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Capturing the Effects of Renewable Resources on Electricity Prices: Evidence from the Czech Republic

Bachelor's thesis

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Declaration of Authorship

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Abstract

In this thesis, we investigate the impact of intermittent renewable energy sources on the level and volatility of the Czech electricity spot prices during the period from 2015 to 2019. The analysis is warranted due to the obligations of the member states of the European Union to augment the share of clean energy in the gross final energy consumption by 2030. The technique applied in the empirical part concerns univariate GARCH-class models (namely, plain vanilla and exponential) which are extended with additional explanatory variables in the form of total load, solar and wind power generations. By constructing daily, peak and off-peak indices from the dataset comprised of hourly observations, we establish a comparative framework throughout the text. More specifically, this approach allows us to contrast price dynamics under the regimes of high and low demand for electricity as well as to explore the patterns of solar and wind production. The findings indicate that both Czech solar and wind power sources induce the so-called merit order effect. In contrast, once the volatility of electricity prices is taken into account, the examined sources of energy behave in a different manner. Owing to the daily index, while solar power generation decreases the volatility of electricity prices, the opposite is found true for wind power generation.

JEL Classification	C22, C50, Q21, Q50
Keywords	electricity spot prices, price volatility, renewable sources, GARCH

Title	Capturing the Effects of Renewable Resources on Electricity Prices: Evidence from the Czech Republic

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Abstrakt

V této bakalářské práci se zabýváme vlivem intermitentních obnovitelných zdrojů energie na úroveň a volatilitu českých spotových cen elektřiny v letech 2015 až 2019. Rozbor je odůvodněn závazkem členských států Evropské unie zvýšit podíl čisté formy energie na hrubé konečné spotřebě energie do roku 2030. Aplikovanou technikou v empirické části práce jsou jednorozměrné modely typu GARCH (konkrétně jde o klasické a exponenciální), které jsou rozšířeny o dodatečné vysvětlující proměnné ve formě celkového zatížení a výroby solární a větrné energie. Tím, že jsme vytvořili ze souboru hodinových dat denní, špičkové a mimošpičkové indexy, položili jsme základ pro komparativní rámec textu. Tento způsob nám umožňuje porovnat chování cen v době velké a malé poptávky po elektřině a zkoumat dynamiku solárních a větrných elektráren. Závěry naší studie ukazují, že oba typy analyzovaných obnovitelných zdrojů energie vyvolávají takzvaný efekt pořadí záslužnosti. Pokud však mluvíme o volatilitě cen elektřiny, zkoumané zdroje energie mají odlišný účinek. Co se týká denního indexu, zatímco výroba solární energie snižuje volatilitu cen elektřiny, výroba té větrné ji naopak zvyšuje.

Klasifikace JEL	C22, C50, Q21, Q50
Klíčová slova	spotová cena elektřiny, cenová volatilita, obnovitelné zdroje, GARCH

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Acronyms

ACF Autocorrelation Function

ADF Augmented Dickey-Fuller

AIC Akaike Information Criterion

AR Autoregressive

ATC Available Transfer Capacity

CZ The Czech Republic

ČEPS Czech Electricity Transmission System

EGARCH Exponential Generalized Autoregressive Conditional Heteroskedasticity

EEX European Energy Exchange

ENTSO-E European Network of Transmission System Operators for Electricity

EPEX European Power Exchange

EU The European Union

GARCH Generalized Autoregressive Conditional Heteroskedasticity

GWh Gigawatt hour

HQC Hannan-Quinn Information Criterion

JB Jarque-Bera

KPSS Kwiatkowski-Phillips-Schmidt-Shin

LM Lagrange Multiplier

MLE Maximum Likelihood Estimation

MOE Merit Order Effect

MWh Megawatt hour

OLS Ordinary Least Squares

OTE Czech Electricity and Gas Market Operator

PV Photovoltaics

RES Renewable Energy Sources

SIC Schwarz Information Criterion

TSO Transmission System Operator

Bachelor's Thesis Proposal

Author	Jan Zítek
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Proposed topic	Capturing the Effects of Renewable Resources on Electricity Prices: Evidence from the Czech Republic

Research question and motivation

The purpose of this thesis is to inspect the effects of renewable resources on electricity prices in the Czech Republic.

Electricity markets currently depart from their traditional role of delivering electricity and acquire many other functions in society. For instance, employment opportunities or the sustainability of energy supply represent some of the new tasks that shall be managed by them (Kyritsis, Andersson, and Serletis, 2017). Therefore, markets of interest undergo intense restructuring; hence, renewable energy sources are integrated into the electricity production mix.

Before I proceed with some elements related to renewable resources, factors regarding electricity prices should be noted as they make the analysis rather challenging. In the first place, since electricity is a non-storable commodity, the balance between supply and demand must be maintained immediately to prevent temporary imbalances. That is why more extreme prices that tend to revert quickly to their long-run level once supply and demand arrive at their equilibrium occur.

Another pattern in electricity prices is seasonality which refers to the observation that demand varies during the particular time periods. Seasonal patterns are also present when renewable energy production is discussed. As a matter of example, solar production peaks during summer and falls gradually during winter, while the reverse process is partially true for wind power production (Kyritsis, Andersson, and Serletis, 2017).

And what is more, intermittent renewables contribute to the already complex electricity market dynamics by inducing the so-called merit order effect. This principle is based on the marginal cost and results in lower electricity prices as renewables with their virtually zero marginal costs acquire priority dispatch. On top of that, investigating the impact of renewable resources stands for a significant piece of information when we consider their increasing shares in electricity markets.

Contribution

As debates related to environmental issues evolve, it is important to recognize the effects of renewable resources on electricity prices. This finding can be beneficial to various Czech electricity market's participants (be it generators, distributors or suppliers). More specifically, assessing the volatility of renewable energy systems is instrumental to risk managers and market traders who determine their trading strategies and energy portfolios. Therefore, the subject matter of this thesis may also be of great concern to policymakers. In particular, taking into account emerging trends, a system operator is responsible for adapting the market design to enhance market efficacy. Social welfare is then improved accordingly.

Methodology

I develop a time series analysis, using day-ahead electricity prices and the total electricity load quoted by OTE and ENTSO-E (the Czech Electricity and Gas Market Operator and the European Network of Transmission System Operators for Electricity, respectively). Additionally, Kyritsis, Andersson, and Serletis (2017) argue that the predicted power generation influences day-ahead electricity prices. However, despite this rule, I am forced to use the values of the actual generation due to the limited data availability for the predicted renewable generation and predicted total load.

The substantial volatility in deregulated markets calls for the generalized autoregressive conditional heteroskedasticity (GARCH) models. They are considered very efficient in capturing the times of irregular price spikes and periods of relative tranquility (Efimova and Serletis, 2014). Furthermore, these models allow researchers to explicitly test the effects of renewable energy generation on the mean and volatility of electricity and are also helpful in detecting the inverse leverage effect. In addition to that, the mean-reverting factor of the analysed prices may result in the autoregressive-generalized specification of the GARCH mean equation known as AR-GARCH (Ketterer, 2014).

Using the aforementioned models, the following hypotheses are to be tested.

Hypotheses

Hypothesis #1: The sensitivities of Czech day-ahead electricity prices to renewable energies vary over time.

Hypothesis #2: Both Czech solar and wind power generation induce a merit order effect.

Hypothesis #3: In the Czech Republic, the penetration of renewables into the power system increases the volatility of day-ahead electricity prices.

Outline

1. Introduction
2. Specifics of electricity prices
3. Literature overview
4. Applied methodology
5. Data description
6. Results and discussion
7. Conclusion and possible extensions of the research

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Author Supervisor

Chapter 1

Introduction

The uniqueness of electricity lies in that it cannot be economically stored, signifying that power systems must balance production and consumption ceaselessly in order to ensure grid stability (Weron, 2014). This non-storability is also reflected in the notion that electricity traded at a particular time of a day is a dissimilar commodity to that traded at different times (Guthrie and Videbeck, 2007). In the same vein, electricity markets exhibit distinct features throughout the day, e.g. flexibility or economic efficiency, that are correspondingly translated into the price dynamics (Kyritsis et al., 2017), which underlines the importance of distinguishing between prices in individual trading periods. Electricity prices, in general, pose non-trivial difficulties modelling-wise as they display intriguing features, such as mean-reversion, periodicity, volatility that varies across time, clustering of volatility, and extreme values in the form of spikes (see, for instance, Knittel and Roberts, 2005, or Simonsen et al., 2004).

To demonstrate the complexity inseparable from electricity price series, the study of Chan et al. (2008) provides a comparison with the area of traditional finance. More specifically, the mean of electricity price changes shall not be assumed inconsequential, as is the case when working with equity indices or exchange rates (and at the same time with high-frequency data), since the drift manifests regular patterns at the daily, weekly, and annual levels as well. Apart from the inability to utilize inventories of electricity to even out supply and demand shocks, the higher degree of volatility of electricity prices, when compared to prices of other commodities, stems from transmission constraints and the activation of miscellaneous types of plants so that the demand will be covered (Hickey et al., 2012).

All of the above-mentioned facts demonstrate that the power system is a very challenging space. In addition to that, the landscape of many power sectors has been transforming due to the increasing presence of variable renewable energy sources (RES) that add another layer to its complexity. Generally speaking, solar[1] and wind power display uncontrollable changeability, are partially unforeseeable and dependent on locational conditions (Pérez-Arriaga and Batlle, 2012). As a result, short-time changes and volatile episodes of time to which RES power generation is subject, meaning that load balance issue arises once again, account for the significant drivers behind electricity prices (Keles et al., 2016). Because of this very reason and also because there are country-specific factors influencing electricity markets, the presented work analyzes the impact of RES on Czech day-ahead spot electricity prices.

Owing to the situation surrounding Czech intermittent renewables, it can be claimed that their position, particularly that of solar power generation, has been gaining its relevance ever since 2004. Previously, RES had been peripheral or almost absent in the country except for water energy sources, most of which had become constituents of the projects intended to regulate the flow of the Vltava river (and hence, their original purpose had not lain in energy production), as noted by Tanil and Jurek (2020). However, due to the fact that the Czech solar capacity increased more than 50 times at the turn of the last decade (Rečka and Ščasný, 2016), European Union (EU) indicative national target of 13% share of RES on gross final energy consumption in the CZ was achieved as early as in 2013, i.e. seven years before the year for which the target was scheduled (Luňáčková et al., 2017). Consequently, that the CZ proposed a renewable energy target of 22% by 2030 in the aspect of decarbonisation (MPO, 2020) represents another motive behind the origin of this thesis. Uncovering how intermittent RES affect the level and variance of Czech day-ahead electricity prices ultimately stands for an essential piece of knowledge for the regulator in its market monitoring. It is also an important input for the policymakers who must accommodate market design in order to enhance social welfare by elevating the effectiveness of the operation. Moreover, it can be informative for risk managers who must have a full comprehension of the underlying processes affecting prices and for agents who seek to quantify the degree of uncertainty to which they are exposed (Karakatsani and Bunn, 2008, and Kyritsis et al., 2017).

1 Since the Czech Republic (CZ) does not experience any concentrating solar power project, the term "photovoltaic" is used interchangeably with the term "solar" in the Czech environment (Luňáčková et al., 2017).

The remainder of this thesis is structured as follows. Chapter 2 provides the reader with insight into the specifics of electricity markets and the behaviour of electricity prices in the presence of intermittent renewable energy. The relevant literature is also summarised. We additionally supplement the respective sections with the information regarding the Czech day-ahead electricity market, thereby the aforesaid country-specific factors will be pointed out. Chapter 3 develops the hypotheses under investigation, taking into account the outcome of similar studies. Chapter 4 describes the data, the argumentation behind their incorporation into the analysis, the corresponding visual representation, and descriptive statistics. Data preprocessing, which comprises of outlier detection and seasonal adjustment, and selected tests regarding normality and stationarity are executed as well. The applied methodology and the detailed description of the estimation procedure and model selection criteria are described in Chapter 5. The empirical analysis is performed and the results are discussed in Chapter 6, while Chapter 7 offers the suggestions for future research and concludes the work.

Chapter 2

Theoretical insight and literature overview

In this chapter divided into three sections, we provide a more thorough description of the phenomena encompassing energy systems. The first section outlines the distinct features of electricity prices and the techniques for capturing such peculiarities. This will be of particular convenience when the data will be considered. Section 2.2 analyses price volatility. Section 2.3 explains the so-called merit order effect (MOE) that represents an inherent concept in the research on the effects of RES on electricity prices. In addition to that, every section offers the corresponding information about the energy market in the CZ.

2.1 Stylized facts of electricity prices

The advent of electricity modelling in the 1990s is related to the shift of electricity industry structure from vertically integrated monopoly towards unbundled entities (Erdogdu, 2016). During the liberalization process, energy transformed from a commodity that had been initially sold by public utilities to a commodity traded on day-ahead and intraday spot markets, and its prices soon became subject to market risk and volatility. Patterns like seasonality, mean-reversion, and price spikes came thereafter under scrutiny. Among the pioneering works concerned with the unique characteristics of electricity prices, there are the studies of Deng (2000) and Lucia and Schwartz (2002). The author of the former work proposes mean-reversion jump-diffusion models including regime-switching and stochastic volatility components to adequately capture genuine features of electricity prices. The authors of the latter study analyze the Nordic

Power Exchange's spot, futures, and forward prices, concluding that the seasonal pattern is instrumental for the explanation of the shape of the respective curves. Broadly speaking, the following stylized facts can be represented by deterministic functions (Erdogdu, 2016).

2.1.1 Price spikes and mean-reversion

In general, supply and demand shocks in power markets stemming from e.g. unanticipated outages of generation units may give rise to extreme prices that usually converge back to the equilibrium level as soon as the imbalance between supply and demand has been resolved. The inherent reason for such spikes is that electricity cannot be effectively stored[1] so the mismatch has to be executed on an instantaneous basis. As a result of price spikes, electricity price distributions have high kurtosis and fat tails which introduce a substantial challenge for energy risk management operations (Kyritsis et al., 2017). Specifically, these fluctuations cause uncertainties about revenues for producers and costs for retail suppliers, implying that higher prices paid by consumers may be warranted (Tashpulatov, 2013). What is particularly remarkable for electricity prices in this respect and also very symptomatic is that a price in a power market can increase by 100 times or even more and then it undergoes a relatively swift return to its normal level (Erdogdu, 2016).

Concerning mean-reversion, Simonsen et al. (2004) argue that the spot price increments are anti-correlated, meaning that the likelihood of a price drop following a positive increment in the past is greater than a price accrual. For curiosity, Barlow (2002), who presents a nonlinear jumpless model for spot power prices, states that the estimate for the time over which the process is corrected to the mean varies from two to six days. This corresponds to the finding of Krištoufek and Luňácková (2013) who report that the Hurst exponent for the electricity price series is around 1.1, indicating that the reversion to the long-term value is rapid. They argue that since the series under question also comprises of spot prices (that is, prices whose purpose lies in covering the demand which has not been accounted for by future contracts), the demand shock is of only a short duration.

Corresponding studies include the work of Huisman et al. (2007) who examine the dynamics of hourly electricity prices using a panel model of 24 cross-

1 This does not hold for pumped-storage hydropower plants and generator fuel storages as mentioned by Krištoufek and Luňácková (2013), and by Escribano et al. (2011).

sectional hours in the day-ahead markets in the Netherlands, Germany, and France.[2] The conclusions uncover that the prices oscillate around a mean price level that is specific for each hour and that the speed of mean-reversion is not stable over the day (the process is less pronounced for super-peak hours, i.e. from 18:00 to 22:00). The authors also report that peak hours correlate highly among each other and that off-peak hours exhibit the same pattern. That these two blocks do not correlate with each other is explained by the lower reserve capacity in the peak hours when volatility and spikes are considerable. Additionally, Huisman and Mahieu (2003) assert that although a large body of literature introduces stochastic jump processes to capture the dynamics of electricity prices (e.g. Lucia and Schwartz, 2002, or Knittel and Roberts, 2005), these models may not be able to specify the true mean-reversion process. The thing is that if mean-reversion occurs during the non-spike ("normal") periods, then the process may become overestimated as a result of having been calibrated with data from the spikes. The assumption that all the shocks, irrespective of their magnitude, take the same amount of time to die out is further challenged by Escribano et al. (2011). The authors also resolve the limitation of estimating the jump-diffusion process by (quasi-)maximum likelihood as this procedure would only detect the smallest and more frequent jumps in the model. Last but not least, Barz and Johnson (1999) work with a collection of data from multiple deregulated markets and investigate the fit of models that either do not incorporate mean reversion and jumps or do so. They ascertain that a mean-reverting model with jumps yield the best fit.

2.1.2 Seasonality

Additional regularity of electricity prices is seasonality as prices follow weekly and yearly patterns. Since this is a consequence of different demand reactions towards different days and seasons, the inelastic short-term electricity demand is considered to be a source of price seasonality (Kyritsis et al., 2017). The demand is highly inelastic because of its weather-dependent characteristic and because energy is a necessary commodity (Escribano et al., 2011). Correspondingly, Li and Sailor (1995) show in their study on the sensitivity of electricity use to climate factors that the most significant weather parameter affecting electricity consumption is temperature. Indeed, electricity demand

2 The respective wholesale power markets are the Amsterdam Power Exchange (APX), then the part of the European Energy Exchange (EEX), and the Paris Power Exchange (PPX).

exhibits seasonal variation with respect to the temperature profile as can be reflected in the usage of electric heating appliances and air conditioners (Pardo et al., 2002).[3] Equally important determinant in electricity price formation is the supply side. Specifically, RES power production also exhibits the seasonal "footprint" as solar generation reaches its maximum during summer, while the opposite is partially true for wind generation (Kyritsis et al., 2017).

