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Electricity markets around the world

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ABSTRACT

We examine wholesale electricity spot prices around the world. Based on a comprehensive dataset of intraday prices for 28 market regions in 19 countries, we compare the markets with regards to price variation and market structure. In particular, seasonal patterns, volatility, and the occurrence of price spikes are examined and compared with respect to determinants such as market design and production characteristics. We find that regional electricity markets in Australia are characterized by relatively low levels of annual, weekly and intra-daily seasonal patterns, but are by far the most volatile markets in this study. We also conduct a principal component analysis (PCA) based on the identified market characteristics to further investigate the differences between the considered markets. Our results illustrate that more than 80% of the variance in the data can be explained by three principal components, that, based on their loadings can be interpreted as a dispersion factor, a weekly and intra-daily seasonality factor and a factor related to price levels. We also find that electricity markets organized as day-ahead markets exhibit a significantly lower overall price variation compared to markets with real-time trading. These differences exist in a cross-market observation, as well as for markets that feature both trading schemes. Our results provide important information for market participants by classifying the considered markets with respect to associated price and volatility risks.

1. Introduction

Over the last decades power markets around the world became deregulated and in many countries electricity is now traded under competitive rules. Often as part of the deregulation, power exchanges or power pools were established, where producers, traders, and large consumers can buy or sell power in organized markets (Pilipovic, 1997; Kaminski, 1999; Weron, 2006; Benth et al., 2008). After initial attempts in the 1980s in South America, the first power exchanges in developed countries appeared in the 1990s, starting with markets in the United Kingdom and Scandinavia. Since then, more and more competitive electricity markets have been established, and by the end of the 1990s various markets in Europe, North America, and Australia were operating. In North America the ambition to further raise power markets was hampered by the electricity crises in California, and the subsequent shut down of the Californian power exchange in 2001 (Wolak, 2003; Sweeney, 2008). Unimpressed by this development, additional markets came into existence in the early years of the 21st century in Europe and other parts of the world. Nowadays, there exist markets around the world, in developed as well as developing countries, and with coverage from regional to international areas. A good overview of the development in the United States is given by Joskow (2006), and information on the development in the European Union can be

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found in, e.g., Newbery (2002).

With the emergence of wholesale markets for power, a new type of commodity became tradeable. But due to some unique characteristics, the behavior of electricity spot prices differs significantly from other commodities, or financial assets. Most important to mention is the need for simultaneous production and consumption of power that, accompanied with the non-storability,[1] leads to distinct price attributes. Knittel and Roberts (2005) list stationarity of prices, seasonal cycles, extreme price swings, and time-varying volatility as relevant characteristics of power prices. The most prominent feature of spot electricity prices are probably so-called price spikes, accounting for a large part of the high volatility in the markets. These characteristics make power prices an interesting field for research and various studies have been conducted on modeling and forecasting electricity prices, as well as on hedging and risk management in power markets, see, e.g. Bessembinder and Lemmon (2002); Lucia and Schwartz (2002); Knittel and Roberts (2005); Geman and Roncoroni (2006); Bierbrauer et al. (2007); Huisman et al. (2007); Kanamura and Ohashi (2008); Coulon et al. (2013); Janczura et al. (2013); Weron (2014); Birkelund et al. (2015); Füss et al. (2015); Ignatieva and Trück (2016); Kiesel and Kusterman (2016); Manner et al. (2016); Secomandi (2016), just to mention a few.

Besides modeling the behavior of electricity spot prices, other studies have focused on understanding the underlying market structure and the determinants of observed electricity prices. Wolak (2000) analyzes the early markets in England and Wales, New Zealand, Victoria, and the Scandinavian Nordpool market, focusing on deregulation and price behavior. Broad studies on comparing international power markets from different perspectives were performed by Li and Flynn (2004a,b); Escribano et al. (2011); Erdogdu (2014); Streimikiene and Siksnelyte (2016). Li and Flynn (2004a,b) analyse spot price behavior of 14 different power markets in North America, Europe, and Australasia.[2] In Li and Flynn (2004a) the seasonal intraday patterns of the markets are described and compared, whereas Li and Flynn (2004b) focus on examining volatility in the considered markets. Escribano et al. (2011) examine the evolution of electricity prices in deregulated markets, considering markets in Argentina, Australia, Canada, New Zealand, the Netherlands, Scandinavia, Spain, and the US. They find strong evidence that electricity prices are seasonal and mean-reverting, and exhibit volatility clustering and jumps with time-dependent intensity. Using panel data from 55 developed and developing countries, Erdogdu (2014) examines the impact of political and economic variables on the liberalization process in electricity markets. Streimikiene and Siksnelyte (2016) provide a sustainability assessment of electricity market models for 12 developed countries, including economic, social and environmental criteria. Pirrong (2017) provides a review on manipulation in commodity markets and suggests that power market manipulations are typically action-based, for example, electricity generators could declare a plant outage in order to drive up the price of electricity and increase the payout on electricity derivatives contracts.

To the best of our knowledge, the studies by Ly and Flynn so far provide the broadest overview of the price behavior in various deregulated power markets around the world. Typically studies on the volatility or behavior of spot electricity prices are focused on a single power exchange or only a few markets. For example, Zareipour et al. (2007) analyze the volatility and market design in Ontario, Bask and Widerberg (2009) the impact of market expansion in the Scandinavian market, or Kalantzis and Milonas (2013) the impact of the introduction of a futures market on the volatility in Germany and France. Bessembinder and Lemmon (2002) analyze the effect of hedging decisions for power producers and consumers on power prices, their season, as well as volatility. A study on the effect of data frequency on the volatility of power prices is performed by Ullrich (2012), considering markets in the United States and Australia. Janczura et al. (2013) examine the impact of identifying spikes on the estimation of seasonal components in electricity spot markets in Germany and Australia. Nowotarski et al. (2014) provide an empirical comparison of alternative schemes for combining electricity spot price forecasts in three major European and US markets.

In this study, we contribute to the literature by examining a unique data set of intraday prices of 28 different power markets across the world, focusing on key features of spot electricity prices such as seasonal behavior, price levels and variation, as well as higher moments of the observed price series. Using data on spot electricity prices from the initiation of each market until the end of 2012, we also relate the price behavior to the structure and characteristics of the individual markets. We use a very comprehensive data set, comprising hourly spot electricity prices from exchanges of 19 different countries in Europe, the US, Asia and Australia. To the best of our knowledge this is the most extensive database that has been considered in the literature so far to examine the behavior of spot electricity prices in various markets around the world.

We find significant differences between the considered markets with respect to price levels, the frequency and magnitude of price jumps and spikes as well as the volatility, skewness and kurtosis of spot electricity prices. While, for our sample period until 2012, the Australian markets were typically characterized by low prices and relatively low levels of annual, weekly and intra-daily seasonality, they were also by far the most volatile markets in this study. On the other hand, European markets in Belgium, Switzerland and Italy as well as the Asian markets in Singapore, India and South Korea had the highest average price levels among all 28 markets considered.

We also conduct a principal component analysis (PCA) and illustrate that a high fraction of the variation (over 80%) between the markets can be explained by three principal components, that can be interpreted as a *dispersion factor*, a *weekly and intra-daily seasonality factor* and a *price level and annual seasonality factor*. The results of the conducted PCA also illustrate that the markets can

[1] Technically, electric power is storable in various ways, but at the large scale, so far mainly hydroelectric resources have been used to store electricity in an economically suitable way. However, hydroelectric resources require suitable geographic conditions and thus are infeasible in many regions. Therefore, storage of electric power is strongly limited and electricity is often classified as non-storable. With significant technical progress in the area of battery storage, this can be expected to change though in the near future.

[2] North America: Alberta, California, New England, PJM. Europe: Germany, Netherlands, Britain, Spain, Scandinavia. Australasia: South Australia, New South Wales, Queensland, Victoria, New Zealand.

typically be classified into different groups according to the three identified factors.

We further find that electricity markets organized as day-ahead markets exhibit a significantly lower overall price variation compared to markets with real-time trading. These differences exist in a cross-market observation, as well as for markets that feature both trading schemes. Overall, our findings suggest that in real-time electricity markets, retailers and large customers with direct access to power exchanges will be required to more thoroughly hedge their risks from extreme price variation and price jumps in the spot market.

Our results provide important information for market participants by classifying the considered markets with respect to associated price and volatility risks. They also illustrate how observed characteristics of spot electricity prices are related to market features such as the organization of the power exchange, electricity generation and fuel sources.

