Charles University

Faculty of Social Sciences
Institute of Economic Studies

MASTER'S THESIS

The Impact of German Renewable Electricity on Czech Electricity Spot Prices

Author: **Bc. Matěj Kouřílek**

Supervisor: **doc. PhDr. Josef Barunik, Ph.D.**

Academic Year: **2018/2019**

Declaration of Authorship

The author hereby declares that he compiled this thesis independently, using only the listed resources and literature, and the thesis has not been used to obtain a different or the same degree.

The author grants to Charles University permission to reproduce and to distribute copies of this thesis document in whole or in part.

Prague, May 8, 2019

Signature

Acknowledgments

I would like to express my gratitude towards doc. PhDr. Jozef Baruník Ph.D. for supervision of my thesis and his valuable notes. I want to thank my family for their support during my studies. I would also like to thank Jan Lomoz for giving me many practical comments to the topic. Last but not least, I want to thank my boss Eike-Wolfgang Grewe for giving me opportunity to work and write diploma thesis at the same time.

This thesis is part of a project that has received funding from the European Union's Horizon 2020 research and innovation programme under the Marie Skłodowska-Curie grant agreement No. 681228

Abstract

Thesis investigates the impact of German wind and solar energy on the dynamics of Czech electricity spot prices in the period between 2015 to 2018. Using pooled panel-GARCH model, a negative merit order effect of German wind and solar energy were observed. More specifically, one additional GW of power produced by wind and solar, reduces the spot price by 0.60 and 0.45 EUR/MWh, respectively. The negative merit order effect was also found in the case of Czech solar energy. Corresponding spot price reduction equals to 1.42 EUR/MWh per additional gigawatt hour. Next, increased volatility in the spot prices was found due to both German wind and Czech solar energy. I also observed that these effects differ during a day. Furthermore, I estimated total financial impact stemming from the negative merit order effect and compared it with the total costs of households that arise in surcharges to support renewable energy. While Czech households pay approximately 270 million euros annually in surcharges, the total financial impact stemming from the merit order is around 145 million euros. The value comprises the merit order effect of both Czech and German renewable sources. In other words, Czech and German households bear the costs of subsidized renewable energy while they do not necessarily profit on the merit order effect. Only spot market participants can make a profit on the negative merit order effect. It is up to national policymakers to set rules which will not promote one part of customers above the other.

JEL Classification	C14, C50, Q42, Q48
Keywords	renewable sources, panel GARCH, spot prices, volatility

Author's e-mail	`matej.kourilek@gmail.com`
Supervisor's e-mail	`barunik@fsv.cuni.cz`

Abstrakt

Práce zkoumá dopad německé solarní a větrné energie na dynamiku českých spotových cen elektřiny v období 2015 až 2018. S použitím GARCH modelu pro panelová data, autor nalezl snižení spotové ceny v závislosti na německé solarní a větrné energii. Přesneji řečeno, jedna gigawatt hodina německé solární a větrné energie, dodaná do systému sniží spotovou cenu elektřiny o 0.45 a 0.60 EUR/MWh. V případě české solární energie to je 1.42 EUR/MWh. Dále byla objevena zvýšená volatilita cen kvůli německé vetrné a české soalrní energii. Tyto závislsoti se mění v průběhu dne. Na základě výsledků regresního modelu byl odhadnut celkový finanční dopad snížení spotových cen plynoucí z obnovitelných zdrojů. Dále byla tato hodnota porovnána s náklady domácností, které plynou z příplatků na podporu obnovitelných zdrojů. Zatímco české domácnosti zaplatí přibližně 270 miliónů euro ročně, celkový efekt snížení spotových cen se pohybuje kolem 145 miliónů euro. Tato hodnota je tvořena efektem záslužnosti pořadí ve výrobě z českých a německých obnovitelných zdrojů. Jinými slovy, české a německé domácnosti nesou náklady plynoucí z podpory obnovitelných zdrojů, ale neprofitují ze snižených spotových cen. Tento užitek je přenechán výhradně účastníkům spotového trhu. Je na vládách jednotlivých států, aby nastavila pravidla, které nebudou zvýhodňovat jen některou část spotřebitelů.

Klasifikace JEL C14, C50, Q42, Q48
Klíčová slova obnovitelne zdroje, panelový GARCH, spotove ceny, volatilita

E-mail autora matej.kourilek@gmail.com
E-mail vedoucího práce barunik@fsv.cuni.cz

Contents

List of Tables

List of Figures

Acronyms

ACF an autocorrelation function

ADF the Augmented Dickey Fuller test

AIC the Akaike information criterion

AR an autoregressive model

ARMA an autoregressive Moving Average model

BIC the Schwarz's Bayesian information criterions

BFGS the Broyden–Fletcher–Goldfarb–Shanno algorithm

EEG the Erneuerbare Energien Gesetz

EEX the European Energy Exchange

EPEX the European Power Exchange

GARCH a generalized autoregressive conditional heteroskedasticity model

HAC a hetoreskedasticity-autocorrelation robust covariance matrix

GW a gigawatt

ICE ENDEX the ICE Energy Exchange

IQR an interquartile range

kWh a kilowatt hour

LSDV a least square dummy variable estimator

MLE Maximum likelihood estimator

MOE a merit order effect

MW a megawatt

MWh a megawatt hour

OTC Over-The-Counter market

PACF a partial autocorrelation function

PP-GARCH pooled panel-GARCH

PV photo-voltaic

RED the Renewable Energy Directive 2009/28/EC

RES a renewable energy source

SVAR a structural vector autoregressive model

TSO a transmission system operator

VAR a vector autoregressive model

VIF the Variance Inflation Factor test

Master's Thesis Proposal

Author	Bc. Matěj Kouřílek
Supervisor	doc. PhDr. Josef Barunik, Ph.D.
Proposed topic	The Impact of German Renewable Electricity on Czech Electricity Spot Prices

Motivation Due to Germany's transition to low carbon energy supply (Energiewende), large energy surpluses flow into the Czech transmission system, potentially affecting the price of electricity in the local market. The Energiewende was accelerated after the accident in Japan's Fukushima nuclear power plant in 2011 and corresponding closing of eight nuclear power reactors. Thereafter, both wind and solar power plants installed capacity almost doubled to today's 55.5 GW and 42.9 GW, respectively.

The Energiewende has a major influence on the functioning of the Central European interconnected electricity market. It affects the regional price of electricity and the way in which electricity is traded (The Ministry of Foreign Affairs of the Czech Republic, 2017). To what extent German renewable electricity affects Czech electricity spot prices is of principal importance for government and local electricity providers. For example, Czech Republic already installed special Phase Shifting Transformers (PST) which allow keeping electricity flows within safe limits. Further, local providers can optimize their business strategies with respect to expected inflows of cheap German electricity.

Recently, many empirical studies were conducted on the topic of renewable electricity, its impact on electricity prices and price volatility. In Haxhimusa (2018), the author estimates cross-border effects of German wind and solar electricity on French spot price volatility. Study finds both, positive and negative effect on the volatility of French prices. The effect depends on the shape of the French supply function and on the French demand. Likewise, Mulder and Scholtens (2013) find German electricity produced by wind farms to have a negative effect on Dutch electricity prices. Both studies use 2SLS method to investigate corresponding dependencies. In contrast, Pham & Lemoine (2015) focus solely on the German market. Using family of GARCH models, authors find a decrease in wholesale prices related to electricity generated from renewable sources. Regarding the Czech electricity market, Lunáčková *et al.* (2017) study the impact of renewable sources on the Czech electricity supply. Further, Czech and German markets are studied with respect to renewables in Líšková (2017). Only increased price volatility due to wind generation is found in the case of the German market. Nevertheless, no cross-border dependencies are considered.

Hypotheses

Hypothesis #1: The German wind and solar power generation decrease Czech electricity spot prices.

Hypothesis #2: The German renewables power generation increase volatility of Czech spot prices.

Hypothesis #3: The impact of Czech renewable power generation has negligible effect on Czech spot prices.

Methodology I will use data on Czech electricity spot prices from the Czech electricity market operator (OTE, a.s.). Further, I will employ data on Czech and German electricity production from both wind and solar power sources. The data are available on transmission system operators' websites ČEPS, a.s. and Amprion, respectively. While data from the Czech market has hourly granularity, German production volumes are given in 15 minutes stamps. Thus, I will compute and work with hour averages.

For classical statistical modelling, the date is assumed to follow a stationary process. Nevertheless, in case of electricity prices, assumption about stationarity is usually rejected (Voronin and Partanen, 2013). To overcome the non-stationarity and seasonal pattern of electricity prices we will use wavelet transformation of an initial time series. Further, as in Tashpulatov (2013), Pham & Lemoine (2015), Conejo et. al (2005), prices and price volatility will be analyzed using various types of autoregressive conditional heteroskedasticity models.

Expected Contribution As the German transition to carbon-free economy accelerates it is important to know to what extent is Czech market affected. The thesis should analyze whether German electricity produced by renewable sources lowers the spot prices on Czech electricity market. Further, volatility of the Czech spot prices with respect to German renewables will be analyzed. In contrast to other studies about Czech electricity market, I will assume cross-border dependencies. Also, I will employ modern techniques for high-frequency data analysis. The estimates can be used by both, the Czech government and Czech local electricity providers for strategy optimization.

Outline

1. Motivation: Introduction to the topic and description of the electricity market.
2. Literature Review: Description of estimation techniques used in recent studies of the electricity market.
3. Data: I will describe the data used for analysis.
4. Methods: A detailed summary of methods I will use in the thesis.
5. Results: I will discuss my findings based on estimated models.
6. Conclusion: Summary of regression results and possible implications for the Czech policy decision maker.

Core bibliography

Mallat, S.G., A theory for multiresolution signal decomposition: the wavelet representation. IEEE Transactions on Pattern Analysis and Machine Intelligence, 11(7), pp.674-693. Available at: http://ieeexplore.ieee.org/document/192463/ [Accessed June 05, 2018].

Engle, R.F., 1982. Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation. Econometrica, 50(4), p.987-. Available at: https://www.jstor.org/stable/1912773?origin=crossref [Accessed June 05, 2018].

Conejo, A.J. et al., 2005. Day-Ahead Electricity Price Forecasting Using the Wavelet Transform and ARIMA Models. IEEE Transactions on Power Systems, 20(2), pp.1035-1042. Available at: http://ieeexplore.ieee.org/document/1425601/ [Accessed June 05, 2018].

Tashpulatov, S.N., 2011. Estimating the Volatility of Electricity Prices: The Case of the England and Wales Wholesale Electricity Market. In Prague: Charles University, CERGE-EI.

Pham, T. K. Lemoine (2015): "Impacts of subsidized renewable electricity generation on spot market prices in Germany: evidence from a GARCH model with panel data." In: CEEM working paper 2015e15 .

Voronin, S. Partanen, J., 2013. Price Forecasting in the Day-Ahead Energy Market by an Iterative Method with Separate Normal Price and Price Spike Frameworks. Energies, 6(11), pp.5897-5920. Available at: http://www.mdpi.com/1996-1073/6/11/5897 [Accessed June 05, 2018].

Mulder, M. Scholtens, B., 2013. The impact of renewable energy on electricity prices in the Netherlands. Renewable Energy, 57, pp.94-100. Available at: http://linkinghub.elsevier.com/retrieve/pii/S0960148113000505 [Accessed June 05, 2018].

Lunáčková, P., Průša, J. Janda, K., 2017. The Merit Order Effect of Czech Renewable Energy, Crawford School of Public Policy: Centre for Applied Macroeconomic Analysis.

Author Supervisor

Chapter 1

Introduction

Over the last decade, a strong emphasis has been put on the promotion of green electricity in the European energy sector. Under the Renewable Energy Directive 2009/28/EC (RED), the European Union (EU) committed itself to reduce its emissions of carbon dioxide (CO_2) by 20 percent compared to preindustrial level. The goal should be met by 2020. Solar and wind energy became the most popular instrument for reaching the target. The energy produced by these renewable energy sources (RES) is cheap and carbon-free. Nevertheless, the transition to RESs brings also many challenges. Since the production of energy from solar and wind depends purely on weather conditions, the increased share of RESs in country's energy mix likely changes dynamics of the spot prices. A situation, when a huge volume of green electricity drives spot prices to negative values, is not unique. Approaching 2020, more and more RESs being connected to the energy grid all around Europe. The leader in the transition to a sustainable energy sector is Germany with 46 percent of installed capacity in RESs. Since the flow of electricity does not respect borders, spillover effects of cheap green electricity influence energy grids of neighbouring countries. For example, the Czech Republic already installed special phase shifting transformers which allow keeping electricity flows from Germany within safe limits. It shows that energy policy should be set internationally. Also for national electricity retailers is of principal importance to know how much is the spot market influenced by both national and foreign green energy production so they can optimize their portfolio accordingly.

The objective of this thesis is to examine the effect of German RESs on the Czech electricity spot prices. More specifically, the effect on both the spot price level and its volatility is studied. Production from the Czech RESs is also considered. Further, I focus on the merit order effect of RESs and its total financial impact on end-customers and spot market participants. To study the price dynamics, I build upon an approach developed by Cermeño & Grier (2003). It allows modelling panel data with time-varying conditional matrix while preserving the simplicity of the model. The model is from the family of multivariate generalized autoregressive conditional heteroskedasticity (GARCH) models. To estimate desired effects, I introduce several external regressors into both the mean and the variance equation. The total financial impact of the merit order effect stemming from RESs is calculated based on the results of the model described above. To do so, I follow a similar approach as in Cludius *et al.* (2014) and Sensfuss *et al.* (2008).

Thesis contributes to the existing literature in several ways. There has not been much research devoted to the effect of RESs on the volatility of Czech spot prices. Also, no cross-border dependencies were considered in the existing literature. As far as the author is aware, the merit order effect of RESs and its total financial impact on end-customers has not been studied either.

This thesis is organized as follows. Chapter 2 describes Czech and German energy markets. Further, the revision of existing literature on price and volatility modelling is provided. Chapter 4 describes the data used in the analysis. Chapter 5 introduces the model and related methods used in this thesis. Chapter 6 presents and discusses the results of the analysis. Chapter 7 provides conclusion.

Chapter 2

European Energy Markets

In this chapter I describe history and transformation of energy industry in Europe from state monopoly to highly competitive market. I review European policy which shapes the development of Czech and German electricity markets. Main focus is given to renewable part of the industry. This section is based on Flášar *et al.* (2016).

2.1 Liberalization of Energy Markets

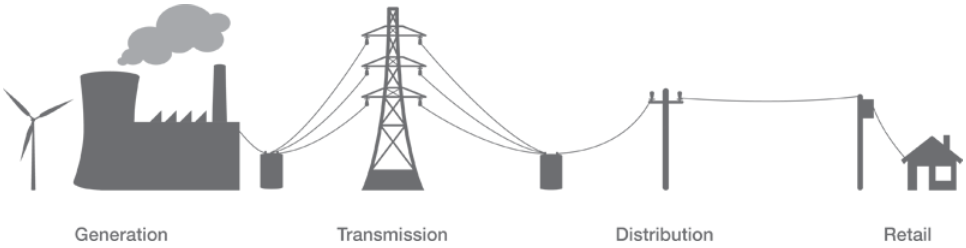
Electricity market is from family of grid industries. An electricity network consists of power generation units, transmission grid, distribution, and consumption units. A common characteristic for a grid industry are large initial costs. Example of such a costs is nuclear power plant, water dam or national transmission system. The opposite is true for a marginal costs of connecting one additional consumer into the grid. Thus, with respect to economies of scale it makes sense to interconnect all local production and consumption units into one electricity grid. Such conditions are perfect for natural monopoly. Indeed, a regional and state monopolies in energy industry were common across Europe before liberalisation of energy markets. The electricity providers used to own production units, transmission grid and distributions, i.e., energy sector was vertical monopoly. The integration of energy sector into the monopoly was due to large entrance costs and conviction that electricity is a public service and everyone should have an access to it for reasonable price.

Liberalisation of energy markets has its origin in the 1970s. Before first oil crisis in 1973, energy companies were either state-owed or regulated by state policy. Unlike Europe, privately owned energy companies were already established in the United States. Private investors gradually took over importance from municipalities and state while being regulated by a state. This was possible due to stable macroeconomic environment and low inflation in 1960s. The turning point were two oil crisis in the 1970s. A sudden surge in the prices of inputs was addressed by a state-budget buffer dedicated for state-owned regulated companies, whereas private companies translated increase in costs into the end-customers tariffs. The inefficiency resulting from such a setup was resolved by liberalisation. The purpose of liberalisation was to introduce elements of competition into the energy market. Thus, increasing efficiency and consequently lowering the prices for customers. The first step was to rethink the structure of entire energy industry and divide it into a smaller units. The ultimate result of such a process was collapse of vertical monopoly. One company could no longer participate in entire industry, i.e, production, transmission, distribution, and retail. While production, delivery, and retail were deregulated completely, transmission, distribution, and system services are still regulated by local states. The regulation is due to the monopolistic nature of transmission systems.

2.2 European Energy Market Structure

Energy markets in the EU are shaped by directive 2009/72/ES. The directive altogether with national laws define the structure of energy market in particular country or area. As mentioned above, the energy market comprises of four areas, generation, transmission, distribution, and retail or customer. The physical interconnection between these is illustrated on Figure 2.1. A generation consists of power plants with large installed capacity. These are usually nuclear, hard coal or lignite. Transmission grid links generation units with local distribution grids. Transmission grid transports electricity over large distances. Hence, electricity in the transmission grid has to be transmitted in high voltages to avoid losses due to grid's electrical resistance. Contrarily, distribution grids transmit electricity in low voltages. The distribution grid has a local character and transports electricity to the end-customer. Connection of a customer directly to the transmission grid is possible when customer has a high offtake like steelworks. Small scale generation units can be connected to the distribution grid, e.g., a single wind turbine, co-generation unit, and small solar farm. As Figure 2.1 depicts, generation units, transmission grid, and distribution grids are connected via transformers. The transformer between generation unit and

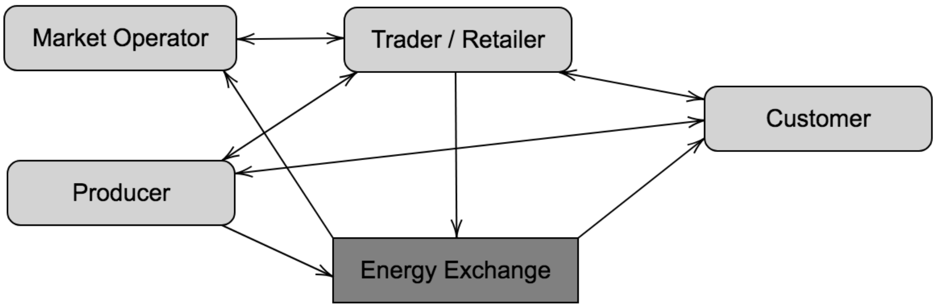
Figure 2.1: Physical Transport of Electricity



Source: SA. (2018)

transmission grid is so-called ”step-up” transformer. It upscales the voltage 115 kilo-volts (kV) and more. The transformer between transmission grid and distribution grid is called ”step-down” transformer and it drops voltage to 35 kV and lower.

