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Impact of Czech intraday market on the electricity prices

Bachelor thesis

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Abstract

We analyse Czech intraday market for electricity and its impact on day-ahead prices. We inspect effect of fundamental drivers of price deviation between intraday and day-ahead market in form of positive and negative forecast errors and examine intraday price's role in explaining next trading period's day-ahead price. Our findings suggest photovoltaic and load forecast errors to be most statistically significant fundamental factors, together with autoregressive term and day-ahead price, determining intraday market price deviation from day-ahead. Variables' influences on intraday market are in accordance with hypothesised expectations, except for the effect of export and excessive import of electricity to and from German TSO, 50 Hertz, and extreme day-ahead prices. We confirmed symmetric effects of forecast errors on intraday price for all observed variables. In the second part, intraday prices are found to be statistically significant factor affecting next day's day-ahead market price. The results support the conclusion that Czech spot market for electricity possesses mean-reverting properties.

Keywords

electricity, intraday market for electricity, price modeling

Abstrakt

Analyzovali sme český vnútrodenný trh pre elektrickú energiu a jeho vplyv na ceny na dennom trhu. Preskúmali sme efekt fundamentálnych faktorov cenovej odchýlky vnútrodenného a denného trhu vo forme kladnej a zápornej chyby v ich predpovedi a otestovali sme úlohu vnútrodennej ceny pri vysvetľovaní ceny na dennom trhu v nasledujúcom obchodujúcom období. Výsledky analýzy ukazujú, že chyby v predpovedi fotovoltaickej výroby a zaťaženia siete sú najsignifikantnejšími fundamentálnymi faktormi, spolu s autoregresívnym členom a cenou na dennom trhu, určujúcimi cenovú odchýlku vnútrodenného a denného trhu. Efekty pozorovaných premenných na vnútrodenný trh sú v súlade s predpokladanými očakávaniami, s výnimkou efektu vývozu a nadmerného dovozu elektriny zo strany nemeckého prevádzkovateľa prenosovej sústavy, 50 Hertz, a efektu extrémnych cien na dennom trhu. Potvrdili sme symetrický efekt chýb v predpovedi na vnútrodenné ceny pre všetky pozorované premenné. V druhej časti analýzy boli vnútrodenné ceny identifikované ako štatisticky dôležitý prvok ovplyvňujúci cenu denného trhu na nasledujúci deň. Výsledky podporujú záver, že ceny na českom krátkodobom trhu pre elektrinu sa približujú k ich strednej hodnote.

Kľúčové slová

elektrická energia, vnútrodenný trh pre elektrickú energiu, modelovanie ceny

Declaration of Authorship

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

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Prague, 31 July 2017

Signature

Acknowledgment

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The Bachelor Thesis Proposal

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Proposed topic	Impact of Czech intraday market on the electricity price

Research question and motivation

Nature of the electricity makes it rather specific commodity. It cannot be stocked, thus supply must equal demand at any time. Historically this was mostly achieved by trading electricity on day-ahead market where trading takes place 12 – 36 hours before the actual power delivery. Substantial changes in sources of electric power across the Europe and considerable shift towards the renewable sources which are unpredictable by nature caused significantly increased short-term volatility in prices and more frequent occurrence of imbalances in futures and day-ahead contracts and actual volume of electricity in the grid. This situation drives electricity market participants' want and need to trade electricity closer to the time of delivery in real time. Consequently, the intraday market, which allows market participants to trade the electric power until one hour before delivery, is becoming more important in balancing supply and demand in the power market. The research question of the thesis will be therefore focused on which determinants play most important role on Czech intraday market and how intraday market influences trading prices at day-ahead market.

Contribution

The main contribution of my thesis will consist in answering the question whether the emerging intraday market in Czech Republic influences other market for electricity and succeeds in supplementing the day-ahead market by offsetting forecast errors and imbalances between day-ahead contracts and produced volume of electricity. Small research has been conducted on German electricity market, yet there is no study focused on Czech market. Results of potential intercorrelation of spot power markets might bring some thought-provoking implications. Secondly, analysis will be conducted to examine price formation on Czech intraday market, more specifically, what extent of intraday price can be explained by fundamental determinants such as renewable generation and what is the role of day-ahead price.

Methodology

Because of autoregressive properties of electricity spot prices, autoregressive time series model will be used in both part of the analysis. Hypotheses for forecast errors of fundamental determinants will be elaborated based on theoretical background and tested in intraday price regression. Renewables will be assumed to play most significant role affecting deviation of intraday prices from day-ahead's. Regression of day-ahead prices on lagged intraday prices will then reveal their explanatory power in Czech electricity spot market. Adjustment for seasonality, peak and off-peak hours and trend will be performed throughout analysis. Data will be gathered primarily from OTE, ČEPS, ENTSOE and EEX.

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1. Abstract
2. Introduction
3. Literature review
4. Czech power market
5. Data
6. Methodology and Hypotheses
7. Results and Discussion
8. Conclusion

Relevant literature

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1 Introduction

In recent decades, power markets have experienced two major momentous points. First, with liberalization of power markets, electricity has become tradable commodity on various markets. Unlike other commodities, nature of electricity makes it rather specific product to trade. Due to current lack of technology capable of efficient storage of electricity, there must be an omnipresent balance between produced and consumed electric power. As a consequence, demand for electricity has to equal supply at any time. Another characteristic feature of electricity market is price-inelastic demand, with perfectly inelastic demand in short run. These particularities of electricity resulted in complex wholesale market and trading systems.

Second significant moment in development of power markets was extensive implementation of intermittent renewable energy sources (RES), i.e. wind and solar generation units. Since we focus on Czech power market and there is no concentrating solar power (CSP) technology in use in Czech Republic, we will later in the thesis use terms solar and photovoltaic (PV) interchangeably. Development of RES generally increases volatility of generated electricity. Consequent higher volatility in price, in combination with unique features of electricity, caused spot market to become vital part of power market. Hence, spot market has become topic of extensive research in pioneering RES countries, such as Germany. Czech day-ahead and intraday markets, although much smaller in size than German spot market, play an important role when it comes to dealing with RES or load forecast error. Especially intraday market, regardless of its size, represents last trading opportunity for market participants to balance their positions on the power market.

The objective of this thesis is to analyse Czech intraday market for electricity in two ways. First, we will try to explain price formation with fundamental variables' forecast errors and attempt to identify significant determinants of intraday prices. Second part will focus on observing effect of intraday price on other spot market price, in this case day-ahead price. Because day-ahead market closes before intraday prices for selected time period are known, we cannot use intraday price from period t as an explanatory variable, but rather price from period $t - 24$. Since day-ahead prices were repeatedly proven to be dependent on previous value (Kristansen, 2012; Ferkingstad et al., 2011), it is probable that lagged day-ahead prices will have more significant explanatory power than lagged intraday prices. Nevertheless, it is worth examining whether intraday price takes part in price formation of day ahead market and testing the hypothesis of intercorrelated short-term markets.

For testing selected price determinants of intraday market, we will perform linear regression of time series data with autoregressive term as partial adjustment aspect. For the second part of our twofold analysis, we will employ autoregressive model as well. During both estimations, we will control for trend and monthly, weekly as well as peak hours (only during weekdays) seasonality using dummy variables.

To the best of our knowledge, there is no literature covering Czech intraday market, hence this thesis will attempt to fill the gap in the overview of Czech spot market. The thesis intends to contribute to existing electricity literature by identifying theoretical price determinants of Czech intraday market, elaborating on Hagemann's research (2015) by further developing his hypotheses on neighbouring market. Moreover, it provides foundation for further investigation of Czech intraday market. Lastly, by testing price relation of Czech spot markets, it opens door for further research regarding electricity inter-market correlation and price influence.

The remainder of this thesis is organised as follows. In section two, overview of relevant literature for the thesis is presented, covering already conducted research in electricity spot price modelling, impact of renewables and intraday market. Third section covers basic structure of Czech power market, with focus on spot market and RES development. Next section provides an overview of gathered time series data for empirical analysis. Section five continues with methodology, models and estimators based on reviewed literature. Specific hypotheses with expected results are elaborated. Besides presentation and interpretation of the results, section six provides a discussion of expected and obtained empirical results. Finally, conclusion summarises results and findings of the thesis and proposes direction for further research opportunities.

2 Literature review

2.1 Electricity spot price modelling

Most research work regarding electricity spot market has been done on Nord Power markets and German spot markets. Due to the development of German power industry after 2011, considerable implementation of renewables, importance of German electricity market as well as increase in transparency and data availability from EPEX, great number of recent papers have focused on German electricity spot market. Ziel et al. (2014) published paper which takes into account particularities of EPEX (most considerably load and percentage of production from solar and wind generators) and developed sophisticated VAR-TARCH time series model for modelling electricity spot prices. Paraschiv et al. (2014) examined effect of developing renewable energy on EEX day-ahead prices. Using state space model with changing coefficients, they concluded that prices continuously adapt to market fundamentals and that infeed from renewables causes spot price sensitivity to gas decrease gradually after 2011 as this fuel is situated very high in merit order curve. Overall findings show that day-ahead prices decreased due to substantial implementation of renewables, yet consumer prices increased because of additional feed-in tariff used for promoting RES. Fundamental modelling is based on a premise that electricity prices are result of joint performance of fundamental variables (e.g. weather data, RES, load). Knittel and Roberts (2005) used autoregressive moving average model with exogenious variables (ARMAX) on Californian electricity prices including weather data such as temperature and dummy variables for treating seasonality. Torro (2007) switched to ARIMAX and expanded model by adding precipitation, reservoir level and differences between future and spot prices to forecast electricity prices at Nord Pool.

Other researchers use autoregressive models when modelling and forecasting day-ahead electricity prices. AR model is often used as benchmark model for spot price when comparing with different approaches of spot price estimation. Based on the work of Weron and Misiorek (2008), who examined twelve variations of AR models for day-ahead spot price forecasting, research on modelling and forecasting Northern European day-ahead market was conducted by Kristansen (2012) and Ferkingstad et al. (2011). Findings of former research suggest hourly mean absolute percentage error ranging from 8 to 11% for day-ahead prices at Nord Pool, while later research found interconnection of Nordic and German electricity prices through gas prices.

Further approaches for modelling and forecasting electricity spot prices can be divided into three streams. GARCH regression models is primarily used on investigating electricity price volatility as for example in research by Ketterer (2014) on the effect of wind generation on price volatility or in work of Kalantzis et Milonas (2013) who examined impact of futures trading on spot price volatility in France and Germany. Other two approaches concern threshold regression models and time-varying parameter models (Erni, 2012), nevertheless since these models are out of scope of this thesis, we will not devote them more space.

2.2 RES effect on electricity spot prices

Based on a mentioned research, importance of spot markets, and intraday market as well, is closely related to the intermittency and continuity of power supply. Hence research on effect of renewables on spot prices play an important role when we will later think of potential hypotheses for Czech intraday market as well as relation between intraday and day-ahead market.

