subgroups, depending on the implied availability of reserve margins, the mean forward premium values change significantly. We see that with the increase of the share of VRES supply, the mean forward premium increases. We can also notice that with the increase of demand, the mean forward premium decreases.

This confirms the expectations emerged from our theoretical framework.



The vertical lines associated with the means represent the 95% confidence intervals around the mean.

Figure 5.2: Mean forward premium in the German day-ahead versus imbalance power prices for the years 2017−2020, categorised by selected demand and VRES supply subgroups.

For the subgroups that interest us the most, the ones which comprise the moments when the power market is the most challenged, we observe, as expected, the most extreme mean forward premiums. In the data subgroup containing the observations exhibiting Low VRES supply and High Demand (thus, low RM_e), the average forward premium is significantly negative having a value of −20.1 EUR/MWh and a standard error of 8.6 EUR/MWh. It is in this data subgroup that we observe the most extreme mean forward premium. Moreover, the high standard error of the mean also tells us that it is in moments with low reserve margins to expand production that volatility of the mean forward premium is the highest. In the data subgroup containing the observations of the moments with High VRES supply and Low Demand (thus, low RM_c), the average forward premium is significantly positive having a value of 5.7 EUR/MWh and a standard error of 1.3 EUR/MWh. As expected, it is in this data subgroup that we observe the highest mean forward premium. For this data subgroup we observe a relatively higher volatility in the forward premium as compared to data subgroups containing moderate levels of either demand, VRES supply or both.

To provide further insights with regards to the mean forward premium formation, appendix figures 5.3 and 5.4 replicate figure 5.2 in separation for the mean forward and, respectively, the mean spot power price. What these two figures show is that forward and spot prices are on average insignificantly different one from another. For the entire dataset, the average German mean power price is 36.7 EUR/MWh in the forward market (with a standard error of 0.1 EUR/MWh) and 36.8 EUR/MWh in the spot market (with a standard error of 0.5 EUR/MWh[15]). However, when we look at the mean forward and spot prices of selected subgroups, we see that the more extreme mean forward prices are, the even more extreme mean spot prices are.[16]

The results above confirm the intuition that there are moments in time when the option to expand production is more valuable than the one to contract it, and vice-versa. We notice that the more a reserve margin is low, the more extreme the mean absolute value of the forward premium is. Another important particularity that arises from the results is that, for similar low levels of RM_e and RM_c, the pay-off of the options to expand or contract production are not the same. For the German power market the value of the option to expand production when RM_e is low appears to be higher than the value of the option to contract production when RM_c is low. We draw this conclusion from the absolute forward premium means and confidence intervals around the means calculated for the most extreme data subgroups.

Moving towards the second empirical test performed, the results based on the equations 5.1, 5.2 and 5.3 are presented in the table 5.2. These results come to further confirm what the previous test shows. On one hand, the β coefficients indicate that demand is increasing both spot and forward power prices, with the impact being significantly stronger on spot power prices. This leads to a significantly negative $\beta_{premium}$ coefficient, meaning that demand is lowering the forward premium. On the other hand, the γ coefficients indicate a significant negative impact of the share

[15] As expected, spot prices exhibit a higher volatility.

[16] When performing robustness checks using different threshold levels for splitting the dataset into subgroups, results presented in figures 5.2, 5.3 and 5.4 do not differ significantly.

of VRES supply on both spot and forward power prices, with the impact being significantly stronger on spot power prices. This leads to a significantly positive $\gamma_{premium}$ coefficient, meaning that the share of VRES supply is increasing the forward premium. We reiterate that these regressions are only used in this piece of research as an indication of the average relation between the reserve margins present in a power system and the forward premium. The lack of forecasting power of forward premiums or spot power prices of such models is put in evidence also by the low R^2 values of these regressions. Especially for the spot power prices, where the hourly balancing needs play a major role in the price formation, these regressions should not be used for forecasting purposes.

Table 5.2: Impact of demand and share of VRES supply on German forward prices, spot prices and forward premiums.

	Forward price	Spot price	Forward premium
	Equation 5.1	Equation 5.2	Equation 5.3
Constant (α)	6.635***	−5.625**	12.260***
	(0.331)	(2.867)	(2.854)
Demand (MW) (β)	0.0009***	0.0012***	−0.0003***
	(0.00001)	(0.00005)	(0.00005)
Share of VRES supply (γ)	−68.67***	−86.34***	17.67***
	(0.33)	(2.90)	(2.88)
Observations	35,060	35,060	35,060
Adjusted R^2	0.651	0.040	0.002

Notes: *$p<0.1$; **$p<0.05$; ***$p<0.01$; *Standard errors in parentheses; German day-ahead prices between 2017-2020 are used as proxy for forward prices; German imbalance prices between 2017-2020 are used as proxy for spot prices.*

Both empirical tests performed show that by using the logic of reserve margins we can form expectations regarding the mean forward premium in power prices. This proves that there is a yield that can be earned by power market players in moments when the reserve margin to either increase (RM_e) or decrease production (RM_c) is low. This empirical evidence confirms our claim that convenience yields based on reserve margins are present and play a role in forward premium formation in prices of non-storable commodities such as power.