Figure 2.2: Financial Structure of the Energy Market



Source: Flášar *et al.* (2016)

The model of financial bonds and responsibilities on energy market is very complex and it is describe in Flášar *et al.* (2016). The fundamental structure of energy market is shown in Figure 2.2. Arrows depict bonds between market participants. Each country has its market operator. A market operator runs register of market participants on an energy exchange. Further, the market operator arranges clearing of the actual and negotiated deliveries. A producer agrees on delivery either with a retailer or directly with end-customer. A retailer buys electricity either on the energy exchange or directly from a producer. Further, the energy market comprises of two parts, regulated and deregulated.

Whereas generation, distribution, and commerce are all competitive markets, transmission due to its characteristic is a monopoly. Hence, government has to impose regulatory policy on it. Additionally, the commerce is further divided into retails and traders. Retail provides electricity to the end-customers. On the other hand, traders resale electricity on the wholesale market to make a profit. Now, there are mainly two ways of trading electricity, via energy exchange or by bilateral trade. The latter is usually referred as over-the-counter (OTC) market. OTC deals are either settled directly between two entities or via broker. The most frequent deals on the OTC market are following:

- **Base load** - a delivery of constant power throughout the whole period.
- **Peak load** - a delivery of constant power from Monday to Friday between 8:00 and 20:00.
- **Off peak** - the opposite of peak load.
- **High tariff** - is sometimes called extended peak and it is a delivery of constant power from Monday to Friday between 6:00 and 22:00.
- **Low tariff** - the opposite of high tariff.

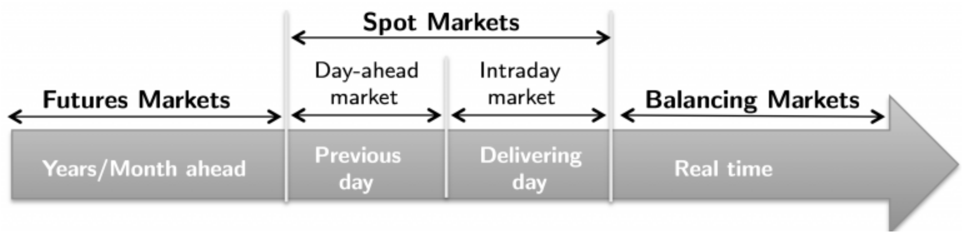
While base load, peak load, and off peak are standard products across Europe, high and low tariff are mainly recognized in eastern European markets. The second option for trading is the energy exchange. The energy exchange allows to trade the same standard products as those on the OTC market. There are three main energy exchange platforms in Europe, the Nordpool, the European Energy Exchange (EEX), and the ICE Energy exchange (ICE ENDEX). The Nordpool exchange organizes a spot market for Scandinavian countries. The EEX is the biggest commodity exchange in Europe. The EEX organizes markets for both future and spot trading. German, French, Austrian, and Swiss electricity is traded here. The ICE ENDEX operates electricity in Benelux region. The spot market organized by energy exchange is the principal element in process of price creation. It guarantees that physical delivery of electricity is efficient, i.e., merit order effect is applied (Flášar *et al.* 2016). The merit order effect is discussed in Section 3.1. Trades with physical delivery for next trading day are settled on the spot market, i.e., the day-ahead spot market [1]. Hence, standard products traded on the spot market are following:

[1]Further, I will use only phrases spot market and spot prices.

- **Hour** - a delivery of power for particular hour for a next day.
- **Base load** - a delivery of constant power for a next day.
- **Peak load** - a delivery of constant power between 8:00 and 20:00 for a next day.

Based on orders of these products energy exchange determines the spot prices for a next day. The auction mechanism is an iterative process. Firstly, products are decomposed to single hours. Secondly, price curves are computed for each hour so all demanded volumes are covered. Finally, auction hall checks whether all submitted orders can be satisfied. If not particular order is discarded and prices are computed again until equilibrium is reached. Highly liquid spot markets also offer trans-border trades. Traders sell electricity on foreign spot market where it is physically present and they buy it on domestic market. Such a deal then determines the price of cross boarder transmission.

Figure 2.3: Type of electricity market with respect to time flow.



Source: www.incite-itn.eu

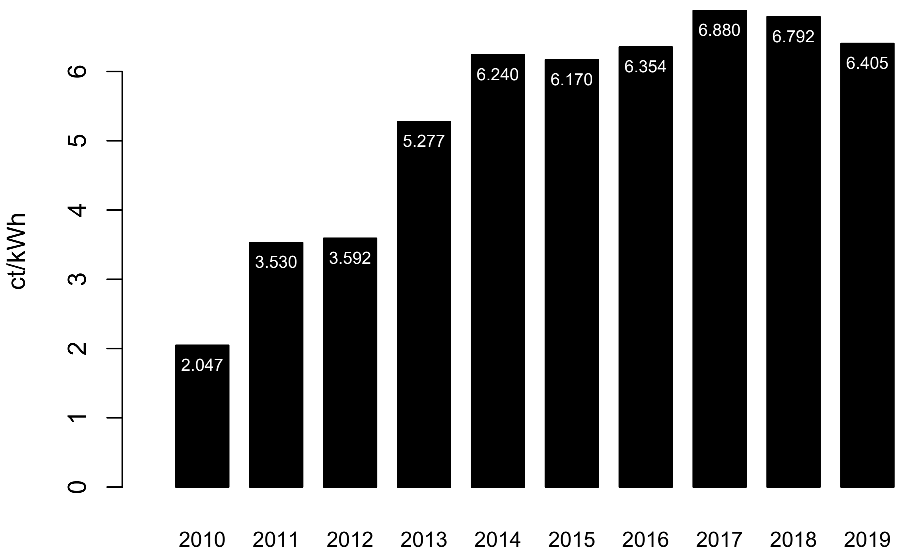
The electricity market can be split with respect to the time of product purchase. I already mentioned possibility of closing future and spot deals. Nevertheless, the energy market recognizes also intraday market and balancing market. The time diagram is shown in Figure 2.3. Standard products on the futures market are year, quarter, and month baseload. The spot market is further divided into day-ahead and intraday market. The intraday market allows to close deals within the day of physical delivery. It helps retailer to optimize their long (short) position one hour ahead before delivery. Thirty minutes before delivery balancing market opens. It is organized by the market operator and the transmission system operator (TSO) is the only participant. The TSO buys (sells) regulation power to offset the system deviation. The costs of regulation power are charged one day after delivery to market participants according to their deviation between agreed and actual offtake.

With the increasing share of wind and solar energy European Commission adopted Regulation No 543/2013. It binds all national TSOs, which have more than one percent feed-in of wind or solar power generation per year to publish day-ahead generation forecast for these fluctuating sources. Even though it came into force in mid 2013, the formal obligation came into effect at the beginning of 2015 (EC 2013). It was an important step for the process of spot prices formation. Only after that could traders on the spot market reflect the cheaper green electricity into the spot prices more accurately.

2.2.1 German Market

In 2009 the European Commission adopted the RED 2009/28/EC setting three main targets which are to be met by 2020. According to European 20-20-20 target, Europe should decrease its CO_2 emission by 20 percent compared to 1990 level, 20 percent of consumed energy should be from the RESs, and energy efficiency should increase by 20 percent. Previously, Germany set its national target to 40 percent reduction in CO_2 emissions. However, the emission target has been soften by German government in January 2018 by the new government treaty (CleanEnergyWire 2018a). Additionally, German government has committed to cover 65 percent of energy consumption covered by the RES by 2030. A baseload production shall be provided by a natural gas (Powermag 2018). Further, German government pledged to announce date when all coal burning power plants will be shut down. Another legal document shaping the German energy policy is the Renewable Energy Sources Act (Erneuerbare Energien Gesetz, EEG). The EEG was issued in 2000 and had several amendments. Recall, TSO has to publish day-ahead forecast for wind and solar power generation from 2015 on. Under revision of EEG, German TSOs have to publish day-ahead forecast from 2010. Last revision of the EEG came into force in 2018. The EEG sets incentive scheme for investments into RES. It guarantees a connection between the transmission grid and preferential dispatch. The main part is a surcharge for the renewable energy which is charged to end-customers. The renewable surcharge is mainly paid by households. Under EEG (2017), large industrial companies are exempt from the renewable surcharge due to the possible loss of competitiveness. Thus, the levy of renewable energy is borne by German households. Figure 2.4 depicts the evolution of the EEG surcharge from 2010. Since the EEG act came to force, the surcharge trippled with peak in 2017. The current amendment of EEG 2019 sets this surcharge to 6.405 ct/kWh. To put it into context, household pays additional 64 EUR/MWh in their energy bill for the RES subsidy. The average spot price in 2018 was 43.26 EUR/MWh[2].

Figure 2.4: The EEG surcharges in respective years.



Source: netztransparenz.de

Further, the German energy market was heavily influenced by the accident in Japan's Fukushima nuclear power plant in 2011. The government closed eight nuclear power reactors right after the accident with plant to close the remaining reactors by 2022. The drop in installed capacity has been offset by lignite and hard coal burning power plants to ensure baseload production. Peak hours were opportunity for the RES. Recent development in the RES installed capacity is displayed in Table 2.1. In 2015 the RES represented 25.8 percent of installed capacity. By the end of 2018 this ratio almost doubled to 46 percent. The ratio rose mainly due to additional 18 GW of wind power and 17 percent drop in total installed capacity. The drop took place in 2016 when a lot of lignite power sources were closed. In 2018, approximately 20 percent of German installed capacity was in photo-voltaic (PV) power plants. Next 24

[2] www.energy-charts.de

percent comprises from onshore wind parks which are spread all over Germany. Last but not least, RES are offshore wind parks accounting for for 2.3 percent of installed capacity. These parks are located in the North and Baltic Sea (CleanEnergyWire 2019). See Table A.1 in Appendix for the development of country's energy mix.

Table 2.1: Installed Capacity of RES in Germany

	2015 [MW]	2016 [MW]	2017 [MW]	2018 [MW]
Solar	37446	38840	40849	42804
Wind Offshore	993	3283	4131	5051
Wind Onshore	37757	41179	47042	51633
Total Capacity	294738	200406	212926	215080

Source: www.entsoe.eu

2.2.2 Czech Market

Due to its weather conditions, the Czech Republic is not suitable for RES. Nevertheless, PV power plants experienced a large boom in period of 2008 to 2010. Installed capacity rose from approximately 40 MW to 1959 MW (oEnergetice 2015). Now, PV installations account for almost 10 percent of country's installed capacity. In 2006, the Act 180/2005 Sb. setting subsidized prices for electricity from PV plants came to effect. Investors were guaranteed with 15 CZK/kWh. The Act 180/2005 Sb. was abolished in 2013. Nevertheless, under the Act 165/2012 Sb. end-customer is obliged to pay surcharge to promote RESs. Its values is not trivial to compute. However, its price ceiling is set to 495 CZK/MWh, i.e., approximately 18.9 EUR/MWh. The surcharge did not change since 2014 (Poncarová 2017). Note, that the Czech fee is three times lower compared to the EEG surcharge.

Table 2.2: Installed Capacity of RES in the Czech Republic

	2015 [MW]	2016 [MW]	2017 [MW]	2018 [MW]
Solar	2050	2067	2027	2040
Wind Onshore	270	277	277	308
Total Capacity	20725	20627	20188	20845

Source: www.entsoe.eu

Recent development of the Czech RES installed capacity is shown in Table 2.2. The Czech energy mix is relatively stable compared to Germany. Indeed, PV installed capacity stagnates since 2012 due to reasons explained above. Compared to Germany, wind farms are not very common in the Czech Republic. Due to its low wind potential installed capacity of wind farms makes roughly 1.5 percent of country's energy mix. Another source of clean energy are water dams and hydro pumped storages. Cumulatively, they account for 10 percent of installed capacity. Baseload power sources are dominated by lignite with approximately 40 percent of installed capacity. Nuclear power follows with 20 percent. Recent development in the Czech Republic energy mix can be found in Table A.2 in appendix.

The Czech balancing market has hourly granularity and two prices. The price differs for electricity providers according to their residual position with respect to the system. In general, if market participant is short (long) and system is long (short), then market participant receives money. On the other hand, if the market participant's position is on the same side as the system deviation, he pays.

Chapter 3

Literature Review

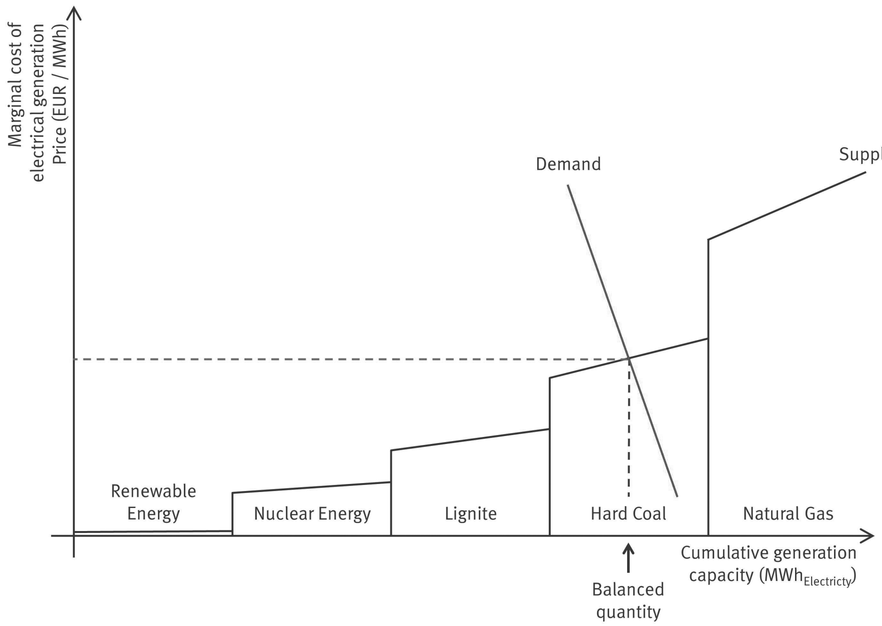
This chapter describes unique characteristics of electricity as a commodity. Further, it reviews some of the latest papers which study the impact of renewable power generation on market prices and price volatility. More precisely, I report author's findings and discus corresponding methodology.

3.1 Electricity As Tradeable Commodity

Unlike other commodities, electricity is still more or less non-storeable. It is impossible to substitute delivery of 3 AM electricity with delivery in 4 AM. Thus, every hour of electricity delivery can be viewed as a distinct commodity.

An electricity flows from production sources to customers through the shortest distance possible, i.e., through the least resistant path. Also, an electricity travels almost instantaneously. As a consequence, an energy has to be consumed at the same time of its production. If one production unit suffers outage, other has to balance for that loss in power grid. By contrast, if one consumer stops off-taking the electricity from the grid there should be equal offset to balance for the excess of an energy. In other words, grid has to be balanced in every point of time so an electricity is delivered in a constant quality. The balancing of a grid is performed by a dispatching facility of particular transmission system owner. Taking all together, an electricity grid is a very fragile and volatile environment where each participant can influence the others. Both, shortages and excesses in a grid, can damage the transmission system and consequently cause blackouts. Recall, that supply and demand have to be met in every point of time. To set a price for a specific hour system, a TSO has to rank available energy sources in ascending order with respect to their marginal costs and amount of energy generated. This type of ranking is called merit order and it is depicted on Figure 3.1.

Figure 3.1: The merit order of power sources.



Source: www.journals.openedition.org

As can be seen from the graph, RESs are first when comes to merit order. Indeed, RES's marginal costs of production are close to zero (Lunáčková *et al.* 2017). The final price is set at the point where forecasted power generation supply meets forecasted demand. In times with low demand and favourable weather conditions for RES a significant portion of a total demand can be met only by production from the RES. Such conditions were seen after the New Year's Eve in Germany. Around 6:00 AM on January 1, 2018, the whole Germany's power demand was covered by the RES (CleanEnergyWire 2018b). At that moment prices "reached" negative values around -72.5 EUR/MWh [3] and production of conventional power sources had to be minimized. Negative prices is another characteristic which can not be seen in any other market. It has several reason such as ramp-up and ramp-down costs for conventional power sources, provisions to the TSO, and already mentioned electricity from the RES, Cludius *et al.* (2014), Nicolosi (2010).

[3]https://www.smard.de

3.2 Price Modelling

Preceding section describes an electricity as a commodity. Due to characteristics explained above, electricity spot prices have several unique properties. Like many financial market data, the distribution of electricity spot prices is usually leptokurtic and departs from normality by exhibiting heavy tails. The presence of heavy tails means that extreme observations occur more frequently than expected by the normal distribution. Such a distribution commonly has excess kurtosis. In Cludius *et al.* (2014) authors find that the distribution of the European Power Exchange (EPEX) spot prices for Germany is indeed highly leptokurtic. Further, Haxhimusa (2018) and Higgs (2009) claim that the electricity spot prices is a mean-reverting process with seasonality patterns and volatility clustering. A volatility clustering occurs when a large price change is followed by a large price change. To control for seasonality, authors in Cludius *et al.* (2014) create vector of time dummies. It consists of twenty three variables to take specific hours into a account, six variables to control for week days, and eleven variables to distinguish between months. Similar approach used Clò *et al.* (2015) and Gelabert *et al.* (2011) in analysis of Italian and Spanish electricity wholesale prices, respectively. In Tashpulatov (2013) author argues that using smooth periodic functions rather then daily dummies should by preferred approach for capturing weekly seasonality. He supports his claim by parsimony of resulting model. This is also in line with propositions in Koopman *et al.* (2007). This paper will follow the same approach.