Ketterer's paper on impact of wind generation on the electricity spot prices in Germany (2014) shows that implementation of more renewables can lead to decreased prices on spot market, but increases price volatility. Trend of decreasing wholesale prices and increased volatility was again found and confirmed in simulation of further integration of renewable sources in next decade. Green and Vasilakos (2011) found these results as a consequence of increased proportion of wind power generation in Britain in 2020. Pöyry's report (2011) concludes similar merit-order effect which will result in decreased wholesale prices in North and West European power markets. Merit order effect related to the development of renewables (predominantly wind and solar) refers to merit order curve, often used in energy sector to rank types of electricity generation based on their price (marginal cost). Since renewable sources have basically zero marginal costs, in theory, merit order effect (MOE) of renewables decreases wholesale prices, as well as reduces electricity output of conventional power plants and pushes highest cost generators out of the market dispatch.

Described effect was confirmed in studies of Australian as well as Spanish electricity markets. Forrest and MacGill (2013) examined the impact of wind on Australian spot market prices and showed that wind energy sources in Australia reduce dispatch of gas generation and recently also brown coal generation. Gelabert et al.'s (2011) conclusion on the effect of renewables on prices at Spanish electricity market suggests that marginal increase of 1 GWh of electricity production from renewables results in price reduction of almost 2 EUR/MWh. MOE in Germany was initially studied by Sensfus et al. (2008) and results indicated strong impact of merit order effect, exceeding amount of additional tariff for renewable energy. Wurzburg et al. (2013) summarised MOE on various European markets concluding general price fall due to increased RES production. Additionally, in their empirical analysis on German-Austrian market, they found day-ahead electricity price decrease by approximately 1 EUR/MWh for each GWh of RES. Results remained stable both before and after deactivoation of seven nuclear power plants in 2011. Tveten et al. (2013) focused solely on solar merit order effect on German electricity prices and found on average 7% decrease in prices, but more importantly substantial decrease in average daily price variation by 23%. Latest study of merit order effect on Czech power market by Lunáčková et al (2017) divides renewable sources into two groups, solar energy and other renewables. MOE is confirmed for later group, but empirical results suggest that solar energy does not cause Czech spot prices to decrease, contradicting results from other European markets and concluding inappropriateness of Czech policy towards solar energy.

2.3 Intraday market

Regarding the research focused on electricity intraday market, great portion of the research was oriented on ideal market design of intraday market, so it would fulfil its primary purpose to assist day-ahead market and ease integration of RES into power systems. Borggrefe and Neuhoff (2011) explores intraday market power designs in European countries and North America and evaluate its capability of dealing with wind intermittency as wind forecast error drops substantially 24h before delivery. Similar assessment of European intraday market designs for wind integration was conducted by Weber (2010). He proposed four alternatives for improving intraday market design mostly oriented on increasing liquidity on intraday market. Furio (2011) tried to cover Spanish intraday market, explaining its design (six consecutive trading sessions organised in an auction make it unique in Europe), prices and evolution of traded volume from 2000 to 2010. In his estimations, he confirmed difference in peak and off-peak hours' prices, daily seasonality, highest willingness to pay for electricity in last hours before delivery and positive relationship between price and volume of electricity traded.

Hagemann and Weber (2013) attempted to explain liquidity determinants at German intraday market. Developing two distinct models, liquidity is far better explained by trading model, assuming profit-maximizing trading behaviour than fundamental merit-order model. Later, Hagemann and Weber (2015) tried to examine the liquidity at European intraday markets by observing trading volume at national markets in comparison with forecasted volume of their benchmark model. Model results lead to two conclusions; small market players typically do not participate in continuous exchange on intraday markets (with exception for Germany) and higher liquidity at auction-based market design cannot be attributed to market design, rather to country specific market peculiarities. Regarding further research of electricity intraday market, Garnier and Madlener (2014) formulated a model for optimized trading strategy of balancing forecast error of renewables. The bidding model, using options valuations and dynamic programming, outperforms on average other efficient alternatives by more than 6%.

Literature concerning modelling of electricity intraday prices is even more limited. Very recently, work of Karanfil and Li (2017) suggested that wind and conventional generation forecast errors play fundamental role in deviation of intraday and day-ahead prices in Danish power market. They concluded that gap between intraday and day-ahead prices is negatively influenced by renewable forecast error, whereas an unexpected increase in combined heat and power (CHP) generation leads to higher intraday prices and wider deviation from day-ahead prices. Kiesel and Paraschiv (2017) were first to examine German 15-minutes intraday prices. They were first to use updated intraday forecasting errors to investigate bidding behaviour. The changes in behaviour as well as influence of errors on prices are in accordance with intuition, intraday prices increases with negative forecast error and vice versa, nevertheless the price adjustment is shown to be asymmetric. Pape et al. (2016) used fundamental modelling approach to explain prices in German intraday market. Results indicated that chosen fundamental variables explained 75 % of price variance. Furthermore, results suggest that including day-ahead prices may improve explaining power of intraday price modelling. Researchers conclude that differences in modelled and actual prices might be caused by disregarded start-up costs, market state (extreme cases of excessive supply or capacity scarcity) and traders' behaviour as they tend to predict prices based on past price information from the markets.

Most relevant research for the first part of our analysis was conducted by Hagemann (2015). He studied price formation process of German intraday prices for two years (2010 - 2011) and tried to identify determinants of price difference between day-ahead and intraday prices. Empirical results are generally in accordance with theoretical sign and magnitude expectation of individual price determinants. Regression indicates stronger impact on intraday prices during the night which can be explained by steeper demand and supply curves at night.

In summary, research explaining spot price determinants and forecasting spot prices is well developed, primarily for day-ahead market. Despite the growing importance of electricity intraday market, research oriented on explaining price formation and interrelation of intraday market with other markets is fairly limited. To the best of our knowledge, the only research directly approaching this question has been done on German power market two years ago, and Czech intraday market has not been studied by any researcher yet. We will build up on previous hypotheses for German market, adjust them with regard to current market situation and test them on Czech power market. Later influence of intraday prices on next day's day-ahead prices will be examined and so we will contribute to overview of Czech electricity spot market.

3 Czech power market

In this section, we will provide a quick overview on structure of Czech power market. Focus will be given to wholesale market, specifically Czech spot market, its development, peculiarities and share of RES in generation.

Over the last decades, electricity markets in most part of the world have been deregulated. This means less government control of power sector and introduction of competition to originally monopolistic market for electric power. Besides development of retail sector and wholesale market for electricity, deregulation led to vertically unbundled power generation and transmission and distribution sector.

Deregulation of Czech electricity market occurred in numerous phases. The process started in 2002 and full liberalization of electricity market was achieved in 2006 (Vitner, 2006). As described above, that means vertical separation of specific power sectors and end-customers were no longer obliged to consume electricity from local supplier but rather gained freedom of choice regarding electricity provider. Electricity became tradable commodity on both long-term and short-term electricity markets. Long-term market is organised by PXE (Power Exchange Central Europe) and ČMKBK (Czech Moravian Commodity Exchange Kladno). Primary product traded at these exchanges are futures, contracts to consume or deliver a certain amount of electricity at agreed time in the future for agreed price today (KU Leuven Energy Institute, 2015). Following continuous trading scheme, futures on PXE are traded anonymously in form of months (up to 6), quarters (up to 4) or years (up to 3) ahead contracts and are divided to base load futures, covering all day, and peak load futures (PXE, 2016). While many researchers consider double peak intraday periods, PXE and OTE follows only single peak period from 8 a.m. to 8 p.m. and the rest is considered as off-peak hours. In order to maintain consistency with market operator's approach and data, we will use single peak structure later in empirical analysis.

Like most of European electricity markets, Czech market for electricity follows price based approach (Luňáčková et al., 2017), under which short-run marginal cost (SRMC) equals price of additionally produced MWh of electricity and power plant choose not to produce if price is below its SRMC (Cramton, 2013). Together with practically perfectly inelastic demand in short run, this creates market conditions in which short-term market plays vital role. Czech short-term regulated market is organised by OTE and divided into block market, day-ahead market, intraday market and balancing market with regulation energy. We will not discuss block market and balancing market as these are not primary focus of this thesis and their size regarding annual traded volume is fairly small. More on these markets can be found in OTE reports and website (OTE, 2016).

Czech day-ahead market for electricity, a platform for trading electricity one day before physical delivery, was launched in 2002, one year after foundation of OTE. From 1.2.2009, OTE became the single market operator for Czech electricity spot market (until 2009, short-term electricity trading was organised by both OTE and PXE). Czech day-ahead market is coupled with Slovak (since 2009), Hungarian (since 2012) and Romanian (since 2014) day-ahead market (OTE, 2014). This means that bids from participants on all four markets are matched jointly without need for acquiring transmission capacity. In contrast to future contracts, for which most of the trades happen on exchange (around 93%, PXE Fact book 2015), on day-ahead market, most of trades are closed over the counter (around 70 %, OTE 2016). Over the counter trading (OTC), is decentralised form of bilateral agreement on volume and price of electricity before actual delivery, independent of market operator intervention. Although OTC prices are not publicly disclosed, it is reasonable to assume that prices of OTC trading do not significantly deviates from prices at regulated market, since market participants would trade only on platform, which yields higher profit. Day-ahead trading is organised as daily anonymous auction, with participants asking buying/selling bids for particular hours of the following day with market closing at 11 a.m. Market operator then sets final spot price for each hour of the day before 2:30 p.m., based on a current market situation, available information and business terms of OTE (OTE, 2017). Using this price determination scheme, market operator can control for demand and supply equilibrium, since after closure of the day-ahead market, after-trading scheduled generation has to equal forecasted demand plus net export. From economic theory, day-ahead market price should be equal to marginal cost of production of last power plant on merit order curve needed to cover market demand (Joskow and Kahn, 2001; Karakatsani and Bunn, 2008). Increasing importance of day-ahead market can be observed on yearly rising proportion of traded volume. In 2016, electricity volume traded on Czech day-ahead spot market totalled to record high of 20.14 TWh (OTE, 2016).

After day-ahead closure, Czech intraday market opens daily at 3 p.m. and closes separately for each hourly period 60 minutes before delivery. Intraday market allows its participants to balance discrepancies and deviations from scheduled day-ahead nominations in case of sudden electricity scarcity/surplus, mostly due to improved RES forecast, change in demand, updated cross border flow or unexpected power plant outages. Trading at intraday market is organised through notice board, where market participants anonymously send their buying/selling bid with exact volume and price they are willing to pay. Unlike most European intraday markets, where these bids are continuously cleared (Germany, France, Belgium), in Czech intraday market bids have to be accepted by another participant through OTE trading platform. Moreover, as opposed to most of European markets, Czech short-term market is opened also during weekends and national holidays. Despite its small share on overall traded volume (544.7 GWh; OTE, 2016), intraday market in particular, gained its importance after implementation of intermittent generation units that are represented primarily by solar and wind power plants.

