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The impact of renewable resources on price volatility in the European power markets

Bachelor thesis

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Abstract

Integration of renewable energy sources impacts electricity spot price and its variation. Remaining open question is, in which direction. Volatility fluctuations threaten security of electricity supply, influence trading strategies and create uncertainty in optimal installed capacity planning. In this thesis, drivers of price volatility in Czech and German day-ahead power market are analysed with an emphasis on penetration of renewable energy sources. To the best of our knowledge, this is the first study focused on this issue in Czech electricity market. We apply recently developed approach of quadratic variation theory with an adjustment for electricity prices. Realised volatility is divided into its continuous and jump component. The continuous part is modelled by three heterogeneous autoregressive models, differing in complexity and inclusion of market-specific fundamental variables. Amendments to each model for the particular market are proposed and the models are evaluated both in-sample and out-of-sample. Addition of exogenous variables − commodity prices, weather conditions and seasonal variables − to simpler heterogeneous autoregressive model is found to improve volatility forecast accuracy. The results suggest higher continuous volatility due to increased penetration of power from wind generators in German market. The effect of photovoltaic penetration on continuous volatility in both studied markets is not significantly different from zero.

Keywords

electricity spot market, price volatility, renewable energy sources, quadratic variation, continuous volatility, heterogeneous autoregressive model

Range of thesis: 124,741 characters with spaces

Abstrakt

Integrácia obnoviteľných zdrojov energie ovplyvňuje spotovú cenu elektriny a jej odchýľku. Otvorenou otázkou zostáva, akým smerom. Fluktuácie volatility ohrozujú stabilitu dodávky elektriny, ovplyvňujú obchodné stratégie a vytvárajú neistotu v plánovaní optimálneho inštalovaného výkonu. V tejto práci sú skúmané faktory ovplyvňujúce cenovú volatilitu na českom a nemeckom dennom trhu elektriny, s dôrazom na penetráciu obnoviteľných zdrojov energie. Pokiaľ je nám známe, ide o prvú štúdiu zameranú na túto problematiku na českom trhu s elektrinou. Je aplikovaná nedávno zavedená metóda kvadratickej variácie s úpravou pre ceny elektriny. Realizovaná volatilita je rozdelená na spojitý a skokový komponent. Spojitá časť je modelovaná pomocou trojice heterogénnych autoregresívnych modelov, ktoré sa líšia zložitosťou a zahrnutím fundamentálnych trhových špecifík. Je navrhnutá úprava každého modelu pre špecifický trh a modely sú porovnané "in-sample" aj "out-of-sample". Pridanie exogénnych premenných – ceny komodít, poveternostné podmienky a sezónne premenné – do jednoduchšieho heterogénneho autoregresívneho modelu zlepšuje presnosť predpovede volatility. Výsledky naznačujú vyššiu spojitú volatilitu na nemeckom trhu v dôsledku zvýšenej penetrácie energie z vetra. Pre oba študované trhy sa vplyv fotovoltaickej penetrácie na spojitú volatilitu významne nelíši od nuly.

Kľúčové slová

spotová cena elektriny, cenová volatilita, obnoviteľné zdroje energie, kvadratická variácia, spojitá volatilita, heterogénny autoregresívny model

Declaration of Authorship

I hereby proclaim that I wrote my bachelor thesis on my own under the leadership of my supervisor and that the references include all resources and literature I have used.

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Prague, 28 July 2017

Signature

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Bachelor Thesis Proposal

Author	Katarína Líšková
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Proposed topic	The impact of renewable resources on price volatility in the European power markets

Research question and motivation

The energy market has been substantially influenced by increasing production of renewable energy in recent years, which is now driving the market of energy commodities. Environmental trends supported by governments and the goals of the European Union are in favour of implementing more renewable sources of energy in the upcoming decades. However, these sources are weather sensitive and unpredictable, and therefore might cause instabilities in the grid and higher volatility of prices in the market. The prevailing view of current literature is that it drives prices down and causes higher variance on spot markets for electricity. Many researchers expect a surge in price volatility due to intermittent energy sources, however opinions differ in various works. Some claim a negative change in price variability in relation to the amount of renewable energy produced. The research question will be to further analyse the impact of renewable resources on price volatility, focusing on the European energy markets.

Contribution

One of the biggest risks for investors and energy companies in the energy market is high price volatility. The thesis will focus on European markets, where usage of renewables is expected to increase in the future due to governmental interventions. Therefore, the contribution of the thesis will be answering the question of whether surging price variation may be caused by the increased usage of intermittent energy sources.

Methodology

Primarily, time series data on renewable energies production and prices of energy commodities will be used. For the Czech Republic, this data is available from ENTSOE-Transparency and OTE. Hourly data for German electricity prices can be gathered from the European Energy Exchange. A regression analysis will be conducted, with adjustment for commodity prices and weather conditions.

Outline

1. Introduction
2. Insight into energy market
3. Literature review
4. Data description
5. Methodology
6. Empirical results
7. Conclusion

Relevant literature

1. Paraschiv, F., Erni, D., and Pietsch, R. (2014). The impact of renewable energies on EEX day-ahead electricity prices. Energy Policy, 73:196 - 210.

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Contents

List of Acronyms

ACF Autocorrelation Function

ADF Augmented Dickey-Fuller Test

BIC Bayesian Information Criterion

BV Bipower Variation

CDD Cooling Degree Days

CV Continuous Component of Realised Volatility

CZ The Czech Republic

DE Germany

DM Diebold-Mariano Test

EU European Union

EEX European Energy Exchange

EUR Euro

HAR-RV Heterogenous Autoregressive Model of Realised Volatility

HDD Heating Degree Days

JV Jump Component of Realised Volatility

KPSS Kwiatkowski-Phillips-Schmidt-Shin Test

MOE Merit Order Effect

MWh Megawatt Hour

OTE Czech Electricity and Gas Market Operator

PACF Partial Autocorrelation Function

PV Photovoltaics

PXE Power Exchange Central Europe

QVar Quadratic Variation

RES Renewable Resources

RV Realised Volatility

TSO Transmission System Operator

TQ Tripower Quarticity

UK The United Kingdom

USA The United States of America

List of Figures

List of Tables

1 Introduction

Electricity price dynamics is significantly influenced by unique characteristics of the commodity, such as non-storability and need for real-time adjustments in balancing of supply and demand. Before the deregulation of electricity industry, the prices were fixed and calculated directly from the costs associated with the whole energy supply process. While there was no need to hedge electricity prices, utilities were vertically-integrated, market entry was inhibited, and investments were largely based only on demand forecasts. However, since 1990s, when the restructuring process took place, prices have been determined by trading electricity in the wholesale market. As the history of this market is rather short and quickly emerging, agents' understanding of the dynamic pricing process is not profound and studies focusing on these issues can lead to important findings that can be directly used by regulators, investors, traders, and other market participants.

The importance of renewable energy sources in the electricity generation has risen substantially over the last decades. By 2020, the European Union (EU) aims to meet its target of 20% share of renewable energy in the consumption mix [1]. The EU specified the target of more than 27% share by 2030 (European Comission, 2015). As observed in various studies, the volatility of spot prices is influenced by the introduction of intermittent energy sources, however the direction of the change is region-specific (Rintamäki et al., 2017). Therefore, it is important to look at each country separately because the results cannot be generalised.

Volatility analysis of electricity prices is important for all market participants because price variation influences the risk and potential returns. It complicates hedging strategies and threatens security of supply, however, those who understand the volatility processes can design financially rewarding strategies. Since price fluctuations are the source of uncertainty about profits for the producers and suppliers, it is in their interest to understand the price development when planning the optimal installed capacity and

[1] Consumption mix is defined as country's production adjusted for imports and exports.

designing trading and pricing strategies.

The aim of this thesis is to study the drivers of volatility changes in Germany in more detail and to provide insights for agents interested in the Czech market. The analysis is conducted using data for German and Czech day-ahead electricity market, relevant commodity prices, forecasts of renewable generation, and weather conditions. Germany is the leading Europe's country in implementation of renewable resources and its market volatility has been studied extensively. However, to the best of our knowledge, Czech market's volatility has not been studied yet and therefore, we aim to fill this gap in the literature. Recently introduced theory of quadratic variation with modification to electricity prices is used to separate continuous and jump component of realised variation. By applying the same methodology for modelling continuous spot price volatility for both countries, we get comparable results that can be related to country's individual specifics.

Results obtained from heterogeneous autoregressive model with exogenous variables suggest higher continuous volatility due to increased penetration of power from wind generators in German market. The effect of photovoltaic penetration on continuous volatility in both studied markets is not significantly different from zero. These market differences are extensively discussed throughout the work.

This bachelor thesis is organised as follows. In Section 2, important features of electricity market, with specific focus on Germany and the Czech republic, are summarised. In Section 3, review of the literature concerning electricity market is provided, focusing on volatility analysis and studies of renewable energy sources in particular. Data used in the analysis are commented in Section 4. Methodology for the analysis is described in Section 5. In Section 6, we summarise the results for estimation of drift in price changes, quadratic variation components, exogenous variables and results and evaluation of all model modifications. In the last section, we summarise the results and conclude by suggesting improvements that can be used in later research.

2 Price Dynamics in the Deregulated Power Markets

Electricity as a traded commodity emerged during the restructuring of European public utilities, that began in the The United Kingdom (UK) and Scandinavia in early 1990s and has spread to many countries by now. In the deregulated electricity market, there is an introduced competition at the level of production and retail. In this section, the main characteristics of the deregulated electricity prices are highlighted.

Electricity is a flow commodity and calls for immediate reaction of demand and supply in order to avoid grid instabilities. The demand for electricity shows strong cyclical patterns following population's daily activities and operation of the industries (Simonsen et al., 2004). Due to absence of effective storage of electricity, the market is characterised by high volatility of prices that cannot be smoothed out by sufficient adjustments in any of the market sides (Escribano et al., 2011). In the periods of low demand and extremely high supply, strengthened by hardly controllable generation from RES, it is possible to ask negative prices for the excess power (e.g., Knittel and Roberts' study of Californian prices (2005); Paraschiv et al. (2014) links negative prices to period of high wind in-feed). High supply cannot always be adjusted quickly because of high capital costs of base-load generators. Therefore, those are for certain amount of time willing to accept negative prices if the losses from this behaviour do not exceed costs associated with temporal shut down and consequent ramping up of the power plant. These costs are generally very high for nuclear power plants that also need state's approval to restart (Keles et al., 2012).

The price setting in the electricity markets is significantly affected by technical constraints that define the maximum capacity of the supply, which together with instantaneous dispatch make the supply curve inelastic. Similarly, the short-term inelasticity of the demand curve is given by the importance of the commodity (Escribano et al., 2011). The electricity dispatch is based on the short-run marginal costs of each power plant and is organised in a way of minimizing the overall costs of production (Moreno et al., 2012).

By the nature of cost differences between power plants structured in the merit order, the supply curve is reasonably flat during base load hours, however, soars in the time of peak hours (Kanamura and Ohashi, 2007; Weigt, 2009). Such behaviour motivates the usage of regime-switching models to model electricity price.

Given the steepness of both curves during hours with high load, even small movements lead to extreme positive jumps and excess volatility. Unexpected events, such as plant outages and short-term congestion in important transmission lines, cause negative supply shocks while unexpected increases in demand cause positive demand shocks, both leading to steep jumps of the prices that are reverting back almost immediately due to temporary nature of these shocks.

As suggested by Bessembinder and Lemmon (2002) and confirmed later by the analysis of Knittel and Roberts (2005), higher volatility is associated with intervals of strong demand. Guthrie and Videbeck (2007) model half-hourly New Zealand electricity spot prices using periodic autoregression and show the existence of more severe shocks in line with rising demand. Compared to lower load[2] periods, these shocks are less persistent, however they reappear once the demand rises during peak-hours.

2.1 German Electricity Market

In this section we review the most important characteristics of the German electricity market with connection to the topic of renewable power generation and day-ahead market. In connection to historical changes in energy mix, we briefly comment on the most important regulatory amendments. Dynamics of the electricity day-ahead market is explained since it serves as a reference for decisions in the further analysis. Since the thesis focus on day-ahead price, we focus solely on the spot market. For more detailed explanation of the German power market we suggest Paraschiv et al. (2014),

[2] Some authors refer to demand and load interchangeably assuming there are no blackouts (Becker et al., 2007). Generally, load is referred to be the electricity supplied to the grid while demand the electricity consumed by the customers. Therefore in the later sections we refer to these terms interchangeably.

who emphasises the need for investments into power grid expansions in order to integrate intermittent energy sources effectively.

Germany's electricity sector was fully liberalised in 1998 following National Energy Act (Brandt, 2006). It is the largest electricity market in Europe with almost 200 GW of net installed generation capacity (Energy Charts, 2017). The market is operated by European Energy Exchange (EEX) and as a joint-venture with Powernext, electricity spot market (EPEX SPOT) was established. According to EEX Group's Annual reports the spot market volume was 342 TWh and 382 TWh in 2013 and 2014, respectively. In 2016, power spot market volume was 535 TWh, 2% up from 524 in 2015 (EEX Group, 2017). The most significant year to year volume change of 37% was between 2014 and 2015.

The transactions at the spot market are physically settled up to two days after the conclusion of the trade. The day-ahead market is part of the spot market and its products can be traded up until one day before delivery. The day-ahead price can be regarded as the reference price for different contracts and therefore can be taken as the main marketplace (Möller, 2010). Therefore, whenever we refer to electricity price (or alternatively, spot price) or spot market, we mean day-ahead electricity price and day-ahead electricity market.

The day-ahead price is determined in an auction that takes place on all days of the week, including statutory holidays. The order book gate closure is set at 12 p.m. The price has to be within bounds of -500 EUR/MWh and 3000 EUR/MWh, while negative prices on the German/Austrian day-ahead market were first introduced in 2008 (EPEX SPOT, 2017b). The electricity is traded for 24 individual hours with minimum price tick of 0.1 EUR/MWh and minimum volume increment of 0.1 MW. With change to winter time, the specific delivery day in October is determined to have 25 hours, while there is a day in March consisting of only 23 delivery hours associated with the change to summer time. Contracts can be traded for Off-Peak 1 (midnight to 8 a.m.), Peakload (8 a.m. to 8 p.m.) and Off-Peak 2 (8 p.m. until midnight) block periods (EPEX SPOT, 2017a).

Germany is Europe's leading market in implementation of renewable energy policies (Cherp et al., 2016). Since 2000, the figures reported by AGEB (2016), Energy Balances Group, has been showing deeper implementation of Renewable Resources (RES) into the power grid, rising from 6.6% in 2000 to 27.4% share in gross electricity consumption in 2014. By 2025, RES are to have a share of at least 40% in electricity consumption, 55-60% share by 2035 and more than 80% by 2050 (Pescia, 2016).

The main driver of intensive implementation of renewable energy sources into the electricity production are feed-in-tariffs introduced in 1991 (Paraschiv et al., 2014). In the later years, Energiewende, the German Energy Transition, transformed the power system significantly. Regulatory change in 2010 changed how the renewable energy is traded in the market. Since then, Transmission System Operators (TSOs) forecast the amount of renewable energy produced from particular source one day-ahead and directly sell this electricity in the day-ahead market. Since the forecasts are understandably more precise than previously used month-ahead forecasts, the increasing effect on variance decreased, however still persists (Ketterer, 2014).

In 2011, following nuclear accident in Fukushima (Japan), German government decided to phase out nuclear power plants by 2022 (RAP, 2015). In 2011, installed nuclear capacity almost halved to 12.07 GW compared to 20.43 GW in 2010. In 2015 it was 10.80 GW and remained stable until now (Energy Charts, 2017). Due to the changes in energy mix while sticking to the 2020 CO_2 emission target (reduction of 40% compared to 1990 levels of greenhouse gas produced), Germany will have to compensate relatively clean nuclear energy by introducing even more RES.

Table 1 provides visual overview of the energy inputs used in the electricity generation. Increasing trend in the usage of renewable energy is evident, while consumption of natural gas and petroleum is slightly decreasing. As a result of governmental decision on shut-down of several nuclear power plants, nuclear energy accounted for 22.7% of electricity generation in 2011, 5.1%

less than in the previous year. The share of nuclear energy on the electricity generation is expected to decrease even more as the complete phase-out, which is planned for 2022, approaches.

Table 1: Share of energy inputs for electricity generation in Germany

Energy input	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**
Renewable energy	**12.6%**	**13.2%**	**16.0%**	**14.2%**	**15.0%**	**16.3%**
Other energy carriers [3]	1.7%	1.8%	1.6%	1.6%	1.6%	1.8%
Lignite	26.1%	24.8%	27.2%	29.5%	28.8%	28.6%
Hard coal	17.9%	18.4%	18.5%	19.9%	21.8%	20.8%
Natural gas	10.3%	10.4%	10.4%	9.7%	8.4%	7.8%
Other gases [4]	1.2%	1.9%	1.8%	1.9%	2.0%	1.9%
Petroleum	1.7%	1.3%	1.2%	1.1%	1.2%	1.2%
Electricity (pump energy)	0.5%	0.6%	0.5%	0.6%	0.5%	0.6%
Nuclear energy	**28.0%**	**27.8%**	**22.7%**	**21.4%**	**20.7%**	**21.1%**

Source: AGEB (2016)

Germany's aggressive renewable implementation policy has been criticised for being too costly. The 2017 Renewable Energy Sources Act advances market auction schemes for determination of renewable support starting January 1, 2017 (BMWi, 2016). The main goal of the amendment is to make RES more competitive and decrease the costs of financial support. The policy can have implications for the pace of installment of renewable generators.

The results presented later in the literature overview are very important for proper construction of policies and maximization of the financial benefit for market agents. The aim of our analysis is to determine in more detail the factors driving volatility and to potentially advise on proper allocation of investments and regulation.

[3] Non-renewable waste, heat

[4] Coke oven and town gas, Blast furnace and converter gas, Petroleum gas, Mine gas

2.2 Czech Electricity Market

Following the deregulation process in other countries, Parliament of the Czech Republic (2000) published Energy Act No. 458/2000 establishing the rules for newly created competitive electricity service industry. ČEPS is entitled to license issued under the Energy Act and is the only Czech TSO. In 2001, Czech Electricity and Gas Market Operator (OTE) was established. Firstly, Czech day-ahead market had been organised by both OTE and Power Exchange Central Europe (PXE). However in April 2009, PXE joined spot market of OTE (PXE, 2010) and it was coupled through implicit auctions with Slovak and Hungarian electricity market in September 2009 and September 2012, respectively (OTE, a.s., 2009b, 2012a). In November 2014, coupling with Romanian day-ahead electricity market was successful (OTE, a.s., 2014). It allows for higher liquidity, lower price variation and more efficient capacity allocation, aiming to at least partially eliminate price impacts of intermittent energy.

OTE is also responsible for the National Register of Greenhouse Gas Emissions and operates gas day-ahead market and electricity intraday market since 2010. Apart from that, block market is also available as a spot sub-market. OTE, a.s. (2017b) divides trading hours during working days between peak (8 a.m. to 8 p.m.) and off-peak hours (the rest of trading hours). Base load is defined for the whole trading day (i.e., also during the weekend). Since the primary purpose of the thesis is not the description of the market in detail, please refer to work by Krejčová (2012) for more information regarding other types of contracts.