5.4 Chapter's concluding remarks and practical relevance

Understanding the forward premium behaviour in financials prices is essential for players who operate in such markets. This fact is recognized and heavily scrutinized by the financial literature. Yet, for a certain category of financial markets, namely markets for non-storable commodities, the existent literature still presents us diverging results, making them harder to interpret and use in practice. Moreover, because of the lack of storage in those markets, academic papers investigating price movements of non-storable commodities predominantly analyse the topic from the expectations theory perspective. As a consequence, most of those papers associate the formation of forward premiums in prices of non-storable commodities to risk premiums, without questioning if other factors, such as convenience yields detailed in storage theory, play a role too. To improve our understanding on this matter, this chapter introduces and empirically tests a fundamentals based theoretical framework aimed at comprehensively explaining the determinants of forward premiums in prices of non-storable commodities.

The proposed theory revolves around the varying balancing needs and reserve margin levels present at each moment in a market. We argue that the balancing needs induce risk premiums in prices of non-storable commodities as they represent unexpected changes in demand and / or supply. Yet, balancing needs are only part of the story. Reserve margins, or in other words the capacities of producers to adjust their output levels in order to flexibly keep demand and supply in balance at all delivery times, represent the other key forward premium determinant in prices of non-storable commodities. As the approximate reserve margin levels are known at forward market bidding time, we further show that the impact of reserve margins on forward premiums in prices of non-storable commodities can be translated into a yield that market players can earn at certain moments in time. Using this logic, we provide both theoretical and empirical support for the presence of convenience yields in markets trading non-storable commodities. The theoretical framework introduced in this chapter suggests that, besides expectations theory, also storage theory applies for markets trading non-storable commodities. More specifically, we show that risk premiums alone cannot fully explain the forward premiums in prices of non-storable commodities as convenience yields determine them too.

To exemplify the rationale of our theoretical framework and to empirically test it, we take power as a representative example for the class of non-storable commodities[17]. For this commodity we show both theoretically and empirically that the level of reserve margins can indicate certain moments when the mean forward premium is expected to be positive or negative. When the reserve margin to expand output at delivery is low, moments associated with low VRES supply and high demand levels, we predict and observe a significantly negative mean forward premium. The opposite, a significantly positive mean forward premium is predicted and observed when the reserve margin to contract output at delivery is low, moments associated with high volumes of supply from VRES and low demand levels.

This simple but comprehensive view on forward premium behaviour in prices of non-storable commodities has important practical relevance. The convenience yields induced by reserve margins can present flexible market players with arbitrage opportunities. In moments when the expected reserve margin to expand production at delivery time is low, it appears to be more profitable for a market player to sell more (producer) or buy less (consumer) in the spot market than in the forward one. Conversely, in moments when the expected reserve margin to contract production at delivery time is low, it appears to be more profitable for a market player to sell less (producer) or buy more (consumer) in the spot market than in the forward one.

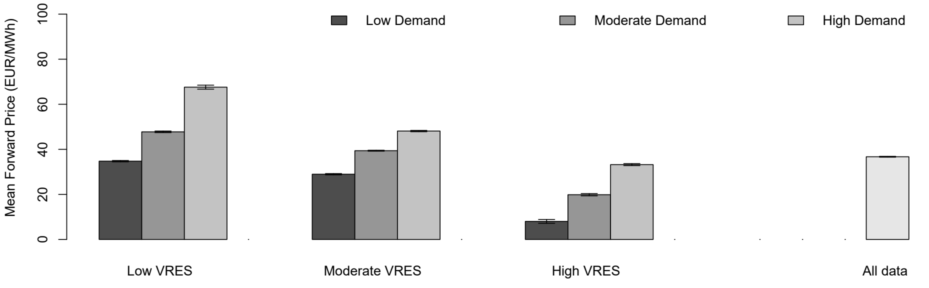
The exploitation of the reserve margin induced convenience yields is closely linked to real options theory. Flexibility providers, which in power markets can be exemplified by operators of storage facilities or demand response applications, have the

[17]Most power markets still lack in significant quantities of direct storage capacities.

options to expand and contract supply / demand at delivery time. They can do this up their maximum production or consumption capacity. If one flexible supplier sells all her production through the forward market, in the spot market she can only contract production. If the flexible supplier does not sell any of her capacity through the forward market, in the spot market she can only expand production. Another alternative is to sell partly the production through the forward market and be positioned in the spot market, if needed, for both expanding or contracting production. Otherwise stated, the more a flexible producer sells forward her output the more she has the option to contract production and the less she has the option to expand production at delivery time. What the reserve margin related convenience yields show is that in certain moments in time the option to contract production can be more valuable than the option to expand production, and the other way around. The value of these options is closely related to the specific state in which a market finds itself in at a certain moment in time. Moreover, the results of this chapter show that the valuations of the two options differ even when we look at similar levels of low reserve margins to expand or contract production. This suggests that the options to expand and contract production do not have mirrored pay-offs and that, as a consequence, flexibility offering assets should value them in separation at each moment in time in order to fully take advantage of them. We exemplify these options only for the supply side of flexibility providers. However, a similar logic can be applied to the real options that operators of demand response applications have.