There has been a lot of research in the area of electricity prices and the RES power production. Cludius *et al.* (2014) studies merit order effect of the RES on the EEX spot prices. For each year in the sample period from January 2008 to December 2012, authors estimate a model by the OLS methodology. The model estimates spot prices dependency on wind and solar feed-in to the system. Further, variable of a total system load is included as an indicator of a total demand. Cludius *et al.* (2014) finds drop in average spot prices between 0.97 to 2.27 EUR/MWh for wind and 0.84 to 1.37 EUR/MWh for solar per GWh fed into the system. As mentioned above, Gelabert *et al.* (2011) studies the electricity wholesale prices in Spain. The paper use OLS and control for various type of power generation sources including hydro, coal, nuclear, and gas plants. On period between years 2005 and 2009, the authors find decrease of 2 EUR/MWh in wholesale price per GWh of electricity produced by the RES. This is approximately four percent of the mean price during sample period.

Another study investigating the impact of the RES on the electricity spot prices by the OLS is Clò *et al.* (2015). The authors estimate that Italian subsidy scheme resulted in the average decrease of spot prices by 2.3 EUR/MWh and 4.2 EUR/MWh for wind and solar, respectively. Further, they find an increase in price volatility.

When investigating the impact of the RES on a spot prices, many studies use daily averages rather then hourly prices. See Gelabert *et al.* (2011), Clò *et al.* (2015) or Higgs (2009). Nevertheless, using daily prices can result in a loss of information contained in hourly granularity. Since the energy output from RES, especially solar, can vary substantially during the day, averaging of spot prices could reduce short run dynamics across hours. Thus, I use similar approach as in Pham & Lemoine (2015) and Haxhimusa (2018).

Recall, the example about impossibility of substitution between specific delivery hours. Does it mean that each hour should be modelled separately? The question is partially answered in Cuaresma *et al.* (2004). By applied variety of auto-regressive (AR) and auto-regressive–moving-average (ARMA) models on the Leipzig Power Exchange spot prices authors find better predictability of price development when each hour is treated separately. Huisman *et al.* (2007) also argues that hourly electricity spot prices do not behave as a single time-series process. Thus, authors deploy model for panel data where each hour is considered as a one cross-sectional entry.

3.3 Price volatility

The knowledge of a price level and a price volatility is one of crucial importance in relation to the development or success of national and business strategy. When it comes to business strategy, electricity provider has to take into account several types of risk. These risks mostly originate from price movements. One example of such a risk is holding risk. Customers are usually offered with certain price along with time period during which they can accept or decline the offer. If prices would suddenly surge during this period, electricity provider suffers loss. Thus, holding risk has to be priced accurately. In Linsmeier & Pearson (2000) authors describe value at risk concept for measuring an entity's exposure to market risk. It uses price volatility of given commodity as key input for determining risk premium. Common property of solar and wind power generations is their dependence on weather. With highly volatile weather conditions I also expect the RESs to have volatile power output, i.e., to increase price volatility.

In Paschen (2016) author studies price dynamics of German spot prices in period from July 2010 to March 2013. Using structural vector auto-regressive model (SVAR) author finds decrease in spot prices to be 2.4 EUR /MWh and 1.7 EUR/MWh due to positive structural shock in solar and wind power generation, respectively. Along with explanatory variables for wind and solar generation, the author controls for the load (demand) and the power generated from conventional sources. The use of the SVAR model is then justified by possibility of inter-dependencies between these explanatory variables and their auto-correlation. Under such conditions coefficients estimated by the OLS could be biased since inter-dependencies remain in the residuals, Paschen (2016). The source of inter-dependencies is claimed to arise from the merit order effect. See example of strong winds. During favourable weather conditions, wind parks generate more power and conventional power sources have to minimize their power output. Such a correlation would be then included in the residuals.

The German spot prices are also analyzed in Ketterer (2014). The paper investigates relationship between renewable electricity generated by wind parks and the spot electricity price from the EEX. The author uses GARCH model to estimate the impact of wind electricity on price level and price volatility. He studies the period from January 2006 to January 2012 when the new revision of EEG came into effect. He finds that one percent increase in wind generation (MWh per day) lowers the price approximately by 0.1 percent. Like in Paschen (2016), author detects higher volatility of prices due to wind power generation. He claims that introduction of the EEG mechanism in January 2010 helped to reduce the price volatility. Instead of month ahead forecast for all types of power generation, the TSO had to start publish day-ahead forecast. Resulting increase in accuracy lower the spread between forecasted and actual in-feed load. Further, he argues the price volatility is additionally smoothed through possibility of export to neighbouring countries. The possibility of import and export electricity to neighbouring country was used as an explanatory variable in Haxhimusa (2018). The paper studies the volatility of the French spot prices due to the import of the electricity produced by the German RES. The author defines volatility as the absolute value of the difference between price in given hour and daily mean. He argues that such a price volatility measure retains more information then the standard volatility computed with daily frequency.

To control for domestics price determinants he employs variables such as day-ahead forecasts of nuclear and wind generation, load, and already mentioned imports from Germany. Further, he use day-ahead forecasts for the German RES generations and dummy variables controlling for the German and French holidays. The use of nuclear generation is justified by its low marginal costs and corresponding downward pressure on the price. The likely endogenity problem stemming from reverse causality between imports and the spot price volatility is addressed by the two-stage-least squares (2SLS) model. The imports are regressed on instrumental variables, i.e., the German RESs generation and holiday dummies. The second-stage equation then accounts for effects of the German imports and the German RESs electricity. The author finds that the effect on the price volatility depends on the shape of French demand function. During the peak hours price volatility was lowered by the German import. This is attributed to the solar energy since its generation coincides with peak hours. On the other hand, volatility has increased during off-peak hours.

Chapter 4

Data

4.1 Data Description

I employ large variety of data. I use the Czech electricity spot prices as our dependent variable. These prices are published by the Czech market operator (OTE a.s.) on the OTE's website [4]. The prices are reported in EUR/MWh. Next, the data from RESs are used. Recall, the spot price is formed one day ahead before actual delivery. Thus, when applicable, I should use day-ahead forecasts of RESs generation. The RESs' forecasts from the German market are collected on the websites of four transmission grid operators TenneT, Amprion, 50Hertz, and TransnetBW. These data have quarter-hourly granularity and megawatt (MW) as a measurement unit. To control for the effect of t he Czech RESs, I also employ the day-ahead forecast of energy produced by the Czech PV plants. Unfortunately, the day-ahead forecasts for the Czech wind energy are not available. Instead, I use the data about actual wind generation as proxy for the day-ahead forecast. I assume there is no systematic departure from the forecasted data. Further, I use day-ahead forecast of total load in the Czech grid as a main determinant of price equilibrium in short term. Load represents the instantaneous power consumption in the system. Unlike Pham & Lemoine (2015), I use day-ahead forecast of load to avoid problem with endogeneity. All Czech data are reported in MWh, have a hour granularity, and are available online on the website of the Czech transmission grid operator ČEPS a.s [5].

In order to have valid inference, all explanatory variables should be exogenous. This is certainly valid assumption in case of RESs. A behaviour of these

[4]www.ote-cr.cz
[5]www.ceps.cz

sources is determined by weather conditions. Also, RESs have priority feed-in and marginal costs close to zero. Thus, producers have no incentive to speculate on current market price and they produce as much energy as possible. Further, I have to assume that in a short run demand (load) is perfectly inelastic with respect to the spot price. Customers do not react to day-to-day or even hour-to-hour changes. Again, there is no incentive to do so since the most energy products have fixed price for longer period. Thus, I conclude this assumption is likely to hold.

Further, several adjustments have to be introduced to the dataset. Firstly, the German data have to be transformed to hourly granularity. I simply take arithmetic average over four observation per each hour for particular day. More precisely, I do the following:

$$x_h = \frac{\sum_{q=1}^{4} x_{h_q}}{4} \tag{4.1}$$

where x_{h_q} represents observation for given quarter of an hour. Recall, the Czech Republic and Germany have daylight saving time changes. Thus, there is one day with 25 hours and one day with 23 hours each year. To have consistent dataset, I delete and add one observation for those days, respectively.

The resulting dataset spans from 1 January 2015 to 30 December 2018 yielding 33 774 observations for hourly data. Table 4.1 presents descriptive statistics of all explanatory variables. The unit of measurement is a gigawatt (GW). Approximately half of observations for both the German and the Czech solar production are zero. This is expected since I use hourly data. Note that *Solar.GE* has fewer null observations then *Solar.CZ*. This difference stemming from the geographic location of German production. Germany extends across more latitudes and longitudes then the Czech Republic. Both variables are positively skewed and have excess kurtosis statistic around 2.2, i.e., they depart from normal distribution. Shapiro-Wilk test also supports this claim. A part from the obvious difference between installed capacities, standard deviation of *Solar.GE* is much higher. On contrary to solar, *Wind.Offshore* and *Wind.Onshore* have no null observations. In other words, there was always some production from wind in Germany during whole study period. On average, German onshore wind parks produce 8.71 GW per hour while offshore parks produce only 1.6 GW. On contrary, the Czech wind production is very small. On average, it is only 0.06 GW of energy per hour. All variables representing wind production have negative excess kurtosis statistics. In other words, their distribution is platykurtic which means that outlires are not that frequent. I attribute this to the technical properties of wind turbines. Wind turbine is capable of producing power until certain level of wind speed. After this speed is reached a turbine has to be artificially braked or shut down completely. The results is distribution with well defined possible values which can not exceed certain level. Further, *Wind.Onshore* and *Wind.CZ* are positively skewed. This is not the case for the *Wind.Offshore* which has slightly negative skewness. It suggests that the mass of its distribution lays on the right, leaving low observations less probable. In other words, offshore wind farms have lower probability of not producing anything. Last explanatory variables is the *Load*. It has minimum equal to 4.33 GW. The maximum is equal to 11.07 GW. The median almost overlap with the mean, i.e., its distribution is close to symmetric. Indeed, skewness statistic equal to -0.01. Nevertheless, Shapiro-Wilk test strongly rejects normality of the data. This is due to its negative excess kurtosis. Thus, the distribution of the *Load* variable is platokurtic. Again, it stems from technical properties of the transmission system. The lowest possible value of load is zero. The maximum cannot reach arbitrarily high values since it would damage the system.

Table 4.1: Descriptive statistics

	Solar.GE	Wind.Offshore	Wind.Onshore	Wind.CZ	Solar.CZ	Load
Observation	33774	33774	33774	33774	33774	33774
Null.obs	14010	0.00	0.00	10.00	14959	0.00
Min	0.00	0.00	0.20	0.00	0.00	4.33
Max	28.82	5.30	37.33	0.28	1.69	11.07
Median	0.18	1.31	6.55	0.05	0.01	7.38
Mean	4.30	1.60	8.71	0.06	0.26	7.40
Std.dev	6.49	1.24	7.12	0.05	0.39	1.27
Skewness	1.83	-0.06	0.73	0.73	1.79	-0.01
Kurtosis	2.35	-1.42	-0.41	-0.28	2.17	-0.84
Shapiro-W.s	0.66	0.93	0.93	0.93	0.66	0.98
Shapiro-W.p	0.00	0.00	0.00	0.00	0.00	0.00

Further, Table 4.2 shows the correlation matrix of all considered variables. The *Solar.GE* is negatively correlated with all variables representing wind production. This is most likely caused by the fact that wind parks have rather off-peak production profiles. Nevertheless, correlation is moderate and it does not exceed 0.2. The opposite is true for the *Solar.CZ*. As expected both solar production are very highly correlated with correlation coefficient equal to 0.89. The *Wind.Onshore* has highest correlation with the *Wind.Onshore* equal to

0.67. Also, it is slightly correlated with the *Load*. Next, the *Wind.Onshore* has negative correlation with the *Spot* equal to -0.29. Conversely, very high correlation is observed with the *Wind.CZ*. Likewise, the *Wind.Onshore* has positive correlation with the *Load*. Nonetheless, the correlation is modest. The *Load* has the largest correlation with the *Spot* equal to 0.53. As mentioned before, the *Load* variable represents an instantaneous demand of electricity in a system. Recall, the merit order effect is depicted in Figure 3.1. From Figure comes that the higher the load the more production sources have to be turned on. And consequently the higher the price is. Figure 4.1 displays normalized *Spot* and normalized *Load* in one graph. Indeed, the spot price rises and falls with the load.

Table 4.2: Correlation matrix

	Solar.GE	Wind.Offshore	Wind.Onshore	Spot	Wind.CZ	Solar.CZ	Load
Solar.GE	1.00	-0.12	-0.18	0.04	-0.17	0.89	0.17
Wind.Offshore	-0.12	1.00	0.67	-0.08	0.33	-0.10	0.13
Wind.Onshore	-0.18	0.67	1.00	-0.29	0.71	-0.15	0.14
Spot	0.04	-0.08	-0.29	1.00	-0.22	0.05	0.53
Wind.CZ	-0.17	0.33	0.71	-0.22	1.00	-0.16	0.12
Solar.CZ	0.89	-0.10	-0.15	0.05	-0.16	1.00	0.17
Load	0.17	0.13	0.14	0.53	0.12	0.17	1.00

4.2 Czech Spot Price

Figure 4.2 displays histogram of the spot prices. By the visual inspection of the histogram one can see that spot price has excess kurtosis. Also, the spot price distribution is slightly positively skewed. Indeed, corresponding excess kurtosis and skewness statistics equal 2.30 and 0.58, respectively. Shapiro-Wilk test for normality rejects null hypothesis of normality even at one percent. Test statistic equals 0.925. Thus, I conclude that the distribution of the spot prices is highly leptokurtic. Also, histogram shows that there are negative prices in the sample. Departure from normality, a lot of outliers, and negative realizations are common features of electricity spot prices.

When modelling the relationship between the spot price and other explanatory variables, outliers turn out have to major influence on the robustness of the results. Thus, I decide to correct price data for outliers. Specifically, I decide to filter all observations which lay three standard deviation off the original spot price variable. Applied filter assigns outliers with a value equal to three

Figure 4.1: Normalized spot price vs. normalized load.

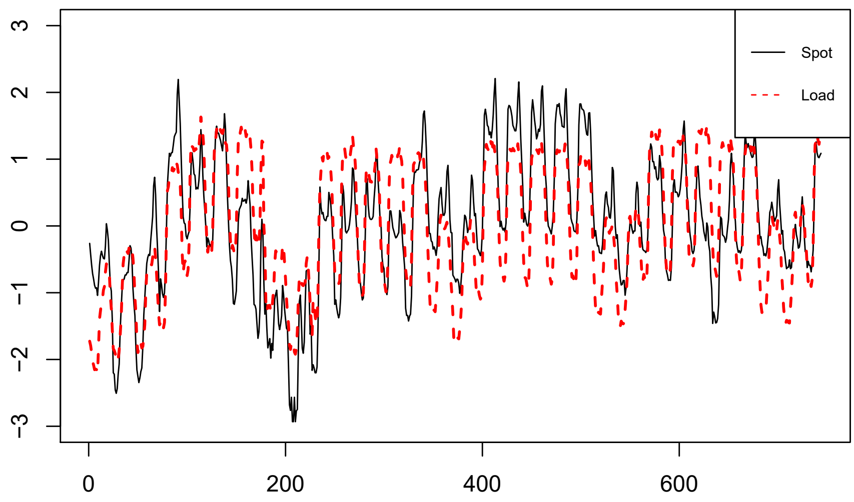
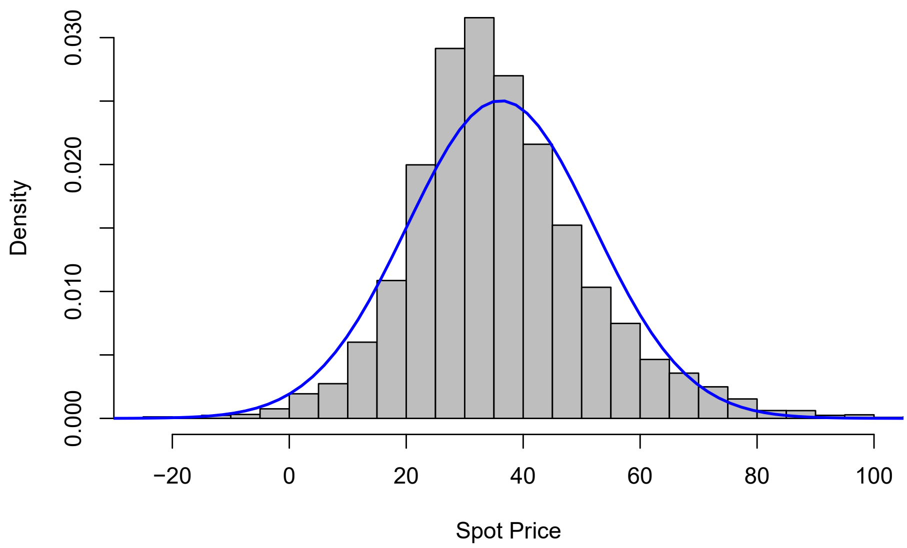


Figure 4.2: Distribution of the Spot price.

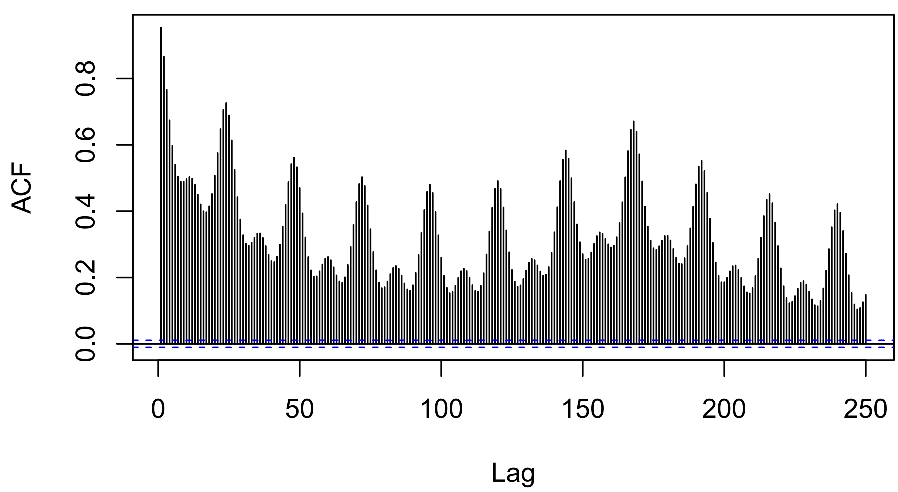


times the standard deviation from the mean. The main reason to eliminate the most extreme prices is that they are usually caused by system failure rather then normal price formation. This is in line with existing literature Ketterer (2014), Haxhimusa (2018), and Wozabal *et al.* (2016).