The dynamics of the day-ahead market influence later analysis heavily. Firstly, all bids for particular hour for the next day need to be submitted before 11 a.m. one day before the delivery day (OTE, a.s., 2017a). This holds for all days as the Czech spot market is open during the weekends and holidays as well. As of delivery day February 1, 2009, all bids for day-ahead market are accepted in EUR and for settlement in CZK, OTE bank exchange rate is used. Starting February 2012, negative prices were allowed for (at that time) CZ-SR coupled spot market (OTE, a.s., 2011).

Market participants can trade from minimum 1 MWh of volume up to 99 999 MWh while traded period is one hour. The buy or sell orders have to be within price range of -500 EUR/MWh and 3000 EUR/MWh. Afterwards, usually around noon or at 2:30 p.m. at the latest, one spot electricity price for each hour of the delivery day is published (OTE, a.s., 2016c).

According to OTE, a.s. (2016b), the energy mix in 2015 mostly consisted of fossil fuels which represented more than half of the primary resources. While nuclear power decreased from 36.67% to 33.12%, RES surged from less than 6% in 2013 to 11.77% in 2015. From RES, solar, hydroelectric power and biomass were the most significant, having 2.88%, 2.67% and 2.34% share, respectively. Even though there is significantly increasing trend in installation of renewable power generators, wind energy accounted only for 0.71% of the national energy mix in 2015. This discrepancy is also a result of the support scheme which was skewed towards solar installations (Luňáčková et al., 2017). Most of the solar power plants operate since 2009 and 2010 when there was a boom in installation of solar generators. That was because of the decrease in payback period due to lower prices of solar panels and continuing validity of 180 ACT of 31 March 2005 (ERÚ, 2008) on the promotion of electricity production from renewable energy sources and its article 6 regarding maximum year-to-year decrease in purchase prices of 5%. The summary of evolution of the energy mix in the Czech Republic can be found in Table 2.

OTE elaborates on different scenarios for the future energy situation in the Czech Republic. The Conceptual variant, which is the closest to the current “State Energy Policy”, expects an increasing trend in utilization of RES (OTE, a.s., 2016a) and decentralization of production, which also follows from the Directive 2009/28/EC the European Parliament and of the Council of April 23, 2009 (European Parliament, 2009) and Paris Agreement.

Generally, in the medium-term, OTE anticipates a partial substitution of coal-fired power plants by gas-fired ones, supported by further increase

Table 2: Evolution of energy mix in the Czech Republic

Energy sources	**2013**	**2014**	**2015**
Renewable sources - total	**5.68%**	**10.95%**	**11.77%**
Solar	1.96%	2.63%	2.88%
Wind	0.47%	0.57%	0.71%
Hydro	1.93%	2.56%	2.67%
Geothermal	0.00%	0.00%	0.00%
Biomass	1.33%	2.19%	2.34%
Others	0.00%	2.99%	3.17%
Fossil fuel sources - total	**57.65%**	**52.77%**	**55.10%**
Lignite	40.71%	41.27%	42.15%
Hard coal	6.11%	5.78%	6.31%
Natural gas	8.30%	5.52%	6.41%
Crude oil and oil products	0.01%	0.06%	0.05%
Secondary sources and others	2.52%	0.14%	0.18%
Nuclear sources - total	**36.67%**	**36.28%**	**33.13%**

Source: OTE, a.s. (2016b)

in photovoltaics and wind turbines. Czech republic's energy policies are strongly influenced by the decisions of the EU. Therefore targets are similar to the ones in other member countries.

3 Literature Review

Electricity is a very special commodity with price dynamics not spotted in any other market. Specifications of power time series make analyses more complicated and call for complex models. This section reviews the most important peculiarities that have implications on research conducted in the thesis (3.1) and also summarises results presented in the literature. These are divided into two parts. The first one focuses on the study of merit order effect (3.2) which is connected with impacts on price volatility explained in the second part (3.3). Throughout the whole text, more references are provided, where appropriate.

3.1 Specifications of Electricity Prices

Despite few similarities to stock prices, electricity prices have unique characteristics and even differ from other commodity prices. Their salient distinct features have been studied extensively by researchers on various datasets and most of them stem from the fact that power is non-storable. This feature persists even though there are limited possibilities to store potential energy in the form of hydro reservoirs, hydroelectric resources and stocks of fuel. However, as the number of these types of power generators is insufficient and also depends on the region, arbitrage possibilities are limited (Bessembinder and Lemmon, 2002; Knittel and Roberts, 2005). Since speculative behaviour can still be applied to electricity markets, Boogert and Dupont (2005) focus on anti-gaming policy implemented by Dutch Independent System Operator to minimise speculative profit seeking strategies in day-ahead and subsequent opposite transactions in imbalance (real-time) market. Regulators implement incentive strategies to discourage such behaviour and minimise imbalance traded volumes and speculative bidding in the day-ahead market.

Intra-day, day-of-the-week and monthly patterns that can be explained by the influence of weather conditions and business cycles are, besides others, observed by Knittel and Roberts (2005), Escribano et al. (2011) and

Krištoufek and Luňáčková (2013). While Li and Flynn (2004) find periodicity in British power prices, in Californian data they find it only for volatility. Koopman et al. (2007) emphasise the importance of day-of-the-week seasonality in the autocovariance function. Besides that, they conclude differences between markets (EEX- Germany, Powernext - France, APX - the Netherlands, Nord Pool - Norway) that stem from non-identical share of primary generation sources. Regarding the yearly seasonality, peaking months differ by geographical location of the country. While in the north of Europe the highest demand is during winter months, in the southern European countries we can observe this trend in the summer when air-conditioning demands high amount of energy (Zachmann, 2008). Even though these cyclical patterns are quite well-known by now and weather forecasts can eliminate much of the surprise in energy consumption as well as production from intermittent renewable sources such as solar and wind, electricity prices tend to be much more volatile than that of financial commodities (Asbury, 1975).

Widely discussed feature of electricity price series is its reversion to the mean. Huisman et al. (2007) apply panel data model to hourly day-ahead power price data for 3 different wholesale markets (APX - the Netherlands, acEEX - Germany and PPX - France) and come up with interesting results. According to their analysis, day-ahead prices mean-revert towards hourly specific price but the speed of mean-reversion differs within the day (strongly lower during peak-hours). According to Krištoufek and Luňáčková (2013), electricity price time series differ from other financial assets by strong mean-reversion in contrast to unit root process often observed for financial time series. Mean-reversion is a consequence of electricity's nature, price incentives for generators and demand drivers such as weather.

Escribano et al. (2011) estimate a flexible model for spot prices applied to 8 power markets with different market composition and price dynamics. They conclude that volatility clustering, mean reversion, seasonality and spikes are all very essential to be included in electricity pricing models simultaneously. Knittel and Roberts (2005) analyse restructured power prices using asset-pricing inspired model. They observe higher order statistically significant autocorrelation even beyond 1000 lags for price levels and beyond several hundred lags for squared prices. The study presents several models estimated by conditional maximum likelihood incorporating unique characteristics of data one by one and compares their forecasting performance. In order to account for leptokurtosis in electricity prices they develop jump-diffusion process with time-varying jump intensity parameter which clearly shows that the likelihood of a spike grows during peak hours and falls in the winter/spring period and during the weekends.

Similar conclusions about jump occurence can be found in Simonsen et al. (2004) while the season with higher spikes occurence is regional-specific. As suggested by Bessembinder and Lemmon (2002) and confirmed later by Knittel and Roberts (2005), spot prices have greater positive skew during the period of higher demand variability. Deng (1998) captures the stochastic volatility, various jumps and regime-switching feature in his analysis and develops tools to value derivatives using Fourier transform.

3.2 Merit Order Effect and Implications for Volatility

There has been numerous studies focusing on elasticity of electricity prices to supply from renewable generators. Some of them focus solely on wind or solar power, which are the two most significant RES and are intermittent at the same time, others combine all RES together. Interesting results have been presented, showing regional differences and conclusions sensitive to shares in the energy production mix.

Deng (1998) applies mean-reversion jump-diffusion models with regime-switching and non-constant volatility to study power prices observed on the spot market. The analysis is conducted on the price data from the The United States of America (USA) that range from 0 $/MWh to 7000 $/MWh in the Midwest region in 1998. He develops pricing model for energy derivatives using Fourier transform. Weigt (2009) analyses German electricity market between 2006 and mid-2008, focusing on the effect of wind feed-in which shows to decrease the market price during peak hours predominantly, by 10 EUR/MWh on average.

Sensfuss et al. (2008) look not only at the Merit Order Effect (MOE) itself, but also at sensitivity analysis of MOE towards prices of primary energy sources and CO_2. Their analysis performed by agent-based simulation platform shows considerable reduction in prices, which more than offsets the amount of net support payments in 2006. Besides that, the MOE is positively correlated with load, which leads to higher reduction in price during peak hours and therefore lower variance of the prices on the spot market. It is shown that higher volumes of RES in the generation mix affect the value of MOE almost linearly. According to Sensfuss et al. (2008), the gas price has the most significant impact on the level of MOE. Change of 20% leads to as high as 30% change in the MOE in the same direction. Since gas-fired power plants are considered to be peaking generators, they set the price in most of the cases of high demand. In contrast, 20% increase of the price of the hard coal causes 10% reduction of the MOE. The authors emphasise that the ratio of gas and coal prices is a significant factor. When prices of coal are high and prices of gas are lower, the slope of the merit order curve is reduced, thus reducing the MOE. Increase of CO_2 prices leads to decreased MOE as well.

Another paper by Frantzen and Hauser (2012), focused on solar power generation, determines an average decrease of 4.2 - 6.8 EUR/MWh in peak price on the EEX. They investigate data from 2002 to 2011 and find different results for specific amounts of solar energy integrated into the grid. For higher shares of solar electricity generation, the peak price was just 11% higher than base price compared to 20-25% difference in the low RES scenario. Despite the fact that the results are in line with literature, authors do not isolate the effects of other factors such as fuel prices or load changes. It is important to note that MOE focuses on the wholesale price elasticity to the changes in supply of renewable electricity, however it does not say anything about the price for the end customer to whom other additional fees (e.g. renewable support, grid improvements contribution (Ketterer, 2014)) apply. Moreno et al. (2012) claim that the deployment of RES has an increasing effect on household electricity prices in the market. Their study covers panel data for the years 1998-2009 from 27 EU member countries. The empirical analysis elaborates on the relations between variables connected to the RES and the competition in the market and takes into account both effects on the wholesale price and tariffs financed by final customers. Similar conclusion is stated by Frondel et al. (2010). Tveten et al. (2013) also inspect MOE of solar energy in Germany with a result of 13% and 23% decrease in average retail price (price charged to end customers) and daily price variation, respectively.

Paraschiv et al. (2014), similarly as us, focus on the German electricity spot market, however they do not model price volatility but only the price level. They distinguish between peak and off-peak hourly blocks which is essential in order to account for different load and production design. They also observe price adaptation and stress importance of linking power prices to fundamentals.

With regards to Czech electricity market, recent study by Luňáčková et al. (2017) analyzes MOE of RES using data for years 2010-2015. By dividing the dataset into solar and other RES, they show noticeable difference between the two subsets. Their results contradict widely used approaches that prefer solar generators as the elasticity of spot price to increased power from these sources is positive, therefore creating double burden on end customers, who are also charged premium for renewable support.

3.3 Volatility Modelling

Literature studying electricity markets emerged just after the deregulation process took place. Therefore the research is not that wide, compared to the one focusing on financial markets. Electricity price modelling is to some extent complicated due to the unique characteristics of the time series. Complex models have to be developed in order to account for cyclical trends, mean reversion, clustering volatility and steep jumps momentarily followed by smoother opposite movements in energy prices (Keppler et al., 2007). Except that, Knittel and Roberts (2005) also mention other peculiarities such as negative values and right censoring. In their work, seasonality and volatility clustering are found in the data constructed of 21 216 observations of hourly data from California, collected since the opening of the market on April 1st, 1998. As demand reaches or exceeds the maximum capacity, clustered spikes in the prices occur. They emphasise an “inverse leverage effect”, which relates to asymmetric reaction of volatility to positive and negative demand shocks.

When modelling volatility time series, possible practise is to contruct a jump-diffusion model, where realised volatility is defined as sum of its continuous and jump component. From econometric point of view, this estimation is rather difficult. Therefore several studies propose to use theory of Quadratic Variation (QVar) as a non-parametrical method to separate these two components (the most recent ones being Chan et al. (2008); Haugom et al. (2011); Haugom and Ullrich (2012)).

An influential article by Corsi (2004) proposes Heterogenous Autoregressive Model of Realised Volatility (HAR-RV), that takes autoregressive terms over different time horizons as regressors and can be used for forecasting realised volatility. Chan et al. (2008) develops this model and constructs HAR-CV-JV model applied to half-hourly prices for Australian electricity market. They find intra-day and seasonal fluctuations in prices and therefore apply modification to standard method of QVar, which includes estimation of the drift in price changes. Besides that, they compare the forecasting performance of HAR-type models (HAR-RV and HAR-CV-JV) with Exponential General Autoregressive Conditional Heteroskedasticity (EGARCH) and do not find reliable evidence for preference of any of these models. Haugom et al. (2011) further elaborate on their work and include exogenous variables in explaining the realised volatility. They construct the average realised volatility over previous five days, instead of seven days, as originally, due to Nord Pool market closure during the weekend. Since this is not the case for any of the markets studied in this thesis, original length for computing average historical volatility is used when dealing with HAR models.

Various studies focusing on impact of renewable generation on volatility of electricity prices have been conducted. Some of them are focusing solely on effects of wind power generation. Traditional time series models are also widely used. Different types of autoregressive moving average models, often with exogenous variables (Knittel and Roberts, 2005) or seasonal components are employed. For example, Mauritzen (2010) applies Seasonal Autoregressive Moving Average model to study daily wholesale price variability on the Danish spot market with the result of negative elasticity. An important factor influencing the direction of the change is a large number of flexible hydro-power reservoirs that are helping to balance the market in case of discrepancies between supply and demand. Various researchers propose EGARCH as the best model for volatility of energy prices. Ketterer (2014) implements GARCH model and concludes increased daily volatility (but decreased price) on the German spot market between 2006 and 2011 even after the regulatory change in 2010 which obliges TSOs to reveal day-ahead forecasts for RES generation.

Green and Vasilakos (2010) study expected price behaviour in the British market in 2020, when the 20% renewable energy target is to be met, projecting demand and wind generation capacity. They find increased volatility in case of fluctuating wind output and inelastic supply curve. This behaviour has implications for profitability of conventional power plants and future investments. Unlike in the situation without renewable generation, plants with lower fixed costs but higher marginal costs will be preferred in order to balance fluctuating supply (Green and Vasilakos, 2011). Country-specific results imply the need to further analyze different datasets and construct policies individually.

Recent paper by Rintamäki et al. (2017), studying German and Danish data, employs distributed lag models to separate effect of wind and solar power and concludes opposite effects of each source on the volatility in German power market. While solar power flattens hourly price profile, wind energy that is produced also during off-peak hours causes increased volatility. In contrast, daily variation in Denmark is decreased as a result of each renewable source. Nevertheless weekly volatility soars in both areas as a result of intermittent character of the resources.

To conclude, the research concentrated on price volatility, either in financial or electricity markets, has various streams. The importance of linking renewable generation to changes in price volatility emerges, as its integration into the power grid advances, forced by laws and regulations. The results often differ, probably driven by distinct methods used and periods that are studied. What is important, the results are country-specific and cannot be generalised. Therefore, further research is needed in terms of expanding number of countries studied and employing different methods to better understand the volatility process. To the best of our knowledge, no analysis studying renewable sources and price volatility has been done for the Czech Republic. This thesis aims to fill this gap, by proposing volatility models with exogenous variables, that, besides other findings, explain impacts of renewable resources. Moreover, two distinct electricity markets (Czech and German) are compared and its individual characteristics are highlighted.

4 Data Description

In this section we describe the data used in the later econometric analysis[5], their nature, frequency, source and reasons for choosing particular sample periods. Firstly, variables that are common for both countries' regressions are described and later on, we individually focus on country specific differences in the datasets.

In order to match the day-ahead horizon of electricity prices (from which the dependent variable is constructed), we have to use appropriate independent variables as well. Therefore, whenever possible, we work with day-ahead forecasts of explanatory variables instead of their realised values. The reason is that at the time of submitting their bids, market participants do not have perfect information (just the forecasts) and their bidding strategy might have been different under the presence of more precise information. Therefore, volatility arising from their decisions under uncertainty have to be taken into account. In the dataset containing forecasted variables, values for some of the days are missing. Following the approach of Rintamäki et al. (2017), we use realised measures for those observations.

Relatively high number of exogenous variables is used in order to capture all important electricity price and volatility-influencing variables. Many of them are included based on suggestions from previous works and general understanding of power price drivers. For example, Bunn et al. (2013) use prices of gas, coal, CO_2, forecasts of demand and price volatility in explaining electricity price quantiles. Sensfuss et al. (2008) state that fuel and carbon prices influence the level of bids placed by market participants. Even though oil is not directly used for electricity production, it has an impact on transportation costs. We follow the variables selection proposed by Paraschiv et al. (2014) (except expected power plant availability, which is not freely accessible) and use the same approach regarding the determination of coal spot price. Data on coal futures prices and prices of EEX Carbon Index (ECarbix) were generously provided by EEX Market Data. Since coal and

[5]For the econometric analysis, we use R, free software for statistical computing and graphics.

oil prices are available in USD, daily exchange rate is downloaded from Federal Reserve (2017) and used for conversion to EUR. For days with missing exchange rate, we use the most recent known value.

Publication of the data on ENTSO-E Transparency (2017) Platform, that we work with, is thanks to EU Regulation No. 543/2013 of 14 June, 2013 on submission and publication of data in electricity markets (European Comission, 2013). TSOs reveal information about the forecasts of renewable energy generation, that are published no later than 6 p.m. CET on the trading day and an update is published at 8 a.m. CET of the delivery day at the latest (European Comission, 2013). Even though the order book closure for both countries is sooner than 6 p.m. and therefore the renewable energy forecasts may not be known to the bidders at the time of submitting their orders, due to the non-existence of more suitable data, we assume that it is not the case. We presuppose that all the market participants do have the information about renewable energy forecasts for the delivery day when deciding about their bids.

It is important to scale the RES feed-in by demand (load) because the effect of the same amount of RES feed-in might be different for various levels of demand. When there are no blackouts, load and demand match and therefore can be used interchangeably (Becker et al., 2007). Due to data availability and comparability of results, total load forecasts published by ENTSO-E Transparency (2017) are used for both Germany and the Czech Republic. The selection of total load as demand proxy is supported by Ketterer (2014). Jónsson et al. (2010) use wind penetration (wind feed-in/total load) as an independent variable. RES generation forecasts divided by total load are referred to as RES penetration and are reported in percentage values.

Various weather conditions (temperature, wind speed, precipitation) and seasonal dummy variables are included in the regression. Since there are various weather forecasts providers, that publish the data free-of-charge, it seems reasonable to assume that this information is available to all bidders on the trading day. To the best of our knowledge, download of such weather data is not freely accessible, however the data can be downloaded in R using packages[6] that rely on web scrapping from Weather Underground (2017). Nonetheless, due to non-availability of historical day-ahead weather forecasts, similarly to Weron and Misiorek (2008), we use actual weather conditions observed on the delivery day instead of the forecasts available on the trading day.