The remainder of this article is organized as follows. Section 2 describes the development of power markets and illustrates differences in the market structure. Section 3 presents the data and methodologies we use. Empirical results are provided in Section 4, while Section 5 concludes.

2. Power markets

2.1. Deregulation and development of power markets

Before deregulation, in most of the countries considered in this study, large, often state owned, monopolies were responsible for production, transmission, and distribution of electric power. Starting from this background, deregulation took place in various forms, but the common aim was to stimulate competition in the electricity sector. Usually the way to achieve this was to split up vertically integrated power producers and privatize state owned utilities. As the power grid is a perfect example of a natural monopoly, regulation on this part is still needed. Therefore, the transmission grids were dissolved from generation and distribution of the pre-existing utility as independent system operator, or are still part of the utilities, but separated from the other businesses, and heavily regulated. Further, even when some countries focused on competition at the retail side to reduce power costs for end customers, the supply side played a crucial role in the deregulation. On the supply, or generation side, many countries and regions established wholesale markets, where the generators can sell generated electricity. In contrast to other markets, where commodities or financial products are traded, electricity markets need to account for the special characteristics of power. Most importantly, the market structure needs to take into account the grid connection and the need to balance generation and demand instantly. As this service was provided by the grid operator, the markets that were established in the beginning usually used the area of the grid operator, and in some cases were also operated by the grid operator. Joskow (2008) describes in more detail the deregulation process and a so called 'text book case' for deregulation.

Two basic models for power markets developed, one where the trading, dispatch, and transmission takes place at the system operators side, the so called power pools, and the other, where trading and an initial dispatch takes place at power exchanges that are independent from the transmission. Thereby, the pool model can be seen more related to the technical issues, whereas the exchange model as being more related to markets in a classical economic school of thought. The participation of generators in trading in the pool model is usually mandatory, as the grid operator manages the whole power demand in this area. Furthermore, the total demand for the area is estimated by the system operator, and no actual consumer participates in trading. All bids from the generators are assembled by an optimization procedure of the system operator to fulfill technical constraints, like transmission capacities, or run-up time and costs. As the pool model takes transmission into account, often a separate price for each node in the network is calculated, so-called locational pricing. Another form is zonal pricing, where for areas without grid limitations a unique price is settled. Theoretically, this model leads to a cost optimal dispatch of the power plants, when the cost information of each power plant is correctly known by the system operator.

In many countries, participation in the exchange is voluntary, and generators and retailers can make additional bilateral transactions outside the exchange. On the demand side in the exchange model are (usually large industrial) consumers, other generators, or power resellers. The drawback of an exchange model is that the location of supply and demand is not considered in the process. As the market is balanced only based on the price, technical limitations can sometimes make it impossible to physically fulfill the trades. For example, when generation and demand are on different locations and the transmission network has a bottleneck, the original power plant dispatch could result in a blackout. In this case, the network operator orders a re-dispatch of the power plants, i.e. the operator directs the producers on the one side of the bottleneck to lower production and producers on the other side to increase production. Usually, the cost associated with this process is covered by a transmission charge to the consumers.

Besides the basic model, there are further differences in the setup of the markets. Due to the non-storability and the constant balancing of generation and demand, a real spot market with immediate delivery cannot exist for power. Therefore, most markets use day-ahead trading, see Fig. 1, where prices and generation amounts for the 24 h of the following day are determined. Often the price determination is done by an auctioning process. In contrast to day-ahead trading, markets with continuous trading until shortly before delivery (usually 5–15 min) exist. These markets are called real-time, or intraday markets. In some markets, both trading mechanisms exist, but then real-time trading is usually used as a kind of balancing market to adjust the predetermined quantities of the day-ahead market.

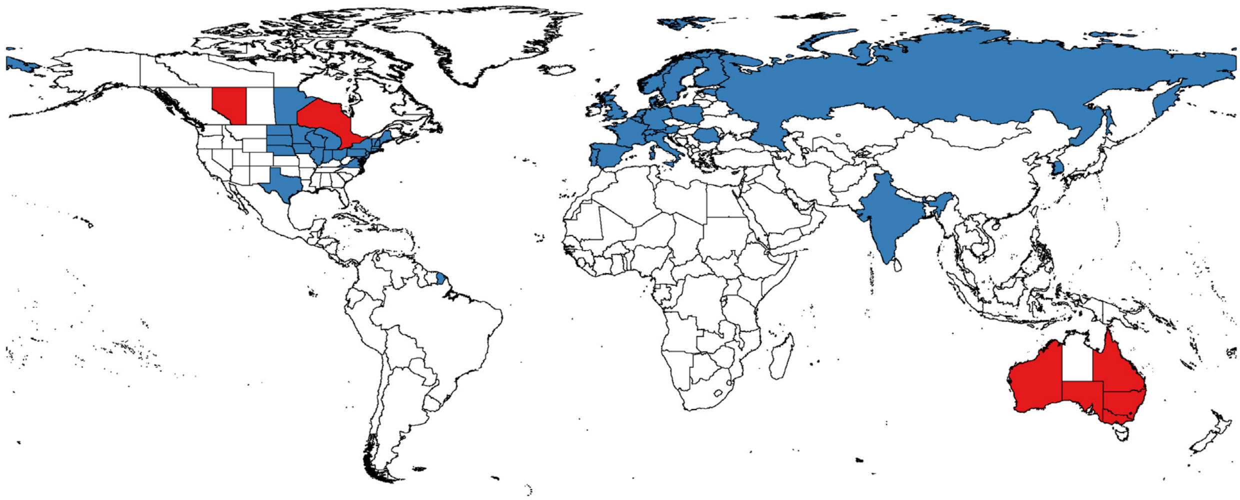

Fig. 1. This figure shows the power markets in our sample. The markets are colored according to their structure, real-time markets red, and day-ahead markets blue.

2.2. Description of markets

2.2.1. Australia

In Australia, the National Electricity Market (NEM) operates with nowadays 5 regions: New South Wales, Queensland, Victoria, South Australia, and since 2005 Tasmania (TAS). This study covers the four major markets of the NEM in New South Wales (NSW), Queensland (QLD), Victoria (VIC), and South Australia (SA). The market is operated by the Australia Energy Market Operator (AEMO) and organized as a power exchange with solely real-time trading. The capacity mix in each market varies from hard coal based power plants in New South Wales and Queensland, to a lignite based power plant fleet in Victoria, and gas based power plants in South Australia. Recently, there has also been a significant increase in installed wind turbines in South Australia, accounting for about 25% of total capacity in 2011. A detailed view on the individual markets' capacities can be found in Table 3, and Fig. 2. On the western side of the Australian continent, an additional wholesale electricity market started in 2006 for the south-western part of Western Australia. The power exchange was operated by the Independent Power Operator (IMO) with similar specifications as the NEM, i.e. real-time trading of half hourly contracts. For Western Australia the generation is dominated by gas fired power plants.

2.2.2. Europe

In Europe, the development of power markets began in the early 90s in England and Wales, continued in Scandinavia, followed by several countries in Central Europe. The market in England and Wales started as a power pool, but after restructuring the market design, it switched to a power exchange model that is operated by the Amsterdam Power Exchange (APX) since 2003. Except for Italy, that in 2013 still had a form of pool model, all other European markets were using the power exchange model at the end of our sample period. The largest operators were Nordpool for the Scandinavian Market, EPEX Spot for markets in Germany, France, and Switzerland, APX for markets in Netherlands and the United Kingdom, as well as OMEL in Spain and Portugal. In Eastern Europe, markets in Poland (POLPX) and Romania (OPCOM) are considered.[3] All markets were using day-ahead auctions as primary trading scheme, but towards the end of the sample period intraday markets as secondary trading platform were introduced, e.g. at EPEX Spot. In Europe, the markets in Scandinavia, Switzerland, and Austria are dominated by hydro power generation that account for more than half of the total capacity in these markets. Further, the French power supply is mainly based on nuclear power plants, which are accompanied by hydro power plants. The most concentrated generation capacities could be observed in Poland, where about 85% of capacity consisted of hard coal and lignite fired power plants. The other European markets typically base there production on a diversified power plant fleet.

2.2.3. North America

This study covers the Canadian markets in Ontario and Alberta, and the markets in New England, New York, Texas, the Midwest, as well as the PJM (Pennsylvania - New Jersey - Maryland) in the United States. The Canadian markets were organized as power exchanges, whereas the markets in the United States were organized as pool model. Both markets in Canada (OIESO in Ontario, AESO in Alberta), were performing only real-time trading, whereas the US markets were applying a standard market design with both, day-ahead and real-time trading.[4] We focus our examinations for the United States on the day-ahead prices, as the major part

[3] Further markets exist, but due to non-available power prices, and data quality, these markets were excluded from this study.