4.2.1 Seasonality

As a part of preliminary analysis, I use autocorrelation function (ACF) to study seasonal patterns in the data. Figure 4.3 shows correlogram of hourly spot prices. Clearly, there are spikes around lags 24, 48, etc. These spikes correspond to the daily seasonality. The highest spike is at lag 168 marking the weekly seasonal pattern. To address these seasonal patterns I introduce trigonometric periodic functions as in Tashpulatov (2013), Erni (2012). I assume that seasonal component of spot prices can be described as following function of time

Figure 4.3: ACF of hourly spot price with 250 lags



$$A \times cos(\frac{2\pi t}{T} - \upsilon) \tag{4.2}$$

where $\frac{1}{T}$ denotes frequency and υ denotes phase shift and A is the amplitude of cosine function. From trigonometric identities I can rewrite (4.2) as

$$A \times cos(\frac{2\pi t}{T})cos(\upsilon) + A \times sin(\frac{2\pi t}{T})sin(\upsilon). \tag{4.3}$$

From the expression (4.3) follows that I need to include $cos(\frac{2\pi t}{T})$ and $sin(\frac{2\pi t}{T})$ as explanatory variables. Sine and cosine value of the phase shift υ together with scalar A will create coefficients in final regression. To find frequencies which fits our data I perform spectral decomposition of spot price time series. According to Fourier analysis any time series with seasonal pattern can be expressed as a sum of periodic functions with different frequencies. More precisely, Fourier transformation of real-valued function $y(t)$ on domain $[0, T]$ is defined as

$$y(\omega) = \int_0^T y(t)e^{-i\omega t}dt. \tag{4.4}$$

In my setting I have $\omega = \frac{2\pi}{T}$. To obtain values of T, I use Fast Fourier Transformation which computes an approximation of (4.4). The most significant values of T are shown in Table 4.3. Values 12, 24, 167, and 8640 represent reasonable time intervals such as half-day, day, week, and year seasonality, respectively. Indeed, these seasonality patterns are usually found in other existing literature Guthrie & Videbeck (2007), Koopman *et al.* (2007). Values 17280, 34560 denotes two and three years. Since our dataset represents three years of data, I will not include these in later analysis.

Table 4.3: Seasonal periods

T	24	34560	8640	17280	12	11520	167

4.3 Panel Data

There are several reasons to treat electricity spot prices as a panel with 24 cross-sections. Recall, electricity is still mostly non-storable commodity and has to be consumed at same time when it is produced. Different hours cannot be traded between each other. Further, a time series is usually described as a sequence of updating information, Huisman *et al.* (2007). The spot prices are updated once per day. One could argue that this suggests use of daily averages for the analysis. Nevertheless, a price for each hour is determined with different set of information. This is true especially for peak hours when PV production comes to effect. Averaging the data could mitigate this effect. Thus, I consider each hour as separate time series. The resulting dataset has 24 cross-sectional entries and 1411 observations in time dimension. The final set of variables used within the analysis for each hour is following:

- **Solar.GE** - Cumulative solar production of all German PV parks. Unit of measurement is GW.
- **Wind.Offshore** - Cumulative wind production of all German offshore wind parks located in North and Baltic Sea. Unit of measurement is GW.
- **Wind.Onshore** - Cumulative wind production of all German onshore wind parks located on land. Unit of measurement is GW.
- **Wind.CZ** - Cumulative wind production of all Czech onshore wind parks. Unit of measurement is GW.
- **Solar.CZ** - Cumulative solar production of all Czech PV parks. Unit of measurement is GW.
- **Load** - Instantaneous offtake of power in the Czech power grid. Unit of measurement is GW.
- **Spot** - The Czech spot price of an electricity. Unit of measurement is EUR/MWh.
- **sinW** - Variable controlling for week seasonality defined as $sin(\frac{2\pi t}{167})$
- **cosW** - Variable controlling for week seasonality defined as $cos(\frac{2\pi t}{167})$
- **sinY** - Variable controlling for yearly seasonality defined as $sin(\frac{2\pi t}{8640})$
- **cosY** - Variable controlling for yearly seasonality defined as $cos(\frac{2\pi t}{8640})$

Further, I provide box plots for each hour to have a notion how distribution of selected variables change during a day. I use box plot which include following elements. A line representing the median value. A box representing the interquartile range (IQR). Vertical lines, or "whiskers" indicating 1.5 times the IQR in either direction from the 75th and 25th percentiles. Short horizonal lines representing the maximum and minimum of given variable. Dots representing outliers.

First set of box plots in Figure 4.4 refers to the spot price. Except 7 PM, all hours have a lot of outliers which confirms previous finding of leptokurtic distribution. By visual inspection it can be seen that hours 8 AM through 7 PM have similar IQR range. Likewise, the average spot price during these hours is higher. These hours are also recognized by the energy market as peak hours. Further, Figure 4.5 depicts box plots of the *Load*. The *Load* has similar distribution across different hours as the spot price. It is not the coincidence since instantaneous demand is the main driver of the spot price. There are only few outliers which occur during night hours. In general, *Load* is stable during whole day. Next, Figure 4.6 display distribution of the German PV production across day. It has expected shape. The production peaks during 1 PM, while there is not production during night. The most of solar production matches peak hours. Actually, solar production is responsible for the small dip in the spot price which can be seen between 9 AM and 6 PM. Further, early morning and late evening hours contain a lot of outliers. Moving to the wind production, Figure 4.7 displays box plots for German onshore production. Clearly, all hours contains a lot of outliers on the right part of their distribution while the mass of distribution is on the left. It suggests that the distribution of an onshore wind production is close to log-normal. IQRs are a little more wider for hours around noon. Lastly, Figure 4.8 captures distribution of German offshore wind production across all hours. Essentially, the distribution does not differ for any hour. Again, it looks like a log-normal distribution. Unlike onshore production, it has no outliers, i.e., the production is stable during the whole day.

Figure 4.4: Box plots of spot price.

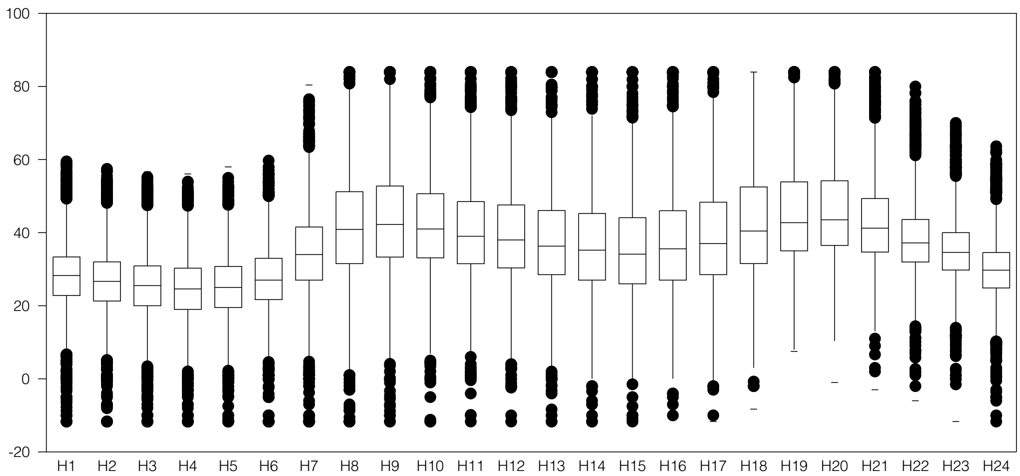


Figure 4.5: Box plots of load.

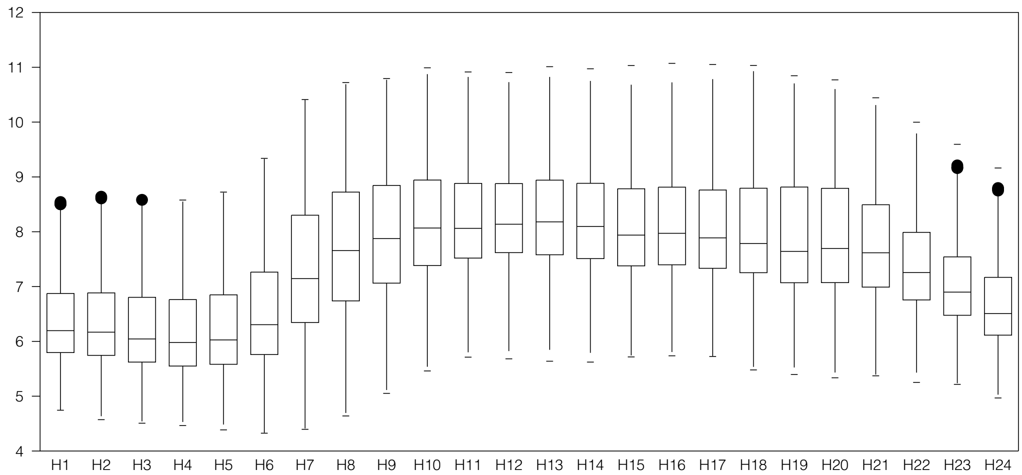


Figure 4.6: Box plots of German PV production.

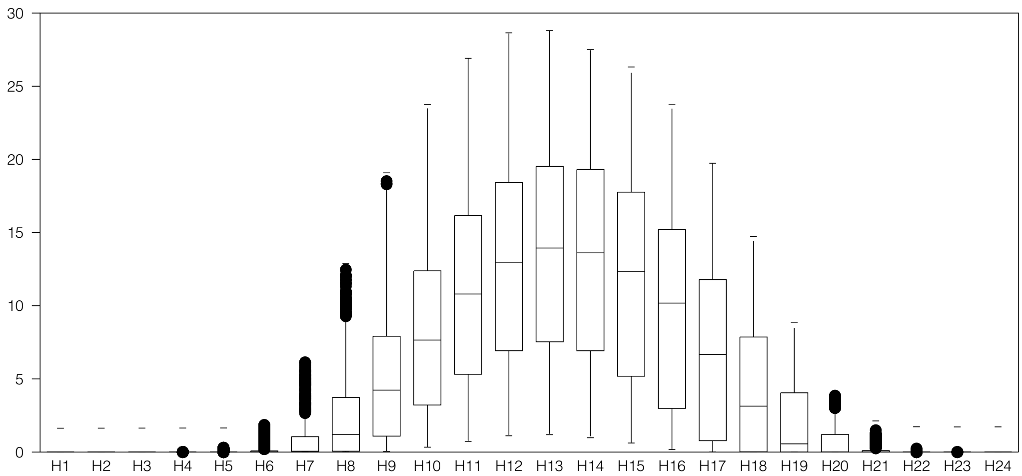


Figure 4.7: Box plots of German wind onshore production.

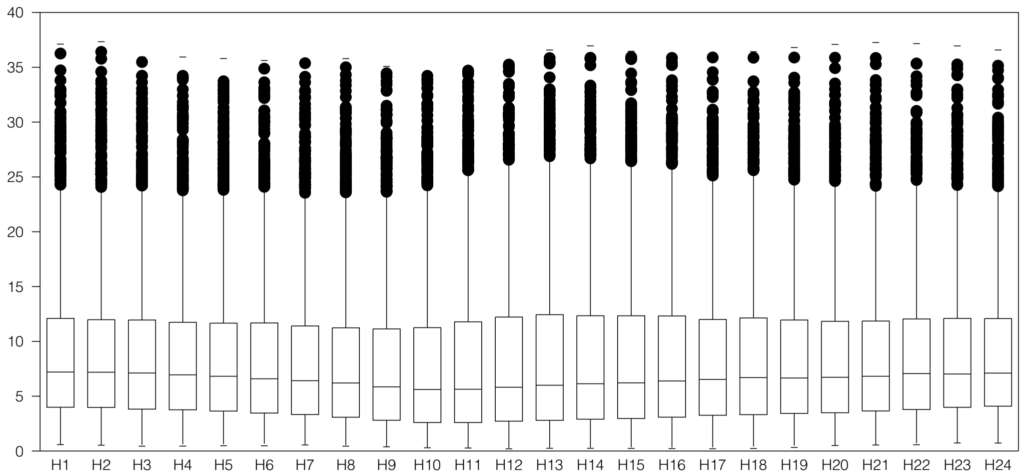
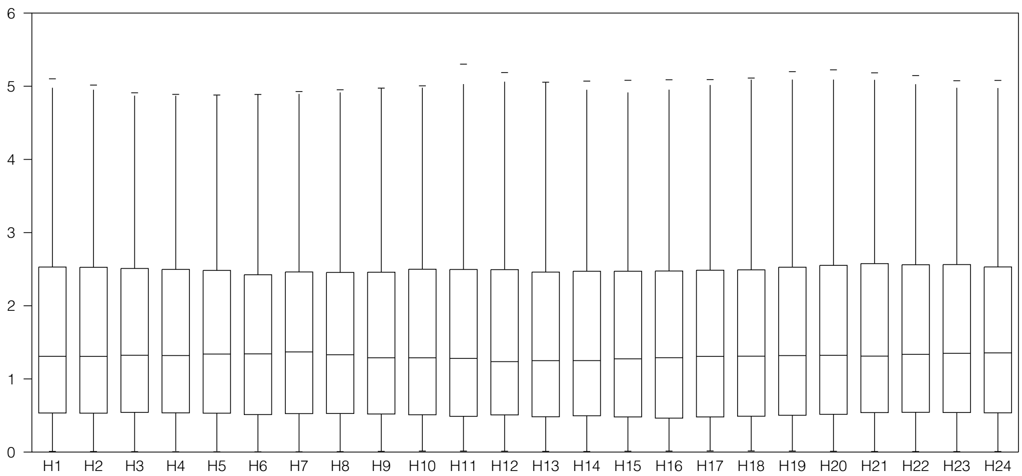


Figure 4.8: Box plots of German wind offshore production.



Chapter 5

Methodology

This section describes theoretical framework that we use for estimating the effects of RESs on Czech spot price. The methodology builds on the approach developed by Cermeño & Grier (2003). Similar model is used in Pham & Lemoine (2015) for analysis of German spot prices. I diverge from it by introducing smooth periodic function to control for seasonality and considering cross-border dependencies. Section is structured as follows. Firstly, I discuss spot price formation and why it should be taken into account when building the model. Secondly, I state several assumptions of Cermeño & Grier (2003) model and argue why it suits well to the purpose of this paper. Thirdly, I present model and procedure for preliminary model estimation. Lastly, I describe several formal tests, which are used throughout the analysis.

In chapter 2, I describe organization of the spot market and the process of price formation. Prices for all 24 hours are submitted at the same time. Thus, I assume they follow same dynamics. Indeed, they are likely to be influenced by same factors and market fluctuations which might be omitted in final model. As discussed in 2, electricity spot price is usually mean reverting process and which exhibits volatility clustering. This type of behaviour is generally described by ARMA-GARCH process. Therefore, appropriate modelling technique would be some vector auto-regressive (VAR) model which also control for conditional variance, i.e., multivariate GARCH model. Widely used models are VECH, BEKK, DCC-GARCH, etc. These models capture dynamics of multiple dependent variables while controlling for their conditional variances and conditional covariances between them. Nonetheless, the major disadvantage of these models is that they become quickly unfeasible to estimate with growing number of dependent variables. Considering panel dataset with 24 cross-section, VECH(1,1) requires 180 300 parameters to estimate, Pham & Lemoine (2015).

5.1 Model

In Cermeño & Grier (2003) authors describe Pooled Panel-GARCH (PP-GARCH) model. It allows modelling panel data with time-varying conditional matrix while preserving the simplicity of the model. The model describes a mean equation, a variance equation, and a covariance equation. I depart from original model by introduction external regressors to the variance equation. The mean equation is characterized as follows

$$y_{it} = \mu_i + \sum_{k=1}^{K} \phi_k y_{it-k} + \boldsymbol{x_{it}}\boldsymbol{\beta} + u_{it}, \quad i = 1, \ldots, N, t = 1, \ldots, T \tag{5.1}$$

where y denotes dependent variable, μ_i marks intercepts, ϕ_k are AR coefficients, $\boldsymbol{x_{it}}$ is a $(1 \times M)$ vector of external regressors, $\boldsymbol{\beta}$ is a $(M \times 1)$ vector of coefficients, and u_{it} denotes disturbances. Disturbances are assumed to be normally distributed with zero mean and following conditional moments:

$$\begin{array}{lllllll}
(1) & E[u_{it}u_{js}|u_{it-1}, u_{js-1}] = \sigma_{it}^2 & for & i = j & and & t = s \\
(2) & E[u_{it}u_{js}|u_{it-1}, u_{js-1}] = \sigma_{ijt} & for & i \neq j & and & t = s \\
(3) & E[u_{it}u_{js}|u_{it-1}, u_{js-1}] = 0 & for & i = j & and & t \neq s \\
(4) & E[u_{it}u_{js}|u_{it-1}, u_{js-1}] = 0 & for & i \neq j & and & t \neq s
\end{array}$$

Assumptions (3) and (4) prohibit autocorrelation and non-contemporaneous correlation between cross-section, respectively. Assumptions (1) and (2) describe variance-covariance process. More specifically, I assume variance-covariance follows GARCH(p,q) process, i.e.,

$$\sigma_{it}^2 = \alpha_i + \boldsymbol{z_{it}\zeta} + \sum_{n=1}^{p} \delta_n \sigma_{i,t-n}^2 + \sum_{m=1}^{q} \gamma_m u_{i,t-m}^2 \quad for \quad i = 1, \ldots, N \tag{5.2}$$

$$\sigma_{ijt} = \eta_{ij} + \sum_{n=1}^{p} \lambda_n \sigma_{ij,t-n} + \sum_{m=1}^{q} \rho_m u_{i,t-m} u_{j,t-m} \quad for \quad i \neq j. \tag{5.3}$$

Equations (5.2) and (5.3) refer to the conditional variance and the conditional covariance, respectively. Both equations assume ARCH process with p lags and GARCH process q lags. Intercepts are denoted by α_i and η_{ij}. In equation (5.2) I assume additional external variables to possibly influence the behaviour of conditional variance. They are denoted by the $(1 \times L)$ vector $\boldsymbol{z_{it}}$ and the corresponding coefficient $(L \times 1)$ vector $\boldsymbol{\zeta}$. To ensure non-negativity and stationarity of the variance process conditions $\alpha_i > O$ and $(\sum_{n=1}^{p} \delta_n + \sum_{m=1}^{q} \gamma_m) < 1$ have to be met. Note, the closer the sum of coefficients is to 1, the more is the volatility clustering persistent. A sufficient condition for stationarity of the covariance process is $(\sum_{n=1}^{p} \lambda_n + \sum_{m=1}^{q} \rho_m) < 1$.