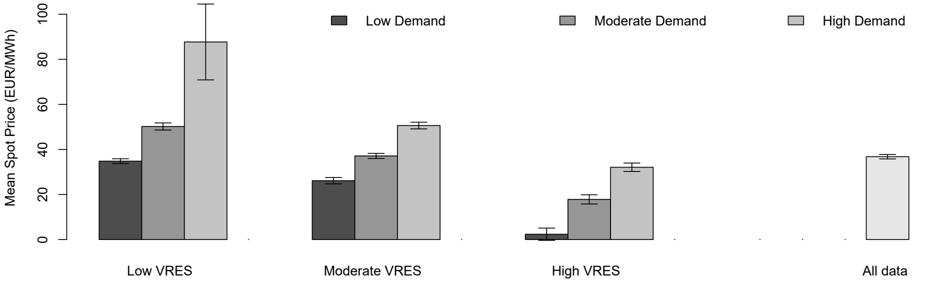
Continuing with the example on power markets, it is exactly in moments with low reserve margin to either expand or contract production at delivery time that the flexibility of a power market is challenged the most. Thus, by exploiting the predictability of the convenience yields induced by reserve margins, power flexibility providers can both generate profit and provide the needed flexibility to the power system. As one of the main policy goals in power systems is to ensure sufficient market flexibility, policy makers could use the occurrence frequency of convenience yields induced by reserve margins as an indication for the (in)flexibility of the power markets they oversee. A frequent occurrence of such moments could potentially signal the fact that a power market is not optimally designed to fully utilise the flexibility already embedded in its supply and demand. It could also signal the need for new investments in flexibility offering assets. Furthermore, with the steady increase of VRES supply installed capacity in various power markets, the presence of convenience yields induced by low reserve margin levels will only increase. Because of their weather dependent production, a higher share of VRES supply in a power market increases the flexibility needs of that market and also the frequency of moments with very low reserve margins to expand or contract output. Therefore, unless the increase in VRES supply is complemented by investments in flexibility offering assets, we will observe that power markets will become increasingly inflexible.

5.5 Additional figures



The lines associated with the means represent the 95% confidence intervals around the mean.

Figure 5.3: Mean German forward (day-ahead) prices between 2017−2020 by demand and VRES supply subgroups.



The lines associated with the means represent the 95% confidence intervals around the mean.

Figure 5.4: Mean German spot (imbalance) prices between 2017−2020 by demand and VRES supply subgroups.

Chapter 6

Conclusions

This concluding chapter presents the main takeaways of the dissertation. Throughout this chapter we revisit the conclusions exposed in the previous chapters. The first chapter introduces the concept of (in)flexibility in power markets with VRES supply and the reasons why we need to research this topic. We define power system's (in)flexibility as the (in)ability of a power system to easily adjust its production and / or consumption level to variations in demand and supply from VRES. As the first chapter details, (in)flexibility represents one of the main issues that current power markets face. In the race towards obtaining a decarbonised power system it is important to ensure that future power markets are flexible enough, such that they can keep the power grid in balance at all times. The inflexibility issues present in power systems can be exacerbated by the installation of a high level of weather dependent VRES supply, as i) their output variation has to be constantly counterbalanced through alterations in demand and / or supply and as ii) the deployment of economically feasible flexibility offering assets, such as storage facilities or demand response applications, is still limited. Therefore, in order to be able to ensure the flexibility of tomorrow's power markets, we need to research and better understand the relation between VRES supply and the need for power flexibility. This dissertation does exactly this. Through the four studies detailed in chapters 2 to 5, this thesis investigates how supply from VRES alters the flexibility needs of power markets. The more we know about this topic, the better we can prepare our power markets to incorporate a higher capacity of VRES and flexibility offering assets.

The second chapter presents a piece of research which investigates the impact of VRES supply on the flexibility of the German day-ahead power market. In this study we identify and isolate moments in which a low share and, respectively, a high share of VRES supply is present in the German day-ahead power market. Next, using extreme value theory, we investigate the shape of the tails of day-ahead power price probability distribution function. This technique allows us to assess how the extreme power prices behave under different levels of flexibility present in the German power system. The current German power system becomes more inflexible when the level of VRES supply and the reserve margin[1] are either both high or low. We argue that ramp up inflexibility and the occurrence of extreme high prices are associated with moments when both the VRES output and the reserve margin are low. In the same way, we argue that ramp down inflexibility and the occurrence of extreme low prices are associated with moments when both VRES output and the reserve margin are high.

As opposed to other studies that use extreme value theory on power markets, we disentangle the left tail from the right one. This approach allows us to investigate separately the impact of VRES supply at each of the two extremities of power price probability distribution function. Furthermore, in addition to analysing this aspect for VRES supply, we also do the same analysis in separation for wind and for solar photovoltaic power output. This further split allows us to verify if the results hold for both technologies that VRES supply comprises.