[4] The New England market was operated in the beginning from 1999 to 2002 as a real-time market, but after restructuring, a standard market design with both types was applied. Therefore, we use for New England only data after the restructuring.

Fig. 2. This figure displays the distribution of installed power plant capacities in the various markets based on Platts WEPP, 2009. The data is based on gross capacities of the power plants and thus, the maximum available capacities may deviate due to own use of electricity, or especially for renewable energies environmental conditions.

of trading took place day-ahead, while real-time trading typically was used for short-term balancing with smaller volumes. Compared to the European markets, the production capacities in the North American markets are less concentrated and the markets use various different fuels and power plants to produce electricity. In Alberta and the Midwest, coal and lignite fired power plants accounted for 40–50% of total capacity, but for the other markets, there was no dominant type of generation.

2.2.4. Asia

The development of wholesale power markets in Asia happened much slower than in Europe or North America. Therefore, this study contains only four Asian markets: Korea (KPX), Singapore (EMC), India (IEX), and Russia (ATS).[5] Among these markets, during our sample period, Singapore operated a real-time power pool, whereas the other markets were organized as bilateral power exchanges with day-ahead auctions. The power production in Singapore was based on gas (≈45%) and oil (≈35%). In India, coal fired power plants were dominating the power production with a share of more than 50%. A crucial role in the Russian electricity sector play gas fired power plants, with about 40% of total capacity. These were accompanied by smaller shares of coal and hydro plants. The Korean market showed a diversified mix of coal, nuclear, and gas capacities.

3. Data and methodology

3.1. Data

For this study we collected power price data of 28 different markets: five markets in Australia, 12 in Europe, seven in North America, and four in Asia. Table 1 lists the markets and their system area. Markets in Australia, Canada, and the United States are covering one or more states, whereas the markets in Europe are usually national or even international markets. Further the table shows information on the time of deregulation, the market organization, as well as some basic information on the area's power consumption and generation. For all markets intraday data on power prices was collected, either from the markets directly, or from the *Thomson Reuters EIKON* Database.[6] We used price data from the beginning of each market until the end of 2012. Information about data sources, the examined time period, as well as further features of the data can be found in Table 2.[7] Power prices of half-hourly frequency were aggregated to hourly prices by averaging to make them comparable to the other markets. In case of locational prices where no common price for the area was provided, the prices were aggregated to a unique price for the markets, based on each node's price and load.

Information on power plant data is based on the *Platts World Electric Power Plant (WEPP)* database and was available for the years 2000–2011. The *WEPP* database contains information on power plants around the world. The data includes information on the owner, size, installation date, fuel type, turbine type, as well as geographical information, where the plant is located. The database provides the most comprehensive information on power plants and covers all countries around the world.[8] For this study we aggregated the data from individual plant data to market level data. Therefore, the geographical information of the plants is used to allocate these plants to power markets, based on the country and area in which they are situated.[9] An overview of production capacities in the different markets can be found in Fig. 2, where the plants are grouped by their fuel and turbine type. The groups represent the major technologies in the markets, as well as renewable sources like wind and solar during the sample period. The composition of the production capacities showed large variation across the markets. Some markets were heavily focused on one type of fuel, for example the market in Queensland, Australia was dominated by hard coal fired power plants. On the other hand, some markets, for example GME in Italy, showed a broad diversification and various different plant and fuel types. Production facilities for renewable energy in most markets were dominated by large shares of hydro power plants. This holds for example for Austria, Switzerland, and Scandinavia. Significant shares in wind turbines could be found in South Australia and Germany. Installation in solar energies accounted only for a small amount in the markets.[10] The different fuel and plant capacities can be found in Fig. 2 and the shares relative to the total capacity in Table 3. As secondary source for capacity data on a less detailed level, and for aggregated production information, we also used data from statistic agencies and other data providers.[11]

3.2. Methodology

The characteristics of electric power and its prices are very specific and therefore, classical measures may be not suitable. The most distinctive feature of electric power is its non-storeability, that impacts the behavior of power prices in various ways. It causes extreme price spikes, strong seasonality in the short run, and even negative prices, see, e.g. Fanone et al. (2013).

[5] More markets in Asia exist, e.g. in Japan or the Philippines, but we excluded these markets as no intraday data, or data for only a short time period was available.

[6] This study selects only markets with intraday prices as the frequency of data plays a crucial role when analyzing volatilities, see, e.g., Ullrich (2012).

[7] Many markets publish the current and historical prices on their website and the data is freely available. Links to the websites of the markets, and to the available data can be found in Tables 1 and 2.

[8] A detailed description of the database is provided by Platts' "data base description and research methodology" (http://www.platts.com/IM.Platts.Content/downloads/udi/wepp/descmeth.pdf). Platts states that "[t]he WEPP Data Base covers electric power plants in every country in the world and includes operating, projected, deactivated, retired, and canceled facilities. Global coverage is comprehensive for medium- and large-sized power plants of all types. Coverage for wind turbines, diesel and gas engines, photovoltaic (PV) solar systems, fuel cells, and mini- and micro-hydroelectric units is considered representative, but is not exhaustive in many countries. Nonetheless, about a quarter of the data base consists of units of less than 1 MW capacity. Generating units of less than 1 kW are not included" (p. 5).

[9] Detailed information on the market areas can be found in Table 1. The classification of the states in the US is based on information provided by the Federal Energy Regulatory Commission (FERC).

[10] To a certain extend the capacities for solar energies are not covered by the WEPP, as they are often of small size and below the inclusion level of the data base.

[11] Capacity data for the United States is taken from *Energy Information Administration (EIA)*, for Canada from *Statistics Canada*, for the European Union from *Eurostat*, for Norway from *Statistics Norway*. The generation data for whole counties is based on *EIA*, and for the markets that operate only in certain parts of a country on *EIA* (United States), *Statistics Canada*, and for Australia the data was provided by *NEM-Review*.

Table 1
Global power markets: Overview.

Market	Country	States	Website	Deregulation	Trading design	Generation (TWh)	Capacity (GW)	Main Capacity
Australia								
AEMO_NSW	Australia	New South Wales	www.aemo.com.au	1998	rt	65	18	coal
AEMO_QLD	Australia	Queensland	www.aemo.com.au	1998	rt	57	13	coal
AEMO_SA	Australia	South Australia	www.aemo.com.au	1998	rt	13	5	gas
AEMO_VIC	Australia	Victoria	www.aemo.com.au	1998	rt	54	10	coal
IMO	Australia	Western Australia	www.imowa.com.au	2004	rt		7	gas
Europe								
APX_NL	Netherlands		www.apxgroup.com	1999	da	97	23	gas
APX_UK	United Kingdom		www.apxgroup.com	2001	da	339	90	coal & gas
BELPEX	Belgium		www.belpex.be	2006	da	74	17	nuclear & gas
EPEX_CH	Switzerland		www.epexspot.com	2007	da	66	17	hydro
EPEX_D	Germany		www.epexspot.com	2000	da	576	134	coal
EPEX_F	France		www.epexspot.com	2001	da	532	117	nuclear
EXAA	Austria		www.exaa.at	2002	da	63	20	gas
GME	Italy		www.mercatoelettrico.org	2004	da	286	107	gas
Nordpool	Norway, Sweden, Finland, Denmark		www.nordpoolspot.com	1995	da	417	96	hydro
OMEL	Spain, Portugal		www.omel.es	1998	da	321	105	gas & hydro
OPCOM	Romania		www.opcom.ro	2005	da		21	coal
POLPX	Poland		www.tge.pl/en	2000	da	151	36	coal
North America								
AESO	Canada	Alberta	www.aeso.ca	2001	rt	66	13	coal
ERCOT	USA	Texas	www.ercot.com	2002	da	430	106	gas
ISO_NE	USA	Conneticut, Maine, Massachusetts, New Hampshire, Rhode Island, Vermont	www.iso-ne.com	1999	da	121	36	gas
MISO	USA, Kanada	Illinois, Indiana, Iowa, Michigan, Minnesota, Nebraska, North Dakota, South Dakota, Wisconsin	www.misoenergy.org	2005	da	708	179	coal
NYISO	USA	New York	www.nyiso.com	1999	da	136	42	gas
OIESO	Canada	Ontario	www.ieso.ca	1999	rt	141	37	nuclear
PJM	USA	Delaware, District of Columbia, Maryland, New Jersey, Ohio, Pennsylvania, Virginia	www.pjm.com	1997	da	536	147	coal
Asia								
ATS	Russia		www.atsenergo.ru	2007	da		230	gas
EMC	Singapore		www.emcsg.com	2003	rt		11	gas
IEX	India		www.iexindia.com	2008	da		165	coal
KPX	South Korea		www.kpx.or.kr	2000	da	495	79	coal

This table shows information about the different power exchanges. Some markets are pure national markets with an market area equal to the country, but some markets spread over various countries, or cover only certain states in a country. The geographical information for the markets in the United States is is based on FERC classifications, where most of the state is covered by the relevant market. The column 'Deregulation' shows the mentioned foundation of the power exchange, or a predecessor of the current market. For all markets the trading design is either day-ahead (da), or real-time (rt). Where both types existed (e.g. in the United States) the more active type is listed. Total generation is based on information of statistic agencies for the year 2012 in the whole market region (based on states, or countries). The capacity information is based on Platts World Electric Power Plant database of year 2009.