By including the most important weather variables, we can account for not only demand influencing conditions, but also those that influence supply. Given the geographical variability, it is difficult to estimate the weather for the whole country areas. Since increased demand of electricity can be expected in the cities with higher population and industry concentration, we focus on the most populated towns from each country and then take population-weighted average of the desired variables. In the Czech Republic, towns with more than 50,000 inhabitants are selected (18 towns in total according to Czech Statistical Office (2017)), whose population represents around 30% of the whole country. For Germany, we select 27 biggest towns (based on Federal Statistical Office of Germany (2016), treshold for selection is set at 250,000 inhabitants) representing 22% of country's population. In the later text, we always refer to population-weighted average as the base variable for weather conditions.

Significantly high or low temperatures lead to increased electricity demand due to cooling and heating, which can therefore influence the price and its variation as noted earlier. Due to climatic nature of Germany and the Czech Republic and demand peaking both in the summer and winter, we have to take into account both Heating and Cooling Degree Days (CDD) as an indication of potential impact of temperature and capacity constraints. Similarly to Paraschiv et al. (2014), we consider comfort temperature to be 18.3 °C. As shown by Pardo et al. (2002), at comfort temperature, demand is inelastic to the temperature changes. Since Heating Degree Days and

[6] Notably recently developed package 'weatherICAO' (Michal Kubista, 2017) with improved localisation matching functionality as an addition to 'weatherData' package (Narasimhan, 2017).

CDD have high correlation with each other, we only include the latter in the regression. Refer to the equation below for calculation of CDD:

$$CDD_t = max(Temperature_t - 18.3, 0) \tag{1}$$

It is important to note that trend analysis has been done on all exogenous variables and if any time trend was found, data-series were de-trended following approach in Wooldridge (2015) of saving residuals of regression on time trend and treating these measures as de-trended time series. We do not provide results of these estimations but they are available upon request.

4.1 Czech Republic

In this section, we only explain the selection of variables that are specific for regressions on Czech data. Sample period of 2 years (from July 2015 to June 2017) is used, while data for the last 3 months are preserved for out-of-sample evaluation. The beginning of the sample period is determined by availability of gas spot price on PXE.

OTE has been publishing Yearly Market Report since 2002 (OTE, a.s., 2017b) and became the sole spot market operator in the Czech Republic on April 1, 2009 (OTE, a.s., 2009a). For this thesis, data starting from July 2015 are used and therefore all changes (EUR as a trading currency and allowance of negative prices) stated in Subsection 2.2 are already implemented. First, we work with hourly spot prices from which we construct daily realised volatility[7]. OTE, a.s. (2017b) divides trading hours during working days between peak (8 a.m. to 8 p.m.) and off-peak hours (the rest of the trading hours). Base load is defined for the whole trading day (i.e., also during the weekend). Because we deal with hourly data, the change to Central European Summer Time that occurs yearly at the end of March results in the trading day having only 23 hours (OTE, a.s., 2012b). In contrast, when changing back to Central European time in October, the corresponding day has 25 trading hours (OTE, a.s., 2012c). Since the observations for the 25th

[7]The concept of realised volatility will be presented in the later sections.

delivery hour were missing for some of the years, they were removed accordingly. Year 2016, which is part of the sample period, was a leap year and therefore 24 more hourly observations are assigned to February 29, 2016. In total, daily volatilities consist of 731 observations.

Since the Czech Republic's wind feed-in is less than 1% of power generation per year, it is not obligatory to submit the forecasts for expected wind generation (European Comission, 2013). Therefore, only day-ahead forecasts of solar power production are available, starting from the year 2015 (ENTSO-E Transparency, 2017).

For summary of used data and their sources, please refer to Table 3. The table contains both country specific data and data that are in common with the models for Germany. Please refer to Section 4 regarding the description of other data mentioned in Table 3.

Table 3: Overview of data for the Czech Republic

Variable	**Description**	**Unit**	**Source**
p	Hourly day-ahead electricity price	EUR/MWh	OTE, a.s.
D	Hourly total load forecast	MW	ENTSO-E Transparency
PV_{gen}	Solar forecasts for net generation	MW	ENTSO-E Transparency
$Temperature$	Daily mean temperature used for calculation of CDD	°C	Weather Underground
$Windspeed$	Mean daily wind speed on the delivery day	km/h	Weather Underground
$Precipitation$	Daily precipitation on the delivery day	mm	Weather Underground
Gas	Gas Spot Reference Price	EUR/MWh	PXE
Oil	Daily Europe Brent spot price FOB	EUR/barrel	EIA
$Coal$	Latest available price (daily auctioned) of the front month Amsterdam Rotterdam Antwerp (ARA) futures contract before the electricity price auction takes place	EUR/t	EEX
$ECarbix$	Latest price of the EEX Carbon Index (Ecarbix), daily auctioned at 10:30 a.m.	EUR/tCO_2	EEX

4.2 Germany

Similarly as in the previous section, we comment on the specific variables used in regression on German data. Refer to Data Description for explanations of all dataseries.

In Germany, there are four Transmission System Operators (Amprion GmbH, Tennet TSO GmbH, 50Hertz Transmission GmbH, TransnetBW GmbH). These have been publishing solar and wind day-ahead forecasts for different time horizons, however since 2011 those are available for all market areas. Therefore the forecasts for each 15-minute interval are combined and aggregated and finally represent day-ahead renewable energy forecast for the whole country. Since 2015, this quantity is also available at the web-site of ENTSO-E Transparency Transparency Platform.

Data on day-ahead spot electricity prices and gas spot prices were obtained from EEX Market Data. For determination of gas spot price, we obtained gas spot reference prices for individual market areas (GPL, NCG) applicable to German area and computed respective traded volumes for each of them. Then, volume-weighted average price was used as the reference price for particular delivery day. It is important to note that there is difference in publishing daily reference price on the EEX website for different trading and delivery days[8], even though the information is always published around 10 a.m. (i.e. before the electricity spot order book closure). This is taken into account in the regressions, where we always refer to gas spot price known at the time of submitting the bids for power spot market. For more details on the adjustment rationale, please refer to EEX (2014).

Regarding the total load forecast, ENTSO-E Transparency publishes concise data since 2015, however in the archive we could find total load forecasts since 2012. Nevertheless, due to significant number of missing observations ($\sim 75\%$ for the year 2012), we decided to restrict the sample period. In 2013, around 2.21% of the data points were missing day-ahead forecasts while only 0.02% were missing both day-ahead forecasts and realised values. Since this is not significant number, it should not influence the regressions negatively given the positive impact of increased sample size.

[8]For delivery days from Tuesday to Thursday, the reference price for the preceding day is known to the trader, while for Saturday, Sunday and Monday delivery days, Friday's reference price is known. For delivery days after National German holiday, reference price from the day preceding the holiday period is used as the last known spot price.

Table 4: Overview of data for Germany

Variable	**Description**	**Unit**	**Source**
p	Hourly day-ahead electricity price	EUR/MWh	EEX
D	Hourly total load forecast	MW	ENTSO-E Transparency
PV_{gen}	Solar day-ahead forecasts for net generation	MW	German TSOs
$Wind_{gen}$	Wind day-ahead forecasts for net generation	MW	German TSOs
$Temperature$	Daily mean temperature used for calculation of CDD	°C	Weather Underground
$Windspeed$	Mean daily wind speed on the delivery day	km/h	Weather Underground
$Precipitation$	Daily precipitation on the delivery day	mm	Weather Underground
Gas	Volume-weighted average of daily reference prices for SPOT NCG & GASPOOL	EUR/MWh	EEX
Oil	Daily Europe Brent spot price FOB	EUR/barrel	EIA
$Coal$	Latest available price (daily auctioned) of the front month Amsterdam Rotterdam Antwerp (ARA) futures contract before the electricity price auction takes place	EUR/t	EEX
$ECarbix$	Latest price of the EEX Carbon Index (Ecarbix), daily auctioned at 10:30 a.m.	EUR/tCO_2	EEX

5 Methodology

In this section, we first briefly review the theory of quadratic variation, realised variance and the concept of bipower variation as a way to decompose quadratic variation into its continuous and jump component. Then we introduce econometric test to detect jumps in the time series process based on their significance. After that, we explain modification to the standard theory of quadratic variation that is more suitable for power price series and suggest country-specific models to estimate the non-zero drift.

5.1 Quadratic Variation and Realised Variance

We briefly introduce the theory of quadratic variation and its separation into continuous and jump component. However, for more detailed explanation, please refer to the original works of Protter (1990), Barndorff-Nielsen (2002), Barndorff-Nielsen and Shephard (2004), Barndorff-Nielsen and Shephard (2006) and Andersen et al. (2007) .

While the conditional variance is not directly observable, various models have been developed in order to estimate it. In one branch of the literature, Autoregressive Conditional Heteroskedasticity (ARCH) and Generalised Autoregressive Conditional Heteroskedasticity (GARCH) family models are widely used (Engle, 1982; Bollerslev, 1986). For an extensive overview of GARCH family models applied to electricity markets, see Higgs and Worthington (2008). The other branch of the literature proposes a non-parametric approach. According to Merton (1980), the sum of squared returns can be used as an accurate measure for estimating conditional volatility of financial assets. Andersen and Bollerslev (1998b) suggest, that using higher frequency data and the sum of intra-day absolute returns (i.e., cumulative absolute returns) as a measure of daily volatility incorporates important information. Even though Andersen and Bollerslev (1998a) confirm the forecasting results of previously developed GARCH models using the so-called realised volatility method, it has been shown in various studies that forecasts using realised volatility perform better than GARCH models

(Andersen et al., 2003; Martens and Zein, 2004). The theory of realised volatility method for estimating conditional variance follows.

Jump-diffusion models are often used to model asset and commodity prices (Andersen et al., 2002; Weron et al., 2004). However, difficult separation of the continuous and jump component makes the model hard to estimate from econometric point of view. The continuous-time semimartingale jump-diffusion process for the price of an asset in time t is defined as:

$$p_t = \int_0^t \mu(s)\mathrm{d}s + \int_0^t \sigma(s)\mathrm{d}W(s) + \sum_{j=1}^{q(t)} \kappa(s_j), \tag{2}$$

or differently, in differential form:

$$\mathrm{d}p_t = \mu(t)\mathrm{d}t + \sigma(t)\mathrm{d}W(t) + \kappa(t)\mathrm{d}q(t), \tag{3}$$

where $\mu(t)$ is the continuous drift with finite variation, $\sigma(t)$ is the càdlàg (continuous from the right, has limit from the left) instantaneous volatility, $W(t)$ is a standard Brownian motion, and finally an independent compound Poisson process $q(t)$ is the contribution of jump counting process such that $\kappa(t)\mathrm{d}q(t)$ is the contribution of jump process to the log-price process (Chan et al., 2008; Haugom et al., 2011). If there is a jump at time t, $\mathrm{d}q(t) = 1$ and $\kappa(t)$ stands for the jump size. Regarding the drift, there may be differences between electricity spot prices and prices of other financial assets. While for the financial assets and higher sampling frequency M we can assume that drift is negligible, as noted by Chan et al. (2008), we cannot ignore it in case of power spot prices.

Even though the logic behind jump-diffusion model suggests that it is composed of diffusion volatility component and jumps, it is not easy to differentiate it econometrically (Haugom et al., 2011). Another option to differentiate between jump and non-jump component non-parametrically is using the theory of quadratic variation. The quadratic variation ($QVar$) of Eq. (2) can be expressed as:

$$QVar_t = \int_0^t \sigma^2(s)\mathrm{d}s + \sum_{j=1}^{q(t)} \kappa^2(s_j), \tag{4}$$

where the quadratic variation is equal to sum of the integrated variance ($IVar_t$) and the sum of squared jumps. In the pure diffusion process, $q(t)$ is zero and therefore $QVar_t$ is directly equal to integrated variation ($IVar_t$) of the continuous sample path process. Under the assumption of no microstructure noise, caused by different time of price record, bid-ask bounce, irregular trading etc. (see, e.g. Bai (2000)), Andersen et al. (2003) show that

$$RVar_t^{all} \xrightarrow{p} IVar_t. \tag{5}$$

$RVar_t^{all}$ stands for the realised variance determined using all available data and is said to be a consistent estimator under the above stated assumption of no measurement error. The $IVar_t$ is known to be the measure of true volatility (McAleer and Medeiros, 2008). Because of the price determination by exchanges, no microstructure noise arises in case of day-ahead prices.

To determine intra-day returns[9], assume a sample period of T days where $t \in \{1, 2, ..., T\}$ and prices are sampled M times per day at equidistant intervals. Then the j-th within t-day return is defined as:

$$r_{t,j} = p_{t,j} - p_{t,j-1}, \qquad j = 1, ..., M, \qquad t = 1, ..., T \tag{6}$$

and as in Andersen and Bollerslev (1998b), the realised variance for day t ($RVar_t$) [10] can be calculated as following:

$$RVar_t = \sum_{j=1}^{M} r_{t,j}^2 \qquad t = 1, ..., T. \tag{7}$$

In theory, when $M \longrightarrow \infty$, $RVar_t$ stands for an ex-post measure of the price variation. Specifically, $RVar_t$ is a consistent estimator of the daily addition of the quadratic variation.

$$RVar_t \longrightarrow \int_{t-1}^{t} \sigma^2(s)\mathrm{d}s + \sum_{j=q(t-1)+1}^{q(t)} \kappa^2(s_j). \tag{8}$$

[9]Even though we refer to price changes $p_{t,j} - p_{t,j-1}$ as intra-day returns, it is important to note that since electricity is a non-storable good, they do not represents returns in a traditional sense (Chan et al., 2008).

[10]While day-ahead electricity prices have hourly granularity, as the realised variance is computed as the aggregation of intra-day price changes, we only refer to daily volatility.

Any extreme value will be squared and therefore has higher impact on the realised variance. In our case, $M = 24$[11] since we use hourly data. Since the electricity market differs from the stock market and the return for first hour of the day is not an overnight return, we do not need to drop any observations as e.g. in the article by Haugom and Ullrich (2012) who calculate forward realised volatility. Even though in theory, we should always aim for the highest sampling frequency possible ($M \longrightarrow \infty$), in practice, it is always the question of market liquidity while we have to be aware of microstructure noise when utilising high-frequency data (Gençay et al., 2001). Due to the usage of hourly data calculated by the exchange, we do not consider any problems arising from microstructure noise.

Since the realised volatility has been developed as an ex-post non-parametric quadratic variation measure, it can be modeled applying usual time-series methods.

Barndorff-Nielsen and Shephard (2005) focus on theoretical foundation of variation measures in financial markets and on the ways to deal with market frictions and jumps. These specifications are typical for power prices, therefore their work can be applied beyond financial markets. McAleer and Medeiros (2008) provide an extensive discussion and critical assessment of approaches to modelling realised volatilities in simple and multivariate framework. They focus on various sampling techniques and mainly on the effects of microstructure noise (both dependent and independent noise processes) on the estimators' properties. Authors draw conclusions for practitioners regarding modelling and forecasting daily realised volatilities. Nonetheless, they exclude the review of jumps which are already broadly studied by Barndorff-Nielsen and Shephard (2004, 2005).

Barndorff-Nielsen and Shephard (2006) emphasise the importance of variance decomposition into jump and continuous path in the financial econometrics. Both Huang and Tauchen (2005) and Andersen et al. (2007)

[11] Due to changes to Central European Summer time, we have days consisting of 25 trading hours as explained in the previous sections. However, as suggested by Haugom et al. (2011) and Haugom and Ullrich (2012), we only use M=24.

conclude that the contribution of jumps to the total daily variation is substantial. Work directly focusing on the Czech electricity market recently proposed by Hortová (2016) emphasises the significance of jumps in day-ahead prices.

Barndorff-Nielsen and Shephard (2004) conclude that unless we make strong parametric assumptions (see, e.g., Eraker et al. (2003)) about log-price, alternative aggregate volatility statistics have to be used to differentiate between individual contributions of continuous and jump parts. They introduced *bipower variation (BV)* as the first model-free method to differentiate between continuous and jump component in the calculation of quadratic variation. In specific cases [12], realised bipower variation is an asymptotically unbiased estimator of integrated variance in SV models, which is moreover robust to rare (i.e., the probability of two continuous jumps goes to zero) but significant jumps typical for power prices as long as the maximum of powers is less than two (Barndorff-Nielsen and Shephard, 2004).

Barndorff-Nielsen and Shephard (2004) define (first-lag) bipower variation as

$$BVar_t = \frac{\pi}{2}\sum_{j=2}^{M}|r_{t,j}||r_{t,j-1}|, \qquad t = 1,...,T \tag{9}$$

and show that for $M \longrightarrow \infty$, the BV becomes robust to jumps and the following holds:

$$BVar_t \xrightarrow{p} \int_{t-1}^{t} \sigma^2 \mathrm{d}s. \qquad t = 1,...,T \tag{10}$$

The logic behind this specification of BV lies in the fact that for large values of M, we can assume that there is at most one jump in two adjoining periods which implies that even though there is a jump in one period, it will be multiplied by smaller return from the adjacent period and therefore there will not be large impact on the variation. According to Ullrich (2012), a lot of jumps does not automatically lead to higher volatility.

However due to volatility clustering of spot price variance it is possible that more than one jump occur in two adjacent period. Huang and Tauchen (2005) proposed alternative to standard first-lag bipower variation, called

[12] Detailed description of all the cases is beyond the scope of the thesis

second-lag bipower variation:

$$BVar_t = \mu_1^{-2} \frac{M}{(M-2)} \sum_{j=3}^{M} |r_{t,j}||r_{t,j-2}|, \qquad t = 1, ..., T \tag{11}$$

where $\mu_1 = E(|Z|) \equiv \sqrt{2/\pi} \approx 0.79788456$ and Z refers to a standard normal random variable.

The concept of bipower variation became popular not only in application to high-frequency financial data (see e.g., Corsi et al. (2008); Patton and Sheppard (2009)) but due to its nature it has been used in energy economics' research (see e.g., Chan et al. (2008); Wang et al. (2008); Ullrich (2012)). In their work, Chan et al. (2008) model jump component of electricity spot price volatility following *second-lag bipower variation*. Later, Ullrich (2012) further elaborates on the previous work of Chan et al. (2008) and makes important remarks regarding the methodology when applied to electricity spot prices.

Barndorff-Nielsen and Shephard (2004) suggest that the quadratic variation of the jump component can be calculated as the difference between realised variance and BV estimate. Formally,

$$RVar_t - BVar_t \longrightarrow QVar_t - IVar_t, \tag{12}$$

and therefore similarly to Bollerslev et al. (2009) we can define

$$JVar_t = RVar_t - BVar_t, \tag{13}$$

where $JVar_t$ is the jump component. In theory, $JVar_t \geq 0$, however if we have finite values of M it can happen that $JVar < 0$.

Another approach is to directly test for jumps and afterwards directly calculate $JVar_t$. In our analysis we use categorization based on results of the Z-test:

$$Z_t = \sqrt{M} \frac{(RVar_t - BVar_t)/RVar_t}{\sqrt{({\mu_1}^{-4} + 2{\mu_1}^{-2} - 5) max(TQ_t/{BVar_t}^2, 1)},} \tag{14}$$

where $\mu_1 = E(|Z|) \equiv \sqrt{2/\pi} \approx 0.79788456$ and Z refers to a standard normal random variable. The numerator measures the contribution of jumps to the total price variation for day t while the denominator is a sample estimate of the integrated quarticity. This estimator is proposed by Huang and Tauchen (2005) as the most robust to sampling frequency with rejection rate close to 1%. For other possibilities of jump detection, please see Barndorff-Nielsen and Shephard (2004); Chan et al. (2008); Christensen et al. (2012).