Recall, in all three equations (5.1), (5.2), and (5.3) I assume heterogeneity in intercepts across all cross-section while assuming homogeneity in slope coefficients. The homogeneity assumption in slope coefficients dramatically reduces the number of coefficients to be estimated. Not taking into account the external regressors, variance-covariance process is described by $2(p+q) + \frac{N(N-1)}{2}$ coefficients. The largest part comes from the heterogeneity in the intercept. Later, I present procedure determining if individual intercepts are needed or common intercept fits the data better.

5.2 Formal Tests

In this section I describe several statistical tests which are used throughout the analysis to correctly specify the final model.

5.2.1 Maddala-Wu Unit-Root Test

To tests for stationarity I use Maddala-Wu test originaly proposed by Maddala & Wu (1999). It is based on Augmented Dickey Fuller (ADF) test adjusted for a panel data. The test is applied to following model:

$$y_{it} = \alpha_i + \phi_i y_{it-1} + \sum_{j=1}^{k_i} \psi_{ij} \Delta y_{it-j} + \varepsilon_{it}, \quad i = 1, \dots, N, t = 1, \dots, T \tag{5.4}$$

where ε_{it} is i.i.d. with $E(\varepsilon_{it}) = 0$, $E(\varepsilon_{it}^2) = \sigma_i^2 < \infty$, and k_i refers to the number of lags tested. The null hypothesis is $H_0 : \phi_i = 1 \quad \forall i$. The so-called heterogeneous alternative hypothesis is H_A : "at least one of the series is $I(0)$". Author claims that the null hypothesis can be tested jointly based on combination of p-values from all N independent ADF tests. Thus, under the null hypotheses, fixed N and $T \to \infty$, test statistic follows

$$P = -2 \sum_{i=1}^{N} log(p_i) \xrightarrow{d} \chi^2(2N).$$

5.2.2 Variance Inflation Factor

Second test applied in following analysis examines whether multicollinearity is an issue in particular model. The Variance Inflation Factor (VIF) test examines the impact of collinearity among independent variables on the precision of estimated coefficients. The test was originally proposed by Fox & Monette (1992). Consider following linear model.

$$y = \alpha + \beta_1 x_1 + \cdots + \beta_k x_k + \varepsilon \tag{5.5}$$

To obtain VIF statistics for x_j, I need to regress x_j on all the other explanatory variables. Then the VIF for x_j is given by

$$VIF(\hat{\beta}_j) = \frac{1}{1 - R_j^2} \tag{5.6}$$

where R_j^2 is the R-squared from corresponding linear regression. Definition (5.6) says how much is the variance of estimated coefficient inflated by the correlation with the other independent variable. If R_j^2 is equal to 0, i.e., there is no correlation between x_j and other covariates, VIF_j equals 1 and the estimate $\hat{\beta}_j$ is not effected by collinearity. The rule of thumb says that VIF larger then 10 suggests high muliticollinearity, Neter *et al.* (1996).

5.2.3 Breusch–Pagan Test

To test whether the assumption of homoskedasticity in the residuals is satisfied I use test introduced in Breusch & Pagan (1979). Homoskedasticity is violated when the variance of residuals is not similar across the values of the independent variables. The test is performed as follows.

Assuming same general linear model as in (5.6), I run corresponding regression and obtain residuals. Secondly, I square the residuals and perform following auxiliary regression

$$\varepsilon^2 = \gamma + \gamma_1 z_1 + \cdots + \gamma_p z_p + \nu \tag{5.7}$$

where z can be substitute by independent variables x. The null hypothesis $H_0 : \gamma_1 = \cdots = \gamma_p = 0$ assumes homoskedasticity. Respective $LM = nR^2$ statistic is asymptotically distributed as χ^2_{p-1} under the null hypothesis. The R-squared corresponds to the regression of (5.7). Rejection of the H_0 in favour of alternative hypothesis suggests presence of heteroskedasticity.

5.2.4 Breusch-Godfrey Test

Last test used throughout the analysis is the Breusch-Godfrey test for serial correlation developed by Godfrey (1978) and Breusch (1978). It tests whether residuals from given linear model follow autoregressive process up tu order p, i.e., AR(p). Specifically, having following dynamic linear model

$$\boldsymbol{y} = \boldsymbol{X\beta} + \boldsymbol{u} \tag{5.8}$$

where $\boldsymbol{y}$ is a $(T\times 1)$ vector of observation on dependent variables, $\boldsymbol{X}$ is a $(T\times k)$ matrix of observation on independent variables and lagged dependent variable, $\boldsymbol{\beta}$ is a $(T \times 1)$ vector of coefficients, and $\boldsymbol{u}$ is a $(T \times 1)$ vector of error terms. After estimating equation (5.8) and obtaining residuals $\hat{u}_t$, the test for AR(p) process in the residuals is done via fitting following auxiliary regression

$$\hat{u}_t = \alpha_0 + \boldsymbol{X\beta} + \rho_1 \hat{u}_{t-1} + \rho_2 \hat{u}_{t-2} + \cdots + \rho_p \hat{u}_{t-p} + \varepsilon_t \tag{5.9}$$

If the null hypothesis $H_0 : \rho_i = 0$ of no serial correlation holds, then corresponding $LM = (T-p)R^2\ \chi^2(p)$ statistics can be used for the distribution of the test.

5.2.5 Bayesian information criterion

There are several metrics commonly used for the model's goodness-of-fit, e.g., Akaike's or Schwarz's Bayesian information criterions (BIC) or likelihood ratio test. Note that lower the information criterion is the better are data fitted.

Akaike information criterion (AIC) emphasizes good prediction power of a model. On the other hand, AIC has higher probability of over-fitting the model with increasing sample size. BIC defined as

$$BIC = ln(n)k - 2ln(\hat{L})$$

where k refers to the number of estimated coefficients and $\hat{L}$ is the maximum of log-likelihood function, values parsimony of a model. While both criterions penalize model complexity, BIC's penalty weight grows with sample size. Thus, BIC has lower probability of both over-fitting and under-fitting with increasing sample size, Dziak *et al.* (2019). Since this thesis use quite large sample of data, I choose to use BIC for final model selection.

5.2.6 Model Estimation

Even though the OLS estimator of equation (5.1) is consistent and possibly most efficient, it does not allow to estimate the whole model simultaneously, Cermeño & Grier (2003). Therefore, I will estimate the model by direct maximization of log-likelihood function. To obtain the log-likelihood function, I rewrite equation (5.1) to matrix notation as follows:

$$\boldsymbol{Y_t} = \boldsymbol{I}\boldsymbol{\mu} + \boldsymbol{Z_t}\boldsymbol{\theta} + \boldsymbol{u_t} \quad t = 1, \dots, T \tag{5.10}$$

where $\boldsymbol{I}$ is a $(N \times N)$ identity matrix, $\boldsymbol{\mu}$ is a $(1 \times N)$ vector of intercept coefficients, $\boldsymbol{Z}$ is $(N \times (K + M))$ matrix, where K and M refer to the number of endogenous lagged variables and the number of exogenous variables, respectively. $\boldsymbol{\theta}$ is corresponding coefficient $((K + M) \times N)$ matrix. They are constructed as follows:

$$\boldsymbol{Z_t} = [\boldsymbol{y_{t-1}} \dots \boldsymbol{y_{t-k}} \quad \boldsymbol{X_t}], \qquad \boldsymbol{\theta} = \begin{bmatrix} \boldsymbol{\theta} \\ \boldsymbol{\beta} \end{bmatrix}$$

The $\boldsymbol{u_t}$ is $(N \times 1)$ vector of disturbances with distribution given as $\boldsymbol{u_t} \sim N(\boldsymbol{0}, \boldsymbol{\Omega_t})$. More specifically, $\boldsymbol{u_t}$ has a multivariate normal distribution with mean equal to zero and variance-covariance matrix $\boldsymbol{\Omega_t}$. Its diagonal and off-diagonal elements are given by equations (5.2) and (5.3), respectively. Thus, vector of observation $\boldsymbol{y_t}$ has a conditional normal distribution given by $\boldsymbol{y_t} \sim N(\boldsymbol{I\mu} + \boldsymbol{Z_t\theta}, \boldsymbol{\Omega_t})$ and its conditional density function is following:

$$f(\boldsymbol{y_t}|\boldsymbol{X_t}, \boldsymbol{\mu}, \boldsymbol{\theta}, \phi) = (2\pi)^{-\frac{N}{2}} |\boldsymbol{\Omega_t}|^{-\frac{1}{2}} e^{-\frac{1}{2}(\boldsymbol{y_t} - \boldsymbol{I\mu} - \boldsymbol{Z_t\theta})' \boldsymbol{\Omega_t^{-1}} (\boldsymbol{y_t} - \boldsymbol{I\mu} + \boldsymbol{Z_t\theta})} \tag{5.11}$$

where ϕ stands for parameters in conditional variance and conditional covariance equations (5.2), (5.3). Thus, the log-likelihood function for whole panel is given as follows:

$$ln(L) = -\frac{NT}{2} ln(2\pi) - \frac{1}{2}\sum_{t=1}^{T} ln|\boldsymbol{\Omega_t}| - \frac{1}{2}\sum_{t=1}^{T} (\boldsymbol{y_t} - \boldsymbol{I\mu} - \boldsymbol{Z_t\theta})' \boldsymbol{\Omega_t^{-1}} (\boldsymbol{y_t} - \boldsymbol{I\mu} - \boldsymbol{Z_t\theta}). \tag{5.12}$$

To maximize the log-likelihood function in (5.12) I will use numerical optimization methods. More specifically, I employ Broyden–Fletcher–Goldfarb–Shanno (BFGS) algorithm which is from family of so-called "hill-climbing" optimization techniques. The algorithm seeks stationary point of the function where conditions for maximum are satisfied, e.g., gradient of the function is equal to zero. Since equation (5.12) can have multiple local maxima I need to specify different starting values for the BFGS algorithm, so the optimization does not cease in only local maximum. Further, the possibility of homogeneity in intercepts needs to be investigated. Therefore, I need to perform preliminary analysis of the data to identify the most suitable model.

Authors in Cermeño & Grier (2003) propose procedure for identification of individual effects in the mean and the variance equation. Testing for ARCH effects is also described. Authors argue that under assumption of cross-sectional independence appropriate model can be determined as follows [6].

- Firstly, a test for individual effects in the mean equation needs to be performed. I estimate the mean equation (5.1) using least square dummy variable (LSDV) estimator. Specifically, I perform Wald test with a null hypothesis $H_0 : \mu_1 = \cdots = \mu_N$. Further, authors suggest to use the autocorrelation-hetoreskedasticity robust covariance (HAC) matrix.

[6] Even though this assumption could be invalid, paper proves preliminary analysis under such a condition is strong tool for correct model identification.

- Secondly, a test for ARCH effects and individual effects in the variance equation (5.2) is performed. Based on the result from first step, I take either OLS or LSDV squared residuals and regress them on its lags. The appropriate number of lags can be determined by estimating autocorrelation (ACF) or partial autocorrelation (PACF) function. More specifically, I perform Breusch–Godfrey test with a null hypothesis $H_0 : \delta_i = 0$ for all i, i.e, ARCH(0) vs. ARCH(p). The corresponding LM-statistics follows χ^2_p distribution. Since GARCH(1,1) describes arbitrarily large number of ARCH lags, testing for small values of p is sufficient, Cermeño & Grier (2003). Finally, I regress ARCH process with and without individual effects and compare models with F test.

- Lastly, final model is estimated via maximum likelihood estimator (MLE). Several alternative specification of the model should be considered. I choose the final model based on corresponding value of BIC. Finally, the plausibility of cross-sectional independence should be tested, i.e., if coefficients in equation (5.3) are statistically significant.

5.3 Merit Order Effect

In order to determine the total average merit order effect (MOE) of RESs in specific year, I follow similar approach as in Cludius *et al.* (2014) and Sensfuss *et al.* (2008). Authors define the total average MOE as the sum of product between volume weighted average of generation source multiplied by the source's marginal effect. More specifically, the MOE is computed as follows

$$MOE_y = \frac{\sum_{j \in J} \beta_j \boldsymbol{x_{j,y}}}{\sum_t z_{t,y}} \tag{5.13}$$

where $\boldsymbol{z_y} = (\boldsymbol{x_{1,y}}, \ldots, \boldsymbol{x_{J,y}})$ denotes system load in given year, $\boldsymbol{x_{j,y}}$ is a production of source j, and β_j is a corresponding marginal effect.

Then it is simple to compute an annual financial volume of the total average MOE in given year by the following equation.

$$\upsilon_y = MOE \times \sum_{t=1}^{T} z_{t,y}. \tag{5.14}$$

The annual financial volume υ represents a total annual costs savings for market participants.

Chapter 6

Results and Discussion

In this chapter, I present all final results. First, I describe how I proceed with the identification of the final model. Second, I present results of the statistical model. Lastly, I discuss obtained results and put them into perspective with the costs borne by households.

6.1 Preliminary Model Identification

In this section, I describe in detail preliminary identification of the final model. Firstly, selection of appropriate independent variables is presented. Secondly, I conduct model identification procedure as described in Chapter 5.

When dealing with times series data, stationarity of data is one of the crucial assumption for validity of final model. Therefore, I perform Maddala-Wu Unit-Root test for the spot price time series. Corresponding χ^2 statistics 508 rejects the null hypothesis of non-stationarity. Secondly, I decide to split the dataset into two smaller ones. One dataset contains "PEAK" hours, i.e., 8 AM to 19 PM. The second one consists of "OFF-PEAK" hours, i.e., 20 PM to 7 AM. Actually, datasets coincide with standard delivery products, peak load and off-peak load. There are two reasons for such a division. First of all, PV power plants do not produce energy during night. Secondly, during peak hours there is a higher demand for electricity which may arise in different price dynamics than during off-peak hours. Detailed identification procedure is presented for the "PEAK" model. The "OFF-PEAK" model is identified analogously. Nevertheless, I only present final model for given equation.

6.1.1 Mean Equation

I start with identification of the mean equation (5.1). Recall, preliminary analysis of data shown large correlation between a *Solar.GE* and a *Solar.CZ* variables. Since one of the main goals of this thesis is to identify the extent the Czech spot prices are effected by the German solar production, I need to make sure that multicollinearity among independent variables does not shift coefficients of interest. In line with Wooldridge (2013), I center both variables by subtracting their means and add interaction term *Solar.GE:Solar.CZ* which is a product of centered variables. The interaction term filters out the common effect of solar production on the spot prices.

Except variables presented in Table 4.1, I also consider seven lags of spot price. As been tested in Chapter 4, spot prices exhibit strong autocorrelation. Including seven lags of dependent variable captures all information in the market from the past week which might not be explained by other independent variables. Similar approach was used in Pham & Lemoine (2015). Further, the *Load* variable should control for a week seasonality in the spot prices. Indeed, preliminary analysis of the spot price frequency in Chapter 4 shown the week pattern. Nevertheless, I test whether inclusion of smooth periodic function *cosW* and *sinW* captures any residual information which might be omitted. More specifically, I examine whether smooth periodic functions captures residual week seasonality as good as lagged dependent variable, which would result in more parsimonious model. Thus, I estimate three possible models for the mean equation with LSDV estimator. Specifically, I estimate three variation of equation (5.1). All regressions use the HAC robust errors. First model is a benchmark model without any control for the residual week seasonal pattern. Second model controls residual week seasonality with smooth periodic functions *cosY* and *sinY*. Third model employs seven lags of dependent variable. Models will be referred to as model A,B, and C, respectively. Results are presented in Table 6.1. It shows estimated coefficients with corresponding standard errors in parentheses. To save space, I do not present coefficients for individual effects. Complete results can be found in Appendix. Nevertheless, all effects are highly statistically significant with t-statistic above 10 and have a negative sign for all three models. First column presents summary results of model A. Both, *cosY* and *sinY*, variables which control for year seasonality are statistically significant even at 1 percent level. As expected *Solar.GE*, *Solar.CZ*, and *Wind.Onshore* have negative effect on the spot price. On the

Table 6.1: Results of the PEAK mean equation identification.

	Dependent variable:		
	Spot		
	(A)	(B)	(C)
Solar.GE	-0.443^{***}	-0.439^{***}	-0.327^{***}
	(0.071)	(0.071)	(0.033)
Wind.Offshore	1.005^{***}	0.993^{***}	-0.396^{***}
	(0.167)	(0.166)	(0.088)
Wind.Onshore	-0.741^{***}	-0.738^{***}	-0.500^{***}
	(0.033)	(0.033)	(0.017)
Wind.CZ	6.055^{*}	6.058^{*}	
	(3.192)	(3.214)	
Solar.CZ	-3.491^{***}	-3.494^{***}	-2.413^{***}
	(0.787)	(0.784)	(0.466)
Load	11.106^{***}	11.218^{***}	7.747^{***}
	(0.154)	(0.178)	(0.136)
cosW		0.006	
		(0.095)	
sinW		0.459^{***}	
		(0.125)	
cosY	-8.307^{***}	-8.400^{***}	-6.970^{***}
	(0.491)	(0.491)	(0.274)
sinY	-8.952^{***}	-8.989^{***}	-4.395^{***}
	(0.395)	(0.398)	(0.147)
lag1_Spot			0.251^{***}
			(0.007)
lag2_Spot			0.026^{***}
			(0.007)
lag3_Spot			0.047^{***}
			(0.007)
lag4_Spot			0.034^{***}
			(0.007)
lag5_Spot			0.047^{***}
			(0.006)
lag6_Spot			0.047^{***}
			(0.006)
lag7_Spot			0.177^{***}
			(0.007)
Solar.GE:Solar.CZ	0.382^{***}	0.380^{***}	0.122^{***}
	(0.080)	(0.080)	(0.039)
Observations	16,882	16,882	16,882
R^2	0.947	0.947	0.965
Adjusted R^2	0.947	0.947	0.965
F Statistic	$14{,}472.680^{***}$	$13{,}226.320^{***}$	$17{,}459.810^{***}$
Note:			$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

other hand, *Load* as a main determinant of instantaneous demand has a positive effect on the spot price. Corresponding coefficient is highly significant at any conventional level. Coefficients of *Wind.Offshore* and *Wind.CZ* are also significant at 1 percent level. Nevertheless, they have a positive sign which is not in line with expectations. Interaction variable *Solar.GE:Solar.CZ* is also highly statistically significant. Model A has F-statistics equal to 14 472 and adjusted R-squared 0.947.