This second chapter provides evidence which supports the fact that at least for the German power market in moments when the supply of flexibility is low, the power price probability distribution function exhibits fatter tails. This evidence is found for both the wind and solar photovoltaic output. As expected, results indicate that i) during periods with high VRES share, German day-ahead power price left tail is fatter than right tail and the difference in fatness is more pronounced when

[1] In this chapter we define the reserve margin as the idle non weather dependent conventional production capacity that can be put into operation when required. In chapter 5, we further differentiate the reserve margin concept into reserve margin to either expand or contract production.

demand is lower, and ii) during periods with low share of VRES, German day-ahead power price right tail is fatter than left tail and the difference in fatness is more pronounced when demand is higher. While the energy finance literature already documented the fact that power prices do not follow the normal distribution, the results of this chapter are novel in the sense that they demonstrate that the level of tail fatness of power prices, of how non-normally distributed the prices are, can be forecasted. This information is useful for risk managers as it indicates that hedging needs vary with the expected demand and supply conditions. Another implication from the results of this chapter is that risk models in power markets should be developed in such a way that they can adapt to the continuously changing demand and supply factors. Moreover, this chapter teaches us that conditional tail estimates can help with assessing bidding strategies and the valuation of flexibility offering assets.

Besides its practical relevance, the second chapter is relevant for policy makers too. For the German day-ahead power market this piece of research provides information on the occurrence patterns of extreme prices depending on VRES supply and demand conditions. This information can be used by policy makers to better understand what are the flexibility needs of that power market. For example, one key takeaway is that with an increasing VRES supply, we will see more often extreme low prices in the German day-ahead power market. This translates into higher downward ramping flexibility requirements for this power market. Further studies replicating this piece of research for other jurisdictions can be used to obtain an indication on the flexibility needs in other power markets. Additionally, using a higher frequency dataset could also increase the accuracy of the results.

Another natural continuation of the work presented in the second chapter is the piece of research displayed in the third chapter of the dissertation. Throughout the second chapter we find that VRES supply impacts the flexibility of the German power market by changing the mean, the volatility and the probability distribution function of power prices. Yet, the literature does not provide us with information about the magnitude of the change that VRES supply imposes on power prices at different moments in time. Using a panel quantile regression approach, a novel technique for the energy finance literature, we argue that the speed with which power prices are reduced by the introduction of VRES supply changes depending on how flexibility constrained a power market is at a certain moment in time. In other words, we claim that in moments when the need for flexibility is higher, the price reducing impact of an increase in the share of supply from VRES will be higher than in moments when the flexibility needs of a power market are moderate or low.

The results of this third chapter confirm our expectations and demonstrate for the two markets investigated that in moments when prices are already very low or very high, an increase in the share of VRES supply will lead to a much higher power price reduction than in other moments. These results hold for both investigated markets: German and Spanish day-ahead power markets. Yet, there are noticeable differences between the results obtained for the two markets. When power prices are extreme, a certain increase in the share of VRES supply leads to a higher price reduction in the relatively less flexible German power market as compared to the relatively more flexible Spanish power market. This suggests the fact that the higher the flexibility of a power system to adapt to changes in demand and / or supply, the lower the variability of the power price reduction induced by changes VRES supply. Another important observation is that, when we analyse the two markets, only for the more inflexible German power market the interaction between the share of VRES supply and demand appears to add value in understanding day-ahead power price behaviour. This result suggests that, in a flexible power market, conventional suppliers can more easily adapt their output levels in order to counterbalance changes in VRES supply. In this way the interplay between demand and share of VRES supply becomes less relevant for power price formation on flexible power markets.

The third chapter's message for policy makers is that "one size fits all" principle cannot be applied to power market policies. Regulators should carefully scrutinize the particularities, especially the pre-existent flexibility conditions, of each power system when they look to adjust policy measures. Furthermore, the results of the third chapter provide also insights to operators of flexibility offering assets. Those assets are in fact real options and their values increase in moments when the range of expected power prices becomes higher. The methodological framework used in the third chapter shows that the output from VRES supply should be included in models which attempt to predict the range within which power prices are expected to move. Furthermore, the model introduces a new way on how one can simultaneously predict expected power price ranges for all hours within a day. We call for further research on applying this technique and on developing upon this methodological framework on different power markets.

In the fourth chapter we move to an analysis on how the introduction of VRES supply in a power system changes the relation between forward and spot power prices. Until the emergence of wind and solar technologies, uncertainties in power markets came mostly from the demand side of the market. With the introduction of VRES, a part of the supply side in power markets becomes a source of uncertainty too. We argue that the structural changes in power prices imposed by this new source of uncertainty impacts the forward premium in power prices. To investigate this claim, in the fourth chapter we use a simulated power market dataset which comprises price observations for three almost identical power systems. The only difference between the three power systems is represented by the share of VRES supply. In each power market design investigated, a sequence of two power markets are operated: forward and spot power market. The dataset used allows us to observe, in a controlled environment, the differences in the forward premium for the three generated markets.