Haugom et al. (2011) propose a way how to estimate integrated quarticity by tripower quarticity (TQ_t):

$$TQ_t \equiv {\mu_{4/3}}^{-3}\left(\frac{M^2}{M-4}\right)\sum_{j=5}^{M}|r_{t,j}|^{4/3}|r_{t,j-2}|^{4/3}|r_{t,j-4}|^{4/3}, \tag{15}$$

where $\mu_{4/3} = (E|Z|^{4/3}) \equiv 2^{2/3}\Gamma(7/6)\Gamma(1/2) \approx 0.8308609$.

For $M \longrightarrow \infty$, Z converges in distribution to standard normal variable (according to asymptotic distribution theory advanced by Barndorff-Nielsen and Shephard (2004)). Therefore we can choose the desired level of significance, compute Z_t for each day t and conclude the occurence of jump if Z_t overreach the critical value $\Phi_{1-\alpha}$ of the standard normal distribution. Finally, to obtain the jump component of variation for day t, we simply define:

$$JVar_t = I_{\{Z_t>\Phi_{1-\alpha}\}}(RVar_t - BVar_t), \tag{16}$$

where $I_{\{Z_t>\Phi_{1-\alpha}\}}$ is the indicator function obtaining value 1 if there is a jump detected based on the value of the test and zero otherwise. Individual specifications of the power market determine the choice of the percentile. That means that in the presence of jump, $JVar_t$ will be calculated as the difference between realised variance (Eq. (7)) and bipower variation (Eq. (11)) as shown in Eq. (13).

The most important implication for our work is the calculation of continuous part of variance defined as:

$$CVar_t = RVar_t - JVar_t, \tag{17}$$

which we will use as dependent variable in upcoming parts of the thesis.

Sometimes the terms realised variance and realised volatility are used interchangeably in the literature. We stick to the traditional notation from the financial literature and in order to be concise, we use notation "realised variance" for the measure from Eq. (7). By "realised volatility" (RV_t) we simply mean the square root of $RVar_t$ (Barndorff-Nielsen and Shephard, 2002).

For the later analysis, it is important to note that we will use square root of $CVar_t$ from Eq. (17) and we will call it Continuous Volatility (CV_t). Similarly, square roots of $JVar_t$ and $RVar_t$ will be called Jump Volatility (JV_t) and Realised Volatility (RV_t), respectively. Using the separated diffusion part may provide better understanding of the real volatility process netted of jumps, since those are stochastic Poisson process and are highly unpredictable.

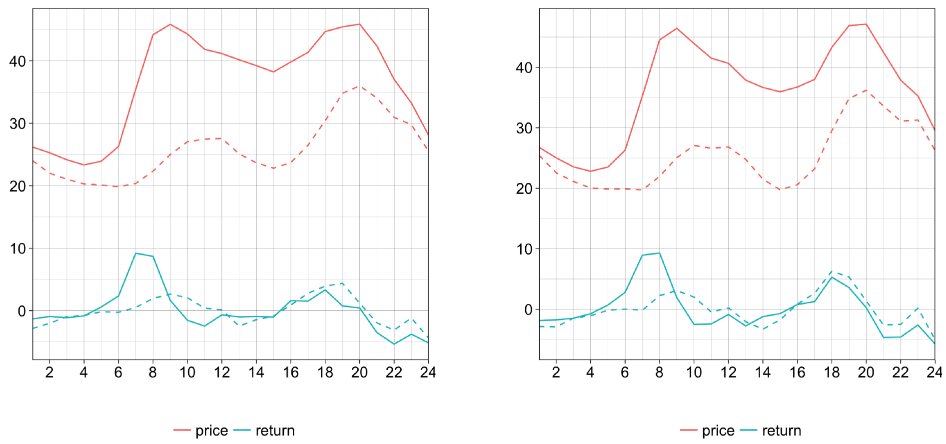
5.2 Modification for Electricity Prices

Quadratic variation theory is widely used in the financial literature, where, providing high sampling frequency, it is generally assumed that the drift $\mu(t)$ from Eq. (3) is close to zero (i.e., price changes are mean-zero). Following that, for example, Huang and Tauchen (2005) use directly computed five-minute returns on the S&P index in identifying the contribution of jumps to the price variance. In contrast to financial time series, the drift is not negligible for electricity price time series (Chan et al., 2008). Refer to Figure 1 to visually check, that power spot prices follow seasonal fluctuations and are subject to distinct features (mean-reversion, intra-day and daily seasonality). Following Knittel and Roberts (2005) and Chan et al. (2008), we adjust the returns for non-zero drift and obtain the so-called de-meaned price changes.

Looking at Figure 1, where mean prices and returns are depicted for each hour of the day, intra-day and intra-week pattern is evident. Price series for both markets are peaking around 9 a.m. and 8 p.m., but weekend price levels are significantly lower, mostly during peak-hours. The dynamics of price changes are quite similar, with slightly more volatile weekend returns in German market.

Seasonal fluctuations are shown in Figure 2, where mean spot price for particular hour of the day and season are summarised. Based on the graphical representation, prices in autumn are highest, while spot prices in spring are lowest. Based on the categorisation of peak-hours, those are associated with higher prices in general.

It is important to note that not all researchers follow the same approach. For example, Haugom et al. (2011) analyze Nord Pool forward high-frequency power data using realised volatility and its separation into continuous and jump component. They conclude better predictability of day-ahead volatility due to partition into diffusion and jump part. However, they use directly obtained intra-day returns in computing $RVar_t$ and ignore the modification defined in this section. Nevertheless, based on the results presented here, we believe the de-meaned price changes will lead to more precise estimations.

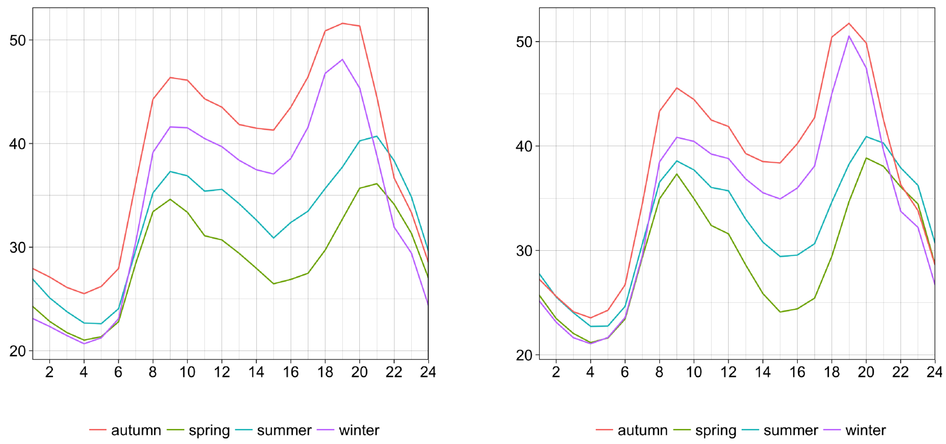


(a) Czech Market (b) German Market

Figure 1: Average intra-week hourly price and return profile

Note: Mean hourly price and return is depicted for weekday and weekend separately, while the latter is represented by dashed lines.
Source: Author's computation.

To obtain the de-meaned price changes, we proceed in three steps. First, we estimate autoregressive model with exogenous variables for electricity



(a) Czech Market (b) German Market

Figure 2: Average hourly price profile for astronomical seasons

Source: Author's computation.

prices in order to obtain the estimate of a drift. Then, the common pattern is netted out from the returns in Eq. (6). Finally, the quadratic variation theory presented in Section 5.1 is applied to de-meaned price changes.

Since there are significant differences in peak and off-peak prices, weekend price level opposed to weekdays, variations between astronomical seasons and memory of electricity prices, following the approach of Knittel and Roberts (2005), we can specify price for Czech electricity market for hour j and day t as:

$$\begin{aligned} p_{t,j} = \quad & \beta_1 Peak_j + \beta_2 OffPeak_j + \beta_3 Weekend_t + \beta_4 Spring_t + \beta_5 Summer_t + \\ & + \beta_6 Autumn_t + \beta_7 p_{t,j-1} + \beta_8 p_{t-1,j} + \epsilon_{t,j}, \end{aligned} \tag{18}$$

where binary variables $Peak_j$ and $OffPeak_j$ indicate, whether the hour j falls between 8 a.m. and 8 p.m. (in that case we have $Peak_j = 1$ and $OffPeak_j = 0$), however these are defined for working days only based on the day-ahead market characteristics explained in Section 2.2. Similarly, binary variable $Weekend_t$ takes on value 1 if day t is Saturday or Sunday and zero otherwise. From that we get: $Peak_j + OffPeak_j = Weekday_t$ and $Weekday_t + Weekend_t = 1$. Accounting for seasonal differences we include dummy variables $Spring_t$, $Summer_t$ and $Autumn_t$, while omitting binary variable $Winter_t$ to avoid multicollinearity problem. Market clearing price for the same hour of the last delivery day is also included following Paraschiv et al. (2014) to account for autocorrelation. Coefficient β_7 determines the rate of mean reversion.

We amend the Eq. (18) for German power price dataseries according to the classification of peak, off-peak 1 and off-peak 2 trading blocks throughout the day. For details on trading blocks on spot market, refer to Section 2.1. Moreover, on the EPEX SPOT market, the peak load is defined also for the weekend. Therefore, for the German market, we can model price for j-th hour on day t as:

$$\begin{aligned} p_{t,j} = \quad & \beta_0 + \beta_1 OffPeak1_j + \beta_2 OffPeak2_j + \beta_3 Weekend_t + \beta_4 Spring_t + \\ & + \beta_5 Summer_t + \beta_6 Autumn_t + \beta_7 p_{t,j-1} + \beta 8 p_{t-1,j} + \epsilon_{t,j}, \end{aligned} \tag{19}$$

The intercept β_0 captures the scenario when t is a weekday during winter season and j lies between 9 a.m. and 8 p.m. (i.e., peak hours as defined for German spot market). The independent variables have the same explanation as for Eq. (18).

The calculation of drift in price changes follows from Eq. (18) and (19). According to Knittel and Roberts (2005), residuals from the equations can be viewed as the drift of price changes in Czech and German electricity market. Therefore $\widehat{\mu(t,j)} \equiv \widehat{\epsilon_{t,j}}$.

In order to adjust the intra-day returns for their predictable component, we simply use the following calculation to obtain de-meaned returns [13]:

$$r^*_{t,j} = r_{t,j} - \widehat{\mu(t,j)}, \qquad j = 1, ..., M \qquad t = 1, ..., T \tag{20}$$

where notation j is used to emphasise hourly granularity and $r_{t,j}$ refers to price change computed as in Eq. (6). De-meaning of returns allows to avoid classifying higher seasonal fluctuations in price changes as jumps and, by construction, leads to lower number of jump days identified.

[13] Given the complexity of drift estimation in electricity price changes, possible misspecification could lead to imprecise results and therefore later calculations of $RVar_t$, $BVar_t$ and TQ should be viewed as approximations only.

Finally, we apply the theory of quadratic variation as explained in Subsection 5.1. That means that $r_{t,j}$ is replaced[14] by $r^*_{t,j}$ in Eq. (7), (9), (11) and (15), respectively.

[14]Therefore in the volatility analysis, we always think of variation defined by de-meaned price changes.

6 Empirical Results

6.1 Electricity Spot Price

Electricity price is the most important variable, as it is an input to calculations of realised volatility and its components. Descriptive statistics with results of statistical tests for both price levels and changes are provided. We also formally determine seasonal fluctuations, that result in estimation of non-zero mean drift in price changes as modification to standard quadratic variation theory.

Figures 3 and 4 depict levels of prices in both markets. Note that for better visibility and comparability, German power prices are depicted only for restricted period, which coincides with sample period for the the Czech Republic. Graph for the whole sample period can be found in Appendix (Figure 11). From the plots of hourly price series, the occurrence of jumps is already evident. Negative bids are allowed in both markets, therefore the prices are limited only by order constraints posed by particular market operator (for details, see Sections 2.1 and 2.2). For 1% of hourly observations in German market, the prices are below zero. Most of them occur during winter, followed by spring, autumn and summer as the season with least number of negative prices. For comparison, 186 hourly observations are negative in winter and 137 in spring, while only 44 and 25 in autumn and summer, respectively. In the Czech Republic, 0.7% of observations are negative, out of which 52 occur in winter, 39 in spring, 19 in summer and only 6 in autumn. These differences can be attributed to demand patterns, seasonal fluctuations in weather conditions and individual characteristics of the country. More than 60% of negative prices occurred during the weekend. Negative prices are rather common finding in power markets and its rationale can be found in Section 2, where pecularities in deregulated electricity markets are discussed.

Descriptive statistics for both country's spot price and price changes are summarised in Table 5. The calculations are made for the whole sample period, consisting of 17,542 and 39,403 observations for the Czech Republic

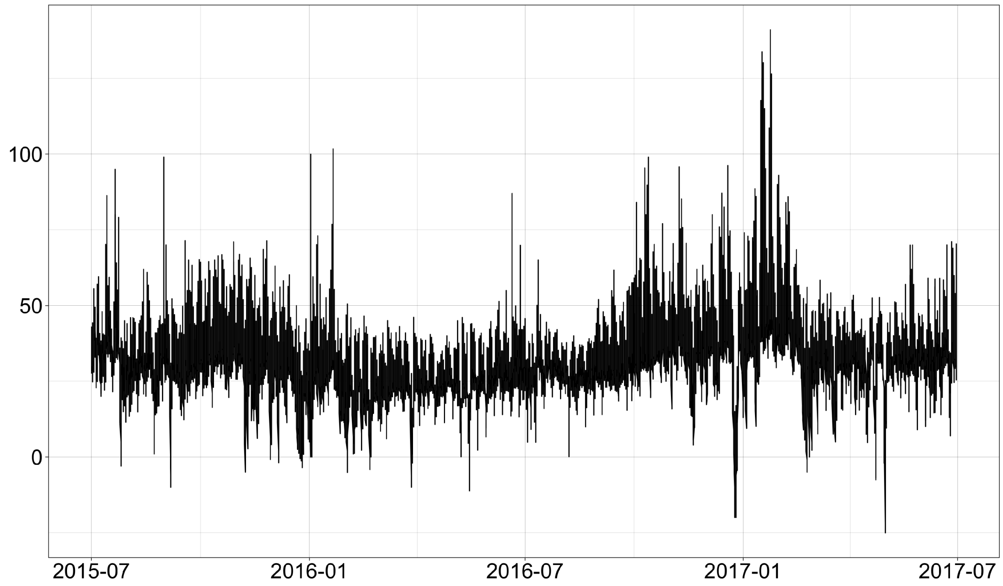


Figure 3: Czech electricity spot price in EUR/MWh

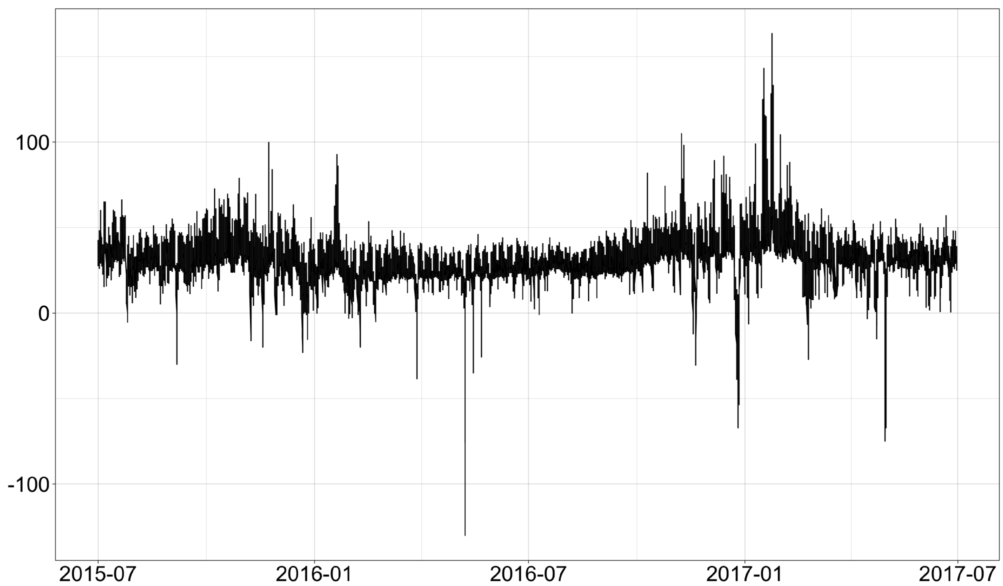


Figure 4: German electricity spot price in EUR/MWh

and Germany, respectively. Minimal prices are negative for both markets, being −25 EUR/MWh for the Czech Republic and even more negative, −130.09 EUR/MWh for Germany. Maximum prices are more than four times the mean price, which is around 33 EUR/MWh for both countries. German market is subject to more extreme prices and has higher ratio of

Table 5: Descriptive statistics for electricity prices and price changes

	CZ		**DE**	
	Spot price	Return	Spot price	Return
N	17,542	17,541	39,403	39,402
Mean	33.52	0.00005	33.09	0.0005
Std dev	14.47	4.76	14.55	5.34
Skewness	1.12	0.64	0.27	0.37
Kurtosis	4.67	10.01	5.94	13.42
Min	−25.0	−42.58	−130.09	−71.03
Max	141.04	48.76	163.52	75.4
25% percentile	24.9	−2.11	25.11	−2.3
Median	32.16	−0.30	31.91	−0.23
75% percentile	40.22	1.84	40.05	1.97
Jarque-Bera test	19,633	74,397	58,443	296,620
	(<0.01)	(<0.01)	(<0.01)	(<0.01)
Dickey-Fuller test	−13.481	−26.063	−20.307	−40.055
	(<0.01)	(<0.01)	(<0.01)	(<0.01)
KPSS test	2.057	0.0012	1.4525	0.0015
	(<0.01)	(>0.1)	(<0.01)	(>0.1)

Note: Spot price refers to hourly day-ahead price and first differences of prices are referred to as returns. p-values for the corresponding test are included in parenthesis.
Source: Author's computation.

standard deviation to mean price. Maximum price is 163.52 EUR/MWh, while in the Czech Republic, it is only 141.04 EUR/MWh.

Interquartile range and mean spot price can be taken as indication of "normal" trading conditions. These are very similar and range from around 25 to 40 EUR/MWh. Mean is higher than median, which suggests positive skewness and occurrence of fewer observations above the mean. The mean is higher due to few extreme observations, that are more likely to occur in particular seasons for each country. In the Czech Republic, for example, 41% of hourly prices in forth quartile occur in autumn, 27% in winter and only 11% in spring. In Germany, the pattern is similar, with 32% of extreme observations occuring in autumn, 31% in winter and 17% in spring. Given previous remarks, winter seems as the most volatile period in terms of the extreme observations.

Standard deviations for both prices and returns are high compared to mean values. There are some extreme observations, that deviate significantly from the mean value, which is close to zero. For example, maximum absolute hourly price change for the Czech market is 48.76 EUR/MWh while being 50% more for German spot price.

Skewness and kurtosis indicate deviations from normal distribution. Both spot prices and returns exhibit positive skewness, which is in line with the literature (see, e.g. Ullrich (2012)) and are leptokurtic, resulting in fat-tailed distributions. This suggests that extreme values are more likely to occur compared to standard normal distribution. Normality is also formally tested by Jarque-Bera test (Jarque and Bera, 1980) and null hypothesis of normality is rejected in all cases, which confirms previous remarks.