Table 2
Global power markets: Data description.

Market	Datasource	Data available from	Data used until	Frequency	Delivery type	Currency
Australia						
AEMO_NSW	www.aemo.com.au/Electricity/Data/Price-and-Demand	01.01.1999	31.12.2012	hh	smp	AUD
AEMO_QLD	www.aemo.com.au/Electricity/Data/Price-and-Demand	01.01.1999	31.12.2012	hh	smp	AUD
AEMO_SA	www.aemo.com.au/Electricity/Data/Price-and-Demand	01.01.1999	31.12.2012	hh	smp	AUD
AEMO_VIC	www.aemo.com.au/Electricity/Data/Price-and-Demand	01.01.1999	31.12.2012	hh	smp	AUD
IMO	www.data.wa.aemo.com.au/	21.09.2006	31.12.2012	hh	smp	AUD
Europe						
APX_NL	Reuters EIKON	01.01.2000	31.12.2012	h	smp	EUR
APX_UK	www.elexon.co.uk/	11.03.2003	31.12.2012	hh	smp	GBP
BELPEX	www.belpex.be	01.01.2007	31.12.2012	h	smp	EUR
EPEX_CH	Reuters EIKON	01.01.2007	31.12.2012	h	smp	EUR
EPEX_D	Reuters EIKON	15.06.2000	31.12.2012	h	smp	EUR
EPEX_F	Reuters EIKON	26.11.2001	31.12.2012	h	smp	EUR
EXAA	www.exaa.at/en/marketdata/historical-data	22.03.2002	31.12.2012	h	smp	EUR
GME	http://www.mercatoelettrico.org	01.04.2004	31.12.2012	h	smp	EUR
Nordpool	Reuters EIKON	01.01.1994	31.12.2012	h	smp	NOK & EUR
OMEL	http://www.omelholding.es/en/omel-holding-en	01.01.1998	31.12.2012	h	smp	EUR
OPCOM	www.opcom.ro/pp/home.php	07.01.2005	31.12.2012	h	smp	EUR
POLPX	wyniki.tge.pl/en/wyniki/archiwum/	01.07.2000	31.12.2012	h	smp	PLN
North America						
AESO	ets.aeso.ca/	01.01.2000	31.12.2012	h	smp	CAD
ERCOT	http://www.ercot.com/mktinfo/prices	01.12.2010	31.12.2012	h	lmp	USD
ISO_NE	www.iso-ne.com/	01.03.2003	31.12.2012	h	lmp	USD
MISO	www.misoenergy.org/	21.01.2006	31.12.2012	h	lmp	USD
NYISO	www.nyiso.com/public/markets_operations/market_data/pricing_data/index.jsp	01.01.2002	31.12.2012	h	lmp	USD
OIESO	http://www.ieso.ca/	01.05.2002	31.12.2012	h	smp	CAD
PJM	www.pjm.com/markets-and-operations/energy/real-time/monthlylmp.aspx	01.04.1998	31.12.2012	h	lmp	USD
Asia						
ATS	Direct Contact	01.01.2007	31.12.2012	h	smp	RUB
EMC	https://www.emcsg.com/MarketData/PriceInformation	01.01.2004	31.12.2012	hh	lmp	SGD
IEX	www.iexindia.com/marketdata/areaprice.aspx	01.09.2008	31.12.2012	h	smp	INR
KPX	www.kpx.or.kr	01.01.2000	31.12.2012	h	smp	WON

This table shows information about the power price data for the different power exchanges. The second column shows source of your data, with links to the corresponding website where the data is publicly available. We used price data from the beginning of the available time series until the end of year 2012. Most markets have prices for hourly contracts (h), but some markets are having half-hourly prices (hh). Furthermore, some markets have nodal pricing, i.e. the price is determined at various nodes, or hubs and have a locational marginal price (lmp), instead of an area wide price, or system marginal price (smp), for the other markets.

3.2.1. Return measure

When observing the prices and their distribution, the characteristics of power prices do not influence the analysis, but when looking at the price movements, especially at the hourly scale, it causes several issues. Usually, the standard deviation of arithmetic, or logarithmic returns is used to measure price variation in the financial literature. However, for spot electricity prices, to base volatility and risk measures on a 'return' causes some problems and may not be appropriate. Most obvious, log-returns, as they are used in financial markets, are not defined for all observations of electricity prices due to possible negative or zero price observations. Further, as electric power cannot be stored, the arithmetic return that expresses a buy-and-hold return is (at least for intraday prices) only of limited use. For example, as the return measures percentage gains based on the buy price, immense returns would occur, when prices are close to zero and recover afterwards. In case of a price increase from 1 USD to 10 USD, the return would be 900%, whereas an increase from 50 USD to 200 USD only yields an increase of 300%. For market participants, the first case may be only of limited impact, whereas the second case with a much lower return could affect companies in the electricity business far more seriously. To overcome this issue, we use price differences instead of returns, and standardize the differences by the average price level in a market, to keep the measure comparable across different markets. Therefore, our measure of change in hourly spot electricity prices is defined as

$$\text{STANDDIFF}_t = \frac{P_t - P_{t-1}}{\frac{1}{T}\sum_{i=1}^{T} P_i}, \tag{1}$$

where P_t denotes the power price at time t, P_{t-1} the power price in the previous hourly period $t-1$ and T the overall number of prices for this market. Our main variable RETURN VARIATION is the standard deviation of this 'return' measure. Fig. 3 shows the relation between different variation measures. The first three measures that are based on the standard deviation of prices, the standard deviation of the price difference, and the standard deviation of standardized price differences, show a very similar appearance. However, the last measure that is based on arithmetic returns differs quite significantly from the other measures.

3.2.2. Seasonality estimation

Power prices show strong oscillations around a more or less constant mean level. Due to the non-storeability, changes in demand for power are directly affecting the power price.[12] The demand for power depends on many outside conditions, for example, day-time, day of the week, or seasons over the year. As these influences are repeated on a regular basis, every 24 hours the time of the day, every seven days the weekday, and every twelve months the month, a big part of the demand can be explained by these seasonal effects. As the seasonal demand is typically directly reflected in observed wholesale prices, we analyze the prices regarding their seasonality on hourly, daily, and monthly characteristics. We use a least square optimization method with dummies for 24 hours, 7 days, and 12 months, as well as year dummies to estimate the seasonal fluctuations around the average price level.[13] To limit the effect of extreme prices on the estimation of seasonal patterns, see, e.g., Janczura et al. (2013), we replace outliers by typical prices for the specific observation, i.e. with the median value of the hour and day in the relevant month.

3.2.3. Jump measures

The most prominent characteristic of power prices are extreme price observations, often referred to as price spikes. These extreme prices typically occur, when the market demand is close to capacity, or when there is a lack of generation capacity, see, e.g., Weron (2006); Hagfors et al. (2016). Often prices are many times higher than the marginal cost of the most expensive power plant and the prices cannot be explained by the merit order anymore. These price jumps may occur due to the bidding behavior of suppliers as well as consumers, or due to expensive demand response actions. As the demand, as well as the supply may be able to react to high prices, the extreme prices often last only for a short period of time and then return to their previous levels. Various methods to measure jumps in power prices exist, see, e.g. Cartea and Figueroa (2005); Geman and Roncoroni (2006); Carmona and Coulon (2014). Some of the measures are based on prices, whereas others are based on relative measures like returns. As we are observing various markets, we use a relative measure to identify jumps and base it on the STANDDIFF measure. We classify all movements that exceed 30% in absolute terms as jumps.[14] Based on this identification, we calculate for each market the jump frequency, jump size, as well as the remaining price variation when the jumps are excluded.