With concerns for climate change, Czech Republic introduced first Act on promotion of electricity production from renewable energy sources back in 2005 (IEA, Act No. 180/2005). This was adopted with aim to reach the EU indicative target for 2010 - 8% share of RES on gross national consumption and presented with support scheme for renewable sources in form of feed-in tariff. TSO was obliged to preferentially connect RES to transmission system and producers were guaranteed to receive so called “green bonus” from TSO. The amount of bonus was set annually by Energy regulatory office (ERU) and differed based on a RES production type. Green bonus was guaranteed to stay fixed for every MWh produced for a whole year. Market incentives in combination with significant decrease in price of photovoltaic technology in 2009, resulted in solar boom in Czech power market in years 2010, 2011. As a consequence, quick achievement of EU indicative target for 2020 - 13% share of RES in gross consumption was reached, however cost of support scheme has become excessive burden for both end-consumers and state budget. As a result, solar tax of 26% for solar producers was introduced for years 2011 - 2013, later extended (IEA, Act No. 165/2012) and followed by cancellation of solar support scheme after 2013. Because of the market situation in years 2010 - 2013 and already achieved EU target, it is reasonable to assume that Czech power market will not experience any major renewable boom in upcoming years. Czech power sector remains dominated by thermal (mostly lignite) and nuclear power, which combined account for 83,8% of annual electricity production and 68,8% of installed capacity (Table 1).

Table 1: Gross generation and installed capacity by production type

	Generation (GWh)		Capacity (MW)	
	2015	2016	2015	2016
Nuclear	26 840.8	24 104.2	4 290.0	4 290.0
Thermal	44 819.2	45 704.1	10 741.9	10 850.0
Combined Cycle	2 749.0	4 049.2	1 363.3	1 363.5
Gas Fired	3 572.1	3 613.9	855.9	874.0
Hydro	1 794.8	2 000.5	1 087.5	1 090.2
Pumped Storage	1 276.0	1 201.5	1 171.5	1 171.5
Wind	572.6	497.0	280.6	282.0
Photovoltaic	2 263.8	2 131.5	2 074.9	2 067.9
Total	83 888.4	83 301.9	21 865.7	21 989.0

Source: ERU, 2016 Yearly report on the operation of Czech electricity grid.

4 Data

We gathered data for later empirical analysis from various sources, mainly using Czech transmission system operator (ČEPS) database, Czech electricity and gas market operator (OTE), European Network of Transmission System Operators for Electricity (ENTSOE) transparency platform and European Energy Exchange (EEX) market data as sources of highest credibility. We decided to use the latest data possible over the span of 2 years, hence our dataset contains data from January 2015 to May 2017 (in January 2015, ENTSOE launched transparency platform and made various energy data available to the public). It is worth mentioning that year 2016 was leap year, thus had 366 days.

4.1 Intraday and day-ahead prices

Electricity spot prices represent vital part in both regression analyses. Electricity intraday price on Czech power market is hourly updated, publicly available information provided by OTE. Hourly data for both intraday prices as well as corresponding traded volume can be obtained from OTE website, in form of Yearly report packages. Regarding previously discussed market design of Czech intraday market, prices are reported as weighted average price per MWh. Since intraday prices were reported in CZK/MWh until August 2016 and in EUR/MWh from 24.8.2016 onwards, we will use Czech National Bank daily conversion rates for data from earlier period in order to achieve desired consistency. We opt for EUR prices due to easier comparison with the prices from day-ahead market as well as simpler comparison with research on other European spot power markets. Data will be firstly used as component of dependent variable in explaining price determinants of deviation of intraday price from day-ahead price and later tested for hypothesis of intraday prices' impact on day-ahead prices.

Day-ahead prices are obtained from the same source, with two minor differences. Due to different market design than intraday market, price is reported as a marginal price and is published directly in EUR/MWh, presumably because of coupled markets with Slovakia, Hungary and Romania. Extreme day-ahead prices will be used for testing hypotheses on intraday price formation and day-ahead prices are expected to exhibit strong autoregressive properties in second model estimation.

4.2 Renewable energy sources

We obtained hourly day-ahead generation forecast for solar energy in Czech Republic from ENTSOE transparency platform. This will be later used to compute solar generation forecast error as difference between actual hourly realised PV generation and PV generation forecast. Real generation data are publicly available on ČEPS website. In order to achieve consistency in data from ENTSOE and ČEPS, we have to work with hourly aggregate average data, since day-ahead forecast is published only for average generation for particular hour. Under the assumption that on intraday market, difference between realised generation from solar power plants and solar forecast available one hour before delivery is negligible, we will be able to test effect of positive and negative forecast error on intraday electricity prices.

As far as wind power production is concerned, data for wind generation forecast are not available for Czech Republic. As a consequence, we would not be able to calculate wind forecast error. Although, wind power generation units represent only 1,28% of Czech installed capacity (Table 1), wind has been repeatedly proven to be important fundamental factor for spot market (Ketterer, 2014; Forrest and MacGill, 2013). Unlike solar, intermittency of wind is present also during night and causes higher fluctuation of intraday prices. Thus, we will estimate wind generation forecast based on large sample of historical hourly realised wind generation values obtained from ČEPS. Methodology of this estimation will be outlined in next section.

4.3 Load

We will also consider load forecast and forecast error. Similarly, to renewable forecast error, load forecast error is defined as a deviation of realised mean load value from forecasted value of load (Haubrich 2008). Hourly data of realised load values as well as day-ahead forecast of load can be obtained from ČEPS database. ČEPS define brutto load as:

$$Load = Generation\ (brutto) + Import - Export - Absorbed\ energy \quad (1)$$

Load values in this dataset include consumption by power plant auxiliary as well as network loses. Load forecast is usually considered as appropriate proxy for supply of electricity that is expected by system operator. Due to consistency in methodology of forecasting and measuring load as well as intention to capture supply in terms of all electricity produced by power plants, we prefer to use data from ČEPS rather than data provided by ENTSOE.

4.4 Cross border power exchange

We will also include inflow/outflow of electricity from/to neighbouring countries. Since the transmission grid is most developed on the border with Germany and at the same time, Germany is one of the most advanced European country in terms of renewable power sources, we will include electricity inflow/outflow with German TSO 50 Hertz in our analysis. According to ČEPS data, 50 Hertz repeatedly imports more electricity than is originally planned and is assumed to occasionally use Czech Republic transmission border for transferring excess electricity from renewables from North to South Germany, in case German transmission network is used close to its capacity.

4.5 Coal and Gas

For second estimation, we have to consider fundamental drivers of day-ahead electricity prices. Based on yearly report of Czech energy regulatory office (ERU, 2016), coal accounts for 50.36% of Czech annual electricity generation (lignite leading with 43,5%). Together with nuclear power, they account for base load generation of Czech power market, hence presumably play immense role in electricity price formation. However, characteristics of lignite do not make it tradable commodity and lignite powered generation units tend to be built in close proximity of lignite mines. For this reason, reference price for lignite is generally unavailable for all electricity markets.

Closest data to trading coal prices we were able to obtain are daily auctioned Amsterdam-Rotterdam-Antwerp (ARA) future contracts for coal from EEX market data website. Published settlement prices in USD per ton (USD/t) will be converted in EUR/t for comparability and consistency with rest of data. These prices will be used as reference price for base load fossil fuel production units. Similarly to Paraschiv et al. (2014), we will use coal's latest available price of front-month future contract before electricity auction.

Although gas production may seem negligible in Czech power market (only 4.11%; ERU, 2016), when considering its operational flexibility and high fuel cost per MWh, gas is located on the right end of merit order curve. Consequently, during high demand periods or peak hours, gas production price is likely to act as a price-setting energy source. That is why, we need to reflect gas trading price when modelling day-ahead prices. Daily data for spot trading price in form of reference prices are provided by CEGH (Central European Gas Hub) and Czech Gas Exchange operated by PXE (Power Exchange Central Europe). Gas spot reference price is calculated as "weighted average of all trades concluded during the trading session on the CEGH Czech Gas Spot Market" (PXE, Gas spot reference price) and uses following formula in case that no trade occurred during trading session:

$$Price = \frac{\sum_{i=1}^{z} \frac{Bid_i + Ask_i}{2}}{z} \quad ; \quad z - number\ of\ constellations \tag{2}$$

4.6 CO2 allowance

With coal being dominant electricity generator in Czech Republic, it is necessary to control for the prices of CO_2 allowances when estimating day-ahead electricity prices. Acting as an additional expense to production cost of power plant, price of CO_2 allowances can lead to so called "fuel switch" and adjust shape of merit order curve. After introduction of EU Emission Trading Scheme (ETS) in 2005, operating under the cap and trade system, which guarantees that emissions are reduced where it cost the least, and after scheme revision for phase 3 (2013-2020), which replaced national cap system with EU-wide cap, we can say that prices for CO_2 allowances have become unified for all EU members plus Norway, Lichtenstein and Iceland. We will use data from EEX on European Carbon Index - ECarbix, which is published on daily basis by EEX and calculated as "exchange-based price for the current market value for EU emission allowances (EUA) in the third trading period" (EEX, Indices).

Table 2: Overview of data used in the analysis

Variable	Description	Unit	Source
IDp	Volume weighted average intraday price	EUR/MWh	OTE
DAp	Marginal day-ahead price	EUR/MWh	OTE
PV	Solar day-ahead generation forecast	MW	ENTSOE
	Generation output of solar power plants	MW	ČEPS
Wind	Generation output of wind power plants	MW	ČEPS
Load	Day-ahead Total Load Forecast	MW	ČEPS
	Total brutto load	MW	ČEPS
GER	Scheduled cross-border power flow (50 Hertz)	MW	ČEPS
	Actual cross-border power flow (50 Hertz)	MW	ČEPS
Gas*	Gas spot reference price	EUR/MWh	PXE
Coal*	Latest available price of the front-month ARA futures contract	EUR/t	EEX
CO_2*	Latest available price of ECarbix index	EUR/tCO_2	EEX

Note: Variables have hourly granularity; * marks daily granularity

5 Methodology and Hypotheses

Following threefold section outlines methods and econometric techniques used in the thesis. We will opt for autoregressive model in all three parts, as electricity prices and wind generation appear to be autocorrelated with their lagged values.

5.1 Wind Forecast

Before focusing on spot market prices, we need to deal with lack of day-ahead forecast for wind generation as we anticipate renewable sources to play significant role explaining electricity spot prices. Especially wind is considered main factor of intraday market volatility and unexpected price movements in countries with high percentage of wind generation such as Germany.

With no access to meteorological information about wind speed and direction, we will use past realised wind generation as input for our forecast. Unlike for physical forecasting model, historical data from wind generation units can be used as input for statistical models (Lei et al., 2009). Xiaodan et al. (2013) examined time series models (AR, ARMA) for short-term wind power generation predictions and concluded effectiveness of proposed methods, especially in case of unavailability of forecast data. Prediction errors appeared to occur in time series turning points due to high randomness of wind speed, nonetheless, when using big enough dataset of high frequency data, time series model managed to give appropriately accurate output for data points.