In order to be able to estimate the equations, stationarity and mean-reversion of time series is checked. Following Krištoufek and Luňáčková (2013), two tests for stationarity, with different null hypotheses, are employed: Augmented Dickey-Fuller Test (ADF) (Dickey and Fuller, 1979) with null hypothesis of unit-root and Kwiatkowski-Phillips-Schmidt-Shin Test (KPSS) (Kwiatkowski et al., 1992) that has null hypothesis of stationarity. Lags for the tests are determined automatically by R software. The null hypothesis of ADF test is rejected in all cases and therefore the series do not contain unit root. However, results of KPSS test suggest non-stationarity in the price series, but stationarity for price changes. These characteristics are in line with findings for other power markets (see, e.g. Knittel and Roberts (2005)) with more details in Section 2.

Literature focusing on electricity price behaviour emphasises the mean reversion effect in contrast to the financial assets (Krištoufek and Luňáčková, 2013; Weron, 2014). The logic behind mean reversion is high dependency on weather conditions which tend to be mean reverting. Other than that, higher electricity price motivates more costly power plants to operate, therefore creating downward pressure on prices. In the case of low prices, generation tends to go down and pushes the price up. Specifically for the Czech power market, Krištoufek and Luňáčková (2013) study mean-reversion of price and report Hurst component of 1.1, which suggests non-stationary but mean-reverting time series.

Based on previous remarks and thanks to mean-reverting nature, we first estimate Eq. (21) to formally determine, whether it is necessary to remove the drift in our case. We test for significant difference between peak and off-peak prices and between weekdays and weekend prices for the Czech Republic. Specifically, we drop out $Peak_j$ from Eq. (18) and add the intercept α_0 which represents the scenario for base period during weekday in winter.

$$\begin{aligned} p_{t,j} = \quad & \beta_0 + \beta_1 \mathit{OffPeak}_j + \beta_2 \mathit{Weekend}_t + \beta_3 \mathit{Spring}_t + \beta_4 \mathit{Summer}_t + \\ & + \beta_5 \mathit{Autumn}_t + \beta_6 p_{t,j-1} + \beta_7 p_{t-1,j} + \epsilon_{t,j}. \end{aligned} \tag{21}$$

The results of this regression are included in Appendix (Table 12). The mean Czech spot price on weekday in winter is estimated to be 37.9429 EUR/MWh, while off-peak price for the same day is lower by 3.3268 EUR/MWh. Ceteris paribus, price on weekend is lower by 6.6684 EUR/MWh. This can be explained by generally lower demand during weekend which, together with price setting dynamics, imply lower price. The last three rows demonstrate seasonal fluctuations. We find prices in spring to be lower compared to winter at 10% significance level.

Similarly, we test for significant difference between peak and off-peak prices and between weekdays and weekend prices for Germany while we do not need to amend Eq. (19). Therefore, it stays in its original form as:

$$\begin{aligned} p_{t,j} = \quad & \beta_0 + \beta_1 \mathit{OffPeak1}_j + \beta_2 \mathit{OffPeak2}_j + \beta_3 \mathit{Weekend}_t + \beta_4 \mathit{Spring}_t + \\ & + \beta_5 \mathit{Summer}_t + \beta_6 \mathit{Autumn}_t + \beta_7 p_{t,j-1} + \beta_8 p_{t-1,j} + \epsilon_{t,j}. \end{aligned} \tag{22}$$

The results of the estimation can be found in Appendix (Table 13). The mean German spot price during peak hours on weekday is estimated to be

35.4820 EUR/MWh, while during weekend the peak-hour mean price is lower by 3.1979 EUR/MWh. Price during off-peak periods is lower, however the magnitude of decrease is higher during off-peak 1 period (between midnight and 8 a.m.). The price decrease is 3.5965 EUR and 2.7048 EUR for off-peak 1 and off-peak 2 period, respectively. The coefficients indicating seasonal fluctuations are qualitatively similar in both countries, showing decrease in price for spring compared to winter season.

Based on the results of the regressions, seasonal, intra-day and intra-week fluctuations were confirmed. These remarks apply to both markets that supports the usage of de-meaned price changes in realised volatility calculations.

6.2 Estimation of Jump and Continuous Component of Realised Volatility

In order to disentangle jump and continuous component of realised volatility, we follow the methodology presented earlier and since significant intra-day, intra-week and seasonal differences were shown, we use de-meaned price changes in the later computations. Theory of quadratic variation is then applied and jump component of realised volatility is determined using Z-test with chosen significance level. For days with significant jumps, continuous variation is computed as realised variation netted off jump component.

Before estimating the jump component and continuous component of realised volatility, we provide results (Table 6) of estimation of autoregressive model with exogenous variables summarised in Eq. (18). Please note that *Peak* and *OffPeak* are in Czech power market defined only during weekdays and therefore the interpretation differs from the German market. Accordingly, for the Czech Republic, mean spot price during peak hours in winter is estimated at 37.9429 EUR/MWh while for offpeak hours for the same season, the mean price is 34.616 EUR/MWh. Qualitatively similar results for Germany are reported in Table 13 and commented in previous section.

Therefore, according to Chan et al. (2008), we continue to use de-meaned

Table 6: Drift estimation for the Czech Republic power price series

	Dependent variable:
	Price
AR(1)	0.8327***
	(0.0039)
AR(24)	0.1461 ***
	(0.0039)
Peak	37.9429***
	(2.0307)
OffPeak	34.6160***
	(2.0294)
Weekend	31.6160***
	(2.0373)
Spring	−3.1694*
	(1.9183)
Summer	−2.443
	(2.1995)
Autumn	0.3929
	(1.9764)
Observations	17,542

Note: *** significance at 1%, ** significance at 5%, * significance at 10%. Standard errors are in parenthesis.
Source: Author's computation.

price changes in computations of realised variance as noted in Eq. (7), where $r_{t,j}$ is replaced by $r^*_{t,j}$ from Eq. (20). Please note that, unless specifically noted, we always refer to de-meaned price changes when talking about returns in the later sections. We compute all measures as described in section Methodology, while we do not further comment on them if it is not necessary.

Once we compute bipower variation (Eq. (11)) and detect the day with a significant jump, we can employ Eq. (16) to estimate the jump component of the total variation and consequently determine the continuous component of the total variation according to Eq. (17). Only continuous component is used in later regression estimations and its rationale is stated in later sections.

For estimating the jump component of the realised variation using the Z-test defined in Eq. (14), we have to first specify the desired level of α in order to capture reasonable amount of jumps. On one hand, if we set α too loosely, we will obtain too many jumps that will decrease the continuous component of the variation. On the other hand, if α is set to be too low, we will not detect some jumps and the omitted jump variation will be counted towards the continuous part of the variation instead.

We aim to avoid both of the extremes and follow the approach of Tauchen and Zhou (2011). They suggest to match a jump contribution of 80% with $\alpha = 0.1\%$ while in the case of a jump contribution being of order 10%, α should be 5%. The latter is the case for the Czech Republic, as mean jump contribution (JV_t/RV_t) is 5.298% when α is set at 5%, while results were qualitatively similar when experimenting with different levels of significance. Jump intensity, that is number of days with significant jumps scaled by all days in sample period, is 12.82%. These results are in line with previous study on Czech power market (Hortová, 2016) with just slightly lower result of 5.2% jump contribution. For the same significance level, mean jump contribution is 7.818% in German power market while jump intensity is 19.36%. These results seem reasonable given the summary statistics and differences between the markets.

We further follow the methodology and obtain the estimated components, that are summarised in Table 7, where variation components are reported in their standard deviation form. By construction of the reported measures, CV has lower mean compared to RV, while JV has high dispersion around its, relatively low, mean. Statistics for skewness and kurtosis signal deviations from normal distribution, which is in line with the results for power markets (Mari, 2006; Chan et al., 2008). We arrive to the same conclusion after performing Jarque-Bera test for normality.

As for the magnitudes of mean realised volatilities, the differences can be attributed to varying sources of energy and possibly to better interconnections with countries rich in storable hydro-power.

Table 7: Summary statistics for volatilities and test results

	CZ			**DE**		
	RV	JV	CV	RV	JV	CV
N	731	731	731	1,642	1,642	1,642
Mean	22.47	2.35	21.57	8.8	0.84	8.49
Std dev	13.6	7.05	13.03	3.91	1.79	3.08
Skewness	2.27	3.32	2.48	2.73	1.94	2.51
Kurtosis	7.61	11.67	9.19	12.38	2.59	10.84
JV/RV	5.298%	-	-	7.818%	-	-
Coefficient of variation	0.6053	3.0	0.604	0.4443	2.131	0.481
Jarque-Bera test	2,411.1	5,525.8	3,346.9	12,567	1,490	9,781.1
	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)
Dickey-Fuller test	−5.4967	−8.4098	−5.4609	−7.6705	−10.612	−7.7648
	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)
KPSS test	0.30023	0.15055	0.2865	0.43956	0.095443	0.42464
	(>0.1)	(>0.1)	(>0.1)	(<0.01)	(>0.1)	(<0.01)

Note: The table reports summary statistics and statistical tests with p-values in parenthesis for realised volatility (RV) and its jump (JV) and continuous (CV) components, that are estimated with significance level $\alpha = 5\%$. Coefficient of variation is defined as standard deviation divided by mean of corresponding data.
Source: Author's computation.

The contribution of jumps to total realised volatility can be seen in Fig. 5. For the Czech market, mean jump contribution is 5.398% compared to 7.818% for Germany. There are more jumps identified in German market and signs of volatility clustering can be observed for both countries, where there are clear high jump intensity periods followed by periods of low volatility. For the clarity and easier comparability, volatilities and jumps are shown just for two-year period, which coincides with the whole sample period used for the Czech Republic. Full graphs for Germany can be found in Appendix (Figure 12).

The distribution of jumps during the week is uneven and differs by country. For instance, 47% of jumps in German market occur during the weekend. Even for continuous volatility, observations in the forth quartile are concentrated during weekend (around 40%). The results are contrasting to the ones obtained for the Czech Republic. In this market, only 16% of jumps are detected on Saturday or Sunday and 14% of continuous volatility observations that belong to the forth quartile are identified during weekend. This suggest possibly different results in the later estimations in terms of coefficients for binary variable *Weekend*.

As opposed to Czech market, volatilities computed for German market exhibit time trend. Therefore, the null hypothesis of KPSS tests is trend-stationarity. Jump component of volatility rises in time with concave structure, while continuous component decreases. Before being used in the models, these volatilities are de-trended. Such transformation leads to level-stationary data. To reduce skewness and kurtosis of volatility distribution, it is possible to do logarithmic transformation. However, this transformation yields in time series that is further from stationarity in contrast to level form. Therefore in the later analysis, we preserve the level form of dependent variables.

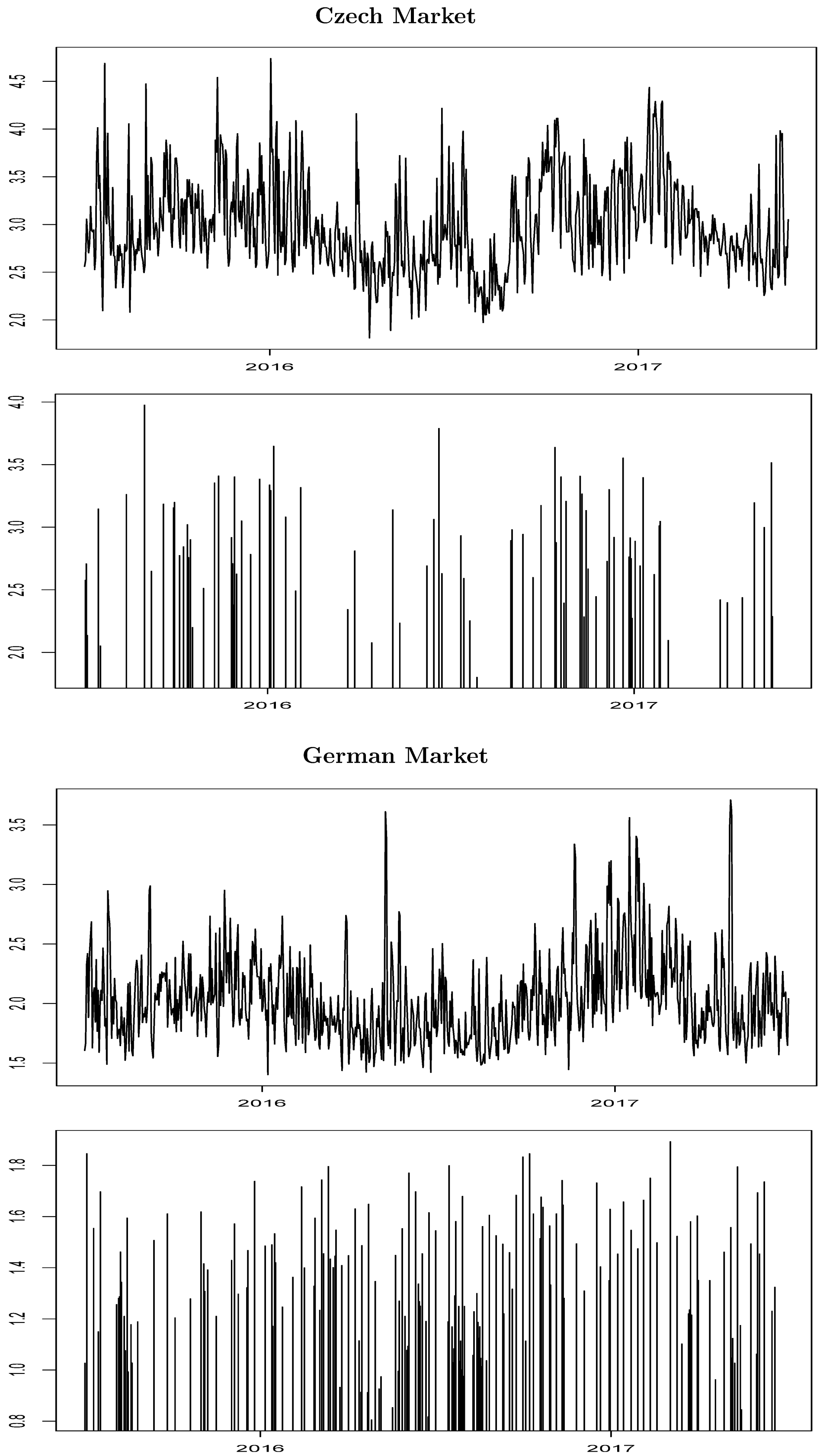


Figure 5: Total realised volatility and jumps identified based on Z-test with significance level of 5%

Note: The vertical axis is in a log scale to preserve clarity in the plots.

6.3 Summary Statistics for Exogenous Variables

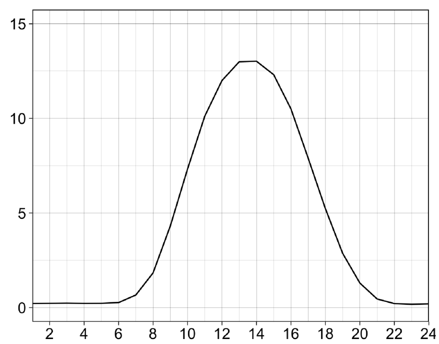
In this section, we briefly comment on exogenous variables that are used in later regressions. Focus is put on penetration of RES and evolution of prices of commodities over time. Summary statistics for all exogenous regressors are provided in Appendix (Table 14 and 15), where the name of the variable is kept the same as in Data Description and regression equations.

Values of daily total load differ in magnitude, which is not surprising given different population size for each country. The same applies to daily total RES generation forecasts, that depend on installed capacity mostly. Therefore, usage of RES penetration is more appropriate for the estimations. Mean percentage values of RES penetration are in line with figures from Section 2.1 and 2.2. Germany has higher mean penetration of energy from photovoltaics and together with wind penetration, on average, it can account for around 20% of electricity demand.

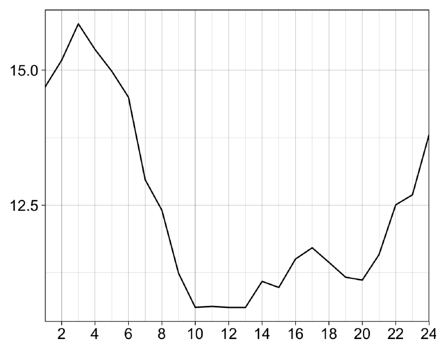
As regards the weather conditions, higher mean values for each variable and more extreme fluctuations in mean daily temperature are observed in the Czech Republic. There is also rather significant difference in *CDD*, which suggests generally higher daily temperatures in the Czech Republic and possible fluctuations in electricity price.

Commodity prices use the same measure and differ only in length of the sample period. The only exception is gas price, which is different for each market and based on the summary statistics, is higher for Germany. Results for oil and coal spot price suggest decreasing time trend. Contrasting remark applies to $ECarbix$.

Figures 6 and 7 depict mean hourly RES penetration for German and Czech market. For the latter, only Photovoltaics (PV) penetration is available and for easier comparability with German market, the same y-axis are used. Combining these insights with Figure 1, we can discuss possible implications on spot price volatility. For example, in German market, deeper drop in spot price and higher (in absolute values) price changes might be associated with peaking solar penetration in the corresponding hour of the day. The level of PV penetration in Czech market is lower and the effects are not that pronounced. From the graph of wind penetration we can say that it probably increases price volatility, as the strongest price-decreasing effect (assumption based on merit order and residual demand) can be observed during off-peak hours, when the prices are already lower, compared to peak prices.



(a) PV penetration



(b) Wind penetration

Figure 6: Mean hourly RES penetration in the German market

Note: The figure presents mean PV and wind penetration [%] for each hour of the day in the German market.
Source: Author's computation.

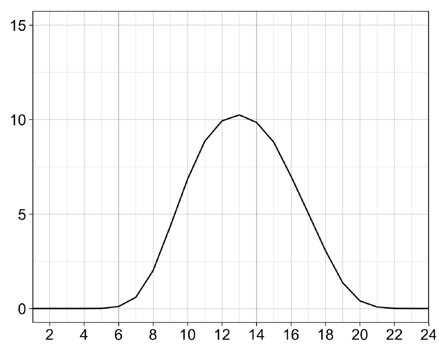


Figure 7: Mean hourly PV penetration in the Czech market

Note: The figure presents mean PV penetration [%] for each hour of the day in the Czech market.
Source: Author's computation.

6.4 Models

The previous analysis clearly separated continuous and jump component of the total realised variation. In the later steps, we focus solely on the continuous component[15] and model it by including lagged dependent variables to reduce autocorrelation and make use of memory of electricity prices. We add market-specific exogenous variables, building on models presented in the literature. Specifically, standard deviation of continuous component of variation is used, denoted as continuous volatility.

As regards the complexity and number of regressors, three models are designed. Due to distinct dynamics of the markets, these models have to be further adjusted to assure validity of the results and therefore, in total, six alternatives are proposed. We inspect the impact of RES penetration and other exogenous variables on the daily volatility and test for effects commonly present in electricity markets. For the Czech Republic with less developed structure of RES, only penetration of PV is available. Two distinct markets are compared; on one side, Germany which is the leading country in integration of renewable energy into power grid, and the Czech Republic with less developed market for RES and restricted availability of data. Comparison with findings in the literature and explanation of possible differences is provided.