[12] Power prices are usually set by the intersection point of demand and merit order, and as the merit order is monotonically increasing with the load, the prices adjust directly to a change in the demand. In case of a (costless) power storage, the storage would be filled when demand (and thus price) is low, and discharged when prices are high. This would lead to more demand from storage when other demand is low and more supply when demand is high, and thus, reduce the price variation.

[13] The estimations are performed with the *Matlab* optimization routine *lsqlin*. We apply constraints on the function to ensure the characteristics of seasonal effects, i.e. the sum of the 24 hourly values has to be zero, as well for the sum over the seven days of a week, and the weighted sum (by number of days in a month) over the monthly values over the year.

[14] We use the recursive filtering algorithm proposed by Clewlow and Strickland (2000) on all markets simultaneously with a threshold of three standard deviations. We also tried alternative levels for the threshold, what changed the size and number of observations classified as jumps, but not the ranking of markets with regards to their spike-prone behavior, nor the regression results in Section 4.

Table 3
Global power markets: Generation structure.

Market	Generation (TWh)	Total Capacity (GW)	Lignite (%)	Coal (%)	Nuclear (%)	Gas CC (%)	Gas OC (%)	Hydro (%)	Wind (%)
Australia									
AEMO_NSW	70	19	0.0%	**61.2%**	0.0%	2.9%	8.8%	18.0%	1.5%
AEMO_QLD	56	13	0.0%	**59.0%**	0.0%	6.6%	15.7%	1.4%	0.1%
AEMO_SA	13	5	0.0%	12.1%	0.0%	9.3%	**46.4%**	0.0%	25.0%
AEMO_VIC	56	11	**62.0%**	0.0%	0.0%	0.0%	25.2%	7.0%	4.7%
IMO	na	9	0.0%	27.0%	0.0%	4.5%	**51.1%**	0.4%	4.7%
Europe									
APX_NL	107	26	0.0%	15.4%	1.9%	32.4%	31.1%	0.1%	5.8%
APX_UK	343	97	0.0%	27.4%	11.7%	25.9%	6.6%	1.7%	8.3%
BELPEX	85	19	0.0%	8.9%	31.9%	17.2%	13.9%	0.6%	3.7%
EPEX_CH	61	18	0.0%	0.0%	18.3%	0.4%	1.4%	**68.8%**	0.3%
EPEX_D	567	132	17.4%	22.0%	9.6%	6.5%	11.2%	3.0%	13.7%
EPEX_F	533	122	1.0%	5.1%	**53.9%**	3.0%	4.5%	16.4%	5.0%
EXAA	60	22	0.0%	6.2%	0.0%	11.0%	9.4%	**46.0%**	4.3%
GME	286	113	0.0%	10.9%	0.0%	19.0%	16.0%	13.7%	6.2%
Nordpool	138	41	0.0%	5.6%	13.8%	9.4%	23.2%	11.3%	3.5%
OMEL	327	118	1.7%	9.4%	6.6%	19.1%	8.0%	15.7%	18.9%
OPCOM	59	24	24.4%	8.4%	6.1%	0.0%	18.7%	27.8%	6.0%
POLPX	153	39	25.2%	**59.4%**	0.0%	0.9%	0.8%	2.1%	4.7%
North America									
AESO	61	13	0.0%	**44.3%**	0.0%	10.6%	20.7%	6.2%	8.0%
ERCOT	436	112	12.0%	9.9%	4.7%	20.1%	30.9%	0.6%	9.9%
ISO_NE	123	38	0.0%	6.9%	12.4%	24.0%	8.5%	5.1%	1.4%
MISO	722	185	2.2%	**40.9%**	11.4%	4.7%	17.7%	4.9%	8.5%
NYISO	386	99	0.1%	7.6%	12.9%	1.8%	6.2%	**48.7%**	4.6%
OIESO	140	38	0.9%	8.0%	36.1%	9.1%	10.7%	20.4%	5.3%
PJM	543	145	0.0%	36.0%	15.3%	8.3%	17.8%	1.6%	1.1%
Asia									
ATS	997	242	4.5%	16.4%	10.5%	2.7%	**41.5%**	19.5%	0.0%
EMC	44	11	0.0%	0.0%	0.0%	44.5%	8.8%	0.0%	0.0%
IEX	975	224	3.2%	**56.7%**	2.1%	4.9%	2.4%	16.6%	3.3%
KPX	490	90	0.0%	29.8%	23.3%	0.6%	24.7%	2.1%	0.4%

This table shows information about the production capacities in the different market regions for the year 2011. The capacity information is based on the Platts WEPP database. Capacity information is presented a selection of fuel and technology types. Capacities exceeding 40% for a specific generation type are reported in bold. Gas fired power plants are listed for combined cycle gas turbines (Gas CC) and open cycle gas turbines (Gas OC). The total generation in the area is taken from statistic agencies.

4. Empirical results

In the following section we describe empirical results for the considered electricity markets around the world. In particular we will focus on a comparison of the markets with regards to price levels, seasonality in prices at the annual, weekly and intra-daily level, price volatility as well as the occurrence and magnitude of price jumps or spikes. We also conduct a principal component analysis and illustrate that the key features of spot price behavior in the markets can be classified based on a relatively small number of three factors. The identified factors explain a high fraction of variation in the characteristics of spot electricity prices across the power exchanges considered in this study. Finally, we examine in more detail the differences between day-ahead and real-time power exchanges.

4.1. Descriptive analysis

In a first step we investigate the considered electricity markets by analyzing price levels, volatility, the occurrence of price jumps and spikes, the dispersion of market prices and returns as well as observed annual, weekly and intra-daily levels of seasonality.

4.1.1. Price behavior

We start with examining descriptive statistics for the considered markets. Note that for several markets, we had access to data on spot electricity prices only for a sub-period of the entire sample period, see Table 2. Therefore, a comparison of the mean prices has to be considered with care. For example, for the Australian NEM markets we have data available from January 1, 1999 to December 31, 2012, while for some of the other markets, for example, ERCOT in North America or IEX in India, we only have data from 2010, respectively 2008 onwards. However, the analysis still allows us to get an overall view of price levels, volatility of prices and the frequency and magnitude of jumps for all markets as well as a comparison of individual market behavior to overall figures.

Table 4 provides descriptive statistics for all 289 market years. We find that the average price level across all markets was around

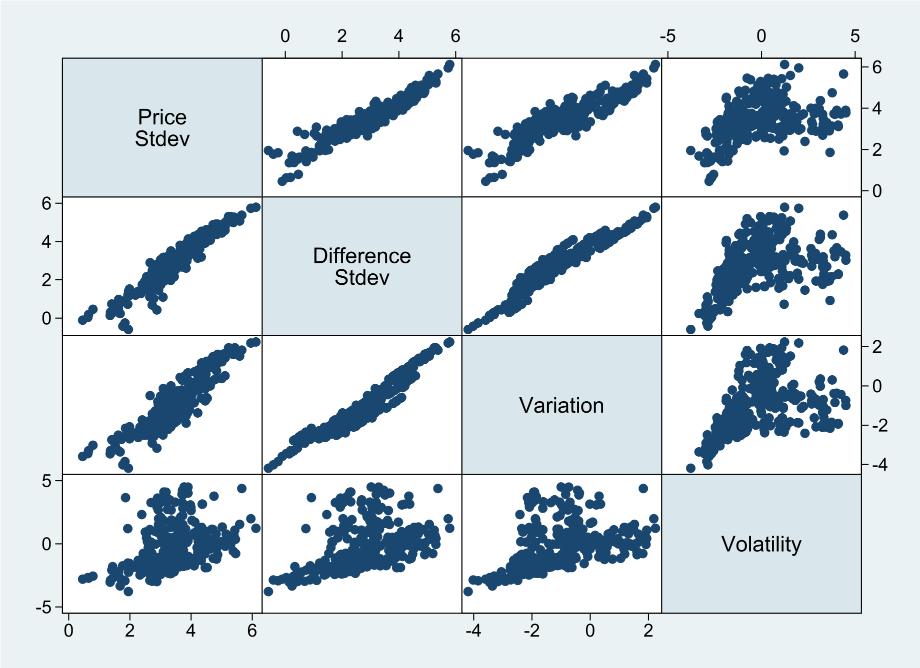

Fig. 3. This figure shows scatter plots of the different variation measures. Starting with the standard deviation of prices, then followed by the standard deviation of USD price differences from one hour to the next. The third measure VARIATION is based on standardized price differences, i.e. the price differences divided by the markets average price level. The measure is calculated as the standard deviation of these standardized differences. The last measure, VOLATILITY is based on classical returns, i.e. the percentage gain from one hour to the next.