Second column of Table 6.1 displays estimation results of the model B. Including *cosW* and *sinW* variables to control for the residual week seasonality did not change any other coefficient significantly. All the other variables remained highly significant with almost the same coefficients. Seasonal variables are themselves highly significant. While adjusted R-squared remained the same, corresponding F-statistics dropped to 13 226. Last column shows results of the model C. All the coefficients shrunk towards zero. The main difference here lays in the effect of the *Wind.Offshore* variable. Its coefficient is now negative which is expected from the economic point of view. Further, the effect of *Wind.CZ* on the spot price become statistically insignificant. Compared to the benchmark model, there is a significant increase in the F-statistics. Indeed, F test finds statistically significant reduction in the residual sum of squares even at 1 percent. Also, corresponding adjusted R-squared increased to 0.965. Finally, I choose model C, without *Wind.CZ* variable, as the best representation of the mean equation for next analysis.

Last, I test whether a multicollinearity is present in the final model. Table 6.2 shows resulting VIF test statistics for variables of interest. All the statistics are below the cut-off value of 10 [7]. Thus, I conclude multicollinearity is not an issue.

Table 6.2: Results of the VIF test for multicollineairty

Solar.GE	Wind.Offshore	Wind.Onshore	Solar.CZ	Solar.GE:Solar.CZ
7.307	5.189	4.927	6.739	2.952

Similar approach was used for determination of the "OFF-PEAK" mean equation. Analogue of model C turns out to be the best fit. Table 6.3 shows results of final model. Model does not contain any variables controlling for

[7] Actually, centering and adding interaction term reduced VIF test statistics considerably. Before this procedure, *Solar.GE* and *Solar.CZ* variables had VIF test statistics as high as 20.

solar production since most of the sample are night hours. Only *Wind.CZ* and *Wind.Offshore* variables are statistically insignificant as their corresponding p-values did not reach any conventional significance level. In line with expectation, coefficient of the *Load* variable is almost two times smaller than in case of the PEAK model. This is the result of lower demand for electricity during night hours. F-statistics obtained from regression is equal to 24 981. Corresponding adjusted R-squared is 0.974.

Note, R-squared obtained from both regressions exceeds 0.95. This means that models explain 95 percent of variation in the spot price. Such a large R-squared usually means presence of autocorrelation in the data or even spurious regression. Roughly speaking, spurious regression occurs when both dependent and independent variables follow same trend. Since stationarity of dependent variables was confirmed by the Maddala-Wu test statistic, spurious regression can be ruled out. Recall that model contains sine and cosine functions with frequencies obtained directly from spectral decomposition of dependent variable. Moreover, *Load* is highly correlated with the spot price as shown in chapter 4. Figure 4.1 confirms that most of variation in the spot price is indeed explained by the load. Indeed, these two effects together capture most of the spot price variability. Therefore, I conclude that model does not violate any standard assumption.

6.1.2 Conditional Variance Equation

Next, I examine squared residuals obtained from the previous regression of model C. The goal is to identify which variables should be included in the final variance equation. Again, the PEAK model is described in detail.

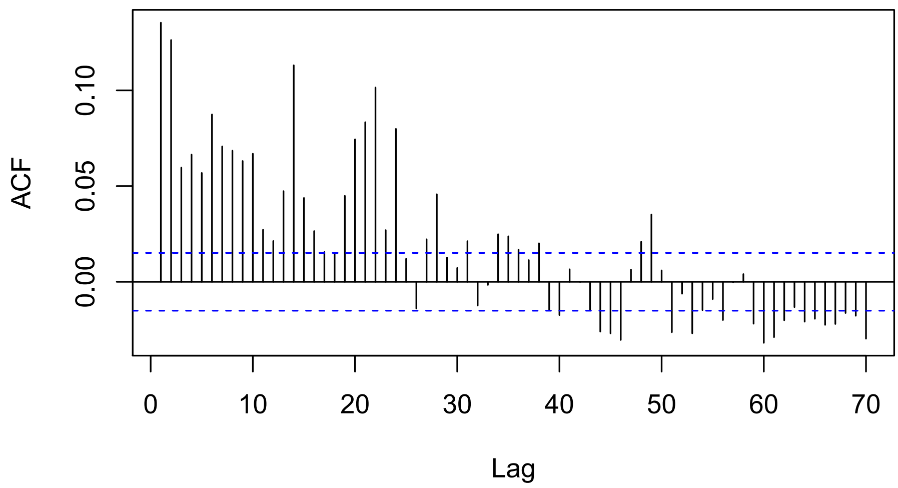
First, I investigate whether squared residuals exhibit autocorrelation. Figure 6.1 shows plot of the ACF for corresponding series. Clearly, there is a strong pattern of autocorrelation up to 24 lags. Second, I perform Breusch–Godfrey test up to lag 24. Resulting LM statistics equal to 3586, rejects null hypothesis of no serial correlation. Recall, GARCH(1,1) describes arbitrarily large number of ARCH effects. Thus, I continue with my analysis with rather small number of lags, i.e., ARCH(3)[8]. Lastly, I test for presence of heteroskedasticity using Breusch–Pagan test. Test statistics equals 476 resulting in rejection of the null hypothesis at 1 percent level. Given all the information above, I estimate following equation with and without individual effects.

[8]More detailed analysis shown that ARCH(3) describes process of squared residuals well.

Table 6.3: Results of the OFF-PEAK mean equation identification.

	Dependent variable:
	Spot
Wind.Offshore	0.048
	(0.075)
Wind.Onshore	-0.680^{***}
	(0.022)
Wind.CZ	1.670
	(1.726)
Load	4.577^{***}
	(0.124)
cosY	-2.161^{***}
	(0.160)
sinY	-2.264^{***}
	(0.111)
lag1_Spot	0.308^{***}
	(0.008)
lag2_Spot	0.032^{***}
	(0.007)
lag3_Spot	0.067^{***}
	(0.007)
lag4_Spot	0.040^{***}
	(0.007)
lag5_Spot	0.052^{***}
	(0.006)
lag6_Spot	0.057^{***}
	(0.006)
lag7_Spot	0.188^{***}
	(0.007)
Observations	16,892
R^2	0.974
Adjusted R^2	0.974
F Statistic	$24{,}981.130^{***}$
Note:	*p<0.1; **p<0.05; ***p<0.01

Figure 6.1: ACF of squared residuals from the PEAK mean equation.



$$u_{it}^2 = \alpha_i + \boldsymbol{z_{it}\zeta} + \sum_{m=1}^{3} \gamma_m u_{i,t-m}^2 + \epsilon_{it} \tag{6.1}$$

As before α_i denotes individual effects, $\boldsymbol{\zeta}$ is a vector of independent variables. Based on F test, I conclude that individual effects are present also in the variance process. Results are presented in Table 6.4. Again, coefficients of individual effects can be found in Appendix. Results suggest that both *Wind.Offshore* and *Wind.Onshore* influence volatility of prices quite heavily. Coefficient corresponding to the German solar production is also positive and significant. Conversely, the effect of the Czech solar production is insignificant.

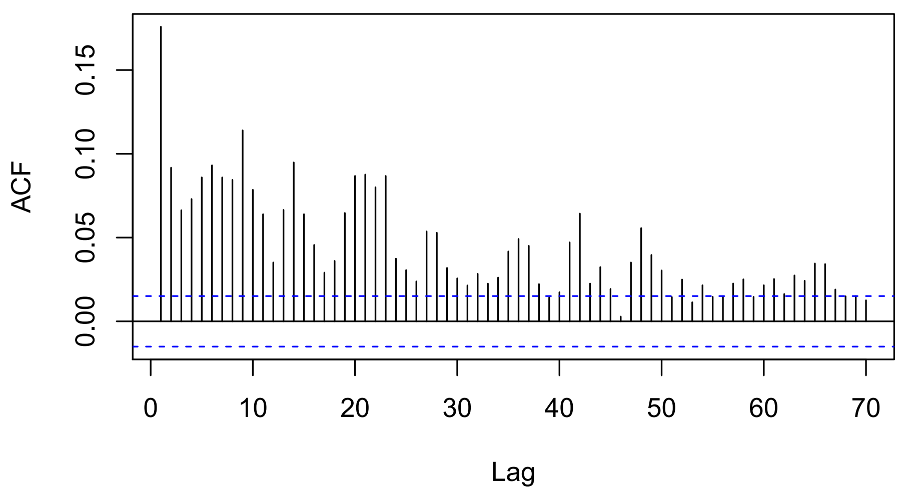
Analog procedure was used to investigate variance process of OFF-PEAK model. I briefly present results of corresponding tests and regression. Figure 6.2 shows the ACF of squared residuals. As can be seen in the plot, serial correlation is more persistent in the spot prices of off-peak hours.

The Breusch–Godfrey test for serial correlation up to 50 lags gives LM statistics equal to 4777, i.e., test rejects the null hypothesis of no serial correlation. Next, Breusch-Pagan test rejects the null hypothesis of homoskedasticity at 1 percent level. Similarly to the PEAK model, I estimate equation with ARCH(3) and two independent variables *Wind.Onshore*, *Wind.Offshore*. Further, I performed F test to find whether model with individual effects is

Table 6.4: Results of the PEAK variance equation identification.

	Dependent variable:
	res
lag1_res	0.107***
	(0.008)
lag2_res	0.102***
	(0.008)
lag3_res	0.026***
	(0.008)
Solar.GE	0.615*
	(0.366)
Wind.Offshore	4.675***
	(1.208)
Wind.Onshore	1.552***
	(0.209)
Solar.CZ	−2.105
	(6.202)
Observations	16,879
R^2	0.196
Adjusted R^2	0.195
F Statistic	215.814***
Note:	*p<0.1; **p<0.05; ***p<0.01

Figure 6.2: ACF of squared residuals from the OFF-PEAK mean equation.



plausible. According to the test, the model with individual effects explains data better. Corresponding F statistic equals 11.8. Thus, I conclude that the OFF-PEAK variance process contains individual effects. Results can be found in tables 6.5 and A.6. *Wind.Offshore* variable is statistically significant on the 5 percent level. All the other variables are significant at 1 percent level.

Table 6.5: Results of the OFF-PEAK variance equation identification.

	Dependent variable:
	res.sq
lag1_res.sq	0.131***
	(0.008)
lag2_res.sq	0.036***
	(0.008)
lag3_res.sq	0.021***
	(0.008)
Wind.Offshore	1.384**
	(0.596)
Wind.Onshore	1.846***
	(0.108)
Observations	16,889
R^2	0.222
Adjusted R^2	0.221
F Statistic	282.682***
Note:	*p<0.1; **p<0.05; ***p<0.01

6.2 Results

In this section, I present results of final models. I describe the results of the PEAK model first.

The final model for the PEAK data is estimated by the MLE. The resulting value of log-likelihood function is -41 343. Corresponding BIC, which was one of the main criteria for the selection of final model, is 84 280. Table 6.6 displays estimated coefficients. Again, coefficients of individual effects are displayed only in appendix since corresponding coefficients are not of top importance for the purpose of this analysis. Nevertheless, all of them are statistically significant at 1 percent. As can be seen from the Table 6.6, variables controlling for the wind energy produced by the German offshore parks and the Czech onshore parks were excluded from the final model since both variables lost its significance while estimating all equations (5.1), (5.2), and (5.3) simultaneously. All estimated coefficients are significant. Actually, the lowest t-statistic is equal to 2.93. Thus, all variables are statistically significant at any conventional level. All AR coefficients are positive. The AR(1) and the AR(7) have the largest and second largest effect on the spot price, respectively. Possible explanation is that the last price for given hour accommodate the most information about latest development of the energy market. Next, the seventh lag of dependent variable corresponds to the spot price of the same hour week ago. Thus, I conclude that it captures the residual information of week seasonality which is not captured by the *Load* variable. As expected *Solar.GE*, *Wind.Onshore*, and *Solar.CZ* have a negative effect on the spot price. Specifically, one additional GW of power fed into the system reduces the spot price by 0.45, 0.60, and 1.42 EUR/MWh, respectively. Conversely, the spot price rises by 7.68 EUR/MWh when one additional GW is consumed. Both smooth periodic functions controlling for year seasonality have negative coefficients equal to -6.97 and -4.23 for $cosY$ and $sinY$, respectively. The interaction term between the Czech and the German solar production has coefficient equal to 0.09.

Moving to the conditional variance, one can see that only two external regressors were included in the final model. It is the Czech solar production and the German onshore wind production. The main driver of the spot price volatility is the Czech solar production with coefficient equal to 2.4. On the other hand, the wind energy from Germany has rather smaller impact on the spot price volatility with coefficient equal to 0.02. The conditional variance follows GARCH(1,1) process with estimated coefficients 0.785 an 0.062, respectively. Same process is found for the conditional covariance with very similar coefficients equal to 0.783 and 0.06. One can see that stationarity condition is satisfied, i.e., the sum of the ARCH and the GARCH coefficients is less than one for both, conditional variance and conditional covariance. Also, all the intercepts in the conditional variance equation are positive. Further, the sum of ARCH and GARCH coefficients in the conditional variance is approximately 0.85 denoting high level of persistence in volatility clustering.

Further, I continue with the results of the OFF-PEAK model. As in case of the PEAK model, I use MLE to estimate final model. The results are displayed in Table A.8. The resulting value of log-likelihood function is -38 340. The BIC criterion equals 78 215. All estimated coefficients are highly statistically significant. The lowest t-statistic corresponds to the AR(3) term and equals

Table 6.6: Results of Dynamic Panel GARCH for PEAK Model

Variable	Coeff	Std Error	T-Stat	Signif
Mean Equation				
AR(1)	0.161	0.008	19.640	0.000
AR(2)	0.030	0.008	3.802	0.000
AR(3)	0.049	0.008	6.418	0.000
AR(4)	0.049	0.007	6.647	0.000
AR(5)	0.037	0.007	5.099	0.000
AR(6)	0.078	0.007	10.831	0.000
AR(7)	0.115	0.007	15.915	0.000
Solar.DE	-0.446	0.022	-20.737	0.000
Wind.Onshore	-0.609	0.016	-38.888	0.000
Solar.CZ	-1.420	0.296	-4.792	0.000
Load	7.682	0.165	46.483	0.000
cosY	-6.975	0.305	-22.886	0.000
sinY	-4.235	0.235	-18.060	0.000
Solar.GE:Solar.CZ	0.093	0.032	2.933	0.003
$\mu_i(12)$	...	...	...	...
Conditional Variance Equation				
ARCH(1)	0.785	0.005	162.249	0.000
GARCH(1)	0.062	0.004	15.507	0.000
Solar.CZ	2.397	0.186	12.862	0.000
Wind.Onshore	0.020	0.001	14.104	0.000
$\alpha_i(12)$	...	...	...	...
Conditional Covariance Equation				
ARCH(1)	0.783	0.005	156.619	0.000
GARCH(1)	0.060	0.004	14.988	0.000
$\eta_{ij}(66)$	...	...	...	...

Estimation by BFGS	
Convergence in	476 Iterations
Usable Observations	1403
BIC	84280.669
Log-likelihood value	-41343.312

Table 6.7: Results of Dynamic Panel GARCH for the OFF-PEAK Model

Variable	Coeff	Std Error	T-Stat	Signif
Mean Equation				
AR(1)	0.158	0.011	13.779	0.000
AR(2)	0.075	0.012	6.169	0.000
AR(3)	0.048	0.012	3.826	0.000
AR(4)	0.042	0.013	3.335	0.001
AR(5)	0.057	0.012	4.539	0.000
AR(6)	0.089	0.011	8.170	0.000
AR(7)	0.144	0.010	14.738	0.000
Wind.Onshore	-0.575	0.014	-42.491	0.000
Load	5.134	0.167	30.678	0.000
cosY	-3.267	0.338	-9.676	0.000
sinY	-2.989	0.283	-10.549	0.000
$\mu_i(12)$	...	...	...	...
Conditional Variance Equation				
ARCH(1)	0.818	0.004	192.878	0.000
GARCH(1)	0.059	0.003	18.186	0.000
Wind.Onshore	0.014	0.001	26.224	0.000
$\alpha_i(12)$	...	...	...	...
Conditional Covariance Equation				
ARCH(1)	0.820	0.004	195.446	0.000
GARCH(1)	0.059	0.003	18.278	0.000
$\eta_{ij}(66)$	...	...	...	...

Estimation by BFGS	
Convergence in	254 Iterations
Usable Observations	1403
BIC	78215.392
Log-likelihood value	-38339.6568

3.33. The AR coefficients are very close to the ones from the PEAK model. Again, first and seventh lags of dependent variable drive the behaviour of the spot price the most. As in case of the PEAK model, *Wind.Offshore* turns out to be insignificant and thus excluded from the final model. The energy from the German onshore parks reduces the price by 0.57 EUR/MWh per one additional GW fed into the system. This is slightly below the effect during peak hours. The *Load* controlling for an energy demand variable has coefficients equal to 5.13. In other words, one GW increase in the system load rises the spot price by 5.13 EUR/MWh. Compared to peak hours, this effect is approximately 2.5 EUR/MWh lower. Since demand for electricity is lower during night, this observation suggests that the relationship between the spot price and demand is non-linear. Next, both seasonal trigonometric function have again negative values. Nevertheless, both coefficients are almost 2 times lower as in case of the PEAK model. Specifically, amplitudes of $cosY$ and $sinY$ are -3.26 and -2.99, respectively.