First model, based on HAR-RV model (Corsi, 2004), however applied to continuous volatility for the purpose of this thesis, takes volatility components over different horizons as regressors. Following the original notation, we refer to this model as HAR-CV model. Second model incorporates all exogenous variables that are documented in the literature as factors possibly influencing electricity price and its volatility. Various binary variables are included to control for seasonal patterns and test for intra-week differences. This model is referred to as HAR-CV-EX and should be viewed as the main one for explaining variation in power prices and effects of exogenous variables, including RES penetration as the variable of interest. The last model

[15] When we refer to "volatility" in explaining the results, we always have continuous component of volatility in mind, unless explicitly stated otherwise.

is constructed as a compromise between complexity and modelling power. It includes only significant regressors, that can benefit modelling and forecasting volatility in the power market. We denote it as HAR-CV-EX reduced model.

Performance of models with exogenous regressors is compared to less complex one that are based only on autoregressive terms. Assessment of the most influencing exogenous variables for each market is made, which can benefit future research in the area of electricity price volatility.

6.4.1 Model 1 - HAR-CV

As a starting point, we first examine the heterogenous autoregressive model proposed by Corsi (2004). Although this AR-type model is not formally a long memory-model, it can reproduce the decay of Autocorrelation Function (ACF) by taking volatility components over different horizons as regressors. It is referred to as HAR-RV model and, as the notation suggests, was originally applied to model Realised Volatility (RV). For the purpose of this thesis, Continuous Component of Realised Volatility (CV) is used as the dependent variable. The model specifically focuses on effects of current and recent-past variation and for the in-sample modelling of CV, we rewrite it as following:

$$CV_t = \beta_0 + \beta_1 CV_{t-1} + \beta_2 CV^w_{t-1} + \epsilon_t, \tag{23}$$

where $CV^w_{t-1} = \frac{1}{7}\sum_{s=2}^{8} CV_{t-s}$ is the average continuous volatility over the seven days preceding day $t-1$. This model assigns more weight to previous day's volatility than to the volatilities over recent past, as those are averaged.

As an additional independent variable, we include binary variable taking on value 1, if the sum of intra-daily returns for day $t-1$ is in the lower quartile and zero otherwise. This is to check for the so-called "(inverse) leverage effect", known from finance, which refers to asymmetric impact of positive and negative shocks on power price volatility. We test, whether the effect is significantly different from zero, which corresponds to the null hypothesis, under which $\beta_3 = 0$ and alternative hypothesis of $\beta_3 \neq 0$. If we want to specifically test for inverse leverage effect, then $H_A : \beta_3 < 0$. This refers to situation, when volatility tends to rise less with negative shocks than positive shocks, which can be attributed to convex shape of marginal costs.

Therefore we amend the Eq. (23) accordingly and estimate it using OLS:

$$CV_t = \beta_0 + \beta_1 CV_{t-1} + \beta_2 CV^w_{t-1} + \beta_3 INV_{t-1} + \epsilon_t. \tag{24}$$

The results reported with robust standard errors are displayed in Table 8. The coefficients show high degree of persistence and volatility clustering. For the Czech market, recent past variation has even higher statistically significant impact on today's volatility than previous day's variation. Haugom et al. (2011) find this characteristic for Nord Pool quarterly contract series while the effect does not impact yearly contracts to such extent. Chan et al. (2008) find the same result for realised volatility of spot power prices in Queensland, Australia, however not for the other regions. Adjusted R^2 for our model is higher compared to their results due to different dependent variables used. While RV also includes the jump component, CV should be more predictable.

When the model, as specified in Eq. (24), was applied to German data, non-stationary residuals were obtained. This is due to different dynamics of the volatility series, which can be seen from the previous analysis. Therefore, the model was amended accordingly by adding autoregressive term for continuous volatility from previous week, CV_{t-7}. The equation for German data therefore looks as following:

$$CV_t = \beta_0 + \beta_1 CV_{t-1} + \beta_2 CV^w_{t-1} + \beta_3 INV_{t-1} + \beta_4 CV_{t-7} + \epsilon_t. \tag{25}$$

The results differ by country and for easier comparability, coefficients are reported in the same table. In Germany, volatility from previous day has much higher impact on day t volatility than averaged volatility over previous week. Weekly pattern is statistically significant, which was visible from ACF plot for residuals from estimation of the original equation.

Regarding the inverse leverage effect for the Czech market, even though the t-statistic of -1.2041 is negative, which would indicate inverse relationship, we fail to reject the null hypothesis of no asymmetric effect at 10% significance level when comparing with critical value for one-sided t-test. The same conclusion applies to German market.

Table 8: Regression results for HAR-CV model

Dependent variable:	CV_t	
	CZ	DE
Intercept	6.1190***	0.1833
	(1.4823)	(0.2653)
CV_{t-1}	0.2219***	0.3391***
	(0.0559)	(0.0498)
CV^w_{t-1}	0.5159***	0.0851
	(0.0498)	(0.0637)
INV_{t-1}	-1.3062	-0.1905
	(1.0848)	(0.1848)
CV_{t-7}	-	0.1895***
	-	(0.0318)
Adjusted R^2	22.84%	18.83%
Breusch-Pagan test	11.088	42.182
	(0.0113)	(<0.01)
Breusch-Godfrey test	2.8637	0.5549
	(0.0906)	(0.4563)
ADF	-7.8835	-11.163
	(<0.01)	(<0.01)
KPSS	0.1553	(0.3044)
	(>0.1)	(>0.1)
Jarque-Bera test	5759.3	6091.7
	(<0.01)	(<0.01)

Note: *** significance at 1%, ** significance at 5%, * significance at 10%.

Robust standard errors and p-values of the tests are reported in parenthesis.

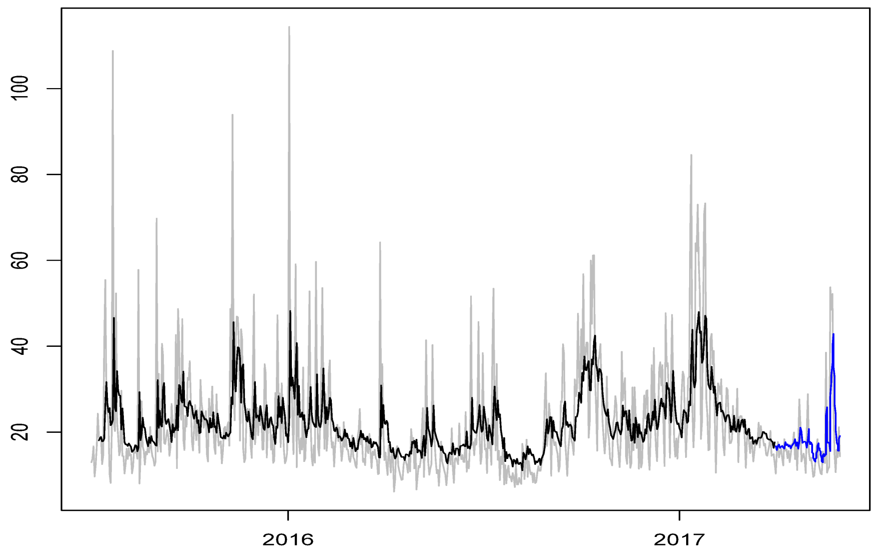
Source: Author's computation.

To comment on the residuals of the regressions, several tests are performed. The following remarks apply to both regressions unless stated otherwise. ADF rejects unit root and KPSS test for residuals does not reject stationarity. Breusch-Pagan test suggests heteroskedasticity, which however does not influence the unbiasedness of coefficients, just the efficiency of variance estimate. This finding is not surprising, as time-varying volatility of the volatility estimator is present in any model (Corsi et al., 2008).

To check for autocorrelation in residuals from the models, we visually inspect ACF and Partial Autocorrelation Function (PACF) plots and formally test by Breusch-Godfrey test. For the models that include lagged dependent variables, Breusch-Godfrey is preferred over Durbin-Watson test (Dezhbakhsh, 1990; Maddala, 2001). Results of the test reject the null hypothesis of no serial correlation at 10% significance level for the Czech market, but not for German one. We therefore use heteroskedasticity and autocorrelation robust standard errors and heteroskedasticity robust standard errors, respectively. The results of previously mentioned tests are in Table 8 while ACF and PACF plots can be found in Appendix (Figure 13). There are few significant lags that are outside the confidence interval, which suggests that model can be improved by adding new information, however autocorrelations are changing sign and decay quickly and do not pose significant issues on the validity of the model.

Finally, graphical representation of the performance of HAR-CV model for both markets is provided in Figure 8.

Czech Market



German Market

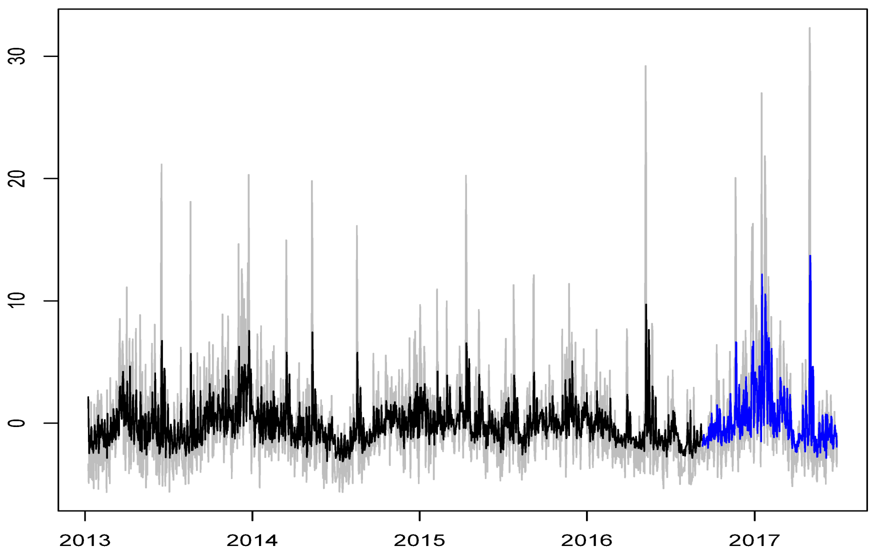


Figure 8: Graphical presentation of in-sample and out-of-sample estimation of HAR-CV model

Note: Realised values are depicted in grey colour, in-sample fitted values are in black colour and out-of-sample forecasts are marked in blue.

Source: Author's computation.

6.4.2 Model 2 - HAR-CV-EX

Several studies have examined the influence of exogenous variables on modelling of electricity price volatility. We therefore further build on the first model, while dropping binary variable *INV* due to its statistical insignificance in explaining the variance. While it is interesting to inspect effects of commodity prices or weather, the main focus should be on the series containing daily RES penetration. Common approach in the literature is to study the impact on realised volatility as a whole, not on its continuous component separately. Therefore, the findings may differ due to exclusion of jump component which is, by its nature and characteristics, a result of unexpected shocks and capacity constraints.

The rationale behind the choice of exogenous variables and its form can be found in section Data Description. It is important to note that all variables with time trend are used in their de-trended form in the later regressions. Another important remark is that t as a subscript to exogenous variables means either forecast of the variable for day t, if such measure is available, or the information known when submitting orders for delivery day t. In the case of commodity prices, it means the most recent known value, while details for the data amendments can be found in Data Description. We also include seasonal dummy variables to account for differences between astronomical seasons and intra-week patterns in all regressors. Binary variables *WeekDay* and *Winter* are dropped out of the equation to avoid multicollinearity problem and are included in the intercept.

Based on the remarks found in the literature, we propose the following model for the Czech market, which includes several exogenous variables, binary variables and autoregressive terms to account for short-term price volatility development:

$$
\begin{aligned}
CV_t = \quad & \beta_0 + \beta_1 CV_{t-1} + \beta_2 CV^w_{t-1} + \beta_3 PV_t + \beta_4 ECarbix_t + \beta_5 Oil_t + \\
& + \beta_6 Coal/gas_t + \beta_7 Precipitation_t + \beta_8 Wind\ speed_t + \beta_9 CDD_t + \\
& + \beta_{10} Weekend_t + \beta_{11} Spring_t + \beta_{12} Summer_t + \beta_{13} Autumn_t + \epsilon_t.
\end{aligned}
\tag{26}
$$

In the above equation, β_3 is the coefficient corresponding to penetration of renewable energy sources, which in the case of the Czech Republic corresponds to solar penetration only. The values are reported in percentages and express average generation forecast divided by average expected load.

For the purpose of modelling volatility for German market, the previous equation is amended by adding one more autoregressive term to assure validity of the results. Since both PV and wind forecasts are available, variable $Wind_t$ represents wind penetration and the estimation is done based on the following equation:

$$
\begin{aligned}
CV_t = \quad & \beta_0 + \beta_1 CV_{t-1} + \beta_2 CV^w_{t-1} + \beta_3 PV_t + \beta_4 ECarbix_t + \beta_5 Oil_t + \\
& + \beta_6 Coal/gas_t + \beta_7 Precipitation_t + \beta_8 Wind\ speed_t + \beta_9 CDD_t + \\
& + \beta_{10} Weekend_t + \beta_{11} Spring_t + \beta_{12} Summer_t + \beta_{13} Autumn_t + \\
& + \beta_{14} CV_{t-7} + \beta_{15} Wind_t + \epsilon_t.
\end{aligned}
\tag{27}
$$

Various studies have been performed on determining impact of renewable resources on price volatility. For example, Mauritzen (2010) studies Danish market and concludes decreased volatility, probably due to high number of hydro-power available in the country. On the other hand, Ketterer (2014) finds increasing effect due to wind generation for German market. Paraschiv et al. (2014) study price levels and find price-decreasing impact caused by PV penetration, however they do not comment on its effect on volatility. As has been already noted, the results differ from country to country and can differ by method used. It is interesting to see whether statistically significant impact can be found in the Czech market, which has not been studied yet.

Regarding the selection of the independent variables, refer to Section 4.

We provide just brief additional comments about expected signs of the coefficients. Sensfuss et al. (2008) emphasise the importance of ratio of coal and gas price when examining the MOE effect. They conclude that when prices of coal are high while prices of gas are low, the MOE is reduced. Since the MOE can be partially linked to price volatility, in this case, we expect β_6 to be positive. Decrease in already low prices can, however, lead to higher volatility. These volatility-decreasing expectations are based on assumption of stronger MOE during periods of high prices. Paraschiv et al. (2014) studies the impact of commodities, CO_2 prices and RES on electricity price in Germany for each hour separately and discovers stronger price-increasing effect of emission certificates during peak hours, implying increasing volatility in the market. Therefore, price of ECarbix is expected to increase volatility. Similar rationale can be applied to oil price, for which positive coefficient is expected.

Concerning the weather forecasts (which are represented by realised values due to data availability), wind speed, precipitation and temperature are considered to be the most influencing variables on electricity price. Precipitation, together with hydro-reservoir level, has decreasing level on volatility, since hydro-power is not intermittent source and therefore can be used to balance extreme conditions on the market. Hydro-reservoir levels are not available and therefore only precipitation is used as a proxy for the increase in such stored energy. Variable *CDD*, which indicates positive deviation from the comfort temperature and can be viewed as a shock leading to higher prices, is expected to have positive sign.

Table 9: Regression results for HAR-CV-EX model

Dependent variable:	CV_t			
	CZ		**DE**	
Intercept	11.4319***	(2.2904)	−0.2509	(0.1909)
CV_{t-1}	0.1639***	(0.0481)	0.3077***	(0.0418)
CV^w_{t-1}	0.4555***	(0.0789)	−0.1311*	(0.0698)
PV_t	−0.0131	(0.1846)	0.0911	(0.0630)
$ECarbix_t$	0.7907 *	(0.4579)	−0.0717	(0.0986)
Oil_t	0.0607	(0.0561)	0.0378***	(0.0119)
$Coal/gas_t$	2.3347*	(1.3503)	−1.3848***	(0.3305)
$Precipitation_t$	−0.0935	(0.1846)	−0.0957	(0.0849)
$Wind\ speed_t$	0.2244*	(0.1304)	−0.0198	(0.0468)
CDD_t	0.5477 *	(0.2936)	0.0010	(0.0133)
$Weekend_t$	−5.0292***	(1.2875)	0.7776***	(0.1619)
$Spring_t$	−2.3609	(1.6088)	−0.2004	(0.2764)
$Summer_t$	−3.0104	(2.2569)	0.5940	(0.2419)
$Autumn_t$	−0.5036	(1.6024)	−0.5322	(0.3295)
CV_{t-7}	-	-	0.1456***	(0.0343)
$Wind_t$	-	-	0.1165***	(0.0198)
Adjusted R^2	25.94%	-	30.6 %	-
Breusch-Pagan test	24.459	(0.0272)	99.345	(<0.01)
Breusch-Godfrey test	13.159	(0.0003)	10.444	(0.0012)
ADF	−7.5871	(<0.01)	−10.749	(<0.01)
KPSS	0.0530	(>0.1)	0.3194	(>0.1)
Jarque-Bera test	6994.8	(<0.01)	4952.9	(<0.01)

Note: *** significance at 1%, ** significance at 5%, * significance at 10%
Robust standard errors and p-values of the tests are reported in parenthesis.
Source: Author's computation.

Coefficient estimates and test results for residuals analysis are summarised in Table 9 and ACF and PACF plots of residuals can be found in Appendix (Figure 14). The same remarks as for HAR-CV model apply to HAR-CV-EX. Again, Newey-West estimator is used due to heteroskedasticity and serial correlation and robust standard errors are reported in parenthesis. ACF and PACF plots show autocorrelations that stay within the 95% confidence interval, except few cases. These results suggest that model coefficients can be used for valid inference.

Starting with the Czech market, first, we comment on the results for photovoltaic penetration, which is the variable of our interest. Looking at the coefficient and its corresponding robust standard error, the variable is not significantly different from zero. Therefore, we fail to draw any conclusion about its increasing or decreasing effect on spot price volatility. The result can have various reasons, one of them being relatively low development and usage of renewable energies in the Czech Republic, compared to conventional power generators. See Figure 1 It might be interesting to investigate this effect, when longer span of data is available or when the energy mix changes in favour of RES. Since no data for wind generation forecasts exist for the Czech Republic, wind-speed can be viewed as a proxy for wind power plant generation, although specific wind speed is associated with start of power producing and also the need to stop the plant due to strong wind, which is not considered here. Since wind is not concentrated during peak hours (as is the case for photovoltaic generation), prices diverge when the residual demand fluctuates during the off-peak hours and therefore wind can contribute positive to price volatility.

We also briefly comment on other coefficients from the regression. The value of robust t-statistics for *Coal/gas* is 1.7269, which enables us to reject the null hypothesis of $\beta_6 = 0$ in two-tailed test at 10% significance level. This result is in line with our expectations stated earlier. Similar conclusion can be drawn for the price of ECarbix. Weather variables, except precipitation, are also statistically significant, as noted in previous studies. Specifically, wind speed has an increasing effect on daily volatility as well as cooling degree days, i.e. positive deviation from comfort temperature.

Regarding the German market, some of the coefficients differ, which is not a surprising result given individual country's characteristics and power price drivers. Note that the results are for de-trended volatility series, as opposed to volatility in the Czech market, which does not exhibit any time trend. Therefore it is possible that volatility, as a non-negative measure, takes on negative values. What is important, de-trending preserves the dynamics of data series and all conclusions are valid.