Table 4
Summary statistics.

	n	mean	sd	p25	p50	p75
Price						
Mean	289	50.79	26.89	30.34	46.39	64.62
Stdev	289	47.74	57.40	17.95	25.66	49.60
Skewness	289	9.27	13.63	0.70	2.21	14.35
Kurtosis	289	345.40	731.80	4.89	22.21	297.20
Return						
Variation (Stdev)	289	0.90	1.56	0.12	0.23	0.80
Skewness	289	−0.20	4.37	−0.18	0.35	0.73
Kurtosis	289	365.30	662.70	11.11	48.18	409.50
Jump						
Frequency	289	0.08	0.07	0.03	0.06	0.10
Stdev	289	3.09	5.43	0.46	0.67	2.58
Non jump Stdev	289	0.09	0.03	0.08	0.10	0.11
Frequency up	289	0.04	0.04	0.02	0.04	0.06
Frequency down	289	0.04	0.04	0.01	0.03	0.05
Mean size up	289	1.07	1.15	0.44	0.56	1.14
Mean size down	289	−1.16	1.36	−1.19	−0.59	−0.44
Stdev size up	289	2.59	5.00	0.14	0.35	1.98
Stdev size down	289	2.95	5.82	0.14	0.37	2.10

This table shows summary statistics of the variables on basis of calendar year data, i.e. 289 years of price data across all markets. The first part shows variables based on the power prices, the second part on the returns, and the third part on the identified jumps. The last part shows variations of the time series, when the jumps are removed, and when solely the jumps are considered.

$50, while the standard deviation of average annual price levels is quite substantial with $26.89.[15] The strong variation between average annual price levels is also indicated by a lower quartile of $30.25 and an upper quartile $64.62. Thus, for 25% of the time, or more than 70 of the considered 289 years of price data, average annual prices were below $30, while for 25% of the considered

[15] When only observing prices from January 2010 to December 2012, the average annual price level is about $59, with a standard deviation of $29.

market years, average annual prices were $64 or higher.

Prices typically also exhibit high levels of standard deviation, skewness and kurtosis throughout the year. The average standard deviation of prices throughout a year is around $48 and prices are heavily skewed to the right with a coefficient of skewness equal to 9.27. As expected, we find prices to exhibit extreme kurtosis with an average kurtosis of 345.30. These results are in line with many previous studies on the behavior of electricity spot prices, see, e.g. Clewlow and Strickland (2000); Weron (2006) who also point out that spot electricity prices are typically skewed to the right and exhibit extreme levels of kurtosis. Interestingly, the high numbers for the average skewness and kurtosis can be attributed to a few markets with extreme outcomes for these measures, for example the regional markets in Australia. This is evidenced by the fact that the average level of skewness (9.27) is well above the median of the skewness for all years (2.24), while the average kurtosis for all markets (345.30) is even higher than the upper quartile of the estimated kurtosis for all market years (297.20). Therefore, the distribution of skewness and kurtosis of annual spot electricity prices for the considered markets is not symmetric but also highly skewed to the right.

For the calculated relative measure of variation[16] we find that the average variation in hourly prices is 0.9. Again we find that the distribution for the variation is not symmetric but highly skewed to the right with the lower quartile of the variation measure equal to 0.12 and the average variation for all markets being higher than the upper quartile of the variation 0.8. Thus, for more than 70 of the considered 289 years of price data, the average variation of prices was below 0.12, while only for 25% of the considered market years, the variation was actually greater than 0.8. Therefore, we observe a small number of market years with extremely high variation in absolute hourly price changes.

With regards to identifying jumps, we also apply a relative measure to identify jumps and base it on the standardized measure of difference between prices, STANDDIFF. We classify all movements that exceed 30% in absolute terms as jumps based on the recursive filtering algorithm initially suggested by Clewlow and Strickland (2000).[17] We find that the average frequency of jumps is 8%, with equal probability of extreme downward and upward price movements. Our results also indicate that upward jumps are of greater magnitude and are usually 2.59 times the magnitude of average price levels in a market, while downward jumps have a size of 1.16 times the average price levels. Again, the jump size is affected by a number of markets with high jumps, since the average upward jump is significantly above the upper quartile for the jump size (1.98).

Table 5 provides descriptive statistics for mean price levels, the standard deviation of prices as well as the skewness and kurtosis of spot electricity prices for the five Australian, 12 European, seven North American and four Asian markets.

For Australia, we find that for the four Eastern and Southeastern Australian markets contributing to the NEM, i.e. NSW, QLD, SA and VIC, have relatively low price levels for the considered time period from January 1999 to December 2012. Average price levels are between $27.15 for Victoria and $34.87 for South Australia, well below the overall average price levels of $50.79. This can be attributed to the very high level of generation by hard coal and lignite, i.e. brown coal. Since Australia is one of the major mining areas for hard and brown coal, the commodities are available at very low prices. On the other hand, we find that standard deviation, skewness and kurtosis for the Eastern Australian NEM markets are well above overall average levels for these measures. The average standard deviation of spot electricity prices ranges from $92.69 for VIC up to $157.60 for SA, the latter being the highest standard deviation of prices for all markets. Skewness is between 25.09 and 36.61 in comparison to an average level of skewness of 9.27 for all markets. Kurtosis of spot electricity prices for the NEM markets is also way above the average level of 345.30 and ranges from 854.60 for SA up to 1680 for VIC. We attribute this specific price behavior of the Eastern Australian electricity markets at least partially to the fact that they are markets with continuous trading, i.e. real-time markets. Therefore, NEM markets are different to the majority of other markets considered in this study, where prices are typically determined in a day-ahead auction. We will investigate the relationship between price behavior, day-ahead and real-time markets more thoroughly later on.

The considered European markets typically exhibit higher price levels, but significantly lower levels of standard deviation, skewness and kurtosis in comparison to the Australian NEM. The lowest price levels in Europe are observed for the POLPX exchange in Poland ($33.43) while in particular the Italian GME ($95.36), the Swiss EPEX CH ($74.86), the APX UK ($70.13) and the Belgium BELPEX ($67.89) exhibit price levels well above the overall average price of $50.79 across all markets. However, for none of the considered European markets, standard deviation of prices reaches the same level as for the NSW, QLD, SA and VIC. The observed standard deviation of prices is between $8.62 for the POLPX up to $45.07 for the APX in the Netherlands. Spot electricity prices in Europe are also significantly less skewed, such that only the BELPEX and the French EPEX exhibit levels of skewness greater than 10. For the Romanian OPCOM market, we find that prices are symmetric, while they are close to being symmetric for the POLPX. Interestingly, for some of the European markets we still find very high levels of kurtosis, in particular for the BELPEX (1042.00), the French EPEX (424.40) and the German EPEX (306.80).

For the seven North American markets, price levels are between $36.67 for the MISO exchange and $58.49 for the Canadian AESO real-time market. Interestingly the AESO market also exhibits the highest level of standard deviation $87.52, what may be another indication for more volatile price behavior of real-time electricity spot markets. A similar level of volatility is only exhibited by the Texas ERCOT market with $83.03, while all other North American markets are significantly less volatile and typically have a standard deviation of spot electricity prices around $20. Markets are slightly right-skewed with skewness coefficients between 1.51 and 5.56, apart from the Texas ERCOT exchange, where prices are significantly more skewed and also exhibit high levels of kurtosis (471.50). The only other American market with a relatively high level of kurtosis is the second real-time market, the Canadian OIESO

[16] Recall that the relative variation is based on a standardized measure of difference between hourly prices for each market $\text{STANDDIFF}_t = (P_t - P_{t-1})/(\frac{1}{T}\sum_{i=1}^{T} P_i)$.

[17] The recursive filtering algorithm with a threshold of three standard deviations suggested to classify absolute movements greater than $3 \cdot 9.73 \approx 30\%$ as jumps.

Table 5
Price variables listed by markets.