When it comes to capturing the periodic components, the widely utilized method accounts for constant piece-wise step functions. The removal of the predictable components through the usage of dummy variables and the subsequent employment of residuals or the so-called "filtered" prices in the estimation is followed by e.g. Haldrup and Nielsen (2006) and Guthrie and Videbeck (2007) in their analyses of spot price dynamics in Nordic and New Zealand electricity markets, respectively. Other approaches towards the approximation of seasonal patterns are based on periodic sine and cosine functions (for instance, Weron et al., 2004) or the combination of binary variables and trigonometric functions (for example, Lucia and Schwartz, 2002). Tashpulatov (2013), who studies the impact of price-cap regulation and divestment on electricity prices in England and Wales, favours the application of periodic smooth functions as it results in a more parsimonious model. The author determines the frequencies of the functions based on the Fourier transform. Last but not least, Janczura et al. (2013) deals with the sensitivity of the long-term or trend-cycle and short-term or periodic seasonal patterns to extreme observations.

Regarding the Czech electricity market, Krištoufek and Luňácková focus on the properties of electricity prices, considering particularly long-term memory of the spot prices. Making use of the detrended fluctuation analysis motivated by complex cyclicality, the authors show that the Czech prices exhibit the salient features described above. More specifically, the Czech price series is non-stationary but mean-reverting, which allows predicting its development to some extent.

2.2 Volatility

Other genuine properties of electricity prices are connected to volatility which stems from the non-storability of electricity. Electricity prices are extremely volatile also because demand is insensitive to price fluctuations in the short-

3 Pardo et al. (2002) note that demand is inelastic to the temperature changes around 18°C.

term and because supply can face binding constraints during peak times (Escribano et al., 2011). Hence, in the markets where both supply and demand curve are steep, one can observe abrupt sharp increases in prices as the quantity demanded is raised. These issues then translate into a substantial risk for market agents. As a result, measuring risk by evaluating price volatility in energy markets represents the essential practice for electricity market stakeholders (Figueiredo and da Silva, 2019). In this regard, the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models are frequently utilized in the analyses of energy markets for their ability to efficiently take account of irregular price behaviour, as Efimova and Serletis (2014) describe. The authors find that univariate and multivariate GARCH models generate similar estimates, yet the former are more accurate for forecasting purposes. Although there are limitations in introducing additional explanatory variables (as each regressor produces the entire vector of parameters) in the latter models, they are indispensable in tracking the interdependence among different markets, which may reveal interesting spillover effects. Estimating trivariate Baba-Engle-Kraft-Kroner (BEKK) of Engle and Kroner (1995) and Dynamic Conditional Correlation (DCC) of Engle (2002), the authors find that the hierarchy of influence from oil to natural gas to electricity markets is present in the U.S. wholesale markets.

2.2.1 Leverage effect

Among the first studies that applied GARCH models to electricity prices, was the one of Knittel and Roberts (2005) who examine the distributional and temporal properties of electricity prices in California with the sample covering the period right after the restructuring process in its electricity supply industry took place. The authors employ the exponential GARCH (EGARCH) model and document an inverse leverage effect, which means that electricity price volatility has a tendency to rise more so with positive shocks than with negative ones. The intuition provided lies in regarding positive price surprises as unanticipated positive demand shocks. These have necessarily a larger effect on price changes relative to negative shocks as marginal costs are convex.

An inverse leverage effect is also detected by Bowden and Payne (2008) in the five hubs of the Midwest Independent System Operator (MISO). Similarly, Erdogdu (2016) analyses asymmetric volatility in 14 European day-ahead power markets using high-frequency spot price data, EGARCH and threshold

ARCH (TARCH) models. The author applies a distinct approach by considering each hour in a day a separate market. The idea behind not treating prices as continuous variables (as most of the literature does) dates back to Huisman et al. (2007) who claim that the market microstructure does not allow for the information set used for setting the price for delivery of energy to be updated moving from one observation to the ensuing one in time. More concretely, day-ahead markets are structured in such a way that agents submit their bids and offers for delivery in all hours in the next day before market closing time, meaning that hourly prices for the next day are determined at the same time. As a result, applying directly the usual time series practice on hourly prices would invalidate the fact that the information set does not vary within the day. Bearing in mind such a procedure, Erdogdu (2016) shows that Poland, the CZ, and Russia have the least volatile markets while the opposite holds for Ireland, France, and Portugal. Moreover, the findings indicate that changes in current volatility would have less effect in CZ, Russia, and Turkey[4] since the time taken for volatility to die out following a shock in the market is shorter there. In contrast, the prices of the power markets in Nordic countries, Ireland, and the United Kingdom exhibit a relatively large persistence in conditional volatility, meaning that large changes in the volatility will affect future volatilities for a longer period of time.

2.2.2 The case of renewable energy sources

Moving to the area in which this thesis believes to have a contribution, the literature on the electricity price volatility regarding RES is presented. In essence, the intermittent nature of renewable generation is considered to be a contributing factor to an increased frequency of price spikes, and thus also to greater volatility (Ballester and Furió, 2015). The riskiness owing to the changeable weather conditions in the form of inaccurate forecasts represents a considerable challenge for investors, energy traders seeking to make informed decisions regarding the volume they can offer or bid and grid operators who must balance supply and demand for regional and national grids (Shen and Ritter, 2016). Hence, the management of conventional power plants has to be adjusted to too little or too much wind and sunshine by providing sufficient capacity in the former event and curtailing the electricity production in the latter one (Ketterer, 2012). For the sake of illustration, Woo et al. (Woo et al.), who

4 The author explains that the term “European” is used in the most inclusive way.

investigate the impact of wind generation on the spot-price variance in Texas by means of simulation techniques, show that a 10% increase in the installed capacity of wind generation leads to about 1-5% accrual in price variance.

One of the most notable studies on renewable energy is that of Ketterer (2012) who examine the effect of wind power generation on the electricity prices in Germany, using an AR-GARCH model and covering the period from 2006 to 2012. The novelty of the works lies in introducing German wind power generation as an explanatory variable in the mean and variance equation of the model. The author is thus able to investigate how wind power generation affects the level and volatility of electricity prices in an integrated manner. The chosen methodology also allows for tracking the dynamics over time. In this regard, the author finds that the volatility of the German electricity price decreased after the regulatory change in wind electricity marketing in 2010, indicating that the market design can be used to lessen the volatility of the electricity price to some degree. Recently, Pereira da Silva and Horta (2019) used a similar method to examine the impact of variable renewable energy supply on price volatility on the Iberian market of electricity. The authors find that RES (particularly, wind power) drive price volatility upwards and quantify the effect of market coupling on the sensitivity of price volatility to renewable power generation. On the example of coupling between French and Spanish markets in 2014, they argue that such enhanced interconnection helps mitigate the effect of RES production on price volatility. The idea is that once markets that experience a transitory surplus in production are allowed to transfer electricity to markets with a temporary supply shortage, price volatility can be less pronounced. Therefore, spatial arbitrage in different zones can be executed even though the non-vanishing correlation in the form of the long-term level of electricity prices does not permit inter-temporal exploitation for profit due to the non-storability of electricity (see, Simonsen et al., 2004 or Krištoufek and Luňácková, 2013). The Czech day-ahead electricity market was coupled through implicit auctions with day-ahead electricity markets in Slovakia, Hungary, and Romania in 2009, 2012, and 2014, respectively (OTE, a.s., 2020a). The market participants registered in these countries submit bids for the purchase or sale of electricity that are matched jointly from the neighbouring countries without the requirement to acquire transmission capacity (OTE, a.s., 2020a).

Furthermore, Rintamäki et al. (2017) build a distributed lag model with the data from Danish and German electricity markets in order to assess the impact of variable renewable energy on price volatility. Their major contribution lies in dividing the dataset into peak (from 9:00 to 21:00) and off-peak hours (the rest), thereby the authors determine the distribution of the price-decreasing effect of RES over the day. They show that the two countries differ in the effect of wind power on daily price volatility. While Denmark wind power decreases the daily price volatility as a result of flattening the hourly price profile, the German wind production behaves in the opposite direction as it has a stronger effect on off-peak prices. The reason for such a contrasting finding is attributed to Denmark's large access to flexible generation in the form of hydropower reservoirs, which is rather limited in Germany. In fact, as it was noted earlier, the existence of these distinct, country-specific results provokes the empirical analysis of this thesis. Daily price volatility in Germany is also lessened by solar power (Danish solar power is omitted from the analysis due to its then negligible capacity). Finally, the prices in both areas exhibit greater weekly volatility which can be the result of the high day-to-day changes of wind and solar power production. The pattern found here for Denmark wind power production is in line with Mauritzen (2010) who works with Seasonal Autoregressive Integrated Moving Average (SARIMA) models.

The effects of RES on the German electricity prices are also investigated by Kyritsis et al. (2017) who analyze daily data from 2010 to 2015, i.e. the onset of the ongoing transition of German electricity market towards renewables (known as "Energiewende"). Under the framework of the GARCH-in-mean (GARCH-M) model, it is shown that solar power generation decreases electricity price volatility since it is characterized by lower variability. This leads to a more efficient adjustment of other power plants to the residual demand. The opposite effect on volatility is induced by wind power generation as highly variable wind production varies the level of residual demand that should be accommodated by the conventional power plants. Furthermore, in the context of Granger (1969), the authors find that past information of solar and wind power generation and total electricity load improves the forecasts of electricity prices beyond the predictions that are built entirely on past electricity prices; that is, these factors Granger-cause electricity prices.

2.3 Electricity markets and renewable generation

2.3.1 Merit order curve

The special attributes of electricity markets indicated in the previous sections play an integral role in the price building mechanism. As mentioned in Section 2.1, electricity demand is absolutely inelastic in the short-run, which reflects the inability of consumers to change their consumption habits at least in the foreseeable future and signifies that the supply curve is the only determinant of prices (Krištoufek and Luňácková, 2013). Electricity supply or the merit-order curve is discontinuous, convex and steeply increasing in the event of high demand (Kyritsis et al., 2017). The formation of the supply curve is crucial for the understanding of the merit order effect (MEO) so it is practical to present a short discourse (which draws on Morales et al., 2013) into this matter. When it comes to an auction-based market structure, agents on the supply side make offers with the specified energy quantity that shall be delivered along with the respective price. This price is related to a short-run marginal cost or (in other words) the cost of generating an extra unit of energy. All generation offers are then ranked based on their short-run marginal costs, giving rise to a global supply curve. The curve is not smooth precisely because its rise occurs only when the market price reaches the marginal cost of the next level plant (Krištoufek and Luňácková, 2013). While the left segment of the curve is occupied by lignite and hard coal power plants, i.e. those with low marginal cost, the right side consists of gas and oil-fired power plants, i.e. those with high marginal cost (Kyritsis et al., 2017).

In terms of renewable energy producers, the cost of generating an additional unit of energy is, in essence, zero, which places offers from renewables on the left part of the supply curve. Therefore, renewable generation is prioritized over more expensive supply offers as it provides large quantities of electricity at near-zero short-run marginal costs (Pereira da Silva and Horta, 2019). Based on these characteristics, RES generation shifts the whole supply curve to the right, pushing the most expensive generations out of the market, and conditional on the particular inelastic demand curve, it induces a lower electricity price (Kyritsis et al., 2017). It is important to stress out that this process known as MOE holds for the wholesale price, the price of consumers is influenced by the costs for the support of renewables as well, implying that the conditions may be opposite for end-users (Ketterer, 2012).

2.3.2 Merit order effect

Numerous papers examine the MOE of RES power generation and they almost unanimously report that renewable generation has a negative impact on electricity prices. The studies assessing the effect are predominantly concerned with the regions where high penetration of RES power generation was established, such as Nordic countries, Germany, or Spain. To show a wide array of methods for detecting the MOE, the works of Azofra et al. (2015) and Maciejowska (2020) represent opposite examples. Using artificial intelligence techniques to model the formation of prices at electricity market auction (a tree model of the spot market is created based on M5P learning algorithm), Azofra et al. (2015) analyze the MOEs induced by photovoltaics (PV) and wind power on electricity prices in Spain. They find that both renewable technologies curtail electricity prices on the spot market, namely by 9.10 EUR/MWh in case of wind power and by 2.18 EUR/MWh in case of PV power. On the other hand, Maciejowska (2020) evaluates the impact of RES on the level and variability of German electricity spot prices employing quantile regression, allowing to account for nonlinearities in the relationship between fundamental variables and the prices of electricity. The effect of renewables and load on the quantiles of the spot prices is thus conditioned on the total demand level. The results indicate that both wind and PV have a similar, negative effect on the level of prices (approximated by their median). However, when the impact of RES on the range of price quantiles is considered, solar has a stronger dampening effect on higher tails, while wind on lower tails of the price distribution. This can be explained by the different impact of each RES on electricity prices as described by Rintamäki et al. (2017).

Moreover, Cataldi et al. (2015) analyse the Italian day-ahead wholesale electricity market over the period from 2005 to 2013; that is, the years that marked a substantial growth in RES power generation there. The authors detect the MEO by determining that 1,000 MWh from solar and wind sources lowered (on average) electricity prices by 2.3 EUR/MWh and 4.2 EUR/MWh, respectively. They also evaluate the impact of RES production on the final consumers of electricity. While monetary saving generated by solar production is found to be insufficient for compensating the cost of accompanying support schemes that are charged on final electricity prices, implying that the consumer surplus is reduced, the opposite happens in case of wind production. This can be explained by the fact that solar production is more prominent in Italy than wind production, and hence larger financial resources are needed for its promotion. In contrast, the decreasing trend in net monetary benefits (i.e. savings minus costs internalized in end-user tariffs) is shown for both solar and wind which is attributed to the increase in intermittent RES power generation. The relationship between household electricity prices and renewable energy sources is additionally investigated by Moreno et al. (2012) who utilize a panel data set comprising of entries from 27 European Union countries during the period from 1998 to 2009. Although it is suggested that final electricity prices rise with the deployment of RES (as a result of RES support systems financed by the households), the additional costs passed on consumers can be offset by indirect benefits to society. More specifically, the high energy dependence of the EU on imported resources (e.g. crude oil or natural gas) may be lowered by the roll-out of renewable energies. This would result in reduced electricity prices as the findings of the study imply that electricity prices increase with the intensified energy dependency.

Paraschiv et al. (2014) also inform about the dampening impact of renewable energies on day-ahead electricity prices at EEX, concluding that the effect of wind power is apparent during afternoon, evening and nights hours, and during noon peak hours in solar power case. The results additionally indicate that the substitution effect in electricity production between traditional fuels and RES came about during the analyzed period (from 2010 to 2013) in Germany as the sensitivity of electricity prices to gas diminished over time. This outcome is attributed to augmented PV infeed because the convenient characteristics of gas power plants in the form of high operational flexibility and short ramp-up time make them, as noted above, price-setting during peak hours, i.e. hours of high demand and high solar radiation. Hence, the margins of traditional producers are decreased by lower price level, which is even more noticeable during night hours when the substantial wind feed-in can cause downside spikes and also negative prices.

2.3.3 Negative prices

Generally speaking, the mechanism behind such a practice is that the generators may be unwilling to generate power at prevailing prices, yet they still bid negative prices since the costs of shutting down and subsequent ramping up of a unit of a power plant is greater than the loss associated with accepting negative prices (Erdogdu, 2016). In case of medium load plants, the actual bid is considered to be very close to zero (Erdogdu, 2016). For baseload plants (lignite and nuclear plants), the situation is more extreme as the utilities may pay up to e.g. 120 EUR/MWh and more at EEX to manage the excess of electricity generated, as Keles et al. (2012) describes. According to these authors, that is probably why the distribution of negative prices is bimodal or two-peaking there (one near 0 EUR/MWh and the other one near -120 EUR/MWh). Furthermore, the latter power plants are reluctant to shut-off also due to opportunity costs which could emerge when the prices above their variable costs (i.e. fuel and CO_2 costs) arise and the plants are not activated in time. This is pointed out by Nicolosi (2010) who investigates the flexibility of the German power market with respect to the increasing share of electricity from wind in the period from 2008 to 2009. The author shows that low load, high wind power penetration combined with an inflexible power mix result in highly negative prices. With regard to the Czech and Slovak electricity market, negative prices were allowed on February 1, 2012 (OTE, a.s., 2012). These day-ahead markets can be reopened to update bids to correct exceptional conditions once the price exceeds the upper threshold value of 500 EUR/MWh or the lower threshold value of -150 EUR/MWh (OTE, a.s., 2012).

2.3.4 Cross-border electricity interconnections

Owing to the interconnection between German and Czech electricity markets through electricity flows and export which is similar to that of Dutch and German electricity markets (Luňáčková et al., 2017), it is reasonable to highlight the work of Mulder and Scholtens (2013). They examine the effects of weather conditions in the Netherlands and Germany on the average daily day-ahead price in the APX market. Over the analyzed period from 2006 to 2011, average wind speed in Germany was found to drive Dutch electricity prices downward (1% increase in German wind energy translated into a 0.03% decrease in the Dutch electricity prices). It did so in a constant manner despite the fact that German wind energy capacity was magnified during the given years. Interestingly, the effect of wind speed in the Netherlands on the Dutch electricity prices was relatively small, reflecting the lower quantity of the installed wind capacity in the Netherlands as opposed to the generation in Germany. Moreover, since no robust impact of the intensity of sunshine on APX prices was discovered, the growth of solar generation did not seem to induce a change in the Dutch average electricity price at that time.

Concerning the Czech cross-border infrastructure, the installation of phase-shifting transformers at Czech-German interconnectors was completed in March 2017, allowing to eliminate possible overflows in the transmission system (ČEPS, a.s., 2017). The congestions arising in the German grid due to its inability to accommodate a large amount of feed-in of intermittent RES had previously propagated to the grids in adjacent countries, the CZ and Poland (Janda et al., 2017). In this respect, Singh et al. (2016) show that the accrual in the number of physical flows from Germany to the region of Central and Eastern Europe was connected to the growth in installed wind power capacity in the first-named country. In total, there are cross-border interconnections with five transmission systems between the CZ and adjoining countries ERÚ (2019a). More specifically, 50Hertz and TenneT (German TSOs), APG (the Austrian TSO), SEPS (the Slovak TSO), and PSE (the Polish TSO) form this system.