The following paragraph discuss the results of the conditional variance and covariance equation. The *Wind.Onshore* is sole external regressor is the conditional variance equation. Positive coefficient suggests that German energy produced by onshore wind parks increases the volatility of spot price. It is equal to 0.014. This is below the effect which it has on the peak hour prices. The conditional variance follows GARCH(1,1) process with estimated coefficients 0.82 an 0.059, respectively. The ARCH term is higher then in case of peak hours suggesting stronger volatility clustering during night hours. Similarly, the conditional covarince follows the same process with coefficients equal to 0.819 and 0.59.

6.3 Discussion

Based on the results above, I conclude that energy production from RESs has negative MOE and the Czech spot prices while the opposite is true for the price volatility. The results of a green energy MOE are in line with many previous studies which focus on energy markets in Western Europe, i.e., Germany, Netherlands. Conversely, not much has been written about the Czech spot market and corresponding MOE of a renewable energy. In Lunáčková *et al.* (2017) authors find slight positive MOE of solar on the spot price. This is in contradiction with the result of this paper. There are three possible explanations for the discrepancy in our findings. First, authors in Lunáčková *et al.* (2017) use data from early stage of the PV boom in the Czech Republic form 2010 to 2015. The relationship might have change since then. Secondly, authors use actual power generation as a determinant of the spot price, but the spot price forms day before actual generation is realized, i.e., the causality is reversed. Nevertheless, actual generation of PV power plant is likely to be correlated with the day-ahead forecast. Recall, national TSOs are obligated to publish day-ahead forecast of solar and wind energy only after 2015. Since only long term forecast were available before, market participants did not have accurate information about the real solar generation resulting in poor translation of the solar MOE into the spot price. Thirdly, former study use daily data which might result in loss of information.

Further, the effect of wind energy was investigated. I found strong statistical evidence that German onshore wind energy reduces the Czech spot price. On the other hand, Czech wind energy and German offshore wind energy has no statistically significant effect. While both do not effect the price, the explanation is different. In case of the Czech wind farms, possible explanation is simply its low installed capacity. Approximately 1.4 percent of total installed capacity in wind is not enough to have any effect on price. On the contrary, the insignificance of German offshore wind production is rather due to its location. Electricity produced in the North Sea and in the Baltic Sea is likely to flow to Germany and its northern neighbouring countries, i.e., Denmark, Netherlands, and Poland.

Focusing on the price volatility, the effect of national and foreign renewable sources is substantial. The energy produced from the Czech PV power plants increase price volatility considerably. The effect comes from the volatility of solar radiation which changes day to day. Even though the effect is much smaller, the German onshore wind production increases price volatility also. Different effects are observed during peak and off-peak hours which further justifies data division. Haxhimusa (2018) also finds different effects of RESs cross-border flows during day.

Recall, estimated coefficients describe the marginal effect of one additional GW of power fed into the system during peak and off-peak. To find whether energy from RESs really reduce price of electricity I compute total average MOE and corresponding financial volume for given year. I use equations (5.13) and (5.14). Further, I compute annual financial volumes steaming from surcharges on RESs. The results are shown in Table 6.8.

Table contains data about households energy consumption in the Czech Re-

Table 6.8: Cost-benefit analysis

		2015	2016	2017
CZ	Households con**	14.38	14.82	15.21
	Costs*	261.69	271.70	286.27
	MOE_{cz}volume*	87	90.76	93.05
GE	Household con**	129	129	129
	Costs*	7959.30	8196.66	8875.20
	MOE_{imp} volume*	51.10	53.33	54.71
Total	MOE volume*	138.10	144.09	147.76
Note:	*(€ million);**(TWh)			

Source: www.eru.cz, www.bdew.de

public and Germany[9]. Costs refer to the total annual amount which households pay in surcharges for RESs. Values are product of households consumption and renewable surcharge in given year. The MOE_{cz} represents total financial volume of MOE stemming from the Czech solar production. Similarly, the MOE_{imp} represents total financial volume of MOEs stemming from German solar and wind production. Last row depicts total average MOE volume which is a sum of both effects above. It captures the whole financial reduction is the Czech spot price. As can be seen from the table total costs for Czech households rose from 261 to 286 million euros between years 2015 and 2017. The MOE financial volume increased from 138 to 147.7 millions euro. The costs for German households are vast. In 2015 German households paid cumulatively over 7.9 billion euros in EEG surcharges. The number surged approximately by one billion to 8.8 billion euros in 2017.

Coming back to the Czech market, it can be seen that costs for households are almost three times higher then the actual financial savings from MOE. After adding the MOE of the German sources, the final price tag is still two times higher then costs. It is important to note that the financial volume from the MOE is not direct reduction of the electricity price for households. Price for end-customers depends on long term contracts. The price reduction is rather enjoyed by the spot market participants, i.e., retailers and traders. Thus, the MOE_{imp} is an estimate of wealth redistribution from German households to

[9]Czech households consumption was obtain from the Yearly Report on the Operation of the Czech Electrical Grid 2017 publish by the Energy Regulatory Office. German households consumption are available on the web page of BDEW Federal Association of Energy.

the market participants on the Czech spot market. The same applies for Czech households with the MOE_{cz}.

Chapter 7

Conclusion

The European energy sector went through substantial development in the last 10 years. After the adoption of the RED 2009/28/EC in 2009, all member states are obliged to reduce their CO_2 emission by 20 percent compared to 1990 level. According to the RED, this target should be met by 2020. The leader in the transition to green energy sources is Germany with its national plan Energiewende. After the accident in Japan's Fukushima nuclear power plant in 2011, the German government closed eight nuclear power reactors which even accelerated country endeavour towards sustainable electricity. In 2018, German had 46 percent of installed capacity in solar and wind energy combined. On the contrary, the Czech Republic experienced its largest boom of RESs in the period of 2008 to 2010. Within this period installed capacity of PV power plants went from 40 MW to 1959 MW. Nowadays, the Czech Republic has approximately 10 percent of installed capacity in PV and wind energy sources.

Electricity flows from production sources to customers through the shortest distance possible, i.e., through the least resistant path. Also, electricity travels almost instantaneously. As a consequence, energy has to be consumed at the same time as it is produced. These fundamental characteristics of electricity play an important role especially when PV and wind energy sources begin to form a significant percentage of the country's energy mix. Since the production of these RESs is driven purely by weather, accurate forecast of wind and solar energy production is essential for the spot price formation. The EU addressed this in 2015 by adopting regulation which bound all national TSOs with more than one percent feed-in of wind or solar power generation per year to publish day-ahead generation forecast for these fluctuating sources. Thus, trades on energy spot markets around Europe could reflect the cheaper green electricity into the spot prices more accurately.

Approaching 2020, more and more RESs being connected to the energy grid all around Europe. Since the flow of electricity does not respect borders, spillover effects of cheap green electricity influence energy grids of neighbouring countries. For governments and national retailers is of principal importance to know how much is the spot market influenced by both national and foreign green energy production. For example, local retailers have to optimize their short (long) position on the spot market which is indeed influenced by green energy production. Also, policymakers can use this information to decide whether the state should support the construction of pumped hydroelectric energy storages or batteries which could benefit on it.

In this thesis, I examine the effect of Czech and German RESs on the Czech spot price of electricity. When investigating the impact of the RES on spot prices, many studies use daily averages rather than hourly prices. Nevertheless, using daily prices can result in a loss of information contained in hourly granularity. Since electricity is non-storeable, I treat each hour as a distinct commodity, i.e., data are regarded as panel. I build upon an approach developed by Cermeño & Grier (2003). It describes Pooled Panel-GARCH model. Compared to other multivariate GARCH models, it allows modelling panel data with time-varying conditional matrix while preserving the simplicity of the model. Therefore, I can estimate the effect of RESs on both the level of spot price and the conditional variance, while controlling for possible cross-sectional correlation. The model suits the purpose well. Prices for all 24 hours are submitted at the same time. Thus, I assume they follow the same dynamics. Also, they are likely to be correlated with each other. In order to capture different price dynamics which might vary during day and night, I split data into two datasets. One containing peak hours while the second one containing off-peak hours.

In the case of peak hours, both main hypotheses were confirmed. As expected energy production from German solar and German wind onshore parks lower the spot price. Likewise, the energy produced by Czech solar farms has a negative effect on the spot price. Specifically, one additional GW of power produced by wind and solar, reduces the spot price by 0.45, 0.60, and 1.42 EUR/MWh, respectively. Further, increased volatility of Czech spot price due to RESs was found. The main driver of the volatility is the Czech solar production. A much lower, but still highly significant effect is also found for the

German onshore wind production. Production from the Czech wind farms has no statistically significant effect on the spot price neither on its volatility. For off-peak hours, only wind production is considered. The energy from the German onshore parks reduces the price by 0.57 EUR/MWh per one additional GW fed into the system. This is slightly below the effect during peak hours. As in the case of peak hours, an increase in the spot price volatility due to German energy produced by onshore wind parks was found. Again, the effect is below the one for peak hours. Moreover, a high level of persistence in volatility clustering was found for all hours.

In general, energy production from RESs has negative MOE on the Czech spot prices while the opposite is true for the price volatility. The results of a green energy MOE are in line with many previous studies which focus on energy markets in Western Europe, i.e., Germany, Netherlands. Also, there are some studies which examine the effect of RESs on the Czech spot price. In Lunáčková *et al.* (2017) authors study the impact of PV farms on the Czech electricity supply. Further, Czech and German markets are studied with respect to RESs in Líšková (2017). Nevertheless, no cross-border dependencies are considered. Next, I used similar methodology as in Cludius *et al.* (2014) and Sensfuss *et al.* (2008) to estimate total average MOE and corresponding financial impact stemming from it. To put it into perspective, I also computed the total financial amount paid by households in surcharges for promotion of RESs. The values were computed for years 2015, 2016, and 2017.

Total costs for Czech households rose from 261 to 286 million euros between the years 2015 and 2017. The MOE financial volume stemming from the Czech solar production increased from 87 to 93 millions euro. Similarly, the MOE financial volume resulting from the German renewable production rose from 51.1 to 54.7 million euro. The costs were also computed for German household. In 2015, German households paid cumulatively over 7.9 billion euros in EEG surcharges. The number surged approximately by one billion to 8.8 billion euros in 2017. Coming back to the Czech market, costs for households were almost three times higher than the actual financial savings from MOE. Adding the MOEs together, annual financial volume from MOE on the Czech market increased from 138 to 147.7 million euro. Comparing the values with annual household costs, the final price reduction is still two times lower than costs. It is important to note that the financial volume from the MOE is not a direct reduction of the electricity price for households. Price for end-customers depends on long term contracts. The price reduction is rather enjoyed by the spot market participants, i.e., retailers and traders. Thus, the volumes from MOE are estimates of wealth redistribution from Czech and German households to the market participants on the Czech spot market.

Clearly, renewable electricity does not bring the same benefits to all consumers. While households bear the costs stemming from surcharges on RESs, they do not necessarily profit from the MOE. It is rather enjoyed by the spot market participants, i.e., retailers and traders. Redistribution of households wealth from neighbouring countries occurs too. The growing share of RESs in Europe's energy mix will even increase this discrepancy in costs and benefits among consumers. It is up to national policymakers to set rules which will not promote one part of customers above the other. My findings also suggest that energy policy needs to be set internationally.

Further research in this field is possible. I analyzed the effect of German and Czech RESs on the Czech spot market. Nevertheless, intraday and balancing markets are likely to be influenced by the electricity from RESs as well. Balancing market is important especially for retailers since their residual position is settled there. The knowledge about the balancing price dynamics with respect to the electricity from RESs could reduce their risk. Also, the national transmission system operator could benefit from information like that. An analysis of balancing market dynamics could be performed by a similar model as in this thesis.

Bibliography

(2013): "Commission regulation (eu) no 543/2013 of 14 june 2013 on submission and publication of data in electricity markets and amending annex i to regulation (ec) no 714/2009 of the european parliament and of the council."

(2018): "Sa.gov.au."

Breusch, T. S. (1978): "Testing for autocorrelation in dynamic linear models*." *Australian Economic Papers* **17(31)**: pp. 334–355.

Breusch, T. S. & A. R. Pagan (1979): "A simple test for heteroscedasticity and random coefficient variation." *Econometrica* **47(5)**: pp. 1287–1294.

Cermeño, R. & K. Grier (2003): "Conditional heteroskedasticity and cross-sectional dependence in panel data: Monte carlo simulations and examples."
.

CleanEnergyWire (2018a): "The new german government and the energy transition."

CleanEnergyWire (2018b): "Renewables cover about 100% of german power use for first time ever."

CleanEnergyWire (2019): "German offshore wind power - output, business and perspectives."

Cludius, J., H. Hermann, F. C. Matthes, & V. Graichen (2014): "The merit order effect of wind and photovoltaic electricity generation in germany 2008–2016: Estimation and distributional implications." *Energy Economics* **44**: pp. 302 – 313.

Clò, S., A. Cataldi, & P. Zoppoli (2015): "The merit-order effect in the italian power market: The impact of solar and wind generation on national wholesale electricity prices." *Energy Policy* **77**: pp. 79 – 88.

Cuaresma, J. C., J. Hlouskova, S. Kossmeier, & M. Obersteiner (2004): "Forecasting electricity spot-prices using linear univariate time-series models." *Applied Energy* **77(1)**: pp. 87 – 106.

Dziak, J. J., D. L. Coffman, S. T. Lanza, R. Li, & L. S. Jermiin (2019): "Sensitivity and specificity of information criteria." .

EEG (2017): "The renewable energy act (eeg 2017)."

Erni, D. (2012): *Day-ahead electricity spot prices: fundamental modelling and the role of expected wind electricity infeed at the European energy exchange.* na.

Flášar, P., J. Fousek, & kol. (2016): *Trh s elektřinou.* Praha: Asociace energetických manažerů, druhé edition.

Fox, J. & G. Monette (1992): "Generalized collinearity diagnostics." *Journal of the American Statistical Association* **87(417)**: pp. 178–183.

Gelabert, L., X. Labandeira, & P. Linares (2011): "An ex-post analysis of the effect of renewables and cogeneration on spanish electricity prices." *Energy Economics* **33**: pp. S59 – S65. Supplemental Issue: Fourth Atlantic Workshop in Energy and Environmental Economics.

Godfrey, L. G. (1978): "Testing against general autoregressive and moving average error models when the regressors include lagged dependent variables." *Econometrica* **46(6)**: pp. 1293–1301.

Guthrie, G. & S. Videbeck (2007): "Electricity spot price dynamics: Beyond financial models." *Energy Policy* **35(11)**: pp. 5614 – 5621.

Haxhimusa, A. (2018): "The effects of german wind and solar electricity on french spot price volatility: An empirical investigation." *Department of Economics Working Paper Series 258*, WU Vienna University of Economics and Business, Vienna.

Higgs, H. (2009): "Modelling price and volatility inter-relationships in the australian wholesale spot electricity markets." *Energy Economics* **31(5)**: pp. 748 – 756.

Huisman, R., C. Huurman, & R. Mahieu (2007): "Hourly electricity prices in day-ahead markets." *Energy Economics* **29(2)**: pp. 240 – 248.

KETTERER, J. (2014): "The impact of wind power generation on the electricity price in germany." *Energy Economics* **44(C)**: pp. 270–280.

KOOPMAN, S. J., M. OOMS, & M. A. CARNERO (2007): "Periodic seasonal reg-arfima–garch models for daily electricity spot prices." *Journal of the American Statistical Association* **102(477)**: pp. 16–27.

LINSMEIER, T. J. & N. D. PEARSON (2000): "Value at risk." *Financial Analysts Journal* **56(2)**: pp. 47–67.

LÍŠKOVÁ, K. (2017): "The impact of renewable resources on price volatility in the european power markets." .

LUNÁČKOVÁ, P., J. PRŮŠA, & K. JANDA (2017): "The merit order effect of czech renewable energy." .

MADDALA, G. S. & S. WU (1999): "A comparative study of unit root tests with panel data and a new simple test." *Oxford Bulletin of Economics and Statistics* **61(0)**: pp. 631–52.

NETER, J., M. H. KUTNER, C. J. NACHTSHEIM, & W. WASSERMAN (1996): *Applied linear statistical models*, volume 4. Irwin Chicago.

NICOLOSI, M. (2010): "Wind power integration and power system flexibility–an empirical analysis of extreme events in germany under the new negative price regime." *Energy Policy* **38(11)**: pp. 7257 – 7268. Energy Efficiency Policies and Strategies with regular papers.

OENERGETICE (2015): "Příčiny solárního boomu v České republice."

PASCHEN, M. (2016): "Dynamic analysis of the german day-ahead electricity spot market." *Energy Economics* **59**: pp. 118 – 128.

PHAM, T. & K. LEMOINE (2015): "Impacts of subsidized renewable electricity generation on spot market prices in germany: evidence from a garch model with panel data." *In: CEEM working paper 2015e15* .

PONCAROVÁ, J. (2017): "Kolik nás stojí obnovitelné zdroje?"

POWERMAG (2018): "Germany's new coalition government agrees to phase out coal, but will miss 2020 emissions targets."

SENSFUSS, F., M. RAGWITZ, & M. GENOESE (2008): "The merit-order effect: A detailed analysis of the price effect of renewable electricity generation on spot market prices in germany." *Energy Policy* **36(8)**: pp. 3086 – 3094.

TASHPULATOV, S. N. (2013): "Estimating the volatility of electricity prices: The case of the england and wales wholesale electricity market." *Energy Policy* **60**: pp. 81 – 90.

WOOLDRIDGE, J. M. (2013): "Introductory econometrics: a modern approach 5th edition." *Mason, OH: South-Western* .

WOZABAL, D., C. GRAF, & D. HIRSCHMANN (2016): "The effect of intermittent renewables on the electricity price variance." *OR Spectrum* **38(3)**: pp. 687–709.