Making use of the theory proposed in the seminal paper of Bessembinder and Lemmon (2002) and of the knowledge provided by the previous chapters of this dissertation, in the fourth chapter we show for the investigated setting that an increase in the share of VRES supply in a power system leads to a decrease in the power price forward premium. Bessembinder and Lemmon (2002) demonstrate that in power markets the skewness of expected spot prices increases the forward premium and that the variance of expected spot prices decreases it. However, this model was develop at a time where VRES output represented an insignificant part of the generation mix in power systems. In our simulated market design we add VRES supply into the rationale of Bessembinder and Lemmon (2002). By doing so, we show that VRES supply adds uncertainty into power markets and, in this way, increases the variance of spot prices. Additionally, VRES supply lowers the skewness of power prices as it increases the frequency of occurrence of extreme low prices. Another aspect demonstrated through this piece of research is the fact that in power markets without storage, the forward basis, defined as the difference between current forward prices and current spot prices, contains information about future spot prices. This result is in line with what the energy finance literature predicts, and suggests that the forward basis in power markets does not contain information about realised risk premiums.

Similarly to the previous chapters, the fourth chapter indicates that with the increase of VRES supply, there is need for higher levels of flexibility in power markets to counterbalance the increased uncertainties. One of the conclusions that can be drawn from the fourth chapter is that in a world with VRES supply, producers are on average more likely to benefit from selling their output forward than in a world without VRES supply. Yet, when extrapolating this conclusion into real power markets, as we learned from the third chapter, we should pay attention to the particularities of each power market we are looking at and on the market conditions at each moment in time. For example, in a power market which already contains a significant amount of flexibility offering assets, those assets would come to complement the increased VRES driven uncertainty and lowered expected spot price skewness. Moreover, the simulated market design does not consider the ramping inflexibility that some producers have in real power markets. A further study considering these particularities would increase our knowledge about how VRES supply impacts the forward premium in power prices.

The fifth chapter continues to investigate the relationship between forward and spot power prices in today's power markets. More specifically, this chapter introduces a theoretical framework which explains the forward premium formation in prices of non-storable commodities, such as power. The energy finance literature provides us with a multitude of empirical studies on the forward premium in power prices. Yet, there is no consensus in the literature on what explains its varying and different patterns observed. Because of the divergent results, it is hard for practitioners to use the information that energy finance literature provides them with on this topic. The fifth chapter of this dissertation comes to overcome this drawback of the pre-existing literature.

The theory proposed in the fifth chapter revolves around the balancing needs and the reserve margins of power systems. The balancing needs at delivery time induce risk premiums in power prices. However, they represent only part of the story as reserve margins to expand or contract production play a determinant role too in the forward premium formation in power prices. We use the information that reserve margins are forecastable at forward bidding time to demonstrate both theoretically and empirically that in power markets which have a certain degree of inflexibility the forward premium cannot be explained solely by a risk premium. At times, a reserve margins induced yield, similar to the convenience yield, plays an important role too. In this way, the fifth chapter shows that not only the expectations theory can be applied to non-storable commodities such as power, but also storage theory.

The conclusions of the fifth chapter have practical relevance for power market players. They show that there are moments in time for which we can forecast that on average the forward power price premium will be positive / negative. This information is crucial for power traders as it indicates moments when it is more advantageous to sell or buy more power on the forward market rather than on the spot market, and the opposite. Such strategies based on the reserve margin induced yield also enrich the field of real options. Flexibility providers, such as owners of storage facilities or demand response applications, have the options to expand or contract supply or demand at each moment in time. The more they sell / buy forward their output, the more they have the option to contract their supply / demand and the less they have have the option to expand their supply / demand at delivery time. We prove that there are moments in time when the option to contract supply / demand is more valuable than the one to expand supply / demand, and vice-versa. Moreover, we prove for the German power markets that these two options do not have symmetric valuations for similar levels of low reserve margins to either expand or contract production. Therefore, these two options must be treated and valued in separation.

Besides practitioners, also policy makers can make use of the theoretical framework presented in the fifth chapter. The frequent presence of reserve margins in a power market points towards the inflexibility of that market. As one of the main policy goals in power markets is to ensure market flexibility, policy makers could use the appearance frequency of reserve margin induced yields as an indicator for how flexible the power market they supervise is. Moreover, the higher the share of VRES supply is and the more inflexible a power market is, the more likely it is to observe frequent forecastable reserve margin induced yields in power markets. This means that, as most power markets tend to encourage the deployment of additional VRES installations, unless additional flexible supply and / or demand is added too, these yields will likely appear more and more frequently in power markets.

There is a key message that emerges from the four studies performed: in a power market, the higher is the share of VRES supply, the higher are the flexibility needs of that market. Therefore, if we want to decarbonise our power markets, the solution of adding more supply from VRES must be corroborated with the inclusion of sufficient supply of flexibility. The positive news is that with the increase in VRES supply, the opportunities for flexibility offering assets also increase. As shown throughout the dissertation, there are ways in which these opportunities can be foreseen and taken advantage of. Owners of flexibility offering assets could use the clues highlighted throughout this dissertation to improve their bidding strategies. In doing so, they will not only raise their profitability, but will also increase the flexibility of power systems and ensure that a higher share of VRES supply can be incorporated into power systems.