2.3.5 Czech electricity market

Among the studies related to Czech renewable energy, Luňáčková et al. (2017) assess the corresponding electricity spot market in the span of 6 years from 2010 to 2015, i.e. the period when the CZ experienced the largest accrual in the number of renewable generation capacity. Using the Prais-Winsten methodology and analysing the two groups of renewables (solar and other RES except for solar) motivated by the prevalence of solar power in the CZ, the authors offer a contrasting perspective on the MOE when compared to the majority of literature. Curiously, the results indicate that the Czech solar power generation did not lower electricity spot prices, which ultimately generated double cost to the end costumers in the form of subsidies and the inverse MOE. Specifically, a 10% increase in solar production resulted in a 0.7% price increase, underlining the improper implementation of support schemes in the CZ. In case of RES excluding solar (particularly, water and wind), the findings are in agreement with other studies reporting the price-dampening effect of RES. A 10% increment in the production of RES excluding solar led to a 2.5% reduction in electricity prices over the investigated period. Overall, it could be said that the absolute value of the Czech MOE is lower than in other countries, which is explained by the dominant position of solar plants that does not reflect the natural environment sufficiently (Luňáčková et al., 2017). Stated differently, the mix of RES is perhaps established in line with geographic conditions better in other locations, inducing each RES to contribute to the total MOE.

Table 2.1: Czech electricity production and installed capacity

Power Plant Type	2015		2016		2017		2018	
	Prod.*	IC**	Prod.	IC	Prod.	IC	Prod.	IC
Nuclear	26,840.8	4,290	24,104.2	4,290	28,339.6	4,290	29,921.3	4,290
Thermal	44,816.5	10,741.9	45,704.1	10,850.0	45,431.7	11,075.4	45,070.8	11,075.4
Combined cycle	2,749.0	1,363.3	4,049.2	1,363.5	3,722.4	1,363.5	3,690.9	1,363.5
Gas fired	3,574.7	855.9	3,613.9	874.0	3,719.6	895.9	3,690.4	910.9
Hydro	1,794.8	1,087.5	2,000.5	1,090.2	1,869.5	1,092.7	1,628.8	1,092.5
Pumped storage	1,276.0	1,171.5	1,201.5	1,171.5	1,170.5	1,171.5	1,050.6	1,171.5
Photovoltaic	2,263.8	2,074.9	2,131.5	2,067.9	2,193.4	2,069.5	2,339.7	2,056.8
Wind	572.6	280.6	497.0	282.0	591.0	308.2	609.3	316.2

Note: *Production ("Prod.") is reported in GWh, while **Installed Capacity ("IC") is reported in MWh.
Source: ERÚ (2019b).

Such facts can also be observed in Table 2.1 which presents the development of the Czech installed capacity and production covering the period from 2015 to 2018. Based on the figures, solar plants do not exhibit reasonable efficiency ratio, i.e. production over installed capacity (Luňáčková et al., 2017). Moreover, unlike the period from 2008 to 2012, when the installed capacity of Czech solar power plants grew from 39.5 MW to 2,086.0 MW (ERÚ, 2019b), the figure seems to stand at a standstill during the recent years. This has arisen due to the abolishment of support for most renewables built after 2014 (Janda et al., 2017). Additionally, it can be traced that wind accounts for the smallest share both in production and installed capacity. Finally, that the difference between installed capacity and production is particularly pronounced is discernible from the case of nuclear power plants. Indeed, domestic coal and nuclear power dominates the Czech energy production (Rečka and Ščasný, 2016).

Chapter 3

Hypothesis formation

The target of this thesis is to investigate the relationship between the intermittent sources of energy and electricity prices in the CZ. This chapter outlines in which directions the analysis will precisely be heading. In accordance with the literature on RES and theoretical background of the MOE, every type of renewable generation can drive prices downward (Kyritsis et al., 2017) because of their low short-run marginal costs, the first hypothesis is formulated as follows:

> Hypothesis #1: Both Czech solar and wind power generations have a dampening effect on Czech day-ahead electricity prices.

Obviously, that we do not treat solar and wind power as a combination of energies under the label of intermittent renewables prevents us from ignoring singular features attached to each generation resource. This is particularly apparent when electricity prices are divided into the different "blocks" of a day, which is also our case. For instance, Ballester and Furió (2015) conclude that only when peak (from 8:00 to 20:00) and off-peak (the remaining hours) prices are regarded separately, some effects stemming from renewables infeed emerge. To put it differently, by dividing the data into these intervals, we would be able to infer how the expected price-depressing effect of either solar or wind power generation is distributed throughout the day (Rintamäki et al., 2017).

Generally, RES installed capacity is indeed subject to fluctuating weather conditions, thereby making prices themselves more sensitive to weather events, and thus more volatile. Additionally, this may change the optimal generation mix to a substantial extent as more flexible generation technologies characterized by high variable costs must be employed to guarantee that electricity supply will meet a high level of demand (see, for example, Pereira da Silva and Horta, 2019, and Pérez-Arriaga and Batlle, 2012). Therefore, the key point is that conventional sources of electricity cannot be merely substituted for intermittent RES that are predominantly characterized by variability and corresponding unpredictability. We would hence test whether RES generation amplifies electricity price volatility in the Czech electricity market. Nevertheless, disentangling again the anticipated impact of solar and wind power generation and conditioning on the above mentioned "blocks" of a day (marked by different load profiles and appropriate production design as described by Paraschiv et al., 2014), the hypothesis has to be adjusted accordingly. That is to say, solar power is produced predominantly during peak hours when excess demand is assumed, and thus its production is easier to accommodate (Luňáčková et al., 2017). Since solar power exhibits low variability (Kyritsis et al., 2017), implying that its dampening impact on high peak hour prices is more or less stable during peak hours (Paraschiv et al., 2014), it should reduce price volatility (Rintamäki et al., 2017).

> Hypothesis #2: In the Czech Republic, the penetration of solar power into the power system decreases the volatility of day-ahead electricity prices.

On the contrary, wind may evolve with greater frequency at nighttime when low demand levels as a result of human diurnality and closed businesses typically occur. Extra supply from wind energy can thus be responsible for plentiful downside spikes (Paraschiv et al., 2014 or Keles et al., 2012). Accordingly, the hypothesis is established in the following way:

> Hypothesis #3: In the Czech Republic, the penetration of wind power into the power system increases the volatility of day-ahead electricity prices.

Chapter 4

Data

In this chapter, data employed in the econometric analysis are described, the motivation for the inclusion of specific variables and the corresponding summary statistics are presented. Necessary unit root and stationarity tests are performed as well.

4.1 Data description

We analyze the Czech day-ahead electricity spot prices. Data with an hourly frequency were obtained from the Yearly Reports of Czech Electricity and Gas Market Operator (OTE). The prices are classified either as peak if they fall within the range from 8:00 to 20:00 or off-peak provided that they belong to the remaining trading hours; the baseload is defined for all hours of the day (OTE, a.s., 2020b). In keeping with Maciejowska (2020), we convert the time series from hourly observations into daily, peak, and off-peak indices. The indices are calculated as the arithmetic mean of the corresponding variables across all hours, peak hours, and off-peak hours, respectively. Furthermore, the peak indices that account for times with the highest electricity demand are limited to working days, and thus the off-peak indices are identical to the daily indices on weekends. Provided that the holiday falls on a working day, we proceed in the same vein. It should be stressed out that the trading practice on the Czech electricity market which is executed in bid blocks (base, peak, and off-peak as described in OTE, a.s., 2019) is not followed in our analysis. If this was a case, then off-peak indices would be restricted to working days as well (OTE, a.s., 2019). Our approach is motivated mainly by the patters of human activity reflected in lower demand for electricity over the weekend when major enterprises do not operate (Simonsen et al., 2004). To unify the period of low demand which also coincides with off-peak hours during working days, the off-peak index is extended to Saturday and Sunday. All of this will allow us to view the prices as three different time series. The prices are denominated in EUR/MWh.

Among other variables of interest, there are solar and wind power generations. Since the aim of this thesis is to track the changes in the behaviour of day-ahead electricity prices induced by RES, the predicted (rather than the realised or actual) power generation should be utilized. This follows from the fact that participants in a day-ahead market do not have the information about the actual power generation at their disposal when they determine their bids, only the respective foreseen values *may* be available for market clearing (Kyritsis et al., 2017). The possibility that the market participants do not have the information about the RES forecasts when submitting their bids is explained as follows. While the participants on Czech day-ahead spot electricity market are no longer eligible to submit their bids after 11:00 when the market closes (OTE, a.s., 2019), the forecasts of RES power generation can still be published up to 18:00 Brussels time, one day before the actual delivery is carried out (European Comission, 2013). Therefore, prices and volatility may not even be influenced by bidding decisions. Since more convenient data do not exist, we continue to assume that the bidders have the knowledge of the generation forecasts (this is in accord with Líšková, 2017). We thus employ forecasts for solar power generation from the Transparency Platform operated by the European Network of Transmission System Operators for Electricity (ENTSO-E). As there are several missing hours in the data, the adjustment is warranted. In line with Rintamäki et al. (2017), the realised values for solar generation are utilized accordingly. Nevertheless, given that the figures for wind power generation forecasts are not published, we opted for using the realized values from the Czech TSO (ČEPS, a.s., 2020) as an approximation. This is in line with the literature; for example, see Nicolosi (2010) or Kyritsis et al. (2017).

To contextualize the position of renewables on the electricity market, load data reflecting the demand for electricity are additionally analysed.[1] That is to say, the same amount of RES electricity can have a different effect during the episodes of high and low electricity demand. In the spirit of Ketterer (2012), we claim that no endogeneity problems should arise by the inclusion of the

1 Total load is defined as “generation and any imports deducting any exports and power used for energy storage.” (European Comission, 2013).

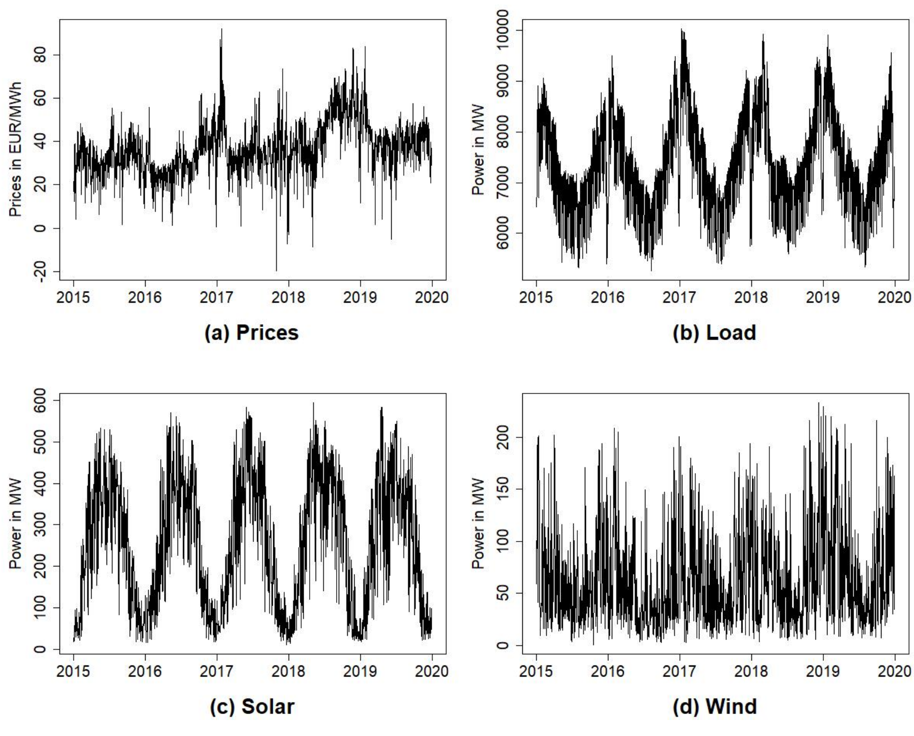
load variable since demand for electricity is supposed to be independent of wind and solar feed-in. The exogeneity of selected variables originates in price insensitivity and inelastic character of daily electricity demand (as explained in Chapter 2) and from weather conditions upon which the RES production is contingent, which excludes any strategic bidding on the basis of price dynamics, as pointed out by Cataldi et al., 2015. In line with these authors, dispatchable sources like gas, coal, and hydro are omitted from the analysis as their inclusion may bring about the endogeneity issue in the regressions due to the dispatching rule. Additionally, omitting weather data from our analysis is motivated by the fact that such a practice would produce bias in the analysis stemming from double counting. More specifically, weather conditions are already considered in the load forecast and forecasts of RES generation as TSOs factor temperature affecting electricity consumption, predicted solar radiation, and wind speed into the information they publish (Lago et al., 2018). To conclude this section, we inform that day-ahead total load forecasts are also obtained from ENTSO-E Transparency Platform (2020), and as well as in case of RES generations, they are quoted in MWh. The resulting sample covers the period spanning from January 1, 2015, to December 31, 2019, since earlier ENTSO-E data are not available.

4.2 Visual inspection

In this section, the graphical representation of the selected variables is explored in order to acquire overall insight into the research questions and to identify elements that will be of particular interest in the econometric part of the thesis.

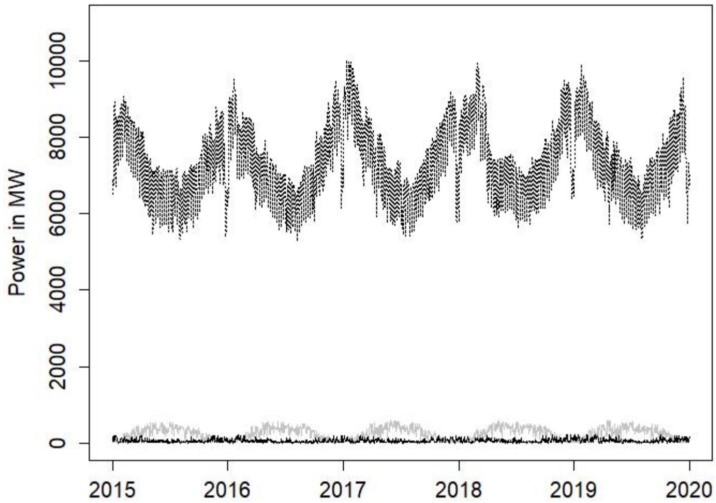
A great variety of stylized facts of electricity prices is noticeable from their time path in Figure 4.1. Year cycles when prices tend to decrease during the first half of the year and subsequently rise gradually upon reaching their peak in the winter are especially pronounced. A mean-reverting aspect of electricity prices, episodes of high volatility following the stages of comparative tranquility, and abrupt price spikes can also be identified. In terms of seasonal patterns of RES, while wind power production generates energy most of the year and exhibits high volatility as a result of its intermittency, solar power production culminates mainly over the summer months due to the extension of daytime and is characterized by greater stability. It can also be recognized that wind generation follows the inverse seasonal path than that of solar generation to some extent. According to Kyritsis et al. (2017), this complementarity may represent a feature on which a hybrid power generation system can capitalize. Furthermore, by occurring at its highest value during the winter and declining progressively in the middle of the year, total electricity load reflecting the demand profile follows a similar year development as wind power production. The differences among the fundamental variables are presented in Figure 4.2 which accentuates the fact that the installed solar capacity in the CZ generates a much higher share of total electricity than the wind capacity (see Table 2.1). The approach towards treating yearly as well as weekly periodicity is described in the next subsection.

Figure 4.1: Electricity prices and fundamental variables by daily index



Note: Time paths of (a) electricity prices, (b) total electricity load, accounting for demand profile, (c) solar power generation, and (d) wind power generation reveal common annual patterns reflecting calendar seasons. Given the geographic conditions of the Czech Republic, the output from solar plants escalates during summer months, while that from wind farms during winter times. Load exhibits the highest values also during winter months due to greater demand for lighting and inhouse heating. This regularity is translated into electricity prices to some extent as upward tendencies during the second halves of the analyzed years are noticeable.
Source: Author's computations.

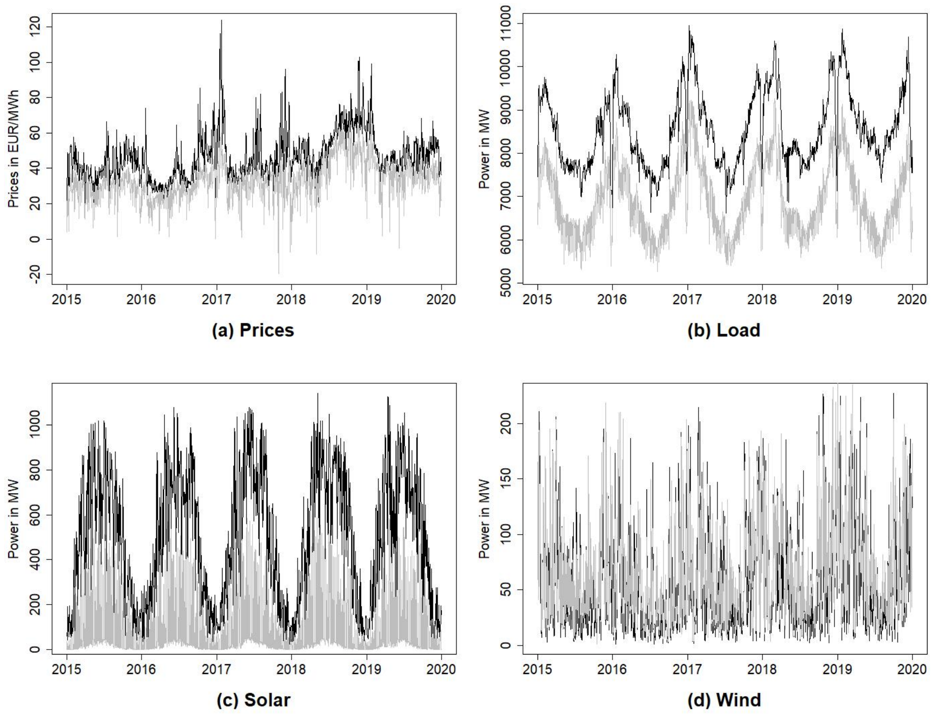
Figure 4.2: Comparison of fundamental variables by daily index



Note: The dotted line illustrates load, while the transparent line and the black line denote solar and wind power generations, respectively. It follows that both RES generations cover only a fraction of the total Czech demand for electricity. Such an actuality also emerges from Table 2.1. This signifies that, for instance, wind feed-in is not able to bring about the same number of negative prices, if any, in the Czech Republic as does onshore and offshore wind in Germany, where it produced 127,200 GWh of power (compare it with the figures for the Czech wind farms in the above mentioned table from Section 2.3) in 2019 (Eckert, 2020).
Source: Author's computations.