In order to ensure reasonably large sample for forecasting, we decided to use first five months of hourly data on wind generation, from January 2015 to May 2015 as input in autoregressive model (AR(p)). Our forecast for wind generation will be obtained in three following steps:

1. Selection of parameter p will be based on Autocorrelation function (ACF) and Partial autocorrelation function (PACF).

2. OLS minimization process will be used to estimate model coefficients.

3. Estimated coefficients and p lagged values will be used to calculate wind generation forecast for the following hour.

Shape of ACF and PACF functions (Appendix, Figure 3) suggests to include two lagged values, hence we use following AR(2) model:

$$wind_t = \alpha + \beta_1 wind_{t-1} + \beta_2 wind_{t-2} + \epsilon_t \tag{3}$$

5.2 Intraday market

Based on a research publication by Hagemann (2015), in which price determinants of German electricity intraday market are examined, we will try to determine significant factors which influence price change between Czech intraday and day-ahead market for electricity. In order to analyse price formation on intraday market, we may establish price difference between intraday and day-ahead market as our dependent variable.

$$dif\_p_t = IDp_t - DAp_t \tag{4}$$

Note: dif_p - deviation of intraday price from day-ahead price in hour t; IDp, DAp - variables from Table 2

It is justifiable to use deviation from day-ahead price for the following reason. By characteristics of intraday market, which is used only after day-ahead market is closed, intraday prices move based on updated, more precise information and forecasts. Hence, deviation from day-ahead price captures development of market situation compared to known day-ahead forecasts. Descriptive statistics in Table 3 may give us a quick look at differences between both prices.

Table 3: Descriptive statistics of electricity spot prices

	dif_p	IDp	DAp
Min	-67.7000	-42.6500	-25.0000
1st Qu.	-7.5500	21.6500	24.7100
Median	0.5194	32.3200	32.0100
Mean	1.3300	34.6900	33.3600
3rd Qu.	8.9600	44.9700	40.0700
Max	211.0000	238.3000	141.0000
Std Deviation	13.6519	18.6428	14.4406
Skewness	0.9507	1.0619	1.1446
Kurtosis	10.7494	6.7647	7.8204
ADF test	-19.0540	-14.1010	-12.6490
	(0.01)	(0.01)	(0.01)
KPSS test	0.2179	1.2142	2.0579
	(0.01)	(0.01)	(0.01)

Note: p-values in parentheses, KPSS test for trend-stationarity

Obtained results show us that range of intraday prices is much larger than in case of day-ahead prices, with intraday maximum and minimum prices being almost twice the values from day-ahead market. Occurrence of such extreme values suggests larger impact of last minute market development on intraday prices than on day-ahead prices. Interquartile range can be considered as reference for usual price range on both markets. Since intraday market have larger interquartile range, it can be perceived as confirmation of intraday market being more price sensitive. Median price of both markets is around 32 EUR/MWh, suggesting similarities of the markets if expected market conditions turn out accurate. Slightly higher mean on both markets indicate few more extreme observations in upper range of electricity spot prices.

Relatively small and roughly symmetric interquartile range of price deviation reveals that the two consecutive spot markets often end up with similar prices. However maximum and minimum values suggest extreme losses for market participants in case of severely incorrect forecasts. As mean and median are close to zero, it proves that intraday price does not differentiate from day-ahead price if forecasts are accurate. This supports the theory of intraday price formation being based on day-ahead price and updated market situation. We can also conclude that under same market conditions, prices on intraday market tend to be slightly higher than on day-ahead market as both mean and median are positive values and third quartile is bigger than absolute value of first quartile. This seems reasonable, since balancing position few hours before delivery is expected to be more expensive than on previous day.

Standard deviations are high for all electricity price variables, indicating relatively wide range of values, with biggest dispersion of values on intraday market. Based on a result of skewness and kurtosis, Czech spot prices and their difference seem to deviate from normal distribution. All three variables appear to have fat-tailed distribution, as they are leptokurtic and exhibit positive skewness.

In accordance with literature on electricity spot price properties, both day-ahead and intraday prices are found non-stationary and without unit-root. Their deviation also manages to reject null hypothesis of unit root (Dickey and Fuller, 1979), but null hypothesis for trend stationarity (spot price deviation is proved to follow trend pattern in next section) still has to be rejected (Kwiatkowski et al., 1992).

Since both day-ahead and intraday prices were repeatedly proven to be correlated with previous hours values, it is reasonable to expect price deviation to be autocorrelated as well. We will deploy ARX (1) model as a partial adjustment for autocorrelation (similarly to Woo et al., 2011) and focus on explaining price deviation with forecast errors of fundamental drivers, which are assumed to have significant influence on electricity market after day-ahead market closure. For our intraday analysis, we will assume realised values to act as proxy for intraday forecasts that is known one hour before delivery, since these forecasts are not available. Based on previous work on German (Hagemann and Weber, 2013) and Danish (Karanfil and Li, 2017) intraday markets, we identified fundamental determinants to be solar, wind, load and cross border flow. For each factor, we differentiate between positive and negative forecast error as this allows to make more elaborated inference about variables impact on price deviation. To pursue consistency in interpretation of estimation, we will use nonnegative values of forecast errors. Finally, day-ahead price will be included in order to test hypothesis about intraday price peaks and sinks. Equation 5 summarises estimation model for spot price deviation.

$$\begin{aligned} dif\_p_t = \quad & \alpha + \beta_1 dif\_p_{t-1} + \beta_2 pos\_PVfe_t + \beta_3 neg\_PVfe_t + \beta_4 pos\_windfe_t \\ & + \beta_5 neg\_windfe_t + \beta_6 pos\_loadfe_t + \beta_7 neg\_loadfe_t \\ & + \beta_8 pos\_GERfe_t + \beta_9 neg\_GERfe_t + \beta_{10} DAp_t + \epsilon_t \end{aligned} \tag{5}$$

In spite of using differences, deviation between intraday and day-ahead market may be suspected to move in seasonal patterns or follow trend. Thus, we will test variables for trend pattern and monthly, weekly and daily seasonality. We expect to find trend and seasonal dummy variables insignificant and work with original dataset. Moreover, we might have to deal with serial correlation as well as heteroskedasticity in model residuals. If this will be the case, Gauss-Markov assumptions are violated and we are not eligible to draw valid inference, as error terms are no longer uncorrelated and uniform. Although linear regression should not lead to biased coefficient estimates, this would give us biased standard errors, more likely to be underestimated (Petersen, 2008). According to Wooldridge (2015), it is recommended to use Newey-West heteroskedasticity and autocorrelation consistent estimator to compute robust standard errors.

Before conducting analysis and examining hypotheses, we will test our dataset for stationarity, using Augmented Dickey-Fuller (ADF) test and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test. Under null hypothesis of ADF test, presence of unit root in dataset will be tested and KPSS test then decides on stationarity of variables, with null hypothesis being stationary data.

We will now present hypotheses for specific fundamental variables and elaborate on their theoretical background (Table 4 summarises expected regression results). As far as lagged price deviation is concerned, we expect it to give our model partial-adjustment character in scaling estimated coefficient and adjusting significance of included fundamental variables. Based on significance of first lag in ACF and PACF functions (Appendix, Figure 4), we anticipate dif_p_{t-1} to have large explanatory power in estimation and strong effect on dependent variable.

Renewable generation depends entirely on weather conditions, hence we can assume it to be exogeneous random variable. Hagemann and Weber (2013) concluded that renewable forecast errors act as main source of liquidity on German intraday market for electricity and therefore we anticipate it to play important role in our estimation for Czech market. Capacities of both renewable production types remained nearly unchanged from 2015 (ERU, 2016), hence generation as well as forecast error is comparable throughout the years.

Our hypothesis regarding solar generation forecast error is based on following assumptions and implications. When positive forecast error occurs, actual solar generation is higher than expected during day-ahead trading, thus participants will try sell additional electricity from solar generation units and cause intraday price to decrease as a consequence of sudden excessive supply. In terms of our dependent variable, positive forecast error will decrease intraday price, causing price difference to decrease in value. For negative forecast error, we can apply reverse logic and assume increase in intraday price as well as increase in value of price deviation.

Since TSO does not disclose data on day-ahead generation forecast for wind on Czech market (most likely due to negligible capacity; see Table 1), we constructed AR(2) model to obtain wind generation forecast as described in the first part of methodology. This allows us to determine forecast error of wind generation. Negative forecast error is expected to push intraday prices up, potentially creating short-term supply shortage and causing deployment of additional generation units on right end of merit order curve, while opposite effect is anticipated for positive forecast error. Nonetheless, we need to bear in mind that wind generation in Czech market might not appear as significant as in other European markets, due to its very limited capacity.

In our estimation, we will also include load forecast error, as system load is strongly affected by time of the day and random effects (e.g. weather), consequently influencing electricity spot price in deregulated markets (Aggarwal et al. 2011). Assuming load is appropriate proxy for supply of electricity, we can work with load forecast error as variable covering unexpected movements on supply side of market. We can anticipate price surge in times of lower load than expected (supply shortage) and price decline for supply surplus. We assume the same hypotheses as for PV and wind generation, since they are directly influencing supply side of electricity. However, load is influenced by more aspects than just RES generation (unexpected outages, export/import, transmission losses, losses in production etc.), therefore the effect of load error forecast on price deviation is more complex than that of sole RES generation.

We will consider effect of import and export of electricity on Czech intraday price and deviation from day-ahead price. As stated in paper by Jorgensen and Ropenus (2008) on West Danish electricity market with high wind penetration, intraday cross border trading is gaining importance, especially with trend of market coupling. Even though Czech intraday market is not coupled for now, we will examine impact of cross border flow from and to North Germany which is known for high number of renewable power plants and intermittent wind generation. Forecast error in this case is defined as actual cross border flow minus planned cross border flow with German TSO 50 Hertz, which operates most renewable power plants in North and Eastern Germany.

We have deliberately chosen neighbour TSO with highest ratio of RES generation as well as highest ratio of imported electricity to Czech Republic. For this transmission border, we can test hypothesis that in case of excessive wind generation, 50 Hertz tries to export electricity (positive forecast error) and sell it at Czech intraday market, which consequently pushes prices down. More traditional hypothesis would assume shortage of electricity and increased intraday prices on Czech market, which consequently result in additional import from Germany (which presumably offer cheapest foreign electricity, depending on RES). However, purpose of the choice of cross border exchange with 50 Hertz was to test unconventional hypothesis in the first place. Negative forecast error (Czech Republic importing less electricity from Germany or exporting more electricity than planned) indicates electricity surplus that should lower intraday prices.

Final hypotheses will concern intraday prices behaviour dependent on day-ahead prices. First, we need to test the significance of day-ahead price in our regression. If day-ahead price appears to be statistically significant variable, we will test hypotheses regarding intraday market response to extreme prices on day-ahead market. For following analysis, "high" and "low" day-ahead price variables will be created as day-ahead price times dummy variable which is 1 if the price is equal to mean day-ahead price plus/minus two standard deviation of day-ahead price sample and 0 otherwise. Re-estimation of equation 5 with added "high" and "low" day-ahead price variables will be performed to examine following hypotheses.