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Summary

With the deployment of variable renewable sources such as wind or photovoltaic solar power, electricity markets, or power markets as they are referred throughout this dissertation, are facing increasing inflexibility constraints, or, in other words, increasing difficulties to swiftly adjust demand or supply in order to keep the grid in balance at all times. The weather dependent variable renewable technologies introduce new challenges into power systems, which now must cater not only the relatively inflexible power demand but also the variation in wind and photovoltaic solar supply. These challenges are exacerbated by the fact that flexibility offering assets, such as storage facilities or demand response applications, are still not deployed at a large scale. This context of increased demand-supply uncertainty puts pressure on power systems to transform themselves such that they can always flexibly adjust their output and keep the grid in balance.

As their output is only set to increase, it is important to understand how supply from variable renewable sources reshapes power markets and their flexibility needs. To shed more light on this topic, this present dissertation puts forward a series of four studies that scrutinise the flexibility or, better said, the inflexibility of power markets in relation to the growing supply from variable renewable sources. Following an initial chapter that presents the concept of (in)flexibility in power markets, the dissertation introduces evidence on how variable renewable supply puts pressure on the power market's ability to rapidly adjust its output when needed. First, the dissertation teaches us that variable renewable supply, besides reducing the mean and changing the volatility of power prices, also affects the probability distribution function of those prices. The more wind and / or solar photovoltaic supply we have in

a power system, the more likely it is to observe extreme low power prices. Second, by using a novel methodology for the energy finance literature, the dissertation provides empirical evidence on the fact that the speed with which variable renewable supply reduces power prices depends on the flexibility constraints that the market has at each particular moment in time. Third, by using simulated power market data, this present work proves that variable renewable supply alters the relation between forward and spot power prices and reduces the power price forward premium. Fourth, through a theoretical framework, the dissertation provides a rationale for what explains the forward premium in power prices showing that convenience yields are present in these markets and that flexibility plays a central role in their formation.

There is one key message that emerges from this dissertation: in a world with more variable renewable supply the flexibility needs of power markets increase. Thus, to integrate more wind and / or solar photovoltaic power supply, we need to incentivise the deployment of flexibility offering assets. Besides building upon the existing energy finance literature, the insights presented throughout this work aim to help policy makers better assess the flexibility needs of the power markets they supervise. Moreover, the studies performed can help practitioners such as risk managers or operators of flexibility offering assets in optimizing their bidding strategies. The results of these studies show ways in which the occurrence of extreme prices can be signalled. By taking advantage of these signals, practitioners not only can improve their profitability and the value of their real options to buy or sell power, but they can also help with providing the needed power market flexibility.

Nederlandse Samenvatting (Summary in Dutch)

Met de ontplooiing van variabele hernieuwbare energiebronnen zoals wind of fotovoltaïsche zonne-energie, krijgen de elektriciteitsmarkten – of energiemarkten, zoals ze in dit proefschrift worden genoemd – te maken met steeds grotere inflexibiliteitsbeperkingen. Met andere woorden: het wordt steeds moeilijker om de vraag of het aanbod snel aan te passen teneinde het elektriciteitsnet op elk moment in evenwicht te houden. De weersafhankelijke variabele hernieuwbare technologieën zorgen voor nieuwe uitdagingen voor de elektriciteitssystemen, die nu niet alleen moeten inspelen op de relatief inflexibele vraag naar elektriciteit, maar ook op de variatie in het aanbod van wind- en fotovoltaïsche zonne-energie. Deze uitdagingen worden nog eens versterkt door het feit dat flexibiliteitsmiddelen, zoals opslagfaciliteiten of vraagresponstoepassingen, nog steeds niet op grote schaal worden ingezet. Deze context van toegenomen onzekerheid in vraag en aanbod zet de elektriciteitssystemen onder druk om zodanig te worden omgevormd dat zij hun productie altijd flexibel kunnen aanpassen en het net in evenwicht kunnen houden.