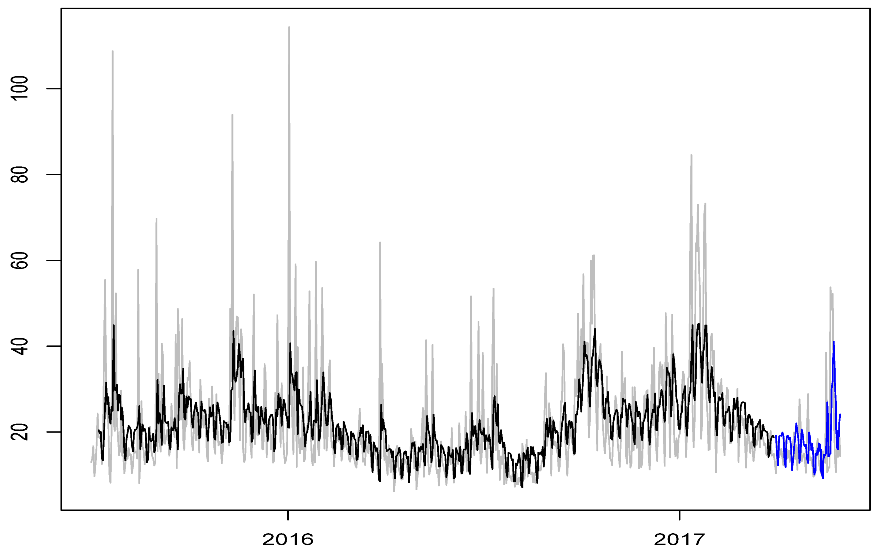
The coefficient for PV penetration is positive, however not statistically significant. This can be attributed to different dependent variables and sample periods used, compared to previous works. From the prior graphical analysis on the dataset used for the estimation, there is no clear indication about the resulting direction of the change in price volatility. Looking at the coefficient for wind penetration, it is positive and statistically significant, which is in consent with other studies on German market. The main reason is its intermittency and higher supply throughout the off-peak hours (results supporting this argument are available upon request), affecting off-peak prices, that diverge and consequently contribute towards volatility. Even though wind speed is in some ways a proxy for wind power generation, including the wind penetration in the regression controls for this effect and ceteris paribus, it does not influence price volatility.

Coefficients for binary variables, associated with intra-week and seasonal fluctuations, do not always have common sign for both markets. It has been shown in previous sections, that electricity prices vary in magnitudes and dynamics. For instance, refer to Section 6.1, where occurrence of extreme price levels is discussed or to Figure 1 for intra-week patterns. Since seasonal differences with regards to volatility are not statistically significant, this applies to coefficient for *Weekend* mostly.

To conclude, wind penetration has statistically significant increasing impact on spot price continuous volatility in German market. The result is in line with the literature. As for the PV penetration, the effect is not significantly different from zero. This can be attributed to double-peaking daily price and bell-shaped PV penetration (see Figure 1, 2 and 6).

Finally, the forecasting performance for HAR-CV-EX model can be found in Figure 9.

Czech Market



German Market

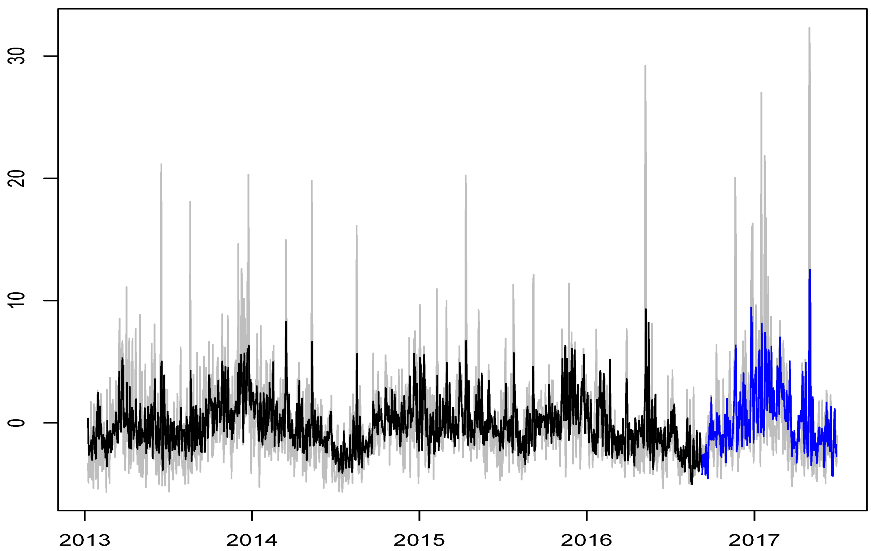


Figure 9: Graphical presentation of in-sample and out-of-sample estimation of HAR-CV-EX model

Note: Realised values are depicted in grey colour, in-sample fitted values are in black colour and out-of-sample forecasts are marked in blue.
Source: Author's computation.

6.4.3 Model 3 - HAR-CV-EX reduced

Finally, for the use of forecasting, we propose modification to HAR-CV-EX model, in which we optimise modelling accuracy and number of predictors by dropping out highly insignificant variables while keeping the ones that positively contribute to the explanation of variation. This model mainly aims to propose a compromise between complexity and forecasting performance. It can serve as a reference for further research on electricity price volatility. Since PV penetration in the Czech Republic does not explain price variation, it is not included in this reduced-form model. In contract, we include both PV and wind penetration, since PV penetration was border-line insignificant and can still be important in explaining the variance.

The construction of the models can be summarised by the following equations, first one corresponding to modelling volatility in the Czech power market and second one for Germany:

$$
\begin{aligned}
CV_t = \quad & \beta_0 + \beta_1 CV_{t-1} + \beta_2 CV^w_{t-1} + \beta_3 ECarbix_t + \beta_4 Coal/gas_t + \\
& + \beta_5 Wind\ speed_t + \beta_6 CDD_t + \beta_7 Weekend_t + \beta_8 Spring_t + \\
& + \beta_9 Summer_t + \beta_{10} Autumn_t + \epsilon_t.
\end{aligned} \tag{28}
$$

$$
\begin{aligned}
CV_t = \quad & \beta_0 + \beta_1 CV_{t-1} + \beta_2 CV^w_{t-1} + \beta_3 PV_t + \beta_4 Wind_t + \beta_5 Coal/gas_t + \\
& + \beta_6 Oil_t + \beta_7 Weekend_t + \beta_8 Spring_t + \beta_9 Summer_t + \\
& + \beta_{10} Autumn_t + \beta_{11} CV_{t-7} + \epsilon_t.
\end{aligned} \tag{29}
$$

Assumptions of these models and results of residual analysis are very similar to Model 2, therefore are not commented here. Numerical results can be found in Table 10. Adjusted R^2 rose in both cases, suggesting similar modelling ability with less complex structure and easier access to data. Graphical representation of model performance can be found in Figure 10.

For both markets, the results are robust and the signs of the coefficients remain unchanged. Seasonal effects are more pronounced, indicating, ceteris

Table 10: Regression results for HAR-CV-EX reduced model

Dependent variable:	CV_t			
	CZ		**DE**	
Intercept	10.8808***	(2.1127)	−0.2134	(0.1852)
CV_{t-1}	0.1632***	(0.0470)	0.3089***	(0.0418)
$CV_{7,t-1}$	0.4718***	(0.0842)	−0.1272*	(0.0708)
PV_t	-	-	0.1060*	(0.0603)
$Wind_t$	-	-	0.1083***	(0.0131)
$ECarbix_t$	0.7878 *	(0.4642)	-	-
$Coal/gas_t$	2.4910*	(1.3082)	−1.3032***	(0.2812)
Oil_t	-	-	0.0372***	(0.0118)
$Wind\ speed_t$	0.2118*	(0.1212)	-	-
CDD_t	0.6228 *	(0.3272)	-	-
$Weekend_t$	-5.0399 ***	(1.3163)	0.7927***	(0.1578)
$Spring_t$	−2.3804 *	(1.2472)	−0.2511	(0.2603)
$Summer_t$	−3.2401*	(1.5415)	0.6214*	(0.3194)
$Autumn_t$	−0.5197	(1.6142)	−0.5834**	(0.2410)
CV_{t-7}	-	-	0.1453***	(0.0344)
Adjusted R^2	26.16%		30.73%	
Breusch-Pagan test	22.486	(0.01281)	99.53	(<0.01)
Breusch-Godfrey test	12.64	(0.0004)	10.073	(0.0015)
ADF	−7.6232	(<0.01)	−10.723	(<0.01)
KPSS	0.0372	(>0.1)	0.3045	(>0.1)
Jarque-Bera test	6832.5	(<0.01)	4947.9	(<0.01)

Note: *** significance at 1%, ** significance at 5%, * significance at 10%

Robust standard errors and p-values of the tests are reported in parenthesis.

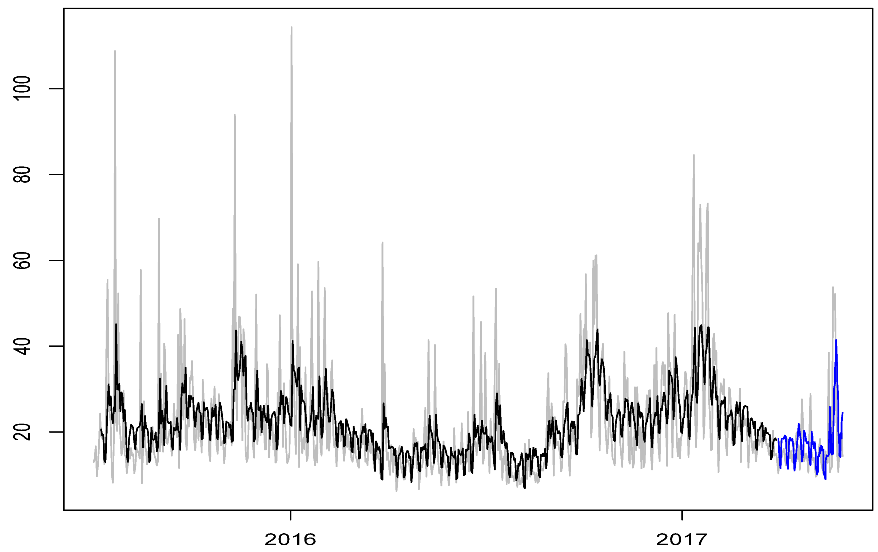
Source: Author's computation.

paribus, lower volatility in Czech power market in spring and summer, compared to winter. Recall the results from drift estimation (Table 12), which also indicate seasonal differences in mean spot prices between seasons. In Germany, the most volatile season is summer, followed by winter. Since the estimation results are very similar to the ones from Model 2, please refer to the previous section for further explanations.

There is only one remark regarding coefficient for PV. In this reduced-form regression, the variable shows to be different from zero at 10% significance level. Such confidence interval, given the previous results, is not high enough to draw reliable conclusion.

Finally, the graphical presentation of model performance can be found in Figure 10.

Czech Market



German Market

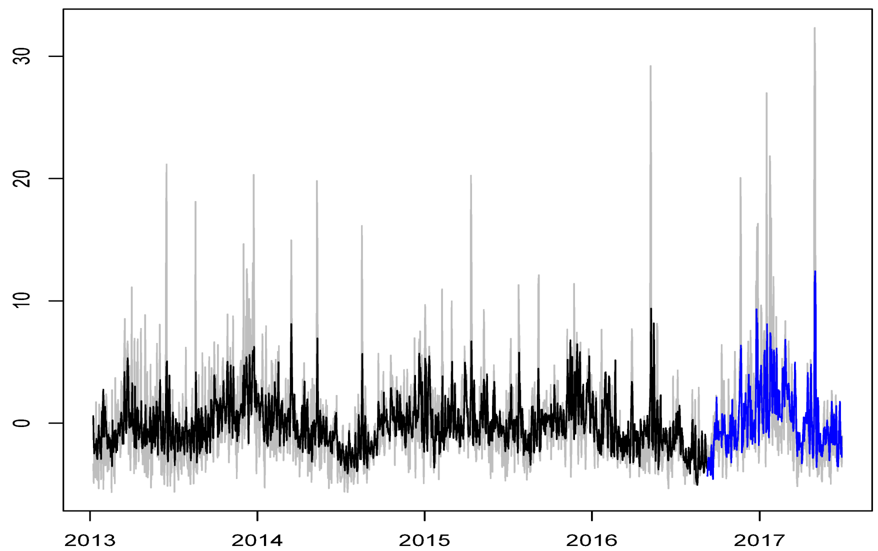


Figure 10: Graphical presentation of in-sample and out-of-sample estimation of reduced HAR-CV-EX model

Note: Realised values are depicted in grey colour, in-sample fitted values are in black colour and out-of-sample forecasts are marked in blue.

Source: Author's computation.

6.5 In-Sample and Out-Of-Sample Evaluation

In this section, we provide in-sample and out-of-sample evaluation of the models. Firstly, we choose the best model for each country based on information criterion, namely Bayesian Information Criterion (BIC) introduced in Schwarz et al. (1978), which is closely related to the Akaike information criterion (AIC), however introduces larger penalty term for the number of parameters in the model. We provide both measures to see, whether there is any difference in the result. However since it is not possible to use BIC to choose between nested models, we first decide between these two based on extra sum of squares test.

For the in-sample selection, we first test HAR-CV-EX vs. HAR-CV-EX reduced. Specifically, we look at extra sum of squares, that indicate whether supplementary predictors explain a substantial additional amount of variability. The numerical results of the test can be found in Table 16 and 17. In this case, we cannot reject the null hypothesis, that added predictors have zero coefficients and therefore we use adjusted R^2 measure to select better performing model. For both markets, the selected model is HAR-CV-EX in its reduced form with adjusted $R^2 = 26.16$ (The Czech Republic (CZ)) and adjusted $R^2 = 30.73$ (Germany (DE)).

Table 11 summarises BIC and AIC values for six variations of the models. Overall, for regressions on Czech data, based on BIC, simple HAR-CV can be considered as the best model, while based on AIC, it is reduced form of HAR-CV-EX. For German regressions, reduced form of HAR-CV-EX is the best according to both criteria. Different results can be attributed to penalty terms for more regressors as noted earlier. AIC score improved after adding exogenous variables to the model, however, since we want to pick the minimal value of the criterion and account for additional variables, BIC is more suitable in this case and finally, Model 1 and Model 3 are chosen as the best performing ones for the Czech Republic and Germany, respectively. Last model's alternative for German market is chosen as the best one based on all 3 criteria (see previous paragraph), while Czech version of Model 1 and 3 are chosen based on BIC and AIC.

Table 11: AIC and BIC summary for models

	CZ		**DE**	
	BIC	AIC	BIC	AIC
HAR-CV	4,934.699*	4,912.447	6,967.928	6,936.743
HAR-CV-EX	4,955.816	4,889.083	6,843.248	6,754.891
HAR-CV-EX reduced	4,937.691	4,884.305*	6,816.056*	6,748.489*

Note: Best performing model based on corresponding criterion is marked with *.
Source: Author's computation.

As the in-sample evaluation can sometimes bring misleading results, we additionally perform out-of-sample evaluation using Diebold-Mariano Test (DM) (Diebold and Mariano, 2002). DM is widely used test for forecasting accuracy with null hypothesis of loss differential between two forecasts having zero expectation for all t. Both two-sided and one sided tests can be specified to construct different alternative hypothesis. Under the null hypothesis, the DM test statistic is asymptotically $N(0,1)$ distributed, however these properties depend on the sample size and degree of serial correlation among the forecast errors. It has been shown that DM test remains asymptotically valid even for nested models if model parameters are estimated using a rolling window instead of an expanding one (Giacomini and White, 2006).

For the Czech Republic, last 3 months of the dataset (April-June 2017) are left for the out-of-sample evaluation. One-day ahead volatility forecasts are obtained each time the model is re-estimated. Estimation is done on a rolling-window basis, where the window length is fixed on 633 observations and each prediction is based on estimation from directly preceding 633 observations. Note that window length was restricted from in-sample 640 observations due to previous computations and adjustments of the data. As already noted, the approach of fixed window length is more suitable for testing forecasting accuracy with DM test.

For German data, last 10 months are left for out-of-sample period (approximately 20% of the sample size). This results in 1336 observations for in-sample estimation (after dropping 4 missing observations) and 295 observations for out-of-sample. Again, rolling window day-ahead forecast with fixed window length is applied.

Starting with model versions for Czech market, under the null hypothesis of DM test, tested models have the same forecast accuracy. Alternative hypothesis is specified such as Model 3 is more accurate that Model 1 regarding the forecasting accuracy. The results (p-value $= 0.05648$) of the test, performed with loss function power of 2, indicate that we can reject the null in favour of alternative hypothesis at 90% confidence interval. This means that Model 3, which includes also exogenous variables as opposed to basic model proposed by Corsi (2004), provides significantly better forecasts. Out-of-sample evaluation in this case contradicts in-sample results. The same procedure is applied to versions for German data and yields to the same conclusion, with p-value of 0.03392 and loss function power of 2.

To conclude, adding exogenous regressors to the model improves modelling accuracy, compared to the simpler version with autoregressive terms only. Applying DM test to HAR-CV-EX model and its reduced form, no significant difference in forecasting accuracy was detected. Therefore, it can be concluded that even though Model 2 includes more exogenous variables, similar forecasting performance can be achieved with fewer regressors. The selection of these variables is country-specific and our results can serve as a guidance for variables selection used for future research.

7 Conclusion

This thesis investigates the effects of renewable resources and other exogenous variables on continuous volatility of electricity prices in Czech and German day-ahead market. Using quadratic variation theory and it's modification for electricity prices, it is possible to divide realised volatility into its jump and continuous component. We determine lower mean continuous volatility in German market with decreasing time trend. In contrast, jump component exhibits an increasing trend. We do not find any time trend in volatility series for the Czech Republic. Mean jump contributions of 5.298% and 7.818%, while the former result is for the Czech Republic, are comparable with other world electricity markets.

We model the continuous volatility using three approaches with varying complexity, studying inverse leverage effect and sensitivities to weather conditions, commodity prices and penetration of renewable sources. Volatility persistence and clustering is found in both markets. To assure validity of the results, six different models are proposed to account for individual characteristics of the markets.

To the best of our knowledge, this is the first study concerning spot price volatility and renewable resources in Czech power market. We do not find significant effect of PV penetration on volatility, probably attributable to low development of these sources. However, we find sensitivities to cooling degree days and wind speed, as well as emission allowances and ratio of coal and gas prices.

Although German market has been studied already, our analysis is different due to continuous volatility used as dependent variable, compared to realised volatility or standard deviation used in the literature. We find increasing effect of wind power penetration, however, not statistically significant effect of PV penetration. Seasonal patterns and sensitivities to commodity prices are determined to be more suitable for volatility forecasting than weather variables.

All models are evaluated in-sample and out-of-sample, resulting in selection of reduced form of HAR-CV-EX model, where exogenous variables are determined based on country-specific selection from regressions. We document positive impact on forecast accuracy, when implementing relevant exogenous variables, compared to purely autoregressive model. This finding builds on previous remarks on power price volatility and provides foundations for future research, potentially conducted on Czech power price series, when longer span of data and wind penetration is available.

To summarise, continuous power price volatility differs in its nature and drivers from country to country. In Germany, which is developed market for renewables sources, higher wind penetration leads to increased volatility. The effect of PV penetration is not significantly different from zero in both studied markets.

For future research, we suggest to use different kind of models, such as SARMA, GARCH or ARFIMA, that capture long-memory behaviour. McAleer and Medeiros (2008) propose multiple-regime model based on regression trees as a superior to HAR and ARFIMA models.

Future changes in penetration of renewable sources will shape the electricity market further and better understanding of these implications is important to assure secure power supply and rational investments into installed and storage capacities.