During hours of high demand, such as peak period, day-ahead prices are generally higher than usual. Due to convex shape of merit order curve, any additional increase in supply is extremely costly and requires deployment of production units at right end of merit order. Moreover, in short run such as intraday market, merit order curve is steeper than in long-run and only technologies with immediate start-up period can be used e.g. gas turbines, which are costlier than unused lignite or coal plants. Thus, our hypothesis is that during high prices periods at day-ahead market, intraday prices will be very sensitive to additional demand and likely to exceed day-ahead prices.

Low day-ahead prices tend to occur in case of base load production being sufficient for given hour or high RES generation forecast. Assuming that electricity demand does not descend under certain base load level, increase in demand for electricity on intraday market is more likely than further decrease in demand. In second case, forecast of extensive RES generation is more likely to have negative forecast error and result in supply shortage. Hence, most cases of extremely low day-ahead prices should lead to higher prices on intraday market.

Moreover, electricity is known to be homogeneous product, thus change by 1 MW in forecast errors in either direction should result in similar effect on electricity price. We assume symmetrical effect in terms of magnitude for positive and negative forecast errors of independent variables. This hypothesis will be tested in a following way.

$$|\beta_{posFE}| - |\beta_{negFE}| = 0 \tag{6}$$

Table 4: Hypotheses summary for intraday analysis

	Positive FE	Negative FE
PV	β_{posFE}<0	β_{negFE}>0
Wind	β_{posFE}<0	β_{negFE}>0
Load	β_{posFE}<0	β_{negFE}>0
50 Hertz border	β_{posFE}<0	β_{negFE}<0
Day-ahead price	$\beta_{highDAp}$>0	β_{lowDAp}>0

Note: Variables will be additionally tested for symmetry. Day-ahead prices will be tested in second estimated model

5.3 Day-ahead market

Understanding price behaviour on intraday market, we will analyse influence and explanatory power of intraday prices on day-ahead market. We are interested in question whether information about intraday price from previous trading period significantly influences and helps to explain current day-ahead price. Significance of results of day-ahead price regression on intraday prices from previous day will be compared to regression on both intraday and day-ahead prices from previous trading session as explaining variables.

Autocorrelation with lagged price values is suggested by extensive literature for hourly day-ahead spot price for electricity. Woo et al. (2011) or Neubarth et al. (2006) used autoregressive model observing impact of wind power generation on electricity spot market price levels on Texas market and German power market respectively. AR modelling is considered fundamental for econometric analysis of electricity spot prices according to Weron and Misiorek (2008), Ferkingstad et al. (2011) or Kristiansen (2012). We will hence use autoregressive model of order p with exogenous variables, ARX(p). Specification of lag length will be determined by examining ACF and PACF functions of day-ahead prices. In order to preserve information about dynamics of electricity spot prices, we will not change our dataset in any way that would influence results of ACF and PACF functions, when establishing appropriate number of lagged values.

Both dependent and independent variables will be tested for stationarity using ADF test for unit root and KPSS test for stationarity of dataset. Since many of the variables are hourly or daily prices of electricity or commodities, we expect to reject null hypothesis of stationary data as suggested by numerous literature on electricity prices (Knittel and Roberts, 2005; Escribano et al., 2011; etc). However, we are still able to obtain valid estimation results and draw correct inference if model residuals pass both ADF and KPSS test.

When it comes to prices, it is always reasonable to consider logarithmic transformation and interpret results as elasticity. However, in our case, both day-ahead and intraday prices are occasionally negative. Since there is no logarithmic transformation of data for both positive and negative values that would not distort results or influence number of chosen lagged values, we will keep nominal price values for further analysis.

Apart from autoregressive terms in our estimation, denoted in equation 7 as DAp_{t-i} and lagged intraday prices, IDp_{t-j}, we will include exogenous variables affecting electricity spot price, in order to avoid issue of endogeneity from omitted variables. RES forecast (PV and wind), load forecast, fossil fuel prices as well as prices of CO_2 allowances on spot market are considered fundamental factors when it comes to electricity spot price (Woo et al., 2011; Parashiv et al., 2014). Paper by Weron and Misiorek (2008), in which different adjusted AR models on California's and Nordic spot market were compared, found evidence that load as an exogenous variable usually contribute to better performing model for spot prices. Thus, load forecast available during day-ahead trading will be included. We will denote these factors as $X_{rt}; r = 1...6$. Data on cross border trade flows are intentionally omitted from our set of exogenous variables as they are often determined or at least influenced by spot prices (Ketterer, 2014).

Model will be adjusted for trend and seasonal patterns by adding time variable t and three sets of seasonal dummies accounting for monthly seasonality - $M_{kt}; k = 1...11$ with January as reference; weekly - $Wend_t$, differencing between weekdays and weekends; and daily seasonality in form of single peak period from 8 a.m. to 8 p.m. - $Peak_t$, with off-peak as reference group.

The estimation model equation for testing intraday price impact on day-ahead market then looks as follows:

$$\begin{aligned} DAp_t = \quad & \alpha + \Sigma\beta_i DAp_{t-i} + \Sigma\gamma_j IDp_{t-j} + \Sigma\delta_r X_{rt} \\ & + \phi t + \Sigma\mu_k M_{kt} + \nu Wend_t + \eta Peak_t + \epsilon_t \end{aligned} \tag{7}$$

Normality of residuals will be formally tested by Jarque-Bera test with null hypothesis of normality. In case of rejection of null hypothesis, we can still consider estimation asymptotically valid, since we are working with large sample of hourly observations and attempt to capture as many dependent variables as possible. Thus, we might assume error term ϵ_t and model residuals to be asymptotically normally distributed based on a theory behind Central Limit Theorem (CLT). In case of suspected violation of assumption of no serial correlation and homoscedasticity in model residuals, recommended Newey-West HAC estimator will be used again to recalculate robust standard errors.

After obtaining coefficient estimates and significance levels for above described model, we will add lagged day-ahead prices matching included intraday prices hours and re-estimate the model. Our hypothesis for intraday prices' significance is that they may contain next day spot price information to limited extent since they are affected by day-ahead prices (as shown in first part of analysis). However, we do not expect them to be statistically significant once lagged day-ahead prices for same hours are added as these are directly autocorrelated with dependent variable and encompass at least same information about day-ahead market as lagged intraday prices.

As far as the rest of exogenous factors are concerned, we will briefly comment on estimated coefficients and discuss reasons for obtained results, nevertheless we remain focused on intraday price's impact on day-ahead market.

6 Results and Discussion

In this section, results of empirical analysis following described methodology will be displayed. Furthermore, presented hypotheses and relations between variables will be discussed.

6.1 Wind Forecast

First, we need to validate results of our AR(2) wind generation forecast model. Original estimation of model using dataset of historical values from January to May 2015 yielded results presented in Table 5:

Table 5: Estimation for wind forecast

	Estimate	Std. Error	t-value	p-value
Intercept	1.5599	0.2472	6.3111	<0.0001 ***
wind_1	1.3532	0.0154	87.7842	<0.0001 ***
wind_2	-0.3746	0.0154	-24.3050	<0.0001 ***
R^2	0.9734		Adj. R^2	0.9734
F (3618)	66240		p value (F)	<0.0001
ADF test	-15.6170		p-value (ADF)	0.01
KPSS test	0.4755		p-value (KPSS)	0.0461

Note: *** significance at 1%, ** significance at 5%, * significance at 10% ; Trend insignificant, R-squared with trend included = 0.9734

Having threshold stationary residuals without unit root, we calculated first wind generation forecast for 01.06.2015 00:00 - 01:00 in following way.

$$\hat{wind\_for}_t = 1.5599 + 1.3532 wind\_gen_{t-1} - 0.3746 wind\_gen_{t-2} \quad (8)$$

After obtaining original estimation and first wind generation forecast for 01.06.2015 (91.31 MW), we moved our estimation dataset by one hour, so that the last sample value would include wind generation from 01.06.2015 00:00 - 01:00 and we could re-estimate wind generation forecast for next hour. The process was repeated for every hour until 31.05.2017 23:00 - 00:00 based on the most recent five months dataset of hourly wind generation, available prior estimated hour.

Calculating wind forecast error using estimated forecast and observing its descriptive statistics in Table 6, we see interquartile range to be narrow as well as symmetric and both mean and median to be close to 0. Additionally, obtained variable passes tests for stationarity, thus we can conclude that our estimation of wind generation forecast is satisfactory for further application in analysis.

Table 6: Descriptive statistics of wind FE

	Wind FE
Min	-75.4000
1st Qu.	-3.9940
Median	-0.4798
Mean	-0.0279
3rd Qu.	3.8230
Max	59.1100
Std Deviation	8.4584
Skewness	0.1668
Kurtosis	7.2744
ADF test	-24.5090
	(0.01)
KPSS test	0.3112
	(0.1)

Note: p-values in parentheses, KPSS test for level stationarity

6.2 Intraday market

In order to draw causal inference from our time series dataset, regressions on time trend and seasonal dummies were performed on all variables. Even though these features are very common in energy related variables, we did not expect to find them significant in price deviation or forecast errors as differencing usually eliminates monthly, weekly or daily patterns. With exception of wind forecast error, both time trend and seasonal dummies appeared jointly significant. In prices and cross border flow, we observe quadratic trend.

For further analysis, we will use detrended and deseasonalised variables obtained as residuals of regressions on trend and seasonality. By using residuals, we should also work with more stationary dataset. To confirm this, ADF test will be performed on all residuals of interest. We are able to reject null hypothesis of unit root in all cases on 99% confidence interval. To challenge robustness of ADF results and confirm stationary dataset, we will perform KPSS test for level stationary data as we already treated trending data. Test managed to not reject null hypothesis of stationary data at least at 90% confidence interval for all residuals expect for positive German border flow forecast error.

Confirming stationarity, we can continue to estimate main ARX(1) regression as presented in equation 5, only with residuals to eliminate possible spurious regression problem and seasonal patterns. Estimated model is tested for suspected serial correlation and heteroskedasticity. Breusch-Godfrey LM test confirms presence of serial correlation on 99% confidence interval. Furthermore, Breusch-Pagan test affirms that variance of error terms is dependent on independent variables, thus heteroskedasticity is an issue in our regression. Newey-West HAC estimator is used to compute robust standard errors. This will widen standard error range and affect coefficients' level of significance but does not change estimates.

Normality of model residuals is formally tested by Jarque-Bera test, resulting in rejection of null hypothesis of normality at 99% confidence interval. Since our dataset consists of 17 248 observations, we can assume asymptotic properties of model and still obtain unbiased estimation. To validate results of estimation, we need to check stationarity of model residuals. ADF and KPSS test are conducted and conclude stationary residuals without unit root at 99% and 90% confidence interval respectively. Table 7 presents results of regression using Newey-West estimator.