The differences between the variables across different hours can be tracked in Figure 4.3. A glance at the price development uncovers the erratic nature of the electricity prices. It can be inferred that positive price spikes are more frequent during peak hours, while negative jumps are considerable during off-peak hours. In total, both time series of prices and load exhibit values of greater magnitude during the off-peak hours. With respect to the intermittent fundamentals, whereas wind generation is distributed during the whole day evenly, solar generation naturally does not conform to the uniform development throughout the day. In fact, that the solar radiation is weak during the off-peak hours, and hence the production executed over this block constitutes a smaller portion of the peak production (Maciejowska, 2020), is another reason for working with different indices. Based on Table 4.1, it can ultimately be determined that the average off-peak solar generation merely represents 18.28% of its mean peak value. These results are consistent with the analysis of Maciejowska (2020).

Figure 4.3: Comparison of peak and off-peak indices



Note: In every figure, the black line illustrates the respective peak series and the transparent line denotes the off-peak series. The comparison between peak and off-peak electricity prices (a) uncovers that upward movements are more frequent in the former case, whilst downward shifts in the latter one. This can be connected to the combination of abundant power generated and low demand during nighttime. Furthermore, both price and load series (b) reach higher values during peak hours and lower values during off-peak hours, which mimics the augmented and reduced level of human activity, respectively (Simonsen et al., 2004). With reference to the solar power, plots in (c) mark out that its production is indeed immensely dependent on hours of interest. In contrast, the difference between the peak and off-peak wind power production (d) seems to be inconsiderable, which is most likely attributable to the Czech natural environment.
Source: Author's computations.

4.3 Descriptive statistics

This part complements the previous section in that it provides quantitative information which will be instrumental in the identification of matters requiring a more in-depth treatment.

Descriptive statistics in Table 4.1 uncovers that with a mean value of 37.23 EUR/MWh, the daily price series reached its minimum and maximum values of -19.59 EUR/MWh and 91.80 EUR/MWh, respectively, during the sample period. As expected in the context of smaller demand, the spread between these two values is lower for off-peak prices. Compared to the standard deviation of peak prices which is 13.793, the one of off-peak prices accounts for 10.595, signifying that higher stability is exhibited during the first 8 and last 4 hours of the day, weekends, and holidays. The signs of the skewness coefficients (that would have been zero for symmetric distribution) are positive in case of all variables, meaning that that the tail on the right side of the corresponding distributions is longer than that on the left side. In other words, high extreme values are more probable than low extreme values. In this respect, it is worth noting that the skewness estimate of off-peak prices (0.045) is much lower than for peak prices (1.185). This highlights the regularity learnt through observation in Figure 4.3 that negative values for price series are less likely to occur during the hours between 8:00 and 20:00. The skewness estimate of off-peak solar power generation is rather exceptional (1.754) and also signifies that a larger amount of sunshine emanated over the morning and early evening hours is not an unusual incident. The estimates of kurtosis for price series exceed the value of three representing the kurtosis for a normal distribution, which means that extremely low and high prices are more probable than what is signalised by a normal distribution (Lucia and Schwartz, 2002). After all, large variations are relatively frequent in electricity prices as displayed in Figure 4.1 and Figure 4.3. The values of kurtosis are similar across all indices (4.315, 5.494, and 4.143 for daily, peak, and off-peak indices, respectively).

Table 4.1: Descriptive statistics

Index	Variables	Mean	Min	Max	St. Dev.	Skewness	Kurtosis
Daily	Prices	37.230	-19.590	91.800	12.502	0.287	4.315
	Load	7434	5267	10029	997.842	0.172	2.429
	Solar	254.560	11.210	594.250	154.996	0.121	1.761
	Wind	63.992	1.012	232.625	46.440	1.095	3.663
Peak	Prices	46.720	20.090	123.690	13.793	1.185	5.494
	Load	8587	6613	10950	869.903	0.389	2.268
	Solar	494.090	22.250	1142.330	293.415	0.101	1.765
	Wind	60.250	0.842	227.442	50.331	1.106	3.531
Off-Peak	Prices	33.270	-19.590	68.200	10.595	0.045	4.143
	Load	6949	5267	9262	831.957	0.410	2.354
	Solar	90.320	0.000	586.540	142.713	1.754	4.772
	Wind	66.125	1.012	237.033	45.456	1.097	3.793

Note: There are 1826 observations in case of day and off-peak indices and 1253 observations in case of peak index. Prices are reported in EUR/MWh, while load, solar, and wind power generations in MWh.
Source: Author's computations.

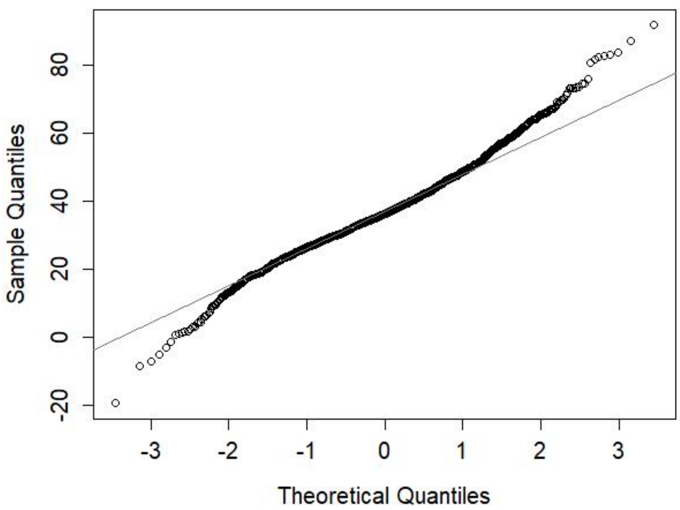
Once more, off-peak solar generation represents an interesting phenomenon in the energy market since its kurtosis estimate of 4.772, far in excess of 3, is more than 2.7 times higher than the respective generation during peak hours. The distribution is leptokurtic (as is also the case for price series across all indices) and more of the variance can be attributed to infrequent extreme deviations contrary to frequent modestly sized deviations (Erdogdu, 2016). When it comes to wind power generation, the differences between the peak and off-peak values of the summary statistics are not critical. As it was mentioned previously, this indicates that wind generation is distributed more or less evenly throughout the day. This can be supported by the fact that the mean of peak wind generation stands for 91.11% of the average of off-peak wind generation and emphasizes the distinct nature of solar and wind power generations when the figure is contrasted with the concluding piece of information in the previous section. Finally, daily load spans from 5267 MWh to 10029 MWh with the mean of 7434 MWh during the sample period. Its excess kurtosis (-0.5712) suggests that it has a platykurtic distribution characterized by short tails (or thinner than a normal distribution). To put it differently, fewer demand shocks, that are frequently connected to short-term changes in temperatures (Lucia and Schwartz, 2002), are present in the load series.

4.4 Data preprocessing

4.4.1 Outliers detection

As we outlined in the preceding chapters, the presence of RES in the electrical power grid is expected to produce extreme prices. The electricity price series plotted in Figure 4.1 and Figure 4.3 indicate that some outliers in the form of large positive and negative spikes could be found in the data. Generally, the analysis of trend, seasonality, and price predictions may be strongly affected by the occurrence of outliers (Benth et al., 2008). Therefore, before estimating parameters in trend and seasonal functions, it is advantageous to remove these outliers. Detecting the possible outliers in data that are not normally distributed is allowed by the statistics presented below. The electricity price series under investigation departs from normal distribution as indicated by the corresponding descriptive statistics in the previous section and shown in Figure 4.4 (this only for daily index). It displays that the empirical or sample quantiles do not coincide with the quantiles of the normal distribution (represented by a line in the plot) at their extremes. The heavy tails of the distribution and mass observations at zero show that electricity prices indeed deviate from normality. It is worth noting that these patterns result from the salient features of electricity prices, along with the possibility of their negative values (Knittel and Roberts, 2005), described in the theoretical background.

Figure 4.4: QQ-plot of electricity prices by daily index



Note: The superimposed transparent line connects the first and third quartile of the data and normally distributed data would appear linear in the plot (Knittel and Roberts, 2005). It is shown that the empirical (or sample) quantiles do not coincide with the theoretical quantiles (that is, those of normal distribution), indicating that the distribution of our electricity price series displays heavy tails. This is linked to the skewness value that is affected by weekly seasonality (Weron, 2006).
Source: Author based on data from OTE.

The ensuing simple statistics pursued by Benth et al. (2008) in their empirical analysis of gas spot prices is used for the detection of outliers. An observation is considered an outlier if it is either smaller than $Q_1 - 3 \times IQR$ or larger than $Q_3 + 3 \times IQR$, where Q_1 and Q_3 are the lower and upper quartiles, respectively, and IQR is the interquartile range defined as the difference between the upper and lower quartiles. Following Benth et al. (2008), the average of the two adjacent observations is substituted for the detected outliers. In the context of unravelling the relationship between RES and electricity prices, such an approach was utilized by Ballester and Furió (2015). After the first round outliers had been treated as described above, the outlier detection was carried out again. The second round captured 2 outliers, suggesting that the pricing mechanism on these days had been particularly non-standard.

4.4.2 Trends and seasonality

Furthermore, as it is was stated in the context of Figure 4.1 and Figure 4.3, strong seasonal cycles are present in our “raw” price series. On that account, the prices would exhibit high correlation across trading blocks even if clustering of power prices did not occur (Guthrie and Videbeck, 2007). We thus intend to guarantee that any high correlation that would be discovered later on is attributed to price clustering and not to some long-run predictable price patterns. These movements arising from intriguing regularities along the time passage are captured by dummy variables using Boolean logic in our case. The reason for the inclusion of dummy variables is that they are more flexible when compared to other cases when the functional form is fixed *a priori* (Lucia and Schwartz, 2002). Therefore, in order to remove as much of the predictable elements in prices as possible and at the same time to conform to the principle of parsimony to avoid overspecification, the following deterministic functions based on Luňáčková et al. (2017) and Pereira da Silva and Horta (2019) are utilized:

$$f_{daily}(t) = \alpha + \sum_{i=2}^{7} \beta_i d_{it} + \gamma h_t + \sum_{j=2}^{4} \delta_j y_{jt} + \zeta t, \tag{4.1}$$

$$f_{off-peak}(t) = \alpha + \sum_{i=2}^{7} \beta_i d_{it} + \gamma h_t + \sum_{j=2}^{4} \delta_j y_{jt} + \zeta t, \tag{4.2}$$

$$f_{peak}(t) = \alpha + \sum_{i=2}^{5} \beta_i d_{it} + \sum_{j=2}^{4} \delta_j y_{jt} + \zeta t, \tag{4.3}$$

where d_{it} is a binary variable that takes the value of 1 on weekday i ($i = 2, \ldots, 7$ for daily and off-peak indices and $i = 2, \ldots, 5$ for peak index) and 0 otherwise, h_t is a dummy variable assuming the value of 1 if holiday falls on date t ($t = 1, \ldots, T$) and 0 otherwise (hence, deterministic function for the peak index does not contain such a parameter), y_{it} is a binary variable that assumes the value of 1 if date t belongs to the j-th month ($j = 2, 3, 4$) and 0 otherwise, and t accounts for a time trend. All coefficients are constant parameters (Lucia and Schwartz, 2002). It is worth noting that linear time trend was used by Weron et al. (2004) in their approximation of the yearly cycle of Nordic spot prices. Similar to Luňáčková et al. (2017), insignificant monthly dummies were discarded based on F-test due to potential overfitting. The same applies to quadratic time trend (see for instance Solibakke, 2002). In our formulation, Monday and year 2015 represent reference variables.

Table 4.2: Determinitic patterns in electricity prices

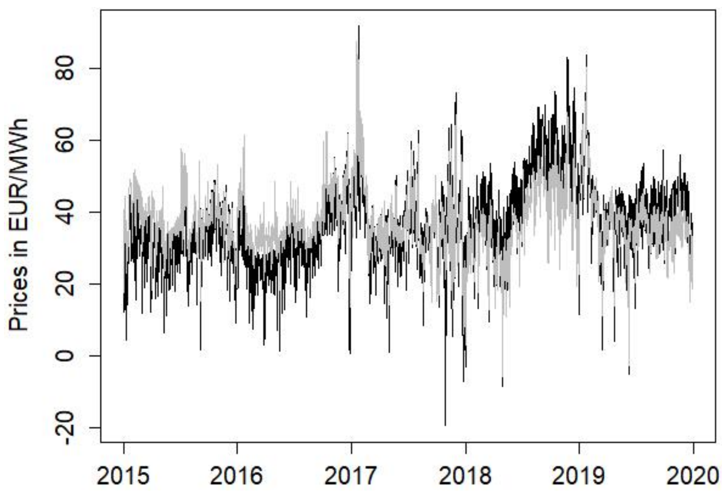
Variables	Daily Index	Peak Index	Off-Peak Index
	coefficient	coefficient	coefficient
Intercept	31.384^{***} (38.253)	36.511^{***} (31.253)	25.940^{***} (35.701)
Tuesday	0.953 (1.164)	−0.101 (−0.095)	1.903^{***} (2.623)
Wednesday	1.50862^{*} (1.840)	0.025 (0.023)	2.331^{***} (3.210)
Thursday	0.850 (1.038)	−1.201 (−1.131)	2.190^{***} (3.018)
Friday	0.505 (0.617)	-1.906^{*} (−1.782)	2.040^{***} (2.813)
Saturday	-7.611^{***} (−9.287)		−1.068 (−1.472)
Sunday	-12.973^{***} (−15.837)		-6.483^{***} (−8.936)
Holiday	-14.134^{***} (−11.921)		-9.455^{***} (−9.005)
Year 2016	-8.797^{***} (−8.559)	-11.114^{***} (−7.054)	-7.599^{***} (−8.348)
Year 2017	-11.030^{***} (−6.603)	-13.083^{***} (−5.109)	-9.462^{***} (−6.396)
Year 2018	-9.198^{***} (−3.861)	-14.726^{***} (−4.036)	-5.519^{***} (−2.616)
Year 2019	-22.642^{***} (−7.266)	-32.048^{***} (−6.715)	-16.749^{***} (−6.069)
Trend	0.021^{***} (10.049)	0.040^{***} (8.590)	0.017^{***} (9.165)

Note: Ordinary least squares (OLS) regression with a time trend and a set of seasonal and annual binary variables implemented to capture the predictable component in the dependent variable, Czech electricity prices that have been corrected for outliers. Monday and the year 2015 are used as base variables. The values in parentheses are t-statistic corresponding to the estimated coefficients. Two-side statistical significance at the 1% level is denoted by '***', at the 5% level by '**', and at the 10% level by '*'.
Source: Author's computations.

The outcome of the deseasonalizing procedure is presented in Table 4.2. It confirms the anticipated development of daily and off-peak prices throughout the week when their values are higher in the beginning and subsequently diminish from Friday, upon reaching their minimum on Sunday that is almost 13 EUR/MWh and 6.5 EUR/MWh less across daily and off-peak indices, respectively. Off-peak prices undergo a similar development over the working days, albeit the coefficients are mostly insignificant. The inclusion of these variables in Equation 4.3 is thus mainly motivated by keeping deterministic functions across indices as similar as possible. Peak prices during Fridays witness relevant price reduction when compared to Mondays (in 2015). In contrast to prices recorded during the first day of the week, the substantial diminution is also observed in case of holidays since daily and off-peak prices are more than

45% and almost 36.5% lower, respectively, during these non-working days. This is perfectly in accordance with our anticipations since these special days are characterized by smaller demand given the closed business operations. The presence of a time trend is detected across all indices. Yearly dummies account for the deviations of the price averages for that particular year from the respective average determined by the time trend, meaning that the corresponding negative coefficients actually do not signify that the price level is lower in years after 2015. Indeed, once the time trend is removed from the analysis, coefficients are positive, underlying the increasing tendency identifiable in Figure 4.1 and Figure 4.3. In line with Ketterer (2012), we ultimately deduct the seasonal and trend component from the original daily price series and add the mean of this original price series to the residuals, i.e. the deseasonalized daily price series. The same is applied to prices across peak and off-peak indices. Last but not least, in order to visualize deseasonalization procedure, the raw and adjusted price series by daily index are plotted in Figure 4.5.

Figure 4.5: Raw and filtered electricity prices by daily index



Note: The black line shows the development of electricity prices that have not been subject to the trend and calendar effects removal (i.e. raw price series). On the other hand, the transparent line illustrates the electricity prices that have been adjusted for daily, holiday, annual, and trend effects (i.e. filtered price series). It is discernible that the deseasonalized prices exhibit less foreseeable patterns than what is true for the unadjusted ones. For instance, notice how the price level during spring and summer of 2016 is greater and during the second half of 2019 lower when compared to the original prices, suggesting that the deterministic function in Equation 4.1 has been successfully implemented.
Source: Author based on data from OTE.