Appendix A

Appendix

Table A.1: Development of the energy mix in Germany

	2015 [MW]	2016 [MW]	2017 [MW]	2018 [MW]
Biomass	6787	6814	6989	7396
Fossil Brown coal/Lignite	121141	21057	21257	21270
Fossil Coal-derived gas	1316	1316	1316	1316
Fossil Gas	29830	30621	31973	31250
Fossil Hard coal	26928	26063	26999	24478
Fossil Oil	3961	4083	4162	3821
Geothermal	33	34	40	38
Hydro Pumped Storage	8397	8384	8733	8748
Hydro Run-of-river and poundage	4775	3904	3929	3493
Hydro Water Reservoir	729	729	734	786
Nuclear	12068	10793	10793	9516
Other	616	1247	1837	1386
Other renewable	454	515	513	496
Solar	37446	38840	40849	42804
Waste	1507	1544	1629	1598
Wind Offshore	993	3283	4131	5051
Wind Onshore	37757	41179	47042	51633
Total Grand capacity	294738	200406	212926	215080

Source: www.entsoe.eu

Table A.2: Development of the energy mix in the Czech Republic

	2015 [MW]	2016 [MW]	2017 [MW]	2018 [MW]
Biomass	0	350	350	350
Fossil Brown coal/Lignite	8500	8334	7929	8542
Fossil Coal-derived gas	380	380	380	380
Fossil Gas	1720	1226	1226	1226
Fossil Hard coal	900	1200	1200	1200
Hydro Pumped Storage	1175	1172	1172	1172
Hydro Run-of-river and poundage	440	431	334	334
Hydro Water Reservoir	650	650	753	753
Nuclear	4040	4040	4040	4040
Other	600	0	0	0
Other renewable	0	500	400	400
Solar	2050	2067	2027	2040
Waste	0	0	100	100
Wind Onshore	270	277	277	308
Total Grand capacity	20725	20627	20188	20845

Source: www.entsoe.eu

Table A.3: Individual effects from the PEAK mean equation identification.

	(A)	(B)	(C)
Hour.8	-43.629^{***}	-44.475^{***}	-41.834^{***}
	(0.751)	(0.821)	(0.693)
Hour.9	-42.342^{***}	-43.225^{***}	-41.583^{***}
	(0.760)	(0.834)	(0.705)
Hour.10	-43.738^{***}	-44.654^{***}	-42.169^{***}
	(0.778)	(0.853)	(0.722)
Hour.11	-44.984^{***}	-45.912^{***}	-42.206^{***}
	(0.785)	(0.861)	(0.728)
Hour.12	-45.589^{***}	-46.529^{***}	-42.239^{***}
	(0.792)	(0.869)	(0.735)
Hour.13	-47.075^{***}	-48.017^{***}	-42.673^{***}
	(0.794)	(0.871)	(0.737)
Hour.14	-47.769^{***}	-48.704^{***}	-42.810^{***}
	(0.786)	(0.864)	(0.731)
Hour.15	-48.274^{***}	-49.193^{***}	-42.961^{***}
	(0.774)	(0.851)	(0.721)
Hour.16	-48.334^{***}	-49.250^{***}	-43.644^{***}
	(0.774)	(0.852)	(0.722)
Hour.17	-47.361^{***}	-48.262^{***}	-43.706^{***}
	(0.774)	(0.850)	(0.719)
Hour.18	-45.018^{***}	-45.903^{***}	-43.205^{***}
	(0.782)	(0.856)	(0.722)
Hour.19	-43.175^{***}	-44.040^{***}	-42.604^{***}
	(0.793)	(0.863)	(0.727)
Observations	16,882	16,882	16,882
R^2	0.947	0.947	0.965
Adjusted R^2	0.947	0.947	0.965
F Statistic	$14{,}472.680^{***}$	$13{,}226.320^{***}$	$17{,}459.810^{***}$
Note:			*p<0.1; **p<0.05; ***p<0.01

Table A.4: Individual effects from the OFF-PEAK mean equation identification.

	(C)
Hour.1	-15.848^{***}
	(0.819)
Hour.2	-16.131^{***}
	(0.808)
Hour.3	-16.083^{***}
	(0.795)
Hour.4	-16.079^{***}
	(0.788)
Hour.5	-16.251^{***}
	(0.792)
Hour.6	-16.959^{***}
	(0.822)
Hour.7	-18.662^{***}
	(0.916)
Hour.20	-18.312^{***}
	(1.027)
Hour.21	-18.356^{***}
	(1.012)
Hour.22	-17.902^{***}
	(0.964)
Hour.23	-17.034^{***}
	(0.922)
Hour.24	-16.699^{***}
	(0.862)
Observations	16,892
R^2	0.974
Adjusted R^2	0.974
F Statistic	$24{,}981.130^{***}$
Note:	*p<0.1; **p<0.05; ***p<0.01

Table A.5: Individual effects from the PEAK variance equation identification.

	Dependent variable:
	res
Hour.8	29.421***
	(4.308)
Hour.9	31.702***
	(4.357)
Hour.10	28.553***
	(4.393)
Hour.11	26.360***
	(4.418)
Hour.12	27.705***
	(4.452)
Hour.13	30.700***
	(4.474)
Hour.14	29.985***
	(4.457)
Hour.15	26.988***
	(4.414)
Hour.16	31.367***
	(4.380)
Hour.17	33.421***
	(4.364)
Hour.18	26.739***
	(4.362)
Hour.19	19.532***
	(4.359)
Observations	16,879
R^2	0.196
Adjusted R^2	0.195
F Statistic	215.814***
Note:	*p<0.1; **p<0.05; ***p<0.01

Table A.6: Individual effects from the OFF-PEAK variance equation identification.

	Dependent variable:
	res
Hour.1	4.554**
	(2.062)
Hour.2	3.495*
	(2.059)
Hour.3	3.854*
	(2.057)
Hour.4	3.673*
	(2.055)
Hour.5	3.184
	(2.053)
Hour.6	3.686*
	(2.052)
Hour.7	18.073***
	(2.074)
Hour.20	19.687***
	(2.087)
Hour.21	16.072***
	(2.080)
Hour.22	8.669***
	(2.068)
Hour.23	0.740
	(2.060)
Hour.24	3.655*
	(2.061)
Observations	16,889
R^2	0.222
Adjusted R^2	0.221
F Statistic	282.682***
Note:	*p<0.1; **p<0.05; ***p<0.01

Table A.7: Individual Effects of Dynamic Panel GARCH for the PEAK Model

Mean Equation

Variable	Coeff	Std Error	T-Stat	Signif
μ_1	-35.271	1.193	-29.558	0.000
μ_2	-36.333	1.235	-29.431	0.000
μ_3	-38.386	1.265	-30.344	0.000
μ_4	-39.593	1.273	-31.095	0.000
μ_5	-40.142	1.282	-31.300	0.000
μ_6	-40.929	1.284	-31.886	0.000
μ_7	-40.880	1.273	-32.116	0.000
μ_8	-40.478	1.253	-32.304	0.000
μ_9	-39.901	1.255	-31.803	0.000
μ_{10}	-38.332	1.243	-30.848	0.000
μ_{11}	-36.183	1.232	-29.370	0.000
μ_{12}	-34.283	1.225	-27.979	0.000

Conditional Variance Equation

Variable	Coeff	Std Error	T-Stat	Signif
α_1	9.569	0.372	25.718	0.000
α_2	10.919	0.378	28.863	0.000
α_3	10.689	0.336	31.778	0.000
α_4	10.275	0.320	32.097	0.000
α_5	10.879	0.386	28.177	0.000
α_6	11.703	0.526	22.247	0.000
α_7	11.572	0.547	21.171	0.000
α_8	10.703	0.526	20.335	0.000
α_9	11.610	0.602	19.295	0.000
α_{10}	11.491	0.601	19.127	0.000
α_{11}	9.523	0.480	19.819	0.000
α_{12}	7.572	0.361	20.971	0.000

Conditional Covariance Equation

Variable	Coeff	Std Error	T-Stat	Signif
$\eta_{2,1}$	9.924	0.362	27.408	0.000
$\eta_{3,1}$	9.253	0.330	28.068	0.000
$\eta_{3,2}$	10.550	0.340	30.989	0.000
$\eta_{4,1}$	8.530	0.311	27.434	0.000
$\eta_{4,2}$	9.592	0.317	30.227	0.000
$\eta_{4,3}$	10.278	0.314	32.747	0.000
$\eta_{5,1}$	8.136	0.325	25.033	0.000
$\eta_{5,2}$	9.218	0.334	27.560	0.000
$\eta_{5,3}$	10.114	0.336	30.121	0.000
$\eta_{5,4}$	10.460	0.341	30.664	0.000
$\eta_{6,1}$	7.855	0.363	21.625	0.000
$\eta_{6,2}$	8.780	0.379	23.183	0.000
$\eta_{6,3}$	9.728	0.389	25.033	0.000
$\eta_{6,4}$	9.949	0.388	25.629	0.000
$\eta_{6,5}$	10.978	0.444	24.721	0.000
$\eta_{7,1}$	7.691	0.372	20.672	0.000
$\eta_{7,2}$	8.552	0.389	22.001	0.000
$\eta_{7,3}$	9.447	0.397	23.781	0.000
$\eta_{7,4}$	9.594	0.394	24.357	0.000
$\eta_{7,5}$	10.632	0.447	23.787	0.000
$\eta_{7,6}$	11.666	0.534	21.829	0.000
$\eta_{8,1}$	7.455	0.371	20.071	0.000
$\eta_{8,2}$	8.170	0.386	21.149	0.000
$\eta_{8,3}$	8.922	0.393	22.696	0.000
$\eta_{8,4}$	9.021	0.390	23.154	0.000
$\eta_{8,5}$	9.854	0.434	22.700	0.000
$\eta_{8,6}$	10.764	0.511	21.052	0.000
$\eta_{8,7}$	11.055	0.531	20.800	0.000
$\eta_{9,1}$	7.679	0.396	19.368	0.000
$\eta_{9,2}$	8.255	0.410	20.127	0.000
$\eta_{9,3}$	8.913	0.418	21.309	0.000
$\eta_{9,4}$	8.946	0.413	21.652	0.000
$\eta_{9,5}$	9.816	0.460	21.354	0.000

Conditional Covariance Equation

Variable	Coeff	Std Error	T-Stat	Signif
$\eta_{9,6}$	10.778	0.539	20.009	0.000
$\eta_{9,7}$	11.041	0.556	19.846	0.000
$\eta_{9,8}$	10.962	0.557	19.698	0.000
$\eta_{10,1}$	7.620	0.393	19.386	0.000
$\eta_{10,2}$	8.206	0.406	20.189	0.000
$\eta_{10,3}$	8.738	0.413	21.180	0.000
$\eta_{10,4}$	8.663	0.407	21.307	0.000
$\eta_{10,5}$	9.475	0.451	20.995	0.000
$\eta_{10,6}$	10.248	0.524	19.547	0.000
$\eta_{10,7}$	10.381	0.539	19.256	0.000
$\eta_{10,8}$	10.151	0.534	19.024	0.000
$\eta_{10,9}$	11.253	0.590	19.068	0.000
$\eta_{11,1}$	7.155	0.355	20.181	0.000
$\eta_{11,2}$	7.764	0.368	21.084	0.000
$\eta_{11,3}$	8.100	0.370	21.906	0.000
$\eta_{11,4}$	7.934	0.364	21.814	0.000
$\eta_{11,5}$	8.467	0.398	21.272	0.000
$\eta_{11,6}$	8.840	0.454	19.455	0.000
$\eta_{11,7}$	8.823	0.464	19.024	0.000
$\eta_{11,8}$	8.473	0.454	18.664	0.000
$\eta_{11,9}$	9.377	0.500	18.757	0.000
$\eta_{11,10}$	10.132	0.523	19.378	0.000
$\eta_{12,1}$	6.401	0.309	20.710	0.000
$\eta_{12,2}$	6.776	0.317	21.399	0.000
$\eta_{12,3}$	6.911	0.309	22.397	0.000
$\eta_{12,4}$	6.889	0.303	22.700	0.000
$\eta_{12,5}$	6.933	0.324	21.382	0.000
$\eta_{12,6}$	6.878	0.359	19.154	0.000
$\eta_{12,7}$	6.782	0.367	18.463	0.000
$\eta_{12,8}$	6.500	0.360	18.065	0.000
$\eta_{12,9}$	6.915	0.388	17.801	0.000
$\eta_{12,10}$	7.445	0.403	18.487	0.000
$\eta_{12,11}$	7.680	0.388	19.776	0.000

Table A.8: Individual Effects of Dynamic Panel GARCH for the OFF-PEAK Model

Mean Equation				
Variable	Coeff	Std Error	T-Stat	Signif
μ_1	-16.631	1.011	-16.450	0.000
μ_2	-17.201	0.997	-17.259	0.000
μ_3	-17.298	0.982	-17.624	0.000
μ_4	-17.322	0.973	-17.798	0.000
μ_5	-17.444	0.979	-17.817	0.000
μ_6	-18.020	1.018	-17.707	0.000
μ_7	-19.101	1.151	-16.600	0.000
μ_8	-17.747	1.326	-13.386	0.000
μ_9	-17.925	1.283	-13.972	0.000
μ_{10}	-17.961	1.200	-14.966	0.000
μ_{11}	-17.375	1.125	-15.441	0.000
μ_{12}	-17.465	1.067	-16.373	0.000
Conditional Variance Equation				
α_1	6.437	0.214	30.103	0.000
α_2	6.175	0.122	50.487	0.000
α_3	6.198	0.142	43.600	0.000
α_4	6.138	0.108	56.838	0.000
α_5	5.870	0.162	36.236	0.000
α_6	5.731	0.231	24.856	0.000
α_7	8.636	0.570	15.138	0.000
α_8	9.785	0.826	11.847	0.000
α_9	8.827	0.712	12.393	0.000
α_{10}	7.002	0.551	12.714	0.000
α_{11}	5.286	0.331	15.984	0.000
α_{12}	5.611	0.350	16.009	0.000

Conditional Covariance Equation				
Variable	Coeff	Std Error	T-Stat	Signif
$\eta_{2,1}$	6.053	0.137	44.273	0.000
$\eta_{3,1}$	5.831	0.123	47.553	0.000
$\eta_{3,2}$	5.994	0.093	64.632	0.000
$\eta_{4,1}$	5.720	0.099	57.868	0.000
$\eta_{4,2}$	5.843	0.003	2115.163	0.000
$\eta_{4,3}$	6.024	0.088	68.275	0.000
$\eta_{5,1}$	5.600	0.130	42.978	0.000
$\eta_{5,2}$	5.658	0.075	75.187	0.000
$\eta_{5,3}$	5.784	0.110	52.512	0.000
$\eta_{5,4}$	5.880	0.118	49.959	0.000
$\eta_{6,1}$	5.475	0.181	30.211	0.000
$\eta_{6,2}$	5.310	0.129	41.218	0.000
$\eta_{6,3}$	5.289	0.135	39.125	0.000
$\eta_{6,4}$	5.339	0.136	39.127	0.000
$\eta_{6,5}$	5.438	0.173	31.460	0.000
$\eta_{7,1}$	4.719	0.270	17.499	0.000
$\eta_{7,2}$	4.614	0.233	19.811	0.000
$\eta_{7,3}$	4.609	0.239	19.259	0.000
$\eta_{7,4}$	4.727	0.247	19.152	0.000
$\eta_{7,5}$	4.966	0.269	18.465	0.000
$\eta_{7,6}$	5.740	0.332	17.308	0.000
$\eta_{8,1}$	3.273	0.424	7.718	0.000
$\eta_{8,2}$	3.179	0.400	7.939	0.000
$\eta_{8,3}$	3.222	0.404	7.976	0.000
$\eta_{8,4}$	3.193	0.396	8.054	0.000
$\eta_{8,5}$	3.379	0.398	8.491	0.000
$\eta_{8,6}$	3.797	0.424	8.944	0.000
$\eta_{8,7}$	6.183	0.601	10.281	0.000
$\eta_{9,1}$	2.969	0.400	7.426	0.000
$\eta_{9,2}$	2.906	0.375	7.753	0.000
$\eta_{9,3}$	2.926	0.377	7.760	0.000
$\eta_{9,4}$	2.903	0.370	7.840	0.000
$\eta_{9,5}$	3.108	0.371	8.371	0.000

Conditional Covariance Equation				
Variable	Coeff	Std Error	T-Stat	Signif
$\eta_{9,6}$	3.505	0.397	8.819	0.000
$\eta_{9,7}$	5.427	0.538	10.078	0.000
$\eta_{9,8}$	8.451	0.731	11.553	0.000
$\eta_{10,1}$	3.241	0.329	9.855	0.000
$\eta_{10,2}$	3.234	0.309	10.480	0.000
$\eta_{10,3}$	3.141	0.314	10.005	0.000
$\eta_{10,4}$	3.131	0.308	10.158	0.000
$\eta_{10,5}$	3.251	0.308	10.566	0.000
$\eta_{10,6}$	3.527	0.331	10.658	0.000
$\eta_{10,7}$	4.684	0.452	10.362	0.000
$\eta_{10,8}$	6.550	0.605	10.825	0.000
$\eta_{10,9}$	7.021	0.592	11.870	0.000
$\eta_{11,1}$	3.205	0.233	13.762	0.000
$\eta_{11,2}$	3.180	0.217	14.661	0.000
$\eta_{11,3}$	3.106	0.224	13.880	0.000
$\eta_{11,4}$	7.934	0.364	21.814	0.000
$\eta_{11,5}$	8.467	0.398	21.272	0.000
$\eta_{11,6}$	8.840	0.454	19.455	0.000
$\eta_{11,7}$	8.823	0.464	19.024	0.000
$\eta_{11,8}$	8.473	0.454	18.664	0.000
$\eta_{11,9}$	9.377	0.500	18.757	0.000
$\eta_{11,10}$	10.132	0.523	19.378	0.000
$\eta_{12,1}$	6.401	0.309	20.710	0.000
$\eta_{12,2}$	6.776	0.317	21.399	0.000
$\eta_{12,3}$	6.911	0.309	22.397	0.000
$\eta_{12,4}$	6.889	0.303	22.700	0.000
$\eta_{12,5}$	6.933	0.324	21.382	0.000
$\eta_{12,6}$	6.878	0.359	19.154	0.000
$\eta_{12,7}$	6.782	0.367	18.463	0.000
$\eta_{12,8}$	6.500	0.360	18.065	0.000
$\eta_{12,9}$	6.915	0.388	17.801	0.000
$\eta_{12,10}$	7.445	0.403	18.487	0.000
$\eta_{12,11}$	7.680	0.388	19.776	0.000