Table 7: Regression results for spot price deviation

	Estimate	Std. Error	t-value	p-value
Intercept	0.0003	0.0879	0.0040	0.9970
$resdif\_p\_1$	0.7449	0.0129	57.5850	<0.0001 ***
$resposPVfe$	-0.0133	0.0012	-11.249	<0.0001 ***
$resnegPVfe$	0.0132	0.0015	8.740	<0.0001 ***
$resposwindfe$	-0.0212	0.0126	-1.6780	0.0933 *
$resnegwindfe$	0.0271	0.0129	2.0920	0.0365 **
$resposloadfe$	-0.0036	0.0005	-7.7640	<0.0001 ***
$resnegloadfe$	0.0063	0.0023	2.7020	0.0068 ***
$resposGERfe$	0.0005	0.0002	2.5540	0.0106 **
$resnegGERfe$	0.0005	0.0013	0.4060	0.6845
$resDAp$	-0.0717	0.0098	-7.3060	<0.0001 ***
R^2	0.6149		Adj. R^2	0.6146
F(17246)	2753		p-value (F)	<0.0001
Breusch–Godfrey test	64.4370		p-value (BG)	<0.0001
Breusch-Pagan test	172.9500		p-value (BP)	<0.0001
Jarque-Bera test	983050		p-value (JB)	<0.0001
ADF test	-18.5380		p-value (ADF)	0.01
KPSS test	0.1208		p-value (KPSS)	0.1

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

As indicated by ACF and PACF functions for price deviation, dif_p_{t-1} is strongly influencing dependent variable. Furthermore, obtained R^2 for estimated ARX(1) model of 0.6149 indicates significant explanatory power of lagged price deviation. For better perspective, we remove dif_p_{t-1} term, re-estimate model (full estimation in Appendix, Table 13) and compare obtained R^2 to our original estimation. Re-estimated model yields R^2 0.0971, which is in accordance with Hagemann's paper on German intraday market (2015), in which he used similar intraday price determinants and chose not to include autoregressive term. R^2 in his estimation was equal to 0.1277 for overall regression and around 0.2 for specific block periods of a trading day. Moreover, results of re-estimated model confirms theory that similarly to electricity spot prices, price deviation of consecutive spot markets is to great extent explained by its lagged values.

Coefficients for solar forecast errors indicate that solar generation is statistically significant in intraday market price formation. P-values smaller than 0.0001 for both forecast errors suggest that intraday market is extensively used to offset solar forecast errors and balance participants' position. Since forecast error is 0 during night time, displayed coefficients, estimated for whole day, are likely to underestimate effect of solar forecast errors during sunshine and peak hours around noon. Nonetheless, we prove hypotheses for both PV forecast errors to be valid as unexpected surplus of solar production causes intraday prices to decline and the opposite holds for loss of solar generation.

Sign of wind generation surplus or shortage estimates are in accordance with our initial expectations as well, thus we can affirm both hypotheses for wind forecast error. Negative forecast error exhibits slightly bigger impact on intraday market prices than positive forecast error (although it will be shown that symmetry cannot be rejected). In other words, for market participants, cost of covering unexpected lack of wind generation is greater than benefit of extra wind production. As assumed before, variables turn out to be less statistically significant, with p-value 0.0933 and 0.0365 respectively, which is mostly caused by negligible importance of wind generation units in Czech Republic. Nonetheless, we can reject null hypothesis of $\beta_{resposwindfe}$ and $\beta_{resnegwindfe}$ equal to 0 at 10% and 5% significance level.

First and foremost, results of load forecast error approve its usage as electricity supply proxy. In case of supply shortage intraday price and consequently price deviation seems to increase, while supply surplus on intraday market pushes price deviation down. As data for forecasted and realised load obtained from ČEPS tend to underestimate predicted load in its forecast most of the time, positive forecast error is yielded in more than 91% of observations. Negative forecast error therefore might be expected to turn out less significant. However, even under Newey-West estimator, negative forecast error for market load maintains same level of statistical significance as positive forecast error and has slightly bigger effect on intraday price increase, proving that shortage of electricity supply in general, not only wind generation, tends to have larger impact on participants' behaviour and willingness to pay for balancing their market position.

We have to reject the hypothesis about positive forecast error of 50 Hertz border flow. This means that Germany is not using Czech intraday market on divesting their excessive RES electricity and relation of cross border electricity flow with German TSO and Czech spot market follows more traditional scheme. In times of supply shortage, if possible, TSO can decide to import more electricity from Germany instead of deploying more costly generation units of last resort. This still results in increase of spot intraday price, although the increase is much more subtle than deployment of balancing generation units.

We cannot reject null hypothesis of lower-tailed test, $\beta_{resnegGERfe}$ equal 0, even at 90% confidence interval. Thus, we conclude that negative forecast error of cross border flow with 50 Hertz has no significant effect on intraday price and spot price deviation. Since the exchange with 50 Hertz was purposefully chosen because of its prevailing higher volume of imported electricity to Czech Republic than is originally scheduled, insignificance of negative forecast error could have been anticipated.

As expected, day-ahead price turned out to be extremely significant in explaining intraday price formation. In order to test effect of day-ahead prices spikes and sinks, we created additional variables $highDAp$ and $lowDAp$ as described in methodology and treated them for trend and seasonality as rest of variables. Results of re-estimated model with added $highDAp$ and $lowDAp$ variables are presented in Table 8.

Table 8: Regression results for spot price deviation with DAp spikes and sinks

	Estimate	Std. Error	t-value	p-value
Intercept	0.0003	0.0878	0.0040	0.9971
$resdif\_p\_1$	0.7445	0.0129	57.6310	<0.0001 ***
$resposPVfe$	-0.0134	0.0012	-11.3880	<0.0001 ***
$resnegPVfe$	0.0133	0.0015	8.8690	<0.0001 ***
$resposwindfe$	-0.0210	0.0126	-1.6660	0.0958 *
$resnegwindfe$	0.0270	0.0129	2.0840	0.0372 **
$resposloadfe$	-0.0036	0.0005	-7.6690	<0.0001 ***
$resnegloadfe$	0.0061	0.0024	2.5940	0.0095 ***
$resposGERfe$	0.0005	0.0002	2.5530	0.0106 **
$resnegGERfe$	0.0006	0.0013	0.5020	0.6158
$resDAp$	-0.0537	0.0118	-4.5590	<0.0001 ***
$reshighDAp$	-0.0157	0.0059	-2.6310	0.0085 ***
$reslowDAp$	0.0064	0.0143	0.4450	0.6561
R^2	0.6151		Adj. R^2	0.6148
F(17244)	2296		p-value (F)	<0.0001
Breusch–Godfrey test	64.3520		p-value (BG)	<0.0001
Breusch-Pagan test	173.0900		p-value (BP)	<0.0001
Jarque-Bera test	982030		p-value (JB)	<0.0001
ADF test	-18.5190		p-value (ADF)	0.01
KPSS test	0.1289		p-value (KPSS)	0.1

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

Residuals of regression were confirmed to be stationary without unit root by ADF and KPSS test and Newey-West estimator was used again to recalculate robust standard errors as Breusch-Godfrey and Breusch-Pagan test indicated serial correlation and heteroskedasticity.

We previously discussed that load forecast error is in most cases positive, hence excessive supply is much more likely to occur than further demand spike during extremely high day-ahead prices. As a result, intraday prices tend to decline in case of high day-ahead prices, which is in accordance with results for load forecast error. Furthermore, incorrectly underestimated RES forecasts causing high day-ahead prices and excessive RES supply on intraday market are in line with estimated coefficient for $highDAp$ as well. Therefore, we reject our original hypothesis about high day-ahead prices' effect on intraday market.

We conclude that low day-ahead price has no effect on spot price deviation as we cannot reject null hypothesis $\beta_{resnegGERfe}$ equal 0 of upper tailed test, even at 90% confidence interval. Such result suggests that intraday prices neither tend to decrease under base load price level, nor bounce back to higher intraday prices as a consequence of low prices on day-ahead market. Occurrence of negative intraday prices is therefore more likely to be explained by intense deviation of forecasted and realised values of fundamental drivers of intraday market and by unexpected severe decrease in demand for electricity. The latter case shows that base load generation units does not have self-sufficient ramping down mechanisms and causes TSO to artificially lower intraday price to incentivise certain participants to negatively balance market (Agora report, 2014).

Overall, we can conclude that price extremes on intraday market does not occur in succession on day-ahead spikes and sinks, but tend to be result of extreme forecast errors of intraday determinants.

Estimation of included variables confirms symmetric effect of opposite forecast errors on homogeneous product such as electricity. Even though, we see negative forecast errors to have slightly larger impact on prices than positive forecast errors e.g. in case of wind and load, this difference seems to be marginal and coefficients for opposite forecast errors in general appear to be symmetric. Formal two-tailed tests are conducted to explore hypotheses based on equation 6. Null hypothesis assuming coefficients' symmetry is not rejected for any tested variable (p-values of F statistics in Table 9). Symmetry is confirmed even in case of $highDAp$ and $lowDAp$, for which we did not expect to find any.

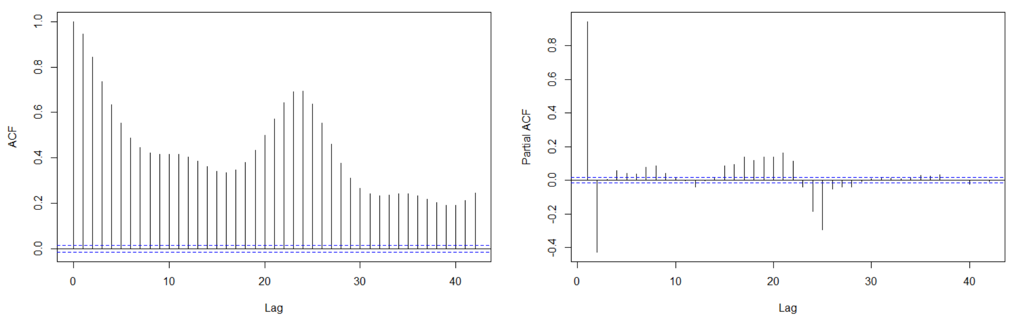
Table 9: Results of symmetry hypotheses

	PV FE	Wind FE	Load FE	50 Hertz FE	DAp extremes
p-value (F)	0.9814	0.6916	0.3853	0.9269	0.5738

6.3 Day-ahead market

For our day-ahead price analysis, first, appropriate order p in our ARX(p) model needs to be determined. Based on drawn ACF and PACF functions for day-ahead prices (Figure 1), it seems that prices for two previous hours greatly influence current day-ahead price. Furthermore, lagged prices from previous day appears to be significant in explaining day-ahead price. The latter observation suggests that hypothesis for day-ahead and intraday price influence from previous day might be valid theory to test.

Figure 1: ACF and PACF functions of day-ahead price



In accordance with finding of Kristoufek and Lunackova (2013), results of ADF and KPSS test reject null hypothesis of unit root and conclude non-stationarity of day-ahead prices, both on 99% confidence interval. Similar results were obtained for rest of variables, with unit root being rejected for every variable and stationarity not rejected only in case of wind forecast. Since our primary goal is to explain spot market relation and price dynamics, we will not opt for using first differences in order to treat non-stationary dataset. For the same reason, trend and seasonality will be included in final regression and will not be treated separately for each variable as in the case of intraday price analysis. As mentioned in methodology, our estimation and findings will be valid, only if residuals of regression will be stable over time and pass tests for not containing unit root and being stationary.