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Appendix

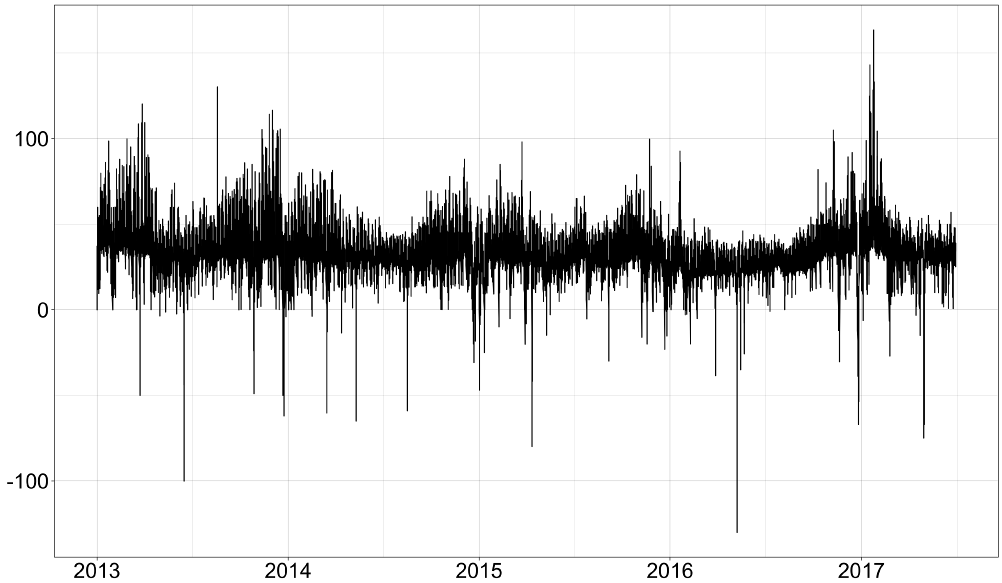


Figure 11: German electricity spot price in EUR/MWh for the whole sample period

Table 12: Relevance of drift estimation in price changes for the Czech Republic

	Dependent variable:
	Price
AR(1)	0.8327***
	(0.0039)
AR(24)	0.1461***
	(0.0039)
Intercept	37.9429***
	(2.0306)
OffPeak	−3.3268***
	(0.1578)
Weekend	−6.6684***
	(0.3036)
Autumn	0.3929
	(1.9765)
Summer	-2.4429
	(2.1996)
Spring	−3.1694*
	(1.9183)
Observations	17,542

Note: *** significance at 1%, ** significance at 5%, * significance at 10%.
Standard errors are reported in parenthesis.
Source: Author's computation.

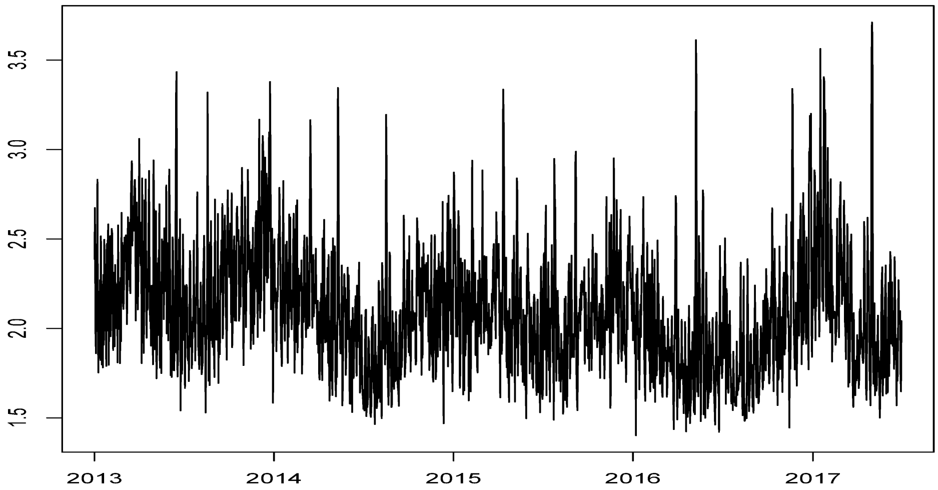
Table 13: Relevance of drift estimation in price changes for Germany

	Dependent variable:
	Price
AR(1)	0.8489***
	(0.0025)
AR(24)	0.1239***
	(0.0024)
Intercept	35.4820***
	(1.4726)
OffPeak1	−3.5965***
	(0.1164)
OffPeak2	−2.7048***
	(0.1165)
Weekend	−3.1979***
	(0.2079)
Spring	−4.0152***
	(1.2321)
Summer	0.2141
	(1.1795)
Autumn	1.4053
	(0.9606)
Observations	39,403

Note: *** significance at 1%, ** significance at 5%, * significance at 10%.

Standard errors are reported in parenthesis.

Source: Author's computation.



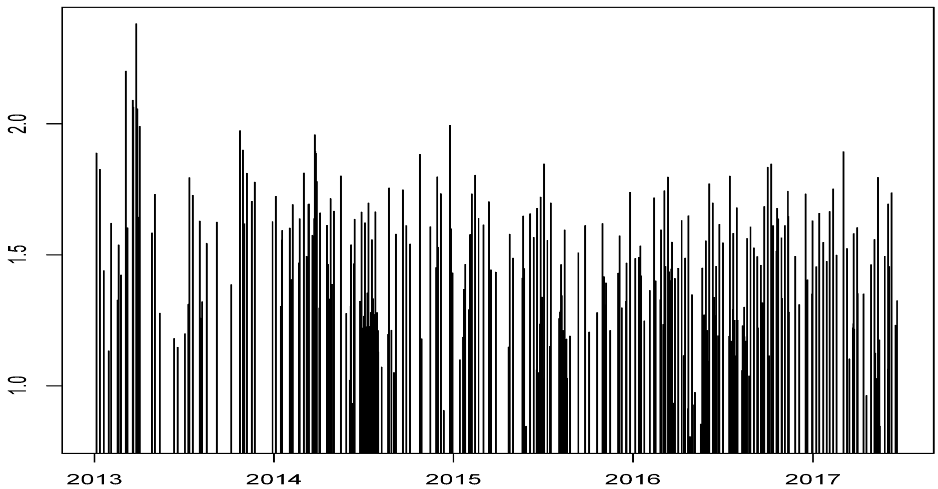


Figure 12: Total realised volatility and jumps identified in German power market for the whole sample period

Note: Results based on Z-test with significance level of 5%. The vertical axis is in a log scale to preserve clarity in the plots.
Source: Author's computation.

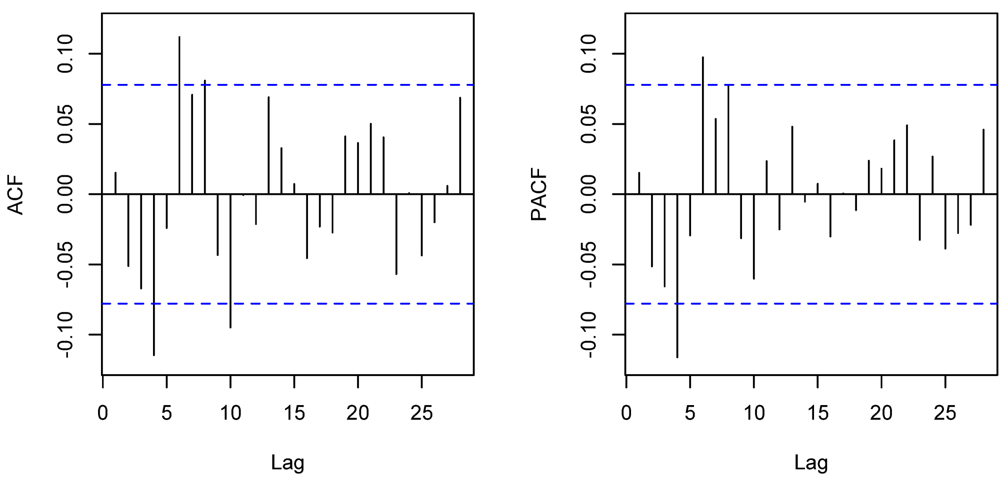
Table 14: Summary statistics for exogenous variables for Czech data

Statistic	N	Mean	St. Dev.	Min	Max
D	731	179,807.600	23,688.130	126,410	240,691
PV_{gen}	731	5,947.818	3,605.970	399	13,993
PV^*	731	3.515	2.336	0.185	10.048
$Temperature$	731	9.668	8.280	−12.424	27.621
$Windspeed$	731	10.996	3.868	3.148	27.552
$Precipitation$	731	0.847	2.024	0.000	23.201
CDD^*	731	0.554	1.530	0.000	9.321
Gas	731	16.188	2.800	11.200	23.388
Oil	731	42.494	6.530	23.845	55.663
$Coal$	731	56.209	13.311	37.423	83.046
$ECarbix$	731	5.952	1.434	3.940	8.630

Note: The table presents summary statistics for all exogenous variables, both for original data and the ones constructed for the purpose of estimation. The latter case is denoted with *.

Source: Author's computation.

Czech market



German market

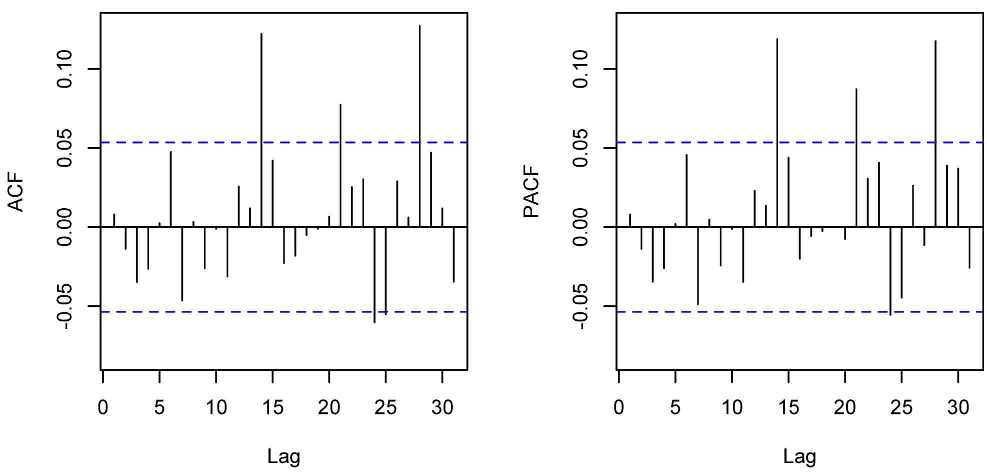


Table 15: Summary statistics for exogenous variables for German data

Statistic	N	Mean	St. Dev.	Min	Max
D	1,638	1,293,167.51	153,051.88	578,481.00	1,618,077.25
PV_{gen}	1,638	61,520.87	36,854.34	2,002.75	151,626.50
$Wind_{gen}$	1,638	184,271.25	148,822.38	10,694.33	810,970.73
PV^*	1,638	4.93	3.15	0.13	15.79
$Wind^*$	1,638	14.16	11.16	0.88	68.35
$Temperature$	1,638	8.03	5.67	−7.55	23.66
$Windspeed$	1,638	9.87	4.10	3.61	29.91
$Precipitation$	1,638	0.40	0.84	0.00	10.53
CDD^*	1,638	0.07	0.47	0.00	5.36
Gas	1,638	20.30	5.02	10.88	39.49
Oil	1,638	59.26	18.40	23.84	88.98
$Coal$	1,638	57.17	9.54	37.42	83.05
$ECarbix$	1,638	5.75	1.32	2.66	8.63

Note: The table presents summary statistics for all exogenous variables, both for original data and the ones constructed for the purpose of estimation. The latter case is denoted with *.

Source: Author's computation.

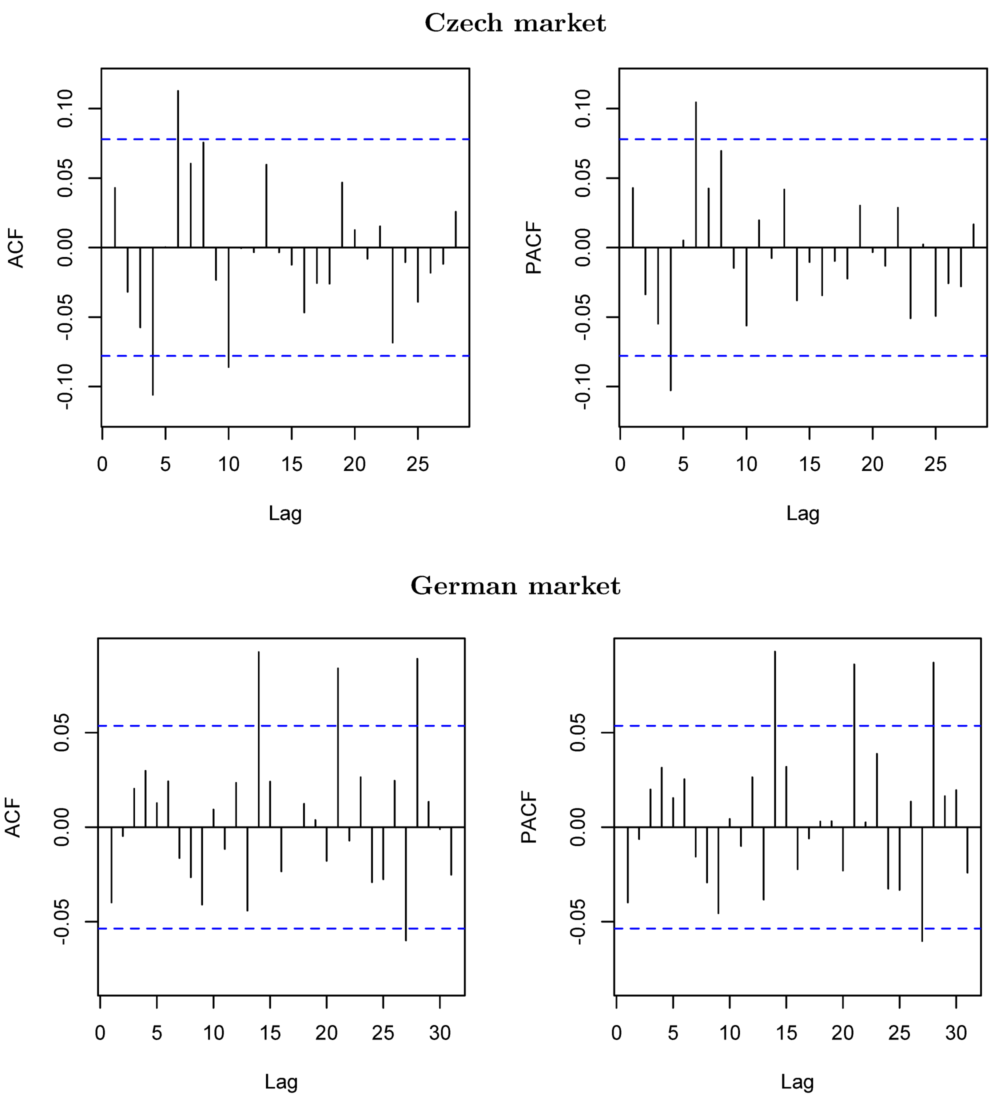


Figure 14: ACF and PACF plot of residuals from HAR-CV-EX model

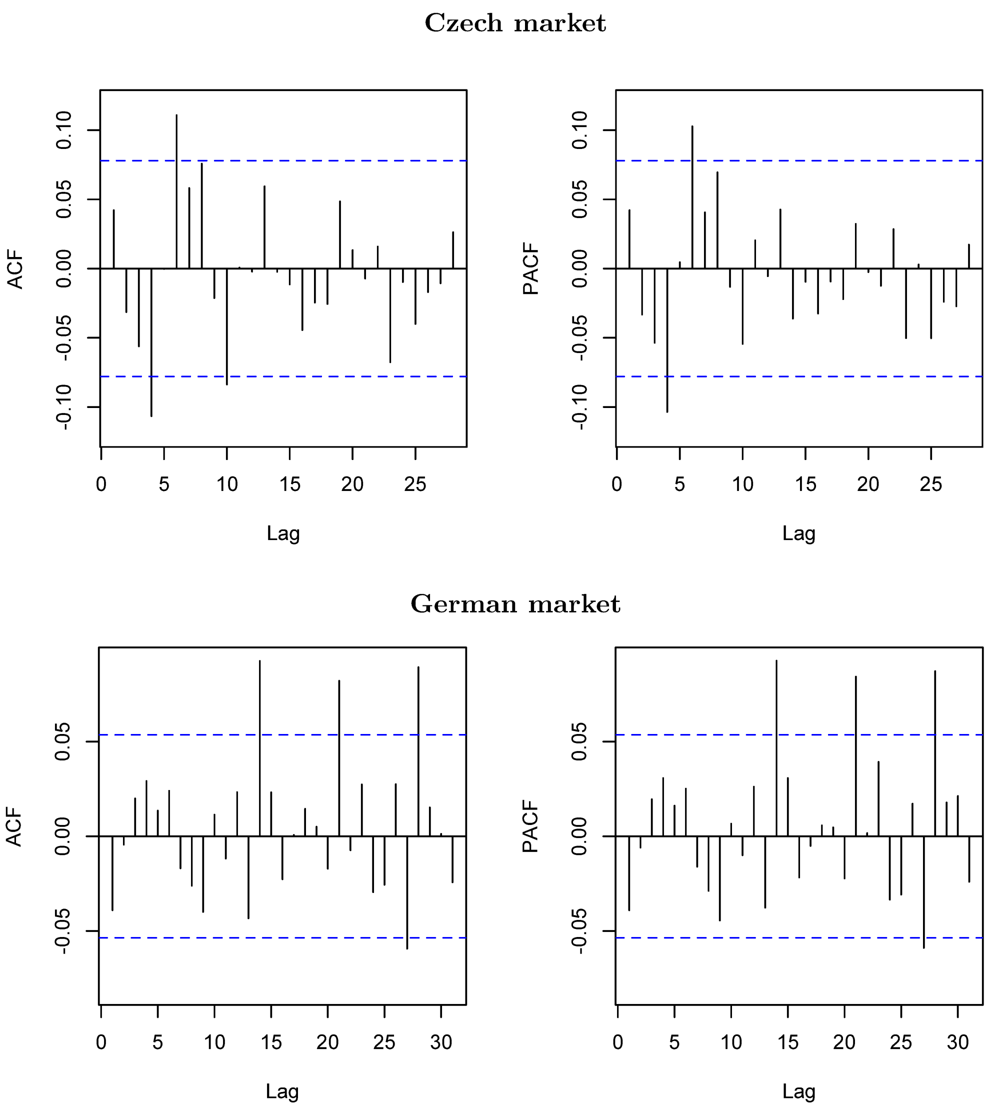


Figure 15: ACF and PACF plot of residuals from reduced HAR-CV-EX model

Table 16: Analysis of variance of two nested models for CZ

Statistic	N	Mean	St. Dev.	Min	Max
Res.Df	2	619.500	2.121	618	621
RSS	2	80,854.110	110.544	80,775.940	80,932.270
Df	1	3.000		3	3
Sum of Sq	1	156.333		156.333	156.333
F	1	0.399		0.399	0.399
Pr(>F)	1	0.754		0.754	0.754

Table 17: Analysis of variance of two nested models for DE

Statistic	N	Mean	St. Dev.	Min	Max
Res.Df	2	1,322.000	2.828	1,320	1,324
RSS	2	11,977.240	10.129	11,970.080	11,984.400
Df	1	4.000		4	4
Sum of Sq	1	14.325		14.325	14.325
F	1	0.395		0.395	0.395
Pr(>F)	1	0.812		0.812	0.812