Finally, in agreement with Líšková (2017), the exogenous variables are also subject to trend analysis. Provided that a trend has been detected in the respective time series, it is removed through the similar procedure performed above. As outlined by Wooldridge (2013), detrended time series are accomplished by saving the residuals from a regression of the exogenous variable on a constant and a time trend. The results of such a procedure are displayed in Table 4.3. It follows that load and wind generation across all indices will be detrended due to the significance of the corresponding trend parameters, while solar generation across all indices will be kept in its original state as no trending behaviour is detected in this case.

Table 4.3: Regressions with a time trend

Index	Variables	Intercept	Time trend
Day	Load	7327*** (157.076)	0.118*** (2.666)
	Solar	249.9*** (34.426)	0.005 (0.746)
	Wind	56.714*** (2.166)	0.008*** (3.879)
Peak	Load	8285*** (171.878)	0.4815*** (7.231)
	Solar	479.348*** (28.898)	0.024 (1.026)
	Wind	53.365*** (18.806)	0.011*** (2.801)
Off-Peak	Load	6879*** (176.740)	0.077** (2.089)
	Solar	90.709*** (13.571)	−0.0004 (−0.068)
	Wind	58.538*** (27.625)	0.008*** (4.134)

Note: The rows of Table 4.3 represent the results of regressing the particular variable listed in that row (load, solar generation, and wind generation across all three indices) against a constant and a time trend. Hence, the outcome of nine ordinary least squares (OLS) regressions in total is displayed. Figures in parentheses are t-statistic corresponding to the estimated coefficients. '***' denote two-side statistical significance at the 1% level, and '**' at the 5% level.
Source: Author's computations.

4.5 Test statistics

Ultimately, the selected test statistics is presented in Table 4.4. Firstly, the test of Jarque and Bera (1987) formally proves previous findings of the distributions of our time series as it rejects the null hypothesis of skewness and kurtosis being equal to that of normal distribution in every instance. Furthermore, to be able to perform modelling procedures explained in the following chapter, tests differentiating between unit-root and no-unit processes in the series must be undertaken. If the latter attribute holds, the results may suffer from the problem of spurious regression, signifying that a relationship between two variables is established despite its non-existence, and the impact of past shocks is permanent (Enders, 2014). We thus perform the augmented Dickey-Fuller (ADF) test (Dickey and Fuller, 1979) where the null hypothesis of a unit root is tested against no unit root. Based on Table 4.4, we can reject the null hypothesis in all cases, and thus no unit root process is present in the remaining series across the three indices. In contrast, Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test (Kwiatkowski et al., 1992), where stationarity against non-stationarity is examined, demonstrates that we fail to reject the null hypothesis in every instance at any conventional significance levels, leading us to conclude that the desired property of stationarity is true for all our series. In other words, their levels are integrated of order 0, I(0).

Table 4.4: Selected test statistics

Index	Variables	JB	ADF	KPSS
Daily	Prices	589.71***	−5.919***	0.2955
	Load	34.51***	−3.9613**	0.2126
	Solar	121.21***	−3.0961	0.2095
	Wind	390.48***	−7.9894***	0.1558
Peak	Prices	1021.40***	−4.881***	0.1878
	Load	68.17***	−3.520**	0.1496
	Solar	81.80***	−2.675	0.1766
	Wind	264.87***	−7.461***	0.1558
Off-Peak	Prices	224.74***	−6.227***	0.3354
	Load	83.67***	−3.2295*	0.2223
	Solar	1175.6***	−5.4561***	0.1525
	Wind	407.36***	−7.997***	0.2305

Note: JB stands for the Jarque-Bera test, ADF for the augmented Dickey-Fuller test, and KPSS for Kwiatkowski-Phillips-Schmidt-Shin test. For the latter two tests, R software enables the automated lag selection. '***' denotes the two-side statistical significance at the 1% level, '**' at the at the 5% level, and '*' at the 10% level.
Source: Author's computations.

Chapter 5

Methodology

This chapter presents our econometric approach to assessing the impact of intermittent RES on price level and volatility. The methodology follows the procedure taken by Ketterer (2012) and Kyritsis et al. (2017) but deviates from them by the supplementary inclusion of EGARCH model as proposed by Pereira da Silva and Horta (2019). In total, GARCH models originated in the work of Bollerslev (1986) who proposed a generalization of the ARCH model introduced by Engle (1982) in order to allow for a longer memory and a more flexible structure of lags. As it was noted in Section 2.2, GARCH family models, which formerly developed in finance, have gained an essential role in short-term volatility modelling of energy prices as they are very efficient in incorporating irregular periods of price volatility and tranquility, i.e. inherent features of energy systems (Figueiredo and da Silva, 2019).

5.1 Model

5.1.1 Conditional mean equation

Let p_t, $t = 1, \ldots, T$, represent the electricity spot price. In line with Papaioannou et al. (2018), p_t is treated as a process with a certain degree of correlation from time $t-1$ to time t. Making use of the correlation structure between these two measurements, p_t can be decomposed into the following two components:

$$p_t = y_t + f(t), \tag{5.1}$$

where $f(t)$ is a deterministic function defined in Equation 4.1 if p_t belongs to daily index, in Equation 4.2 if p_t is an off-peak price, or in Equation 4.3 if p_t

is a peak price. The second part, y_t, is a stochastic component that comprises of the information set available at time t and other relevant variables $\boldsymbol{x}_{it}$ (e.g. load or power generations).

A starting point for the derivation of the conditional mean equation represents the mean-reverting pattern of electricity prices. In line with Ketterer (2012), a model that is particular convenient for such a task is the Ornstein-Uhlenbeck process (Uhlenbeck and Ornstein, 1930). As can be seen from the following specification, it is a continuous time model that permits autocorrelation (Knittel and Roberts, 2005):

$$\mathrm{d}p(t) = \kappa[\mu - p(t)]\mathrm{d}t + \sigma \mathrm{d}b(t), \quad p(0) = p_0, \tag{5.2}$$

where $p(t)$ is the electricity price at time t, κ and μ and σ are real constants, and $b(t)$ is a standard Wiener process. The idea related to this formula is that the fluctuations of the price around the equilibrium level or mean, $[\mu - p(t)]$, are only of a transitory nature. From the perspective of power markets, these fluctuations and the resulting price peaks are caused by capacity shortages or power plant outages (Keles et al., 2012). The speed of the reversion is given by κ, and the fact that the price deviations are affected by random perturbations is denoted by σdb_t.

As Knittel and Roberts (2005) point out, Equation 5.2 represents a well-known autoregressive process of order one, AR(1), in continuous time, which can be inferred from its integration:

$$p(t) = \mathrm{e}^{-\kappa t} p_0 + \mu(1 - \mathrm{e}^{-t\kappa}) + \sigma \int_0^t \mathrm{e}^{\kappa(s-t)} \mathrm{d}b(s). \tag{5.3}$$

Due to estimation, however, the Ornstein-Uhlenbeck process will be regarded in a discrete time form with a deseasonalized "version" of prices (see Bierbrauer et al., 2007), in which case we have:

$$y_t = a + \phi_1 y_{t-1} + \eta_t, \tag{5.4}$$

where $y_t = p_t - f(t)$ from Equation 5.1, and η_t is an iid with 0 mean and variance $\sigma_\eta^2 = \sigma^2 \frac{(1-\mathrm{e}^{-2\kappa})}{2}$ (Knittel and Roberts, 2005). The link between the AR(1) parameters in this discretized form in Equation 5.4 and the original parameters in Equation 5.3 is thus given by $a = \mu(1 - \mathrm{e}^{-\kappa})$, $\phi_1 = \mathrm{e}^{-\kappa}$, $\eta_t = \sigma \int_{t-1}^t \mathrm{e}^{\kappa(s-t)} \mathrm{d}b(s)$. Hence, using the approach of Ketterer (2012), the conditional mean equation is specified as:

$$y_t = \mu + \sum_{i=1}^{p} \phi_i y_{t-i} + \boldsymbol{x}_{it}\boldsymbol{\gamma} + \epsilon_t, \tag{5.5}$$

where additional exogenous explanatory variables are allowed in the conditional mean equation through the vector of external regressors $\boldsymbol{x}_{it}$ as we want to explicitly detect the effect of wind and PV generations on the first two moments of electricity prices. $i = 1, 2$, and 3 accounts for the total electricity load l_t, solar power generation s_t, and wind power generation w_t, respectively. The vector $\boldsymbol{\gamma}$ denotes the weights of each variable. Correspondingly, Equation 5.5 represents an AR-X process. In addition to that, y_t consists of a random innovation process ϵ_t for which the identities $\mathbb{E}[\epsilon_t] = 0$ and $\mathbb{E}[\epsilon_{t_1}\epsilon_{t_2}] = 0, t_1 \neq t_2$, are assumed. That is, random disturbances have zero mean and are uncorrelated across adjacent periods. Although disturbances are uncorrelated, it does not imply their independence since successive values are related to each other as follows:

$$\epsilon_t = \sqrt{h_t} z_t, \tag{5.6}$$

where $\sqrt{h_t}$ denotes the conditional standard deviation and z_t is a standardized and independent, identically distributed (iid) random variable with zero mean and unity variance. Note that Equation 5.6 means that ϵ_t rescales an idd sequence z_t with a conditional standard deviation $\sqrt{h_t}$ which incorporates the serial dependence of innovations (Papaioannou et al., 2018). Therefore, a standardized disturbance $\frac{\epsilon_t}{\sqrt{h_t}}$ is also an iid sequence.

5.1.2 Conditional variance equation

The conditional variance of innovations ϵ_t takes the following form:

$$h_t = \mathrm{Var}_{t-1}[y_t] = \mathbb{E}[\epsilon_t^2] - \mathbb{E}[\epsilon_t]^2 = \mathbb{E}[\epsilon_t^2]. \tag{5.7}$$

Proceeding according to Bollerslev (1986) and Papaioannou et al. (2018), ϵ_t denotes a real-valued discrete-time stochastic process and Ψ_t the information set or $\sigma-$field of all of the information up to time $t-1$. The GARCH(m,n) model for conditional variance h_t is then given by

$$\epsilon_t \,|\, \Psi_{t-1} \sim N(0, h_t), \tag{5.8}$$

$$h_t = \omega + \sum_{i=1}^{m} \alpha_i \epsilon_{t-i}^2 + \sum_{j=1}^{n} \beta_j h_{t-j} + \boldsymbol{x}_{it}\boldsymbol{\delta}, \tag{5.9}$$

where ω is long-run variance[1], ϵ_{t-i}^2 the ARCH term and h_{t-j} the GARCH term. The vector $\boldsymbol{x}_{it}$ represents the exogenous covariates presented under Equation 5.5, each of which is weighted by a parameter of the vector $\boldsymbol{\delta}$. Thus, Equation 5.9 is in fact a GARCH-X model. The parameters must meet the following conditions in order to ensure stationarity and positive conditional variance: $\omega > 0$, $\alpha_i \geq 0$ for $i = 1, \ldots, m$, $\beta_j \geq 0$ for $j = 1, \ldots, n$, $\sum_i^n \alpha_i + \sum_j^m \beta_j < 1$, and $\boldsymbol{\delta} \geq 0$ (Neusser, 2016). In general, GARCH models are useful for their ability to accurately capture certain characteristics of volatility. For instance, time series of electricity prices can exhibit volatility clustering, meaning that the periods of high volatility tend to be followed by the periods of volatility of the similar magnitude and vice versa (Tsay, 2010). This persistence is captured by $\beta_j, j = 1, \ldots, n$, as its high value indicates a high dependence of future volatility on past volatility, and similarly, its low value implies a lower carry-over effect of past to future volatility (Papaioannou et al., 2018). The impact of new shocks is reflected by $\alpha_i, i = 1, \ldots, m$.

Despite the fact that any order of the GARCH model is realizable, the stylized facts of prices are satisfied sufficiently within the GARCH(1,1) framework (Shen and Ritter, 2016). Conditioning on Equation 5.8 and determining $m = n = 1$, Equation 5.9 becomes

$$h_t = \omega + \alpha_1 \epsilon_{t-1}^2 + \beta_1 h_{t-1} + \boldsymbol{x}_{it}\boldsymbol{\delta}, \tag{5.10}$$

where $\omega > 0$, $\alpha_1 \geq 0$, $\beta_1 \geq 0$, and $\alpha_1 + \beta_1 < 1$. The latter condition indicates that the unconditional variance of ϵ_t is finite, while its conditional variance h_t develops over time (Tsay, 2010). To put the matter another way, $\alpha_1 + \beta_1$ denotes the time that the volatility needs to shift halfway back to its unconditional mean value, and thus if it is less than one, the mean reverting conditional volatility mechanism occurs (Papaioannou et al., 2018).

Furthermore, although the GARCH(1,1) process is convenient in that its tail distribution is leptokurtic, it is not able to capture the (asymmetric) leverage effect when volatility tends to react differently to positive and negative price shocks (Tsay, 2010). Inspecting the asymmetric impact of innovations is allowed by the exponential GARCH (EGARCH) model of Nelson (1991).

1 More precisely, ω represents the value towards which the variance will converge in the long-run (Ketterer, 2012).

To ensure that the conditional variance of ϵ_t given information Ψ_t at time t remains nonnegative, the EGARCH(m,n) variance equation is suggested:

$$\ln(h_t) = \omega + \sum_{i=1}^{n} \alpha_i \left\{ \frac{|\epsilon_{t-i}|}{h_{t-i}} - \mathbb{E}\left[\frac{|\epsilon_{t-i}|}{h_{t-i}}\right] \right\} + \sum_{i=1}^{n} \lambda_i \frac{\epsilon_{t-i}}{h_{t-i}} + \sum_{j=1}^{n} \beta_j \ln(h_{t-j}) + \boldsymbol{x}_{it}\boldsymbol{\delta}, \tag{5.11}$$

where $\mathbb{E}|z_{t-i}| = \mathbb{E}\left[\frac{|\epsilon_{t-i}|}{\sqrt{h_{t-i}}}\right] = \sqrt{\frac{2}{\pi}}$ for the standard Gaussian random variable $z_{t-i}, i = 1, \ldots, m$, $\mathbb{E}|z_{t-i}| = \mathbb{E}\left[\frac{|\epsilon_{t-i}|}{\sqrt{h_{t-i}}}\right] = \frac{2}{\nu-1}\sqrt{\frac{\nu-2}{\pi}}\frac{\Gamma(\frac{\nu+1}{2})}{\Gamma(\frac{\nu}{2})}$ for the standardized Student-t distribution with degrees of freedom $\nu > 2$, and $\lambda_i, i = 1, \ldots, n$, denotes the leverage term (Tsay, 2010, and Papaioannou et al., 2018).

It follows that the constraints imposed on coefficients of classical GARCH-type models exclude any random oscillatory behaviour in the h_t process since Equation 5.9 and Equation 5.10 imply that increasing ϵ_t^2 in any period increases h_{t+l} for all $l \geq 1$. This means that only the size, not the sign, of lagged residuals explains the conditional variance h_t. However, both the magnitude and the cycling pattern of ϵ_t's is permitted under the EGARCH model since the β_j terms can be either positive or negative (Nelson, 1991). Finally, the usage of the level of standardized value of ϵ_t, i.e. z_t, instead of its squared value is beneficial as standardization provides a more natural interpretation of the size and persistence of shocks (Nelson, 1991).

Setting $m = n = 1$, we obtain the EGARCH(1,1) model of the conditional variance h_t:

$$\ln(h_t) = \omega + \alpha_1 \left[\frac{|\epsilon_{t-1}|}{h_{t-1}} - \sqrt{\frac{2}{\pi}}\right] + \lambda_1 \frac{\epsilon_{t-1}}{h_{t-1}} + \beta_1 \ln(h_{t-1}) + \boldsymbol{x}_{it}\boldsymbol{\delta}, \tag{5.12}$$

where β_1 stands for the persistence in conditional volatility regardless of the events taking place in the market. Hence, if it is relatively large, then volatility dies out more slowly as a result of the shock that has developed there. $\alpha_1\left[\frac{|\epsilon_{t-1}|}{h_{t-1}} - \sqrt{\frac{2}{\pi}}\right]$ accounts for the magnitude or symmetry effect in the context of the GARCH model. α_1 thus reflects to what extent the change in variable z_t deviates from its long-run average (Erdogdu, 2016). Moreover, $\lambda_1\frac{\epsilon_{t-1}}{h_{t-1}}$ indicates the sign effect. That is, λ_1 represents the asymmetry parameter since a positive shock raises variance less than a negative shock if $-1 < \lambda_1 < 0$, and if $0 < \lambda_1 < 1$, unanticipated price increases are more disrupting than price decreases. Provided that there is a leverage effect (the former case), λ_1 must be both statistically significant and negative. On the other hand, statistically significant and positive λ_1 marks the existence of the inverse leverage effect (the latter case). Should $\lambda_1 = 0$, no asymmetric effect of past shocks on current variance exists; the model is symmetric. All of these features justify the substitution of the EGARCH model for the GARCH model in Pereira da Silva and Horta (2019).[2] In our case, the extensions of the classical GARCH will be analyzed mainly due to the robustness check.

Another volatility model proposed by Zakoian (1994) that can be used to manage the leverage effect is the threshold GARCH (TGARCH) model which makes use of the indicator variable that detects the impact of positive shocks or good news (i.e. $\epsilon_{t-i} \geq 0$) and the negative shocks or bad news (i.e. $\epsilon_{t-i} < 0$) evolving in the market.[3] Since Glosten et al. (1993) introduced virtually the same process, the GJR nomenclature for this type of model is also used.