	Mean Price	Stdev Price	Skewness Price	Kurtosis Price
Australia				
AEMO_NSW	29.59	120.80	29.41	1215.00
AEMO_QLD	28.97	113.20	29.56	1213.00
AEMO_SA	34.87	157.50	25.09	854.90
AEMO_VIC	27.16	92.68	36.61	1680.00
IMO	44.64	33.06	3.08	23.50
Europe				
APX_NL	57.16	45.07	5.64	86.70
APX_UK	70.12	30.77	4.27	50.44
BELPEX	67.88	40.40	15.21	1042.00
EPEX_CH	74.84	30.97	1.14	12.91
EPEX_D	51.69	29.13	7.30	306.80
EPEX_F	56.21	41.33	11.59	424.50
EXAA	58.42	27.44	2.73	44.59
GME	95.36	36.20	0.85	5.04
Nordpool	36.57	11.07	2.40	52.66
OMEL	48.15	15.19	0.32	4.33
OPCOM	58.94	23.90	0.00	2.60
POLPX	33.43	8.62	0.41	6.93
North America				
AESO	58.48	87.50	5.05	39.20
ERCOT	36.85	82.94	18.78	471.80
ISO_NE	57.17	20.14	2.77	28.24
MISO	36.67	17.74	1.51	9.47
NYISO	57.57	21.89	2.04	14.47
OIESO	37.93	23.22	5.56	198.20
PJM	41.60	25.38	3.89	43.64
Asia				
ATS	21.64	5.32	0.32	4.79
EMC	108.20	61.26	21.35	848.70
IEX	84.94	39.89	1.03	4.48
KPX	74.86	19.03	−0.93	5.16

This table shows the average values of the price variables for each market over all available years.

in Ontario.

For the Asian markets we find relatively high price levels for three of the four markets that are considered in this study. The Korean KPX, the Indian IEX and the Singaporean EMC market exhibit price levels between \$74.85 and \$108.20, well above the overall mean of \$50.79. Interestingly, the Singaporean exchange is also organized as a real-time market. On the other hand, the Russian ATS exchange has the lowest price levels of all markets with average prices of \$21.64 for the period 2007 to 2012. For the real-time Singapore EMC exchange we also observe by far the highest levels of standard deviation, skewness and kurtosis in comparison to the other markets.

4.1.2. Return behavior

The second panel in Table 4 lists summary statistics of the price evolution from one hour to the next. The numbers are based on the standardized measure of price difference in equation (1). In contrast to the variation based on prices in the first panel of Table 4 and in Table 5 that is a measure for the price variation over the year, the relative measure provides information on how fast spot electricity prices are fluctuating on an hourly basis. The standard deviation of the return shows a high average level of about 90% (relative to the markets' price level), but similar to the standard deviation of prices, the average level across all markets is upward-biased by some extreme values. Nevertheless, with a median level of approximately 23%, the hourly price movements are immense. Note that unlike actual spot prices, standardized 'returns' of spot electricity prices are almost symmetric, indicating that after a sudden increase of spot electricity prices, they usually drop back to their normal price levels in a similar manner. While the skewness of price differences across all markets is slightly negative ($skew = -0.20$, the median value of skewness across all markets exhibits a low positive value ($skew = 0.35$) such that there are no clear-cut results with respect to returns typically being positively or negatively skewed in the considered markets. Similar to the prices, the kurtosis for the returns shows high numbers for most markets with a median level of about 48. The fat tails, both to the upside as well as the downside are commonly addressed by models that include jump components (Lucia and Schwartz, 2002; Weron et al., 2004; Cartea and Figueroa, 2005; Geman and Roncoroni, 2006; Seifert and Uhrig-Homburg, 2007) or a regime-switching mechanism (Huisman and Mahieu, 2003; Misiorek et al., 2006; Mount et al., 2006; Bierbrauer et al., 2007; Kanamura and Ohashi, 2008; Janczura and Weron, 2010).

Table 6 presents the mean levels of the return variables for the individual markets. Additional to the standard deviation, skewness, and kurtosis of the standardized measure of US-Dollar differences from Table 4, average levels of the standard deviation of price differences, as well as arithmetic returns are presented. As for the considered measures of price variations, we see the highest level in

Table 6
Return variables listed by markets.

	Return Variation	Return Skewness	Return Kurtosis	Stdev Price Differences	Volatility (classic)
Australia					
AEMO_NSW	3.60	−3.05	1023.00	106.50	1.29
AEMO_QLD	3.43	−3.19	860.80	99.38	1.46
AEMO_SA	3.63	−2.01	817.10	126.60	7.93
AEMO_VIC	3.12	−5.52	1415.00	84.69	1.22
IMO	0.27	0.83	78.11	12.33	0.90
Europe					
APX_NL	0.50	0.49	173.60	28.50	21.57
APX_UK	0.23	−0.22	80.91	15.29	0.15
BELPEX	0.45	0.50	1019.00	30.24	25.62
EPEX_CH	0.16	0.57	47.82	11.67	1.39
EPEX_D	0.37	1.31	655.30	18.33	7.50
EPEX_F	0.44	1.75	735.80	24.77	12.92
EXAA	0.21	1.76	132.70	11.53	24.48
GME	0.20	0.14	12.32	18.26	0.20
Nordpool	0.07	2.67	297.50	2.64	0.08
OMEL	0.13	0.32	10.51	6.38	3.40
OPCOM	0.18	0.25	8.37	10.49	0.72
POLPX	0.12	0.36	18.65	3.91	0.12
North America					
AESO	1.02	−0.33	42.03	59.44	1.20
ERCOT	1.48	−6.36	516.60	54.15	0.25
ISO_NE	0.11	0.80	21.79	6.04	0.10
MISO	0.18	0.73	8.57	6.71	0.31
NYISO	0.11	0.38	14.21	6.54	0.12
OIESO	0.46	−1.65	333.40	17.31	4.40
PJM	0.24	0.37	36.48	9.83	0.34
Asia					
ATS	0.08	0.44	11.18	1.78	7.10
EMC	0.41	1.16	937.30	44.33	2.34
IEX	0.16	0.19	12.03	13.96	0.22
KPX	0.13	0.08	16.38	9.75	0.26

This table shows the average values of the return variables for each market over all available years.

the NEM markets in Australia, with values of more than 3 for the return variation and high negative values for the skewness ranging from −2 to −5.5. It is in inteparticular these markets that also lead to an overall average negative value of the return skewness across all markets. Price returns in Australian markets also exhibit very high values of kurtosis between 800 and 1400. The findings for the NEM-markets confirm our results for the price variation in Section 4.1.1 also for the 'return' of relative price differences, indicating that for the NEM extreme price differences occur really fast. Nevertheless, the negative values for the skewness for the returns in the NEM indicate even more extreme downward than upward movements. The European markets show much lower levels of variation, with the highest value of the return variation at the APX_NL in the Netherlands (0.5), and the lowest variation in the Scandinavian Nordpool exchange with 0.07.[18] Similar to the results for the price variation, we find a very low return variation for the markets POLPX and OME of 0.12 and 0.13, respectively. For all markets, except the British (APX_UK) exchange, we find a positive skewness,[19] that is in line with the findings in Section 4.1.1 and indicates sharp price increases and more gentle price drops.

In North America, the market in Texas, ERCOT, shows the strongest variation with a standard deviation of the returns of 1.5, and a skewness coefficient that is even more negative than for the NEM-markets. The extreme price behavior in Texas is often attributed to a relatively high share of intermittent wind energy, the state's susceptibility to heat waves and other extreme weather, see, e.g., Coulon et al. (2013). Except for the ERCOT market, the other US-markets show a below average standard deviation and kurtosis, typically accompanied by a positive skewness around the median level across all markets. In contrast, the Canadian markets in Alberta (AESO), and Ontario (OIESO) exhibit more extreme returns, with variation of about 1.0 (AESO), and 0.5 (OIESO, as well as a negative skewness in both markets, that is stronger in Ontario (−1.65).

For the Asian markets we find low return variations for Russia (ATS), India (IEX), as well as South Korea (KPX) that show standard deviations between 0.08 and 0.16. We also observe relatively low values for the kurtosis between 11–16, and slightly positive values for the skewness. The market with the highest price level in Singapore shows again higher standard deviation, skewness, and a very high level of kurtosis.

Column four (*Stdev Price Differences*) and five (*Volatility (classic)*) in Table 6 present the standard deviation of other return

[18] In relative terms the Nordic market shows slightly lower variation as the Russian market ATS (0.08) that can be attributed to a higher price level and therefore, a stronger normalization.

[19] The extreme kurtosis in the BELPEX market is the result of only three extreme prices during the sample period, and the low number of observations for this market.