Aangezien de productie ervan alleen maar zal toenemen, is het belangrijk om te begrijpen hoe het aanbod van variabele hernieuwbare bronnen de energiemarkten en hun flexibiliteitsbehoeften verandert. Om dit onderwerp meer in het licht te brengen, worden in dit proefschrift vier studies gepresenteerd waarin de flexibiliteit, of beter gezegd de inflexibiliteit, van de energiemarkten wordt onderzocht met betrekking tot het toenemende aanbod van variabele hernieuwbare bronnen. Na een inleidend hoofdstuk waarin het concept van (in)flexibiliteit op de energiemarkten wordt gepresenteerd, wordt in het proefschrift aangetoond hoe het aanbod van variabele hernieuwbare energie druk uitoefent op het vermogen van de energiemarkt om de productie snel aan te passen wanneer dat nodig is. Ten eerste leert het proefschrift ons dat een variabel hernieuwbaar aanbod niet alleen het gemiddelde van de elektriciteitsprijzen verlaagt en de volatiliteit ervan verandert, maar ook de waarschijnlijkheidsverdelingsfunctie van die prijzen beïnvloedt. Hoe meer wind- en/of fotovoltaïsch aanbod we in een stroomsysteem hebben, hoe groter de kans op extreem lage stroomprijzen. Ten tweede: door gebruik te maken van een nieuwe methodiek binnen de literatuur over energiefinanciering, levert het proefschrift empirisch bewijs voor het feit dat de snelheid waarmee een variabel aanbod van hernieuwbare energie de elektriciteitsprijzen doet dalen, afhangt van de flexibiliteitsbeperkingen die de markt op elk specifiek moment kent. Ten derde wordt in dit werk aan de hand van experimentele resultaten bewezen dat een variabel hernieuwbaar aanbod de relatie tussen termijn- en contantprijzen verandert en de termijnpremie voor de elektriciteitsprijs omlaag brengt. Ten vierde levert het proefschrift, aan de hand van een theoretisch kader, een verklaring voor de termijnpremie op de elektriciteitsprijzen, waaruit blijkt dat er in deze markten convenience yields bestaan en dat flexibiliteit een centrale rol speelt bij de vorming daarvan.

Er is één belangrijke conclusie die uit dit proefschrift naar voren komt: in een wereld met een variabeler aanbod van hernieuwbare energie nemen de flexibiliteitsbehoeften van de energiemarkten toe. Om meer wind- en/of fotovoltaïsche energie te integreren, moeten we dus de inzet van flexibiliteitsmiddelen stimuleren. De in dit werk gepresenteerde inzichten bouwen niet alleen voort op de bestaande literatuur over energiefinanciering. Ze zijn ook bedoeld om beleidsmakers te helpen de flexibiliteitsbehoeften van de energiemarkten waarop zij toezicht houden, beter in te schatten. Bovendien kunnen de uitgevoerde studies mensen uit de praktijk, zoals risicomanagers of exploitanten van flexibiliteitsmiddelen, helpen bij het optimaliseren van hun biedstrategieën. De resultaten van deze studies laten manieren zien waarop het optreden van extreme prijzen kan worden gesignaleerd. Door van deze signalen gebruik te maken, kunnen de exploitanten niet alleen hun winstgevendheid en de waarde van hun reële opties om stroom te kopen of te verkopen verbeteren. Ook kunnen zij zo helpen om de benodigde flexibiliteit op de stroommarkt tot stand te brengen.

About the Author

Vasile Cristian Ştet̡ was born in 1990 in Sighetu Marmaţiei, Romania. He holds a BSc in Business Administration from Babeş-Bolyai University in Romania (2011), being the valedictorian of a cohort of more than 500 students. Cristian also holds a MSc in Finance and Investments from Rotterdam School of Management, Erasmus University Rotterdam (2013). Within his MSc studies he spent a semester at Ross School of Business, University of Michigan, taking classes within their MBA programme (2012). In 2017, under the supervision of Han J.T.J Smit and Ronald Huisman, Cristian started his journey as a PhD Candidate in Energy Finance within the Business Economics Department, Finance Group at Erasmus School of Economics, Erasmus University Rotterdam. Before embarking on his PhD track, he worked in the financial world at ABN AMRO, Rabobank and EOS Investment Management, where he acquired experience in the energy field from an advisory point of view. He also gained practical experience by managing a small family owned business within the hospitality sector.

His main fields of research interests revolve around energy economics, energy finance and sustainability. More specifically, his research focuses on providing a better understanding on the flexibility needs of power systems in the context of an increasing share of variable renewable sources. Cristian's work was presented at international academic conferences held in Argentina, China, Greece, New Zealand, The Netherlands and United States of America. During his PhD, he was member of Erasmus Research

Institute of Management PhD Council and of Erasmus School of Economics PhD Council. Moreover, he is currently a Council member and Student Representative of the International Association for Energy Economics. In parallel with developing his research, Cristian dedicated time to teaching the Energy Finance (2017-2019) and Finance for Sustainability (2020) Seminars alongside Ronald Huisman.

Author's Portfolio

Research papers

- ✧ Fat tails due to variable renewables and insufficient flexibility. Evidence from Germany, in collaboration with Huisman, Ronald and Kyritsis, Evangelos;
- ✧ How panel quantile regressions may help to better accommodate the varying supply from renewable energy sources, in collaboration with Huisman, Ronald;
- ✧ Simulating forward pricing in power markets with renewable energy, in collaboration with Huisman, Ronald and Koolen, Derck;
- ✧ A (re)view on the forward premium in prices of non-storable commodities. Evidence from power markets, in collaboration with Huisman, Ronald.