5.2 Model estimation

The maximum likelihood estimation (MLE) for the GARCH(m,n) regression model in Equation 5.9 is described as follows.[4] Continue to perceive that ϵ_t is the error term in the linear equation of the form $\epsilon_t = y_t - \mu - \sum_{i=1}^{p} \phi_i y_{t-i} - \boldsymbol{x}_{it}\boldsymbol{\delta}$ and that it is also given by $\epsilon_t = \sqrt{h_t} z_t$ with $z_t \overset{iid}{\sim} N(0,1)$; see Equation 5.6 and Equation 5.2. Therefore, the distribution of ϵ_t conditional on the information set available at time $t-1$, i.e. Ψ_{t-1}, is normal with conditional variance h_t from Equation 5.9. The conditional density function of ϵ_t is then:

$$f(\epsilon_t \,|\, \Psi_{t-1}) = \frac{1}{\sqrt{2\pi h_t}} \exp\left(\frac{-\epsilon_t^2}{2h_t}\right), \tag{5.13}$$

2 The authors also argue that EGARCH permits price and variance to exhibit a correlation different from zero.

3 In this case, the threshold is 0 as it separates the effects of past shocks.

4 For illustrative purposes, we present the MLE only in the GARCH case. Although the same procedure yields the log-likelihood function for the EGARCH model in Equation 5.11, the result is distinct as a consequence of the different form of the conditional variance h_t.

According to Tsay (2010), the corresponding likelihood function of the GARCH(m, n) model is:

$$
\begin{aligned}
f(\epsilon_1, \dots, \epsilon_T \,|\, \boldsymbol{\theta}) &= f(\epsilon_T \,|\, \Psi_{T-1}) f(\epsilon_{T-1} \,|\, \Psi_{T-2}) \dots f(y_{q+1} \,|\, \Psi_q) f(\epsilon_1, \epsilon_2, \dots, \epsilon_q \,|\, \boldsymbol{\theta}) \\
&= \left[\prod_{t=q+1}^{T} f(\epsilon_t \,|\, \Psi_{t-1}) \right] f(\epsilon_1, \dots, \epsilon_q \,|\, \boldsymbol{\theta}) \\
&= \left[\prod_{t=q+1}^{T} \frac{1}{\sqrt{2\pi h_t}} \exp\left(\frac{-\epsilon_t^2}{2h_t} \right) \right] f(\epsilon_1, \dots, \epsilon_q \,|\, \boldsymbol{\theta}),
\end{aligned}
\tag{5.14}
$$

where $\boldsymbol{\theta}$ consists of the parameters in the conditional mean and conditional variance equations, i.e. $\boldsymbol{\phi} = (\mu, \phi_1, \dots, \phi_p)'$, $\boldsymbol{\alpha} = (\alpha_0, \alpha_1, \dots, \alpha_m)'$, $\boldsymbol{\beta} = (\beta_1, \dots, \beta_n)'$ plus the parameters on additional explanatory variables $\boldsymbol{\gamma}$ and $\boldsymbol{\delta}$. The joint probability density function of $\epsilon_1, \dots, \epsilon_q$, $f(\epsilon_1, \dots, \epsilon_q \,|\, \boldsymbol{\theta})$, deserves a special remark. Since its exact form is complex, it is usually omitted when defining the likelihood function (Tsay, 2010). The resulting form of Equation 5.14 is thus the conditional-likelihood function defined as:

$$
f(\epsilon_{q+1}, \dots, \epsilon_T \,|\, \boldsymbol{\theta}, \epsilon_1, \dots, \epsilon_q) = \prod_{t=q+1}^{T} f(\epsilon_t \,|\, \Psi_{t-1}) = \prod_{t=q+1}^{T} \frac{1}{\sqrt{2\pi h_t}} \exp\left(\frac{-\epsilon_t^2}{2h_t} \right),
\tag{5.15}
$$

where the random variables in Ψ_{t-1} are replaced by their realizations (Neusser, 2016). The value of $\boldsymbol{\theta}$ that maximizes Equation 5.15 is the conditional maximum-likelihood estimate (MLEs) of $\boldsymbol{\theta}$ under normality. Moreover, due to a far easier computation with a sum than with a product, it is more practical to take the natural log of each side of the above equation. It leads to the following log-likelihood function:

$$
\ell(\epsilon_{q+1}, \dots, \epsilon_T \,|\, \boldsymbol{\theta}, \epsilon_1, \dots, \epsilon_q) = -\frac{T}{2} \ln(2\pi) - \frac{1}{2} \sum_{t=q+1}^{T} \ln(h_t) - \frac{1}{2} \sum_{t=q+1}^{T} \frac{\epsilon_t^2}{h_t},
\tag{5.16}
$$

Since the first term does not comprise of any parameters, it is treated as a fixed constant and can be omitted from optimization (Tsay, 2010). The log-likelihood function thus becomes

$$\ell(\epsilon_{q+1}, \ldots, \epsilon_T \,|\, \boldsymbol{\theta}, \epsilon_1, \ldots, \epsilon_q) = -\frac{1}{2} \sum_{t=q+1}^{T} \ln(h_t) - \frac{1}{2} \sum_{t=q+1}^{T} \frac{\epsilon_t^2}{h_t}, \tag{5.17}$$

At this point, recall that $\epsilon_t = y_t - \mu - \sum_{i=1}^{p} \phi_i y_{t-i} - \boldsymbol{x}_{it}\boldsymbol{\gamma}$ and suppose that the conditional variance h_t follows the GARCH(m,n) process defined in Equation 5.9. Substituting these values for ϵ_t and h_t, we can perform the maximization of the log-likelihood function with respect to individual parameters in $\boldsymbol{\theta}$. However, since this optimization yields nonlinear first-order equations, no analytic solutions for a maximum are provided and the whole process has to be done numerically (Weber, 2005). Nonetheless, it is important to stress out that exact solutions for the estimated coefficients cannot be guaranteed by the numerical optimization Enders, 2014). Instead, the so-called "hill-climbing" methods to find the parameter values which maximize log-likelihood functions are employed. In this respect, the conventional Broyden-Fletcher-Goldfarb-Shanno (BFGS) algorithm for numerical maximization can be applied.

Finally, due to the characteristics of some applications, one may also assume that ϵ_t follows a heavy-tailed or skewed distribution (for example, Student-t or skewed Student-t distribution, respectively) or a generalized error distribution (GED). We would then obtain the quasi-maximum likelihood estimator.

5.3 Model selection criteria

For their ability to trade-off a reduction in the sum of squares of the estimated residuals (induced by the increasing number of explanatory variables) for more parsimonious models (Enders, 2014), various model selection criteria will be used in the subsequent chapter. One of the most common ones are the Akaike (1974) Information Criterion (AIC), Schwarz (1978) or Bayesian Information Criterion (SIC), and Hannan and Quinn (1979) Information Criterion (HQC). The corresponding definitions have the ensuing form (Medel, 2013):

$$\text{AIC} = -2\frac{\ell}{T} + 2n\frac{1}{T}, \tag{5.18}$$

$$\text{SIC} = -2\frac{\ell}{T} + n\frac{\log(T)}{T}, \tag{5.19}$$

$$\text{HQC} = -2\frac{\ell}{T} + 2n\frac{\log(T)}{T}, \tag{5.20}$$

where ℓ is the value of the log-likelihood function from Equation 5.17 and n is the number of parameters estimated using T observations. The first factors in the above-presented formulas measure the goodness of fit of the model to the data, while the second components are known as penalty or cost functions of the criteria as they penalize the candidate model based on the number of parameters employed (Tsay, 2010). It follows that since SIC imposes a larger cost on each parameter estimated than AIC, simpler models are selected by SIC rather than by AIC when the sample is of middle or large size (Tsay, 2010). More specifically, as $T \to \infty$, the term $\log(T)$ in Equation 5.19 guarantees that the penalty of incorporating an additional regressor turns out to be large, ruling out the possibility of selecting an overfitted model (Maïnassara and Kokonendji, 2016). For large samples, Hannan and Quinn (1979) proposed their version of information criteria to mitigate the penalty of SIC. Ultimately, the most appropriate model is the one that has the lowest information criteria. In fact, information criteria approach $-\infty$ each time the fit of the model improves (Enders, 2014).

Chapter 6

Empirical analysis and discussion of findings

In this chapter, the empirical analysis itself is carried out. The first section presents the specification of a mean equation and the resulting residuals are subsequently subject to tests for ARCH effects. Section 6.2 provides the results obtained through the modelling technique described in the previous chapter, consisting of a simultaneous estimation of the conditional mean and volatility equation, and executed in R statistical software. The discussion of findings concerning the existing literature on RES position on the electricity markets, particularly the Czech one, is also incorporated into the section. The final part of this chapter presents the approach that would add another layer to our work.

6.1 Preliminary analysis

For all indices, two versions of the mean equation are estimated in order to determine the most appropriate specification that will be extended in Section 6.2 with additional terms. An analogous procedure was applied by Mugele et al. (2005) in their assessment of the electricity price behaviour in German, Nordic and Polish power markets, and by Benhmad and Percebois (2016) who evaluate the effect of wind power on EEX day-ahead prices. Firstly, based on the comments made in the context of Ornstein-Uhlenbeck process in Equation 5.3, we will model the equation with one autoregressive term, i.e. the price from the previous period, and external regressors (model A) in the form of electricity load l_t, solar power generation s_t, and wind power generation w_t. An AR(1) structure also stems from the expectation of volatility persistence with regards to events on the previous day (Pereira da Silva and Horta, 2019). In the second modification (model B), a more dynamic version of the equation will be established by the inclusion of seven lags to reflect the weekly cycles for prices across day and off-peak indices, as is also the case in the analysis of e.g. Ketterer (2012) and Kyritsis et al. (2017). Concerning peak prices, five lags will be incorporated into the model as Saturdays and Sundays are omitted from this classification (see Equation 4.2 and Maciejowska, 2020). The three external regressors from model A are retained.

Several patterns conforming to the theoretical underpinnings presented in the preceding chapters can be detected from Table 6.1. Namely, coefficients on s_t and w_t signalize that the MOE is indeed present in the Czech day-ahead electricity market. In this regard, it is worth noting that solar power generation is, as expected, an insignificant driver of electricity prices when it comes to off-peak index due to weak solar activity. Hence, the positivity of the coefficient on off-peak s_t does not represent any unusual or peculiar outcome. Furthermore, based on the information criteria (which are a case in point as the marginal cost of including additional explanatory variables is truly greater with SIC; see Section 5.3 and Enders, 2014), every model that is favoured across all three indices is the one which incorporates electricity prices lags up to order 7 (and 5), which is in accord with the line of reasoning presented in the previous paragraph where model B was introduced. Not employing AR(1) specification is similar to the procedure taken by Knittel and Roberts (2005) who eventually employ 1, 24, and 25 period lags, accounting for the high correlation between the current price and prices of the preceding day. Incidentally, one can even determine the speed of reversion to the equilibrium level from Table 6.1. This follows from the fact that the coefficient on the autoregressive parameter in model A is equal to (Bierbrauer et al., 2007):

$$\phi = 1 - \kappa, \tag{6.1}$$

where ϕ and κ have the same definition as in the context of Equation 5.4.

At this stage, we want to additionally demonstrate that our final specification of the mean equation is adequate in that the entertained AR model has been successful in removing linear dependence in the price series. This can be accomplished by saving the residuals of model B for daily index (the same procedure applies to the remaining two types of indices) and plotting their autocorrelation function (ACF). ACFs of the residuals from the three models are

Table 6.1: Results of the AR models

	Daily Index		Peak Index		Off-Peak Index	
	A	B	A	B	A	B
Conditional Mean Equation						
μ	41.839*** (1.842)	41.118*** (2.056)	13.866** (5.617)	8.701 (6.018)	24.165*** (2.851)	20.637*** (3.361)
p_{t-1}	0.733*** (0.016)	0.534*** (0.024)	0.688*** (0.021)	0.506*** (0.028)	0.712*** (0.017)	0.519*** (0.024)
p_{t-2}		0.052* (0.027)		0.119*** (0.032)		0.019 (0.027)
p_{t-3}		0.080*** (0.027)		0.080** (0.032)		0.091*** (0.026)
p_{t-4}		0.022 (0.027)		−0.024 (0.032)		0.016 (0.026)
p_{t-5}		0.140*** (0.028)		0.087*** (0.032)		0.067** (0.026)
p_{t-6}		0.005 (0.027)				0.028 (0.027)
p_{t-7}		0.090*** (0.024)				0.131*** (0.024)
l_t	0.0003** (0.0002)	0.0005** (0.0002)	0.005*** (0.0006)	0.005*** (0.0007)	0.002*** (0.0004)	0.003*** (0.0005)
s_t	−0.013*** (0.002)	−0.011*** (0.002)	−0.009*** (0.001)	−0.009*** (0.001)	−0.0002 (0.001)	0.0006 (0.001)
w_t	−0.063*** (0.004)	−0.073*** (0.004)	−0.056*** (0.005)	−0.061*** (0.005)	−0.069*** (0.003)	−0.076*** (0.003)
Various Information Criteria						
AIC	11545	11395	8537	8446	11108	10936
SIC	11578	11461	8568	8497	11141	11002
HQC	11557	11420	8549	8465	11121	10960

Note: The table reports the results of the regression where the dependent variable is the Czech electricity spot price, adjusted for outliers, trend and calendar effects. The mean equation is modelled by means of AR(1)-X, AR(7)-X (this only for daily and off-peak indices), and AR(5)-X processes (this only for peak index) whose outcomes are displayed in columns A and B, respectively. The processes incorporate exogenous variables as additional regressors, i.e. electricity load l_t, solar power generation s_t, and wind power generation w_t. The values in parentheses are standard errors corresponding to the estimated coefficients. AIC stands for Akaike Information Criterion, SIC for Schwarz Information Criterion, and HQC for Hannan-Quinn Information Criterion. Two-side statistical significance at the 1% level is denoted by '***', at the 5% level by '**', and at the 10% level by '*'. The analysed sample spans from 01.01.2015 to 31.12.2019.
Source: Author's computations.

displayed in Figure A.1 in the Appendix which indicates that no significant serial correlations apart from minor ones at lag 7 in case of the daily and peak indices and lag 5 when the peak index is considered. Although some higher lags appear in the plots of ACFs, greater importance is attributed to lower lags (Tsay, 2010), and thus we suggest that the residuals are no longer serially correlated. Quantification of this conclusion is practicable thanks to Ljung and Box (1978) test, where it holds that the Q(I) statistic follows asymptotically a χ^2 distribution with I time lags under the null hypothesis of no serial correlation. The results of this test are presented in Table A.1 in the Appendix, which implies that the residuals are independently distributed across the individual models B of the three indices. Owing to the peak residuals, since the mentioned null hypothesis can be rejected only under the 10% significance level and since the corresponding ACF in Figure A.1 does show extreme lags on no account, we consider the proposed mean specifications for all the indices appropriate. Final remarks evolve around the squared residuals (saved after regressing the models B) whose ACFs are also presented in Figure A.1. They uncover that the squared residuals, particularly residuals from the peak index mean equation specification, are squared dependent as large spikes loom in the plots. To validate such a statement, Engle's (1982) Lagrange multiplier (LM) test for detecting ARCH disturbances is carried out in Table A.1. As the hypothesis of no ARCH effects in the residuals is rejected in every instance, the presence of conditional heteroskedasticity (i.e. variance which is not constant and which is conditioned on the past information) in our time series is formally acknowledged. This leads to the application of the GARCH-class models in the subsequent section.

6.2 Presentation and discussion of results

As it was delineated in the previous section, all models B are reestimated as additional terms enter the regressions due to the significant ACFs of squared residuals. Three variants of the new models, from which the optimal one is also selected based on the information criteria, are proposed. Column C in Table 6.2 for daily index, as well as in the Appendix in Table A.2 for peak index and Table A.3 for off-peak index,[1] exposes the results of the specification where model B is supplemented with the standard GARCH(1,1) component.

1 For the space-saving purpose, the results of the regressions for peak and off-peak indices were placed in the Appendix.

Columns D in the same tables contain the results of the models C that are expanded with external regressors. Specifically, forecasted total load representing the predicted demand profile l_t, foreseen solar power generation s_t, and wind power generation (assumed forecasted) w_t are supplementary explanatory variables in the variance equations of models D. Models E in the above mentioned tables extend models C by employing the EGARCH term with the same independent variables as in columns D. This will ultimately be helpful in verifying the variance stability as EGARCH is invariable under the presence of negative coefficients in a variance equation (see Subsection 5.1.2 and Ketterer, 2012).

Before we proceed with the presentation of outcomes, some notes regarding the ensuing analysis are required. Specifically, the following text describes the empirical estimates of our models for the three indices all at once as we want to preserve the comparative approach of the work. Moreover, the references to the corresponding tables containing the outcomes of our modelling method are dropped in this section in order to maintain the continuity of reading. Therefore, whenever we report the results of daily, peak, and off-peak models, please always consult Table 6.2, Table A.2, and Table A.3, respectively.