Estimation based on equation 7 for day-ahead market yielded results presented in Table 10. Newey-West HAC estimator is again adopted, based on results of Breusch-Godfrey and Breusch-Pagan test.

Table 10: Regression results for day-ahead price with lagged intraday prices

	Estimate	Std. Error	t-value	p-value
Intercept	-16.1900	1.3590	-11.9070	<0.0001 ***
DAp_1	1.1330	0.0249	45.5260	<0.0001 ***
DAp_2	-0.3624	0.01699	-21.3260	<0.0001 ***
PV	-0.0031	0.0002	-17.4990	<0.0001 ***
$wind$	-0.0129	0.0014	-9.4210	<0.0001 ***
$load$	0.0023	0.0001	17.8640	<0.0001 ***
gas	0.1470	0.0658	2.2340	0.0255 **
$coal$	0.0191	0.0185	1.0310	0.3026
$co2$	0.2169	0.1430	1.5160	0.1294
IDp_24	0.0576	0.0077	7.4940	<0.0001 ***
IDp_25	-0.0593	0.0072	-8.2110	<0.0001 ***
R^2	0.9266		Adj. R^2	0.9265
F(17208)	9049		p-value (F)	<0.0001
Breusch–Godfrey test	342.1300		p-value (BG)	<0.0001
Breusch-Pagan test	981.6000		p-value (BP)	<0.0001
Jarque-Bera test	218210		p-value (JB)	<0.0001
ADF test	-11.6340		p-value (ADF)	0.01
KPSS test	0.0699		p-value (KPSS)	0.1

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

Full estimate with trend and seasonal dummies can be found in appendix, Table 14

Even though Jarque-Bera test strongly reject null hypothesis of normality in regression residuals, results of ADF na KPSS test confirm asymptotically valid estimation output by rejecting unit root and not rejecting stationary residuals.

Hypothesis about previous trading day intraday prices is confirmed as p-value for both intraday price included is lower than 0.0001. Thus, we know that intraday price affect next day's spot price, but for now, we cannot say whether it is because of information from day-ahead market that is passed on intraday price or intraday market itself is significant factor influencing day-ahead price. For that reason, we will add lagged day-ahead prices from previous trading day and re-estimate regression (Table 11) to see whether intraday prices loses certain level of significance.

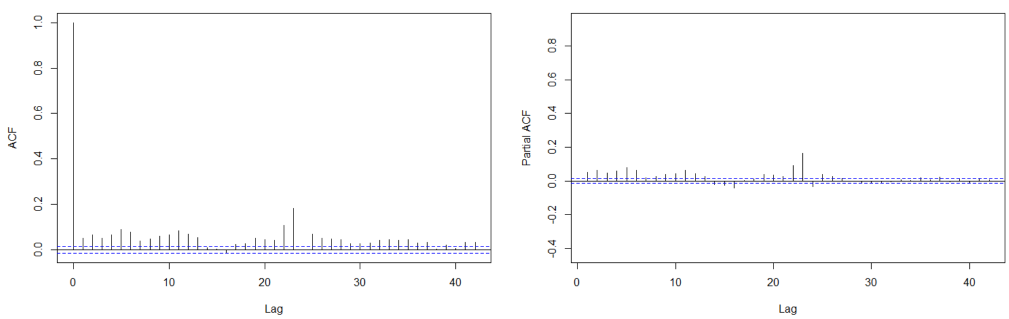
Table 11: Regression results for day-ahead price with lagged intraday and day-ahead prices

	Estimate	Std. Error	t-value	p-value
Intercept	-13.1600	1.3080	-10.0610	<0.0001 ***
DAp_1	1.0550	0.0196	53.7860	<0.0001 ***
DAp_2	-0.2522	0.0141	-17.9230	<0.0001 ***
PV	-0.0024	0.0002	-12.8290	<0.0001 ***
$wind$	-0.0104	0.0012	-8.6090	<0.0001 ***
$load$	0.0019	0.0001	14.2740	<0.0001 ***
gas	0.1314	0.0544	2.4180	0.0156 **
$coal$	0.0152	0.0153	0.9950	0.3196
$co2$	0.1667	0.1193	1.3970	0.1625
IDp_24	0.0159	0.0043	3.6970	0.0002 ***
IDp_25	-0.0169	0.0047	-3.5830	0.0003 ***
DAp_24	0.3290	0.0210	15.6450	<0.0001 ***
DAp_25	-0.3261	0.0169	-19.3020	<0.0001 ***
R^2	0.9353		Adj. R^2	0.9352
F(17206)	9563		p-value (F)	<0.0001
Breusch–Godfrey test	163.3200		p-value (BG)	<0.0001
Breusch-Pagan test	954.0800		p-value (BP)	<0.0001
Ljung-Box test	680.1200		p-value (LB)	<0.0001
Jarque-Bera test	267890		p-value (JB)	<0.0001
ADF test	-15.6070		p-value (ADF)	0.01
KPSS test	0.0673		p-value (KPSS)	0.1

Note: *** significance at 1%, ** significance at 5%, * significance at 10%
Full estimate with trend and seasonal dummies can be found in appendix, Table 15

Newey-West estimator was used to treat persistent issue with residuals' serial correlation and heteroskedasticity. Residuals were again confirmed to be stationary without unit root by ADF and KPSS test. Furthermore, additional Ljung-Box test, together with ACF and PACF functions of regression residuals are performed and plotted. Ljung-Box test confirmed persistent autocorrelation in residuals as we would need to include up to 29 lagged values to account for whole autoregressive properties, based on original ACF and PACF functions. Nevertheless, presented model managed to capture most significant autoregressive components and determined clear relation between day-ahead and lagged intraday prices, which was our primary objective. In Figure 2, obtained ACF and PACF functions of residuals are presented to further inspect how satisfactorily was autoregressive feature of day-ahead prices accounted for in estimation.

Figure 2: ACF and PACF functions of day-ahead price model residuals



Based on a result of re-estimated regression, we can conclude that intraday prices are proved to be influential factor of next trading day electricity spot price on Czech power market. As expected, day-ahead prices from previous trading day appears to affect spot price in stronger magnitude than intraday prices. Even though, much of the impact of intraday prices in original estimation was caused by omitting day-ahead prices, intraday prices preserved same level of statistical significance, with p-value equal to 0.0002 and 0.0003 respectively.

Furthermore, in both estimations, we observe that both day-ahead and intraday prices from previous trading day have opposite symmetrical effect. Such results indicate that when dependence on historical prices will shift spot price strongly in one direction, dependence on consecutive historical value will drive shift in opposite direction, back to original, potentially mean value (unless the price is negative). These results support theory of mean-reverting electricity spot price, which was previously confirmed for Czech electricity market by Kristoufek and Lunackova (2013). Moreover, symmetrical coefficients do not appear in most recent lagged prices, but rather as the effect of prices from previous day. This suggest that mean-reverting property does require certain amount of time to affect Czech electricity spot price.

Observing results for rest of exogenous factors, we can conclude that findings are in accordance with majority of the relevant literature. In both estimations, RES forecast for both solar and wind pushes day-ahead prices down with more expected RES generation. In contrast, load forecast being supply proxy, drive day-ahead prices up, with larger supply causing deployment of costlier generation unit on right end of merit order curve. As expected, increase in prices of primary energy sources and emission allowances cause electricity spot price to rise. Statistical significance of these variables is naturally anticipated to be lower on spot market than that of RES and load forecast. Since coal and other base load fossil fuels are mostly traded in futures contract or bilaterally via forwards, their insignificance in explaining electricity day-ahead price is in line with our expectation (we also have to bear in mind that coal future price serves only as reference for base load fossil fuel generation units' production costs). Slightly unexpected result is not rejecting null hypothesis of upper-tailed test for β_{co2} equal to 0 and consequent insignificance of emission allowance prices. This might be caused by very low trading prices (median value in two year dataset is 5.580 EUR/t and maximum is 8.630 EUR/t), which do not force emitters to consider allowance price as significant deciding factor. We should also bear in mind that most polluting electricity sources are not primarily traded on spot market.

To assess goodness of fit of the model and justify chosen exogenous variables, we need to perform additional regressions. First, we need to eliminate trend and seasonality in dependent variable in order to observe what percentage of detrended and deseasonalised price is explained by chosen factors. Residuals of purged day-ahead prices are regressed on exogenous variables and lagged intraday prices as shown in equation 9.

$$resDAp_t = \alpha + \beta_1 IDp_{t-24} + \beta_2 IDp_{t-25} + \Sigma\beta_r X_{rt} + \epsilon_t \tag{9}$$

If intraday prices are removed from estimation, we can observe true explanatory power of additionally chosen independent factors on Czech electricity day-ahead prices. Difference in R^2 of the first two estimations from Table 12 reveals, by what percentage, inclusion of intraday prices improves explanatory power of independent variables. Regression of residuals on intraday prices in third column then shows percentage of day-ahead prices explained by sole intraday prices from previous trading session.

Table 12: Explanatory power of independent factors in DAp regression

	$IDp_{t-24} + IDp_{t-25} + \Sigma X_{rt}$	ΣX_{rt}	$IDp_{t-24} + IDp_{t-25}$
R^2	0.3125	0.2660	0.1454
Adj. R^2	0.3122	0.2658	0.1453

Note: Full estimation output of these partial regressions can be found in appendix, Table 16,17,18

7 Conclusion

In this thesis, we have inspected Czech intraday market for electricity. After a quick overview of relevant literature and Czech power market, notably Czech spot market, in analytical part of the thesis, we focused on examining electricity intraday price formation process and later on intraday price's impact on next trading day's day-ahead price. Analysis was conducted on two-year dataset from June 2015 to May 2017 as first five months of 2015 were used for wind generation forecast estimation.

In the first section of analytical part, we concentrated on price formation on intraday market by explaining deviation between intraday and day-ahead prices by fundamental variables' forecast errors in ARX(1) time series model. Expected effects on intraday prices were confirmed in case of RES and load forecast errors, supporting price increasing impact in case of unexpected supply shortage and decreasing prices when actual supply exceeds forecast values. Solar, together with load forecast error appear to be most statistically significant determinants of intraday price deviation from day-ahead price, although the size of their effect on intraday market is subtler than wind's. We inferred that persistently greater import of electricity from Germany than planned can subtly increase spot intraday prices. Nonetheless, 50 Hertz seems to be the most rational choice of neighbour TSO to import from because of high RES generation, which is precisely forecasted during intraday trading and consequent most competitive price.

We managed to dispute occurrence of extreme intraday prices as a consequence of price spikes on day-ahead market. We conclude that negative prices on intraday market are more result of not foreseen intense RES surplus or negative demand shocks, but are not connected to low or negative day-ahead prices. Furthermore, in accordance with homogenous properties of electricity, symmetry of forecast errors' effects on intraday market was confirmed for all observed variables.