Conference presentations

- ✧ *2018 International Conference on Energy Finance.* Beijing, China (14-15 April 2018);
- ✧ 3rd *HAEE Annual Conference, Energy Transition: European and Global Perspectives*, Athens, Greece (3-5 May 2018);
- ✧ 41st *IAEE International Conference, Transforming Energy Markets*, Groningen, The Netherlands (10-13 June 2018);
- ✧ 4th *IAFOR Independence and Interdependence Conference, Clean and Affordable Energy Session*, Honolulu, United States of America (3-5 January 2019);

- 7^{th} *ELAEE Conference, Decarbonization, Efficiency and Affordability: New Energy Markets in Latin America*, Buenos Aires, Argentina (10-12 March 2019);
- 7^{th} *IAEE Asia-Oceania Conference, Energy in Transition*, Auckland, New Zealand, February 12-15, 2020.
- 1^{st} *IAEE Online International Conference, Energy, COVID and Climate Change*, June 7-9, 2021.

Other presentations and publications

- Presentation: *PhD Day at Finance Departments of Erasmus School of Economics and Rotterdam School of Management*, Rotterdam, The Netherlands (10 October 2018);
- Presentation: *PhD Seminar Series at Finance Departments of Erasmus School of Economics and Rotterdam School of Management*, Rotterdam, The Netherlands (6 July 2020);
- Presentation: *PhD Seminar Series at Finance Departments of Erasmus School of Economics and Rotterdam School of Management*, Rotterdam, The Netherlands (31 May 2021);
- Publication: Ştet̡, C. Oil prices in negative territory? In power markets frequent negative prices could become the norm. *IAEE Energy Forum, Special Covid-19 Edition 2020, 17-19.*

Teaching activities

- Finance part of Energy Markets, Law, Regulation and Finance Course at University of Groningen (Autumn 2017);
- Seminar Energy Finance at Erasmus School of Economics, Erasmus University Rotterdam (Autumn 2017, Autumn 2018, and Autumn 2019);
- Seminar Finance for Sustainability at Erasmus School of Economics, Erasmus University Rotterdam (Autumn 2020).

Administrative positions

- Erasmus Research Institute of Management PhD Council Member 2017-2018;
- Erasmus School of Economics PhD Council Member 2018-2019;
- Part of organization team of PhD Seminar Series at Finance Departments of Erasmus School of Economics and Rotterdam School of Management 2020-2021;
- International Association for Energy Economics Council Member and Student Representative 2021-2022.

PhD courses and certificates

- Topics in Philosophy of Science
- Mathematics and Statistics
- Statistical Methods
- Economic Foundations
- Fundamentals of Qualitative Research
- Planning Under Uncertainty (Winter School)
- Topics in FinTech
- Necessary Condition Analysis: Theory and Practice
- Mediation, Moderation, and Conditional Process Modelling
- Introduction to Data Analysis with R
- Advanced Data Analysis with R
- Scientific Integrity
- Publishing Strategy
- English Cambridge Proficiency Certificate (CPE, C2)

- ✧ Basic Didactic Skills
- ✧ Group Dynamics Didactic Skills

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The ERIM PhD Series contains PhD dissertations in the field of Research in Management defended at Erasmus University Rotterdam and supervised by senior researchers affiliated to the Erasmus Research Institute of Management (ERIM). All dissertations in the ERIM PhD Series are available in full text through the ERIM Electronic Series Portal: http://repub.eur.nl/pub. ERIM is the joint research institute of the Rotterdam School of Management (RSM) and the Erasmus School of Economics (ESE) at the Erasmus University Rotterdam (EUR).

Dissertations in the last four years

Ahmadi, S., A motivational perspective to decision-making and behavior in organizations, Promotors: Prof. J.J.P. Jansen & Dr T.J.M. Mom, EPS-2019-477-S&E, https://repub.eur.nl/pub/116727

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Anantavrasilp, S., Essays on Ownership Structures, Corporate Finance Policies and Financial Reporting Decisions, Promotors: Prof. A. de Jong & Prof. P.G.J. Roosenboom, EPS-2021-516-F&E, https://repub.eur.nl/pub/134947

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With the deployment of variable renewable sources such as wind or photovoltaic solar power, electricity markets face increasing inflexibility constraints, or, in other words, increasing difficulties to swiftly adjust demand or supply in order to keep the grid in balance. The weather dependent variable renewable technologies introduce new challenges into power systems, which now must cater not only the relatively inflexible power demand but also the variation in wind and solar photovoltaic supply.

As their output is only set to increase, it is important to understand how variable renewable sources reshape power markets and their flexibility needs. To shed more light on this topic, this dissertation puts forward a series of four studies which scrutinise the flexibility of power markets in relation to the growing supply from variable renewable sources. The dissertation teaches us that supply from variable renewable sources affects the flexibility needs of a power market by changing the probability distribution function of power prices and altering the relation between forward and spot power prices, reducing the power price forward premium.

There is one key message that emerges from this dissertation: in a world with more variable renewables the flexibility needs of power markets increase. Thus, to integrate more wind and/or solar photovoltaic power supply, we need to incentivise the deployment of flexibility offering assets. Besides building upon the existing energy finance literature, the insights presented throughout this thesis aim to help policy makers and risk managers better assess the flexibility needs of the power markets.

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