6.2.1 Conditional mean equation

In relation to the conditional mean equations, most of the coefficients of the autoregressive component of every single model estimated, especially AR(1) and AR(7) for all and off-peak hours and AR(1) and AR(5) for peak hours, are statistically significant under the 1% significance level. This is attributed to the regularity when current prices are contingent upon the prices on the previous day and upon those of the same day the preceding week (Pham and Lemoine, 2015). Interestingly, the coefficients on the load variable for the daily index models are negative, which goes against the anticipated nature of demand in that its increasing value has an augmenting impact on electricity prices. However, these coefficients are not significant under any conventional significance levels, signifying that the results do not clash with either intuition or literature. Such a statement is underlined by the outcomes of the estimated peak and off-peak mean equations where electricity prices truly rise with higher electricity demand. It is also interesting to point out that the impact is more pronounced during the peak interval (as opposed to the first 8 and last 8 hours of a day). This periodicity is attributable to the fact that the electricity system is tight

Table 6.2: Results of the GARCH models for daily index

	Daily Index		
	C	D	E
Conditional Mean Equation			
μ	44.057*** (23.620)	44.031*** (23.299)	44.570*** (24.351)
p_{t-1}	0.554*** (20.307)	0.553*** (20.201)	0.560*** (26.778)
p_{t-2}	0.022 (0.729)	0.018 (0.593)	0.001 (0.123)
p_{t-3}	0.125*** (4.392)	0.127*** (4.689)	0.127*** (7.981)
p_{t-4}	0.011 (0.397)	0.004 (0.164)	0.005 (0.977)
p_{t-5}	0.099*** (3.731)	0.114*** (4.565)	0.113*** (6.951)
p_{t-6}	−0.008 (−0.299)	0.001 (0.028)	−0.002 (−0.326)
p_{t-7}	0.074*** (3.300)	0.065*** (3.068)	0.064*** (3.779)
l_t	−0.0001 (−0.232)	−0.0001 (−0.265)	−0.0001 (−0.259)
s_t	−0.011*** (−7.434)	−0.011*** (−7.565)	−0.010*** (−7.504)
w_t	−0.066*** (−19.678)	−0.066*** (−19.318)	−0.066*** (−20.673)
Conditional Variance Equation			
ω	2.263*** (5.777)	37.005*** (5.789)	2.262*** (5.785)
ϵ^2_{t-1}	0.204*** (5.380)	0.235*** (7.024)	0.061** (2.124)
h_{t-1}	0.524*** (9.205)	0.379*** (5.533)	0.600*** (8.658)
$\frac{\epsilon_{t-1}}{h_{t-1}}$			0.399*** (9.203)
l_t		−0.003*** (−3.286)	−0.0001** (−2.390)
s_t		−0.020*** (−2.763)	−0.001** (−2.176)
w_t		0.065** (2.184)	0.002** (1.978)
Various Information Criteria			
AIC	6.147	6.126	6.137
SIC	6.190	6.177	6.191
HQC	6.163	6.145	6.157

Note: The table reports the results of the regression where the dependent variable is the Czech electricity spot price, adjusted for outliers, trend, and calendar effects. The conditional mean and variance equations are modelled by means of AR(7)-X-GARCH(1,1), AR(7)-X-GARCH(1,1)-X, and AR(7)-X-EGARCH(1,1)-X processes whose outcomes are displayed in columns C, D, and E, respectively. The processes include exogenous variables as additional regressors, i.e. electricity load l_t, solar power generation s_t, and wind power generation w_t. The values in parentheses are t-statistics corresponding to the estimated coefficients. AIC marks Akaike Information Criterion, SIC Schwarz Information Criterion, and HQC Hannan-Quinn Information Criterion. Two-side statistical significance at the 1% level is denoted by '***', at the 5% level by '**', and at the 10% level by '*'. The analysed sample spans from 01.01.2015 to 31.12.2019.
Source: Author's computations.

during these hours (Kyritsis et al., 2017) and does, in fact, provide empirical evidence for remarks mentioned in relation to hypothesis 2 in Chapter 3.

Furthermore, both coefficients associated with solar and wind power generations are negative and statistically significant at the 1% significance level in every model for daily and peak indices, proving that the MOE indeed plays a non-negligible role in the formation of Czech day-ahead electricity prices. Based on the most adequate models (see the corresponding information criteria) which turned out to be the one presented in column D in case of daily index and column C in case of peak index, we can also provide some numeric terms for the subject matter. More concretely, 10 additional MWs of power that is produced by solar and wind per day decreases, on average, electricity price by 0.11 and 0.66 EUR/MWh, respectively. Regarding peak index, 10 additional MWs of power generated by solar and wind reduces the average electricity price by 0.09 and 0.53 EUR/MWh, respectively. That wind power generation elicits some effect is in contrast with insignificant coefficients on wind in the study of Kouřílek (2019), who investigates to what extent German RES affects Czech day-ahead electricity prices. Nevertheless, our findings concerning the Czech solar MOE are in agreement with the aforesaid work and also with that of Tůma (2015) who assesses the prospects of solar power production in the CZ. This may possibly accentuate the idea of Kouřílek (2019) that the results of Luňáčková et al. (2017) presented in Section 2.3 might have been affected by the choice of the sampling period. Otherwise stated, since the data were collected partially from the times when the CZ was experiencing a prominent accrual in the number of solar installations, their analysis might have detected patterns that can no longer be found on the current Czech electricity market. Having said that, Luňáčková et al. (2017) do inform about the price-dampening effect of RES except solar, mainly that of hydro and wind.

Additionally, the results for off-peak index show that solar power is irrelevant for explaining the price-setting procedure during the night, early morning, and evening times. The finding is in harmony with Table 6.1 from the previous section and is, after all, instinctive since the hours of sunshine are rather limited during the analyzed block of a day. This is naturally not the issue with off-peak wind power production as its effect is greater here than in case of peak index. Noticing that SIC and HQC report the smallest value for the off-peak model in column D, we determine that the respective MOE accounts for 0.68 EUR/MWh (with 10 additional MWs produced by wind). It is worth to note that this inference corresponds to the line of reasoning anteceding hypothesis

3 in Chapter 3. Therefore, provided that wind output rises during off-peak hours, then prices will lessen more than during peak hours for a comparative price accrual in wind power production. According to Rintamäki et al. (2017), such an observation is connected to the greater sensitivity of the supply curves for off-peak hours when compared to the supply curves for peak hours.

6.2.2 Conditional variance equation

Proceeding with the variance equations, let us first discuss the coefficients on the ARCH term ϵ_{t-1}^2 accounting for the impact of new shocks and the coefficients on the GARCH term h_{t-1} that mirror the lasting effect of past shocks. It is important to notify that models C and D across all indices comply with the constraints associated with GARCH models stated under Equation 5.10. This corroborates that our volatility processes are covariance stationary. The same conclusion holds for the EGARCH models in columns E since β_1's, i.e. the coefficients on past shocks (see for example Equation 5.12) are less than 1 in every case (concerning the stationarity condition for EGARCH, consult the work of Zivot, 2009). In this respect, the coefficients associated with the asymmetry element $\frac{\epsilon_{t-1}}{h_{t-1}}$ are positive in columns E for every index, implying that the positive shocks to electricity prices increase the conditional variance more than negative shocks (Knittel and Roberts, 2005). Moreover, guided by Ketterer (2012) who employed EGARCH to investigate the variance stability of standard GARCH models under the presence of negative coefficients in their variance equations, we ultimately can assert that our models are adequate candidates for capturing the time-varying volatility.

The magnitudes of α_1's, i.e. the coefficients explaining the influence of newly emerged shocks, are always discovered to be rather low. They are approximately 0.22 in case of models C and D across all the indices, while those of β_1's are only moderately high; for example, 0.524 for daily index model in column C. Incidentally, since the point estimate of persistence $\alpha+\beta$ is less than one in all our model specifications, it is possible to calculate the time during which the volatility reaches the point that is exactly half-way from its mean value. The following formula from Hadsell (2007) enables such a computation:

$$\frac{\ln(\frac{1}{2})}{\ln(\alpha+\beta)}. \tag{6.2}$$

On that account, the model C for daily index suggests that the half-life of shocks is 2.18 days. For comparison, the same parameter is reported to be 1.33 and 17 days on Greek and Spanish (Iberian) electricity markets, respectively (Papaioannou et al., 2018). Furthermore, it is also worth mentioning that the persistence estimate reaches the highest value in case of peak index (approximately 0.899 for model D), indicating that the innovations arising during peak hours do not fade out sufficiently quickly. Otherwise speaking, there is a high degree of volatility persistence in the process of peak electricity prices (Wang and Wu, 2012).

What is particularly notable is that once additional explanatory variables are incorporated into the variance equations of models C for daily and off-peak indices (i.e. once our selected models D are taken into account), the coefficients on the ARCH terms raises to some extent, while the GARCH coefficients experience a mild downward adaptation. The same findings are reported by Ketterer (2012 who attributes the alteration to the bias stemming from the underspecification issue. In our assessment, it seems to be the case of daily and off-peak models C. Curiously, the model C for peak index does not appear to exhibit bias arising from the exclusion of relevant variables, implying that its coefficients are not misrepresented or skewed, since the fit is not elevated if external regressors are included in its variance equation. Indeed, as it was mentioned earlier, the model in column C is the optimal one for treating conditional heteroskedasticity in peak prices as determined by SIC and HQC. A rather surprising dynamics thus operates during the hours from 8:00 to 20:00 on working days since demand does not play a significant role in the behaviour of electricity price variance throughout this block of a day. Nonetheless, Kouřílek (2019) draws the same conclusions with regard to the function of load in the conditional variance equation. Besides that, some extraordinary conditions are also true for peak wind and solar power generations since neither of these RES stands for the drivers behind the volatility of peak electricity prices. It is informatory to say that the results were re-examined in column E, which yields a similar outcome. The reasons behind the irrelevance of intermittent sources of energy may be due to the low level of installed wind capacity in the CZ (see Table 2.1) and to the surmise adapted from Kyritsis et al. (2017). Namely, the Czech mid-load power plants might be able to accommodate their production to residual demand in an efficient manner since the operators have the knowledge of low changeability associated with solar power production (refer to Figure 4.1 or Figure 4.3). They thus can mitigate any effects of solar feed-in on electricity price volatility. To put it differently, since the largest amount of energy is generated by solar plants during the same hours every day, flexible plants do anticipate these times and treat their production accordingly.

The opposite findings are suggested by columns D for daily and off-peak indices. It is important to point out that these results were also cross-checked by means of the EGARCH estimation in columns E, which confirm that the results do not suffer from any obvious misspecifications. Corresponding to demand in conditional variance equations, daily index load (whose coefficient is significantly different from 0) decreases the volatility of electricity prices, whereas that of off-peak index amplifies it (although here, the coefficient is significant under 5% significance level). The former conclusions are somewhat contrasting with what is instinctively anticipated since more extreme prices in the form of jumps tend to occur during the times of higher demand when the limits of capacities might be reached. This is remarked by Ketterer (2012) who also reports the counterintuitive results of this for one of her model variants. Along the same lines, all of the outcomes of univariate GARCH-M base, peak, and off-peak models of Kyritsis et al. (2017), which are thoroughly described in Section 2.2, indicate that total electricity load decreases the volatility of electricity prices. In this case, that our findings are different for off-peak load may be ascribed to the disparate market dynamics in Germany.

Another remarkable feature is linked to the solar power generation whose coefficient is statistically significant under at least 5% significance level in case of both daily and off-peak indices but whose sign is dissimilar across the two blocks of a day. The results are robust to different versions of the models as can be discerned from the columns E and columns D. More specifically, the integration of additional MW of solar power brings about a reduction in the variance of daily prices. The coefficient is equal to -0.020. This finding represents the empirical evidence for hypothesis 2, thereby the reasoning introduced for motivating the formulation of this hypothesis is formally proven. Nonetheless, solar feed-in during off-peak hours elevates electricity price variance. Taking into account weak solar radiance over early morning and evening hours, the result is rather interesting but not unusual. For instance, see Kyritsis et al. (2017) whose off-peak solar power generation is also unimportant when it comes to the effect of RES on the level of prices but is significant provided that the center of the analysis is price volatility. It should be noted that the outcome of our off-peak model C does not contradict that of Kouřílek (2019) as the author omits solar variable from the assessment of off-peak prices altogether. What may, however, also play a role in this matter (and in the matter of values of off-peak solar skewness and kurtosis in Section 4.3) is the fact that off-peak index additionally encompasses the whole non-working days.

Last but not least, coefficients on wind outputs in the daily and off-peak variance equations in columns D and columns E are positive and their significance operates under the 5% and 10% significance levels, respectively. This is relatively astonishing given the smaller number of wind farms in the CZ as can be inferred from Table 2.1. Yet, what is not startling is the nonnegativity of the related coefficients. The corresponding values are 0.065 and 0.116 for daily and off-peak indices, respectively, suggesting that the wind intermittency transmits into the price development in the form of abundant price spikes. This underlines the relevance of discussion around hypothesis 3 in Chapter 3 and at the same time emphasizes the importance of future hedging against price risk in the Czech spot market as the integration of RES will be rising in connection to the EU target outlined in Chapter 1.

Before closing this subsection, we remark that models in columns D and E for daily index were reestimated with new external regressors in the form of solar and wind power penetration ratios, i.e. the respective renewable source divided by load. These new variables were defined based on Jónsson et al. (2010), who investigate the impact of day-ahead wind power forecasts on electricity spot prices in Denmark. They argue that once we include the forecasts of wind power as the proportional contribution to meeting the total electricity demand in place of the absolute contribution in the regressions, more accurate results will be obtained. The idea behind this is outlined in Section 4.1, where we assert that load puts RES in perspective in that the same quantity of energy produced has a distinct impact on prices during the times of high and low electricity demand. More concretely, demand reaches the highest values during peak hours, meaning that a large volume of wind energy generated during this interval of a day will constitute a smaller share of total demand than the same quantity would during nighttime (Jónsson et al., 2010). On that account, only daily index models were subject to further analysis since peak and off-peak indices implicitly assume high and low levels of electricity demand, respectively. In line with the literature (for example, Pereira da Silva and Horta, 2019), the coefficients are now higher. This is understandable since solar and wind power generation must increase considerably if the shares are to be augmented by 1%. In the spirit of Ketterer (2012), this is connected to the ensuing argumentation. The average values of load, solar, and wind accounts for 7434, 254.560, and 63.992 MWh per day (see Table 4.1), in the order given. The mean solar and wind penetration ratios are thus 3.424% and 0.861%. In order to reach 4.424% (1.861%), solar (wind) power generation needs to increase its original mean value by 74.346 (74.323) or by 29.206% (116.144%). Furthermore, the significance of new coefficients remains the same as in columns D and E except for solar which is insignificant in the variance equation of the EGARCH model. Information criteria, however, still prefer our initial specifications. Consequently, we do not present the results of these models in the current work but they are available upon request.

6.2.3 Standardized residual diagnostics

The standardized residuals, i.e. $\hat{z}_t = \frac{\epsilon_t}{\sqrt{h_t}}$ (for theoretical background, please refer to the discussion concerning Equation 5.6 in the preceding chapter), and standardized squared residuals, i.e. $\hat{z}_t^2 = \frac{\epsilon_t^2}{h_t}$, from the selected models are subsequently examined through the lens of the Ljung-Box test. The lag length employed in the testing procedure was chosen with regards to Efimova and Serletis (2014) and Kyritsis et al. (2017) who analyze electricity price volatility with similar GARCH models. The results are reported in Table A.4 in the Appendix and imply that the null hypothesis of no serial correlation can be rejected under the 10% singificance level for daily and off-peak residuals and under the 5% significance level for peak residuals, which corresponds to the findings of the two studies mentioned above. In order to observe the autocorrelations, we also plot the ACFs (see Figure A.2 in the Appendix) of standardized residuals of all the preferred models. On the basis of these plots, we can, nevertheless, observe that only very little autocorrelation, if any in case of daily index, is exhibited by the residuals of interest. Furthermore, no patterns attributed to seasonality can be tracked down in Figure A.2. All of this leads us to conclude that our conditional mean equations from models D for daily and off-peak indices and from model C for peak index are correctly specified.

Moreover, being cognizant of the fact that any successful GARCH model is the one whose squared standardized residuals do not exhibit dependence on each other (Papaioannou et al., 2018), we also perform McLeod and Li (1983) test for squared residual autocorrelation, which is presented in Table A.4. In relation to the corresponding Q^2 test statistics reported for 30 lags as well that are statistically nonsignificant at any conventional significant level, we claim that the null hypothesis of independently distributed data is not rejected in any case of any index. That is to say, the squared residuals from our models are not serially correlated up to order 30, signifying that the models are able to capture volatility clustering in the original electricity price series correctly (Papaioannou et al., 2018). In a similar vein, the ARCH-LM test in Table A.4 confirms that no ARCH effects are present in the standardized squared residuals. These results are cross-checked by way of plotting the ACFs of standardized squared residuals (in Figure A.2) which do not imply that any conditional heteroskedasticity is looming in the residuals either. Therefore, conditional variance equations used in this work are adequate. Eventually, in the spirit of Solibakke (2002), we can thus state that AR(7)-X-GARCH(1,1)-X models concerning the daily and off-peak indices and AR(5)-X-GARCH(1,1) model pertaining to the peak index do not suffer from misspecification. In other terms, they are appropriate for describing the electricity price dynamics as they have survived the utilized specification tests.

6.3 Special remarks

An interesting direction for future work lies in taking into consideration the nature of the electric power transmission network in Central Europe. More specifically, the interested researcher may evaluate the effect of market coupling (for details refer to Section 2.2) on the sensitivity of the level and volatility of prices to changes in the output of wind and solar generations. One potential avenue for assessing this topic would be the inclusion of a binary variable that would assume the value of 1 after September 11, 2012 (including), when Czech-Slovak-Hungarian market coupling took place (HUPX, 2020), and 0 otherwise. Analogously, the Czech conditions after November 19, 2014, the date the operation of this formation was extended to the Romanian day-ahead market (HUPX, 2020), could be investigated. The method employed by Pereira da Silva and Horta (2019), however, cannot be reproduced for the case of Czech and Slovak market coupling as it was carried out on September 1, 2009 (CEER, 2010), and not all of the necessary datasets are available for these times. Alternatively, it is possible to employ a proxy variable for market coupling in the form of the price differential between the respective countries, i.e. the spread (Benhmad and Percebois, 2016).

Another method for detecting the effect of the integration of electricity markets is offered by Ketterer (2012). The author assesses whether the curtailment of price variance after 2010 in Germany was caused by the better interconnection between this country and the Northern region, and not by the regulatory change (see Section 2.2). In order to resolve such a matter, she includes the so-called available transfer capacity (ATC) as an explanatory variable into the model. ATC is a feature of an interconnector, representing the maximum available amount of power that can be delivered in the interconnector's direction (NEMO Committee, 2018) and that is not yet allocated, making it useful for exporting excess wind production (Ketterer, 2012). Since data on this variable is limited for the Czech-German cross-border, our work neglects it. We attempted to remedy this issue by calculating ATC with ENTSO-E data for the bidding zone of Germany-Luxembourg-Austria. However, given the division of the common bidding zone into the German-Luxembourgish and Austrian ones on October 1, 2018 (ECC, 2018), a consistent dataset would not be acquired. Furthermore, although the figures regarding the electricity trade flows are at our disposal, they were not integrated into the analysis due to the problem of endogeneity as these flows represent an outcome variable (Ketterer, 2012).