In the second part of the analysis, we managed to establish relation between electricity day-ahead and intraday market and confirm impact of intraday prices on next day's day-ahead price. Compared to included autoregressive components of day-ahead price, intraday prices have rather subtle effect on next trading period's day-ahead prices, in terms of coefficients' magnitude. Nevertheless, empirical analysis showed that intraday prices are statistically significant even with day-ahead prices included in model estimation and that including intraday prices in estimation have non-negligible impact on its R^2. Moreover, results supported mean-reverting properties of electricity day-ahead prices on Czech power market. Effect of remaining factors in estimation were in accordance with our expectations and extensive previous research results, with PV, wind and load forecasts having crucial significance on day-ahead market.

Additional research on intraday market might be interested in exploring merit order effect on intraday market. However, this study would need to take place in countries with significant RES production and well-established intraday market, such as Germany or North European countries. Additionally, further intercorrelation of power markets in Czech Republic remains topic for future investigation. Apart from price, more areas of interest might be inspected, such as power markets' volatility. It could be also tested, whether connections between markets have any additional value in forecasting markets for electricity.

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Appendix

Figure 3: ACF and PACF functions of wind generation

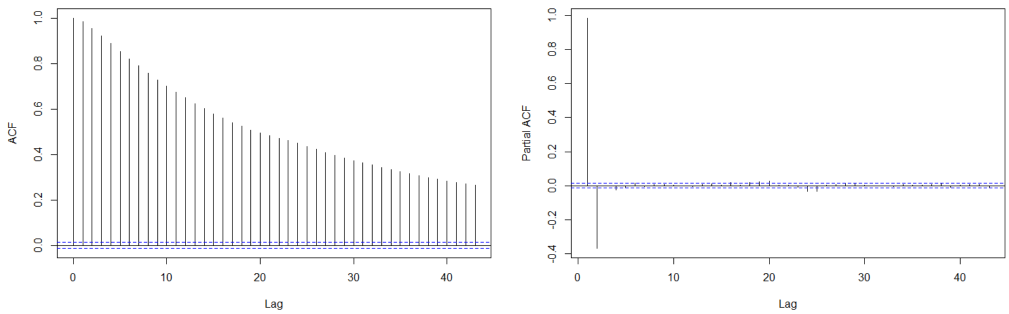

Figure 4: ACF and PACF functions of price deviation between intraday and day-ahead price

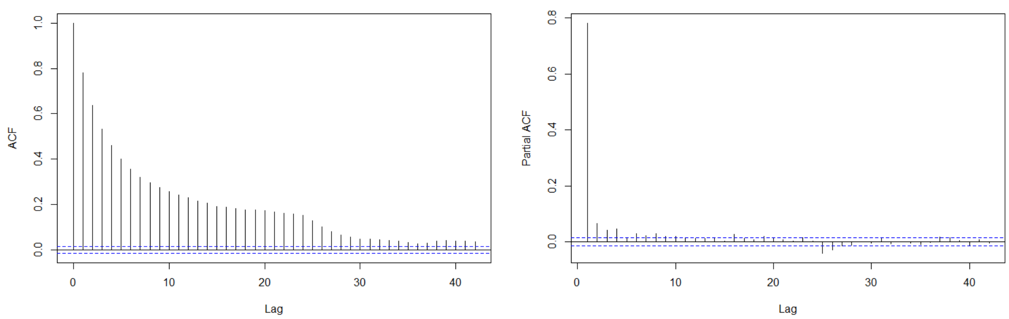

Table 13: Regression results for spot price deviation without autoregressive component

	Estimate	Std. Error	t-value	p-value
Intercept	0.0000	0.3331	0.0000	1.0000
$resposPVfe$	-0.0309	0.0034	-9.1800	<0.0001 ***
$resnegPVfe$	0.0321	0.0045	7.1490	<0.0001 ***
$resposwindfe$	-0.0528	0.0297	-1.7730	0.0762 *
$resnegwindfe$	0.0651	0.0256	2.5380	0.0112 **
$resposloadfe$	-0.0119	0.0016	-7.6200	<0.0001 ***
$resnegloadfe$	0.0131	0.0078	1.6710	0.0947 *
$resposGERfe$	0.0020	0.0007	2.7448	0.0061 ***
$resnegGERfe$	0.0011	0.0036	0.2923	0.7700
$resDAp$	-0.1579	0.0307	-5.1440	<0.0001 ***
R^2	0.0971		Adj. R^2	0.0966
F(17248)	206.1		p-value (F)	<0.0001

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

Newey-West estimator used

Table 14: Full regression results for day-ahead price with lagged intraday prices

	Estimate	Std. Error	t-value	p-value
Intercept	-16.1900	1.3590	-11.9070	<0.0001 ***
DAp_1	1.1330	0.0249	45.526	<0.0001 ***
DAp_2	-0.3624	0.01699	-21.3260	<0.0001 ***
PV	-0.0031	0.0002	-17.4990	<0.0001 ***
$wind$	-0.0129	0.0014	-9.4210	<0.0001 ***
$load$	0.0023	0.0001	17.8640	<0.0001 ***
gas	0.1470	0.0658	2.2340	0.0255 **
$coal$	0.0191	0.0185	1.0310	0.3026
$co2$	0.2169	0.1430	1.5160	0.1294
IDp_24	0.0576	0.0077	7.4940	<0.0001 ***
IDp_25	-0.0593	0.0072	-8.2110	<0.0001 ***
t	0.0001	0.0000	2.6940	0.0071***
feb	-0.8322	0.4349	-1.9130	0.0557 *
mar	-0.1846	0.3718	-0.4970	0.6195
apr	1.3200	0.3920	3.3680	0.0008 ***
may	2.4450	0.4585	5.3320	<0.0001 ***
jun	3.2820	0.5130	6.3990	<0.0001 ***
jul	4.2400	0.5893	7.1960	<0.0001 ***
aug	3.4860	0.5089	6.8500	<0.0001 ***
sep	3.2720	0.5018	6.5200	<0.0001 ***
oct	2.8350	0.5263	5.3860	<0.0001 ***
nov	0.8692	0.4934	1.7620	0.0781 *
dec	0.3149	0.4104	0.7670	0.4428
$wend$	0.4996	0.1258	3.9720	<0.0001 ***
$peak$	0.3739	0.1429	2.6160	0.0089 ***
R^2	0.9266		Adj. R^2	0.9265
F(17208)	9049		p-value (F)	<0.0001
Breusch–Godfrey test	342.1300		p-value (BG)	<0.0001
Breusch-Pagan test	981.6000		p-value (BP)	<0.0001
Jarque-Bera test	218210		p-value (JB)	<0.0001
ADF test	-11.6340		p-value (ADF)	0.01
KPSS test	0.0699		p-value (KPSS)	0.1

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

Table 15: Full regression results for day-ahead price with intraday and day-ahead prices

	Estimate	Std. Error	t-value	p-value
Intercept	-13.1600	1.3080	-10.0610	<0.0001 ***
DAp_1	1.0550	0.0196	53.7860	<0.0001 ***
DAp_2	-0.2522	0.0141	-17.9230	<0.0001 ***
PV	-0.0024	0.0002	-12.8290	<0.0001 ***
$wind$	-0.0104	0.0012	-8.6090	<0.0001 ***
$load$	0.0019	0.0001	14.2740	<0.0001 ***
gas	0.1314	0.0544	2.4180	0.0156 **
$coal$	0.0152	0.0153	0.9950	0.3196
$co2$	0.1667	0.1193	1.3970	0.1625
IDp_24	0.0159	0.0043	3.6970	0.0002 ***
IDp_25	-0.0169	0.0047	-3.5830	0.0003 ***
DAp_24	0.3290	0.0210	15.6450	<0.0001 ***
DAp_25	-0.3261	0.0169	-19.3020	<0.0001 ***
t	0.0001	0.0000	2.6600	0.0078***
feb	-0.7599	0.3566	-2.1310	0.0331 **
mar	-0.2552	0.3070	-0.8310	0.4058
apr	0.9802	0.3366	2.9120	0.0036 ***
may	1.9080	0.4000	4.7700	<0.0001 ***
jun	2.6070	0.4572	5.7020	<0.0001 ***
jul	3.4000	0.5326	6.3830	<0.0001 ***
aug	2.7910	0.4554	6.1290	<0.0001 ***
sep	2.6390	0.4485	5.8840	<0.0001 ***
oct	2.3390	0.4629	5.0530	<0.0001 ***
nov	0.7016	0.4122	1.7020	0.0887 *
dec	0.2264	0.3413	0.6630	0.5071
$wend$	0.2107	0.1281	1.6450	0.1001
$peak$	0.0322	0.1330	0.2420	0.8087
R^2	0.9353		Adj. R^2	0.9352
F(17206)	9563		p-value (F)	<0.0001
Breusch–Godfrey test	163.3200		p-value (BG)	<0.0001
Breusch-Pagan test	954.0800		p-value (BP)	<0.0001
Jarque-Bera test	267890		p-value (JB)	<0.0001
ADF test	-15.6070		p-value (ADF)	0.01
KPSS test	0.0673		p-value (KPSS)	0.1

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

Table 16: Regression results of independent factors on DAp residuals

	Estimate	Std. Error	t-value	p-value
Intercept	-12.4800	3.0350	-4.1120	<0.0001 ***
PV	-0.0076	0.0006	-12.1360	<0.0001 ***
$wind$	-0.0665	0.0065	-10.1170	<0.0001 ***
$load$	0.0024	0.0003	8.2680	<0.0001 ***
gas	0.7927	0.1972	4.0200	<0.0001 ***
$coal$	-0.1664	0.0402	-4.1420	<0.0001 ***
$co2$	-1.3650	0.4067	-3.3570	0.0008 ***
IDp_24	0.1242	0.0134	9.2650	<0.0001 ***
IDp_25	0.0219	0.0094	2.3470	0.0189 **
R^2	0.3125		Adj. R^2	0.3122
F(17224)	978.8		p-value (F)	<0.0001

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

Newey-West estimator used

Table 17: Regression results of exogenous independent factors on DAp residuals

	Estimate	Std. Error	t-value	p-value
Intercept	-16.3900	3.5170	-4.6600	<0.0001 ***
PV	-0.0080	0.0007	-11.7090	<0.0001 ***
$wind$	-0.0770	0.0074	-10.4510	<0.0001 ***
$load$	0.0031	0.0003	8.9440	<0.0001 ***
gas	0.8757	0.2176	4.0250	<0.0001 ***
$coal$	-0.1356	0.0457	-2.9650	0.0030 ***
$co2$	-1.1910	0.4464	-2.6680	0.0077 ***
R^2	0.2660		Adj. R^2	0.2658
F(17226)	1042		p-value (F)	<0.0001

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

Newey-West estimator used

Table 18: Regression results of intraday prices on DAp residuals

	Estimate	Std. Error	t-value	p-value
Intercept	-7.9915	0.8278	-9.6540	<0.0001 ***
IDp_24	0.1917	0.0186	10.3030	<0.0001 ***
IDp_25	0.0388	0.0109	3.5440	0.0004 ***
R^2	0.1454		Adj. R^2	0.1453
F(17230)	1466		p-value (F)	<0.0001

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

Newey-West estimator used