Chapter 7

Conclusion

This thesis investigates the impact of variable RES generation on spot day-ahead electricity prices in the CZ between 2015 and 2019. One of the reasons behind the assessment is the so-called "Winter Package", the legislative act of the European Commission known also as "Clean and Secure Energy for All Europeans", that marks out the objectives necessary to establish a more sustainable energy system in Europe (Ringel and Knodt, 2018). On the EU level, RES should cover 32% of gross final consumption by 2030, while the individual member states shall cover 10% to 49% of gross final consumption with renewables (no national obligatory objectives for the member states were defined) in order to ensure this target (Gilardoni, 2020). The state of affairs on the Czech day-ahead electricity market is examined through the family of univariate GARCH models that are convenient for such an analysis due to their ability to successfully capture the dynamics of volatility (Wang and Wu, 2012) and most importantly because they allow simultaneous estimation of mean and variance equations.

Using the standard GARCH and EGARCH models, we capture the price-dampening impact of solar and wind power generations on Czech day-ahead electricity prices, meaning that our hypothesis 1 from Chapter 3, which lies on the outcomes of the studies on the same theme in that low marginal cost RES generation when dispatched into the electricity system decreases electricity prices, is empirically proven. In other words, the MOE plays its part in the price formation on the Czech day-ahead electricity market. Concerning the volatility of the analyzed price series that is hypothesized to be lessened due to solar feed-in and augmented as a result of wind feed-in, we can conclude that the corresponding hypotheses 2 and 3 (also from Chapter 3) are formally acknowledged. The most striking feature in this respect is the statistically significant (under the 5% significance level) Czech wind power generation in our conditional variance equations, which has not yet been tracked, to the best of our knowledge. Furthermore, as EGARCH models are incorporated into the analysis, we can claim that once some unanticipated price increases emerge on the Czech electricity market, they will have a more disrupting effect than when some unexpected price decreases come up to the surface.

The novelty of our work is twofold. Firstly, no preceding works in the context of Czech electricity prices employed univariate GARCH models (including the exponential one) from the seminal studies of Ketterer (2012) and Kyritsis et al. (2017). Of course, Tůma (2015) works with autoregressive moving average GARCH (ARMA-GARCH) models; nevertheless, the usage of the system imbalance as a dependent variable and the inclusion of time dummies into the equations of the respective models accounts for different interpretations and modelling procedure. Secondly, the present thesis seeks to discover how the price behaviour varies when it comes to the different levels of demand, for which the proxy variable load is utilized. On that account, following the approach of Maciejowska (2020), we created daily, peak, and off-peak indices of the respective price series. It is important to point out that peak index encompasses observations from working days between 8:00 and 20:00, while off-peak index covers observations from first 8 and last 8 hours (this is disparate on 1 day in March and 1 day in October due to daylight saving time) on working days and all 24 hours on weekends and holidays. In this case, the findings stemming from the assessment suggest that volatility of peak prices is not influenced by either solar or wind power generation, whilst that of off-peak prices is heightened by both of the intermittent renewable sources.

The results of our study can be of use to practitioners and participants on the Czech day-ahead electricity market as they elucidate how sensitive the level and changeability of electricity prices are in relation to the composition of RES power generation. More specifically, these pieces of information are particularly desirable for generators who may employ them when bidding at a power exchange or assessing the possible competition from other suppliers and the prospective opportunities connected to servicing customers in various locations of the country (Higgs and Worthington, 2010). The knowledge of price dynamics under the current RES regime is also an important input for policymakers who evaluate the functioning of existing systems with regards to policy objectives and who determine the targets of their schemes out of consideration for optimal generation mix, and thus for the potential reduction of uncertainty. The findings are therefore also beneficial to large energy consumers who are involved in hedging strategies and can specify electricity derivatives' financial worth based on the evaluation of volatility. Moreover, since the intermittency of RES generation can propagate towards the intraday market (Ballester and Furió, 2015), it would also be convenient to analyse the effect of sustainable generation on markets besides the day-ahead one.

Apart from this suggested extension of the present work and the proposed future exploration of the effects of market coupling on price development in the CZ described in the previous chapter, it would be interesting to study the distribution of Czech prices for different intervals of solar and wind power penetration. To execute this issue, one can refer to Kyritsis et al. (2017). Furthermore, the methodology used in this work can be expanded with jumps. The channel for this investigation is offered by Escribano et al. (2011) who also allow GARCH models to detect the impact of non-constant volatility on price spikes as these two elements are more of the complements rather than substitutes when it comes to modelling electricity prices. Other particularly appealing models are proposed by Bollerslev and Ghysels (1996), whose periodic GARCH (P-GARCH) models are able to capture the recurrent seasonal shifts in the second-order moments, and by Rintamäki et al. (2017), who apply seasonally adjusted ARMA model (SARMA). Another remarkable research area revolves around the inspection of the role of the geographic diversification or the spatial aggregation in the process of reduction of the MOE on prices. This would unravel how the value of a solar or wind resource correlates with other existing RES resources (Forrest and MacGill, 2013) and how efficient it is from the economic, rather than from the physical, point of view (Boccard, 2009).

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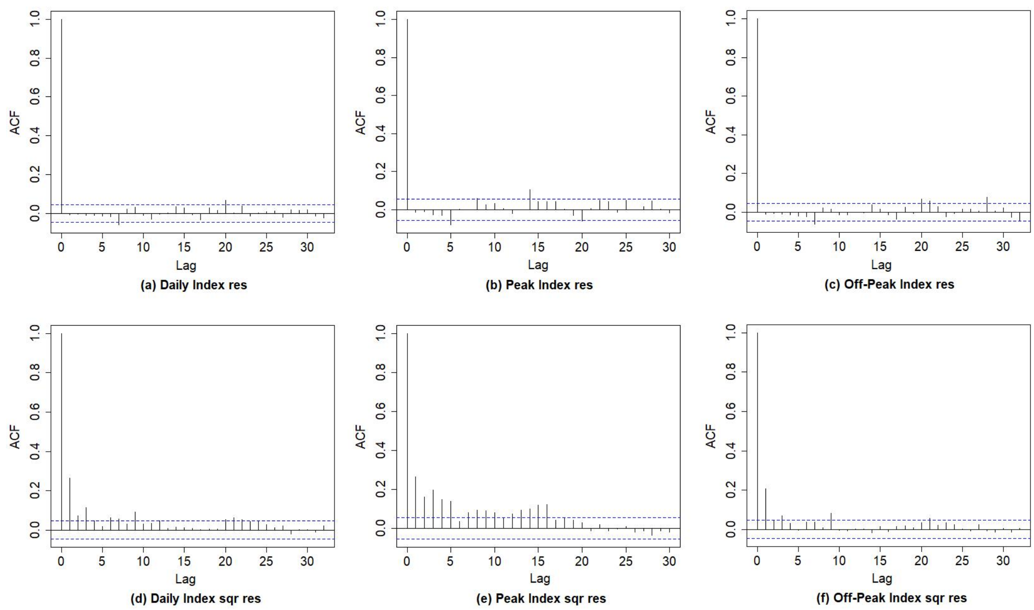
Appendix

Figure A.1: ACFs of the residuals from the AR models



Note: (a) autocorrelation function (ACF) of the residuals of the AR(7)-X model for daily index, (b) ACF of the residuals of the AR(5)-X model for peak index, (c) ACF of the residuals of the AR(7)-X model for off-peak index, (d) ACF of the squared (sqr) residuals of the AR(7)-X model for daily index, (e) ACF of the sqr residuals of the AR(5)-X model for peak index, and (f) ACF of the sqr residuals of the AR(7)-X model for off-peak index. The horizontal dashed lines represent two standard error limits of the ACF.
Source: Author's computations.

Table A.1: Diagnostics of the residuals from the AR models

Index	Residuals	Q(I)	ARCH-LM
Daily	Levels	7.937	
	Squares		58.327***
Peak	Levels	10.220*	
	Squares		19.328***
Off-Peak	Levels	9.441	
	Squares		14.005**

Note: Q(I) represents the Ljung-Box test statistic for the residuals of AR(7)-X (for daily and off-peak indices) and AR(5)-X (for peak index) models. I in parentheses signifies the order of autocorrelation we seek to examine (i.e. 7 in case of daily and off-peak indices, and 5 in case of peak index). ARCH-LM denotes the Lagrange multiplier test, where the lag order was chosen uniformly with that of the Ljung-Box test. Regarding the asterisks, '***' denotes the two-side statistical significance at the 1% level, '**' at the 5% level, and '*' at the 10% level.
Source: Author's computations.

Table A.2: Results of the GARCH models for peak index

	Peak Index		
	C	D	E
Conditional Mean Equation			
μ	6.982 (1.213)	8.238 (1.372)	13.069*** (7.656)
p_{t-1}	0.473*** (14.671)	0.475*** (14.617)	0.476*** (16.360)
p_{t-2}	0.125*** (3.562)	0.124*** (3.532)	0.128*** (6.809)
p_{t-3}	0.116*** (3.350)	0.115*** (3.307)	0.109*** (5.792)
p_{t-4}	0.049 (1.465)	0.047 (1.395)	0.041*** (2.720)
p_{t-5}	0.120*** (4.143)	0.120*** (4.108)	0.117*** (7.205)
l_t	0.005*** (8.369)	0.005*** (7.724)	0.005*** (22.899)
s_t	−0.009*** (−8.654)	−0.009*** (−8.576)	−0.008*** (−10.763)
w_t	−0.053*** (−14.267)	−0.053*** (−14.010)	−0.052*** (−16.290)
Conditional Variance Equation			
ω	5.317** (4.066)	15.367* (1.824)	0.537** (2.560)
ϵ^2_{t-1}	0.224*** (5.167)	0.221*** (4.898)	0.120*** (4.084)
h_{t-1}	0.678*** (12.386)	0.678*** (11.012)	0.908*** (25.557)
$\frac{\epsilon_{t-1}}{h_{t-1}}$			0.274** (2.457)
l_t		−0.001 (−1.127)	−0.00002 (−0.923)
s_t		−0.003 (−1.242)	−0.0001 (−1.318)
w_t		0.002 (0.093)	−0.0001 (−0.381)
Various Information Criteria			
AIC	6.565	6.569	6.552
SIC	6.614	6.630	6.617
HQC	6.576	6.592	6.584

Note: The table reports the results of the regression where the dependent variable is the Czech electricity spot price, adjusted for outliers, trend and calendar effects. The conditional mean and variance equations are modelled by means of AR(5)-X-GARCH(1,1), AR(5)-X-GARCH(1,1)-X, and AR(5)-X-EGARCH(1,1)-X processes whose outcomes are displayed in columns C, D, and E, respectively. The processes include exogenous variables as additional regressors, i.e. electricity load l_t, solar power generation s_t, and wind power generation w_t. The values in parentheses are t-statistics corresponding to the estimated coefficients. AIC marks Akaike Information Criterion, SIC Schwarz Information Criterion, and HQC Hannan-Quinn Information Criterion. Two-side statistical significance at the 1% level is denoted by '***', at the 5% level by '**', and at the 10% level by '*'. The analysed sample spans from 01.01.2015 to 31.12.2019.
Source: Author's computations.

Table A.3: Results of the GARCH models for off-peak index

	Off-Peak Index		
	C	D	E
Conditional Mean Equation			
μ	24.566*** (7.366)	27.311*** (8.415)	25.820*** (12.580)
p_{t-1}	0.599*** (21.078)	0.589*** (21.173)	0.585*** (24.193)
p_{t-2}	−0.044 (−1.371)	−0.023 (−0.785)	−0.013 (−0.894)
p_{t-3}	0.122*** (4.105)	0.128*** (4.962)	0.131*** (7.046)
p_{t-4}	0.024 (0.860)	0.017 (0.695)	0.010 (0.785)
p_{t-5}	0.058** (2.194)	0.061*** (2.584)	0.072*** (4.304)
p_{t-6}	0.022 (0.837)	0.024 (0.997)	0.022 (1.415)
p_{t-7}	0.110*** (4.793)	0.096*** (4.497)	0.093*** (5.013)
l_t	0.002*** (4.063)	0.001*** (3.145)	0.002*** (5.833)
s_t	−0.0001 (−0.049)	−0.0004 (−0.371)	−0.0001 (−0.389)
w_t	−0.067*** (−20.460)	−0.068*** (−20.787)	−0.066*** (−21.369)
Conditional Variance Equation			
ω	7.042*** (3.687)	6.784 (1.249)	0.699** (2.439)
ϵ^2_{t-1}	0.213*** (5.056)	0.218*** (6.170)	0.023 (0.707)
h_{t-1}	0.491*** (4.485)	0.216*** (3.688)	0.421*** (6.312)
$\frac{\epsilon_{t-1}}{h_{t-1}}$			0.452*** (8.984)
l_t		0.0003** (2.547)	0.0001* (1.914)
s_t		0.033*** (5.838)	0.002*** (7.506)
w_t		0.116* (7.094)	0.006*** (7.319)
Various Information Criteria			
AIC	5.914	5.840	5.838
SIC	5.956	5.891	5.893
HQC	5.929	5.858	5.859

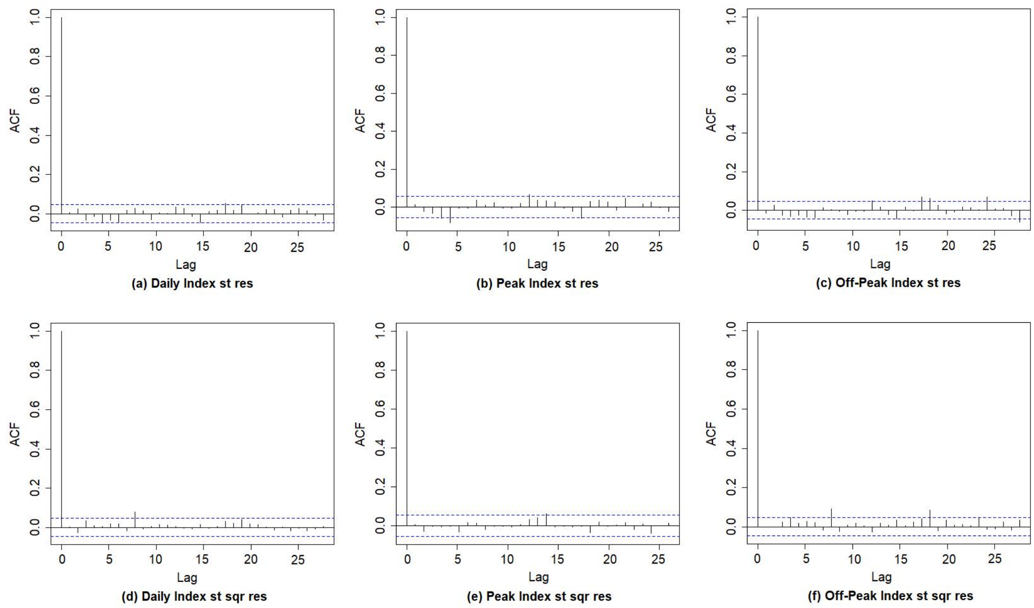
Note: The table reports the results of the regression where the dependent variable is the Czech electricity spot price, adjusted for outliers, trend and calendar effects. The conditional mean and variance equations are modelled by means of AR(7)-X-GARCH(1,1), AR(7)-X-GARCH(1,1)-X, and AR(7)-X-EGARCH(1,1)-X processes whose outcomes are displayed in columns C, D, and E, respectively. The processes include exogenous regressors as additional explanatory variables, i.e. electricity load l_t, solar power generation s_t, and wind power generation w_t. The values in parentheses are t-statistics corresponding to the estimated coefficients. AIC marks Akaike Information Criterion, SIC Schwarz Information Criterion, and HQC Hannan-Quinn Information Criterion. Two-side statistical significance at the 1% level is denoted by '***', at the 5% level by '**', and at the 10% level by '*'. The analysed sample spans from 01.01.2015 to 31.12.2019.
Source: Author's computations.

Table A.4: Diagnostics of the standardized residuals from the GARCH models

Index	Residuals	Q(30)	$Q^2(30)$	ARCH-LM
Daily	Levels	39.535*		
	Squares		26.547	8.854
Peak	Levels	42.754**		
	Squares		17.561	7.383
Off-Peak	Levels	40.865*		
	Squares		27.750	24.884

Note: Q(30) represents the Ljung-Box test statistic for the standardized residuals of AR(7)-X-GARCH(1,1)-X (for daily and off-peak indices) and AR(5)-X-GARCH(1,1) (for peak index) models. Analogous interpretation holds for the $Q^2(30)$ statistic of the McLeod-Li test for the standardized squared residuals. The number in parentheses signifies the order of autocorrelation we seek to examine and was chosen based on the studies of Efimova and Serletis (2014) and Kyritsis et al. (2017). ARCH-LM denotes the Lagrange multiplier test, where the lag order was chosen uniformly with that of the Ljung-Box test. Regarding the asterisks, '***' denotes the two-side statistical significance at the 1% level, '**' at the 5% level, and '*' at the 10% level.
Source: Author's computations.

Figure A.2: ACFs of the standardized residuals from the GARCH models



Note: (a) autocorrelation function (ACF) of the standardized (st) residuals of the AR(7)-X-GARCH(1,1)-X model for daily index, (b) ACF of the st residuals of the AR(5)-X-GARCH(1,1) model for peak index, (c) ACF of the st residuals of the AR(7)-X-GARCH(1,1)-X model for off-peak index, (d) ACF of the st squared (sqr) residuals of the AR(7)-X-GARCH(1,1)-X model for daily index, (e) ACF of the st sqr residuals of the AR(5)-X-GARCH(1,1) model for peak index, and (f) ACF of the st sqr of the AR(7)-X-GARCH(1,1)-X model for off-peak index. The horizontal dashed lines represent two standard error limits of the ACF.
Source: Author's computations.