Table 7
Summary statistics of seasonal patterns.

	n	mean	sd	p25	p50	p75
Months Range	28	13.75	10.17	8.427	11.13	14.48
Days Range	28	10.27	6.76	5.154	7.677	16.96
Hours Range	28	30.44	14.12	20.44	28.7	40.44
Months Stdev	28	4.324	3.057	2.725	3.455	4.367
Days Stdev	28	3.868	2.519	1.961	2.969	6.369
Hours Stdev	28	9.705	4.646	6.493	9.703	12.72

This table shows descriptive statistics of the seasonal patterns in the time series. Seasonal patterns are based on average prices for months, days in a week, and hours in a day. The range variables thereby, show the difference between the highest and the lowest value for the average month, day, or hour respectively.

measures, in column four for the price differences in US-Dollar, and in column five for arithmetic returns. As it can be expected, the differences between column one and four are quite small and the order of the markets remains fairly the same. On the other hand, column 5 indicates very different results for the variation in price changes for the considered markets in comparison to the other two measures. For example, the NEM markets that exhibit the highest variation for prices as well as for the other return measures, are in the average range of markets now. Further, the Russian market (ATS) with the lowest values for the other measures shows a larger standard deviation of arithmetic returns than most of the other markets.[20] Therefore, we argue that a variation measure based on the standardized price differences is clearly more suitable for the analysis of high-frequency power prices than using actual returns or log-returns.

4.1.3. Seasonal behavior

Let us now consider seasonal patterns and price differences for the examined markets. Table 7 provides a summary of the range of average prices throughout the year, the week and at the intra-daily or hourly level. The measures are calculated for each of the considered 28 markets separately, using the entire sample period for each market, see Table 2.

Following Janczura et al. (2013), we also decided to estimate the annual, weekly and intra-daily seasonal patterns based on outlier-filtered data. The authors find significant evidence for a superior estimation of both the seasonal short-term and long-term components when the data on electricity spot prices have been treated carefully for outliers. Among the approaches suggested for outlier detection, the authors find a particularly good performance for a 'recursive filter' technique, where prices corresponding to the price increments or returns exceeding three standard deviations of all returns are removed one by one in an iterative procedure, see, e.g., Clewlow and Strickland (2000); Cartea and Figueroa (2005); Bierbrauer et al. (2007). We decided to follow a similar approach and classified all prices exceeding the median price by more than three standard deviations as outliers. These prices were then replaced by a 'typical' observations for this hour, day and month, i.e. the median of all prices for a particular hour on a particular day of a particular month. The conducted procedure should guarantee a more robust estimate of the annual, weekly and intra-daily seasonal pattern for each market.

We report descriptive statistics for the price range based on a monthly frequency the following way: for each of the 28 markets, we calculate mean prices for each of the twelve months. Then, for each market, we calculate the monthly price range as the difference between the month with the maximum average price level and the month with the minimum average price level. This statistic provides a proxy for seasonal price behavior throughout the year, or, more exactly, it illustrates how much average monthly price levels can deviate throughout the year for the considered markets. We find that the mean monthly price range is approximately $13.75 with a standard deviation of $10.17, indicating overall substantial differences between price levels throughout the year. We also report additional descriptive statistics for the monthly price range and find that the lower quartile is around $8.43, while the upper quartile is $14.48. Thus, for 25% of the considered markets, the difference between the maximum average monthly price and the minimum average monthly price was greater than $14.

Let us now consider the price range based on a daily frequency that yields an indication of the weekly seasonal pattern: for each of the 28 markets, we calculate mean prices for Monday, Tuesday, Wednesday,…, Sunday. Then we calculate the daily price range as the difference between the day with the maximum average price level and the day with the minimum average price level. Clearly, we would expect that usually the day with the highest average price level will be a week-day, while the lowest average price level is usually observed on a Sunday. The statistic provides a proxy for average seasonal price behavior throughout the week. As expected, we also find evidence for a strong weekly seasonal pattern for the considered markets. On average, the difference between the day with the highest average price and the day with the lowest average price is around $10 with a standard deviation of $6.76. As indicated by the lower and upper quartile, only for approximately 25% of the markets, the daily range is less than $5.15, while it is above $17.96 for one quarter of the electricity spot markets considered in this study. Overall, for the considered markets, seasonality throughout the year, indicated by the monthly price range, seems to be more pronounced than the weekly seasonal pattern that is

[20] This change in order can be attributed to the occurrence of low prices as basis for arithmetic returns. Therefore, markets where prices often reach levels close to zero show much higher volatilities than markets with higher prices and positive price jumps. As mentioned earlier this questions the appropriateness of using standard return-based measures of volatility for electricity markets.

measured by the daily price range.

Finally, we have a look at the price range based on an hourly frequency that provides information on the intra-daily seasonal pattern. To do this, in a first step we calculate mean prices for each of the 24 hours, i.e. $h = 1, 2, 3,\ldots, 24$, for each of the markets. The hourly range is then calculated as the difference between the hour of the day with the maximum average price level and the hour of the day with the minimum average price level. We would expect that usually the hour with the highest average price level will be during a peak period around noon, while the lowest average price level is usually observed during one of the off-peak hours at the beginning of the day. We find that in comparison to the monthly and daily price range, the intra-daily seasonal pattern is even more pronounced and yields an average hourly price range of approximately $30 with a standard deviation of $14.12. For one quarter of the markets, the range between the hour with the maximum average price level and the one with a minimum average price level is even above $40, pointing towards a substantial intra-daily effect on electricity prices. This does not really come as a surprise, as generally the difference between demand for electricity during off-peak hours, e.g. during the night, and peak business hours during the day is often quite substantial.

In a next step we have a look at these statistics for the markets individually. Table 8 provides information on the monthly, daily and hourly price range for the five Australian, 12 European, seven North American and four Asian markets. For Australia, we find that for the four Eastern and Southeastern Australian markets contributing to the NEM, i.e. NSW, QLD, SA and VIC, the annual seasonal pattern measured by the monthly range is relatively weak. The average monthly range for these markets is between $4.46 and $9.85 and, therefore well below the average range for the entire sample. On the other hand, the IMO market in Western Australia shows much stronger seasonal effects with a range of $14.88 between the month with the maximum average price level and the month with the minimum average price level. Considering the weekly seasonal pattern, again we measure the difference between the day with the highest average price and the day with the lowest average price. For the NEM we find that the difference is between $4.05 for NSW and $6.19 for SA, while it is $8.62 for the Western Australian IMO. These values clearly are all below the average spread for all markets reported in Table 7 indicating that also seasonality throughout the week is less pronounced for the Australian markets. Finally, for the intra-daily seasonal pattern, the hourly range is between $15.85 and $20.48 for the NEM, what is well below the hourly range of $30.44 for all markets considered. Again the intra-daily seasonal pattern is significantly more pronounced for the IMO in Western Australia with a range of $32.15. Overall, we find that in comparison to electricity markets around the world, the annual, weekly and intra-daily seasonal pattern is clearly less pronounced in the five regions of the National Electricity Market (NEM) that contains the interconnected markets of NSW, QLD, VIC, SA and TAS. On the other hand, the isolated IMO market in Western Australia exhibits a significantly stronger seasonal pattern at the annual, weekly and intra-daily frequency. Our findings for the annual seasonal pattern may be a result of clearly less variability in the temperature for the Eastern Australian states. However, it is noteworthy that the markets also exhibit less seasonality on the weekly and intra-daily scale.

Considering the 12 European markets, we generally find significantly higher levels of seasonality throughout the year for most markets. Overall, the magnitude of the intra-daily seasonal pattern is the strongest, followed be the annual one, while the weekly pattern shows the smallest variation but still yields relatively large differences between price levels for different days of the week. Typically, the difference between the month with the maximum average price level and the month with the minimum average price level is between $5 and $15 for ten of the considered markets. Exceptions are the Belgian and Swiss electricity markets with a higher monthly range of $22.38 (BELPEX) and $26.80 (EPEX CH). As illustrated in Table 5, these markets were also among the ones with the highest price levels in Europe. Also for the weekly seasonal pattern we find strong effects for the European markets. The effects are most pronounced for the Dutch APX NL, the BELPEX, the EPEX CH, the German EPEX, the French EPEX, the Austrian EXAA and the Italian GME exchange, where the difference between the day with the highest average price and the day with the lowest average price is greater than $18. Also intraday patterns are typically more pronounced than for Australia, such that the range between the hour of the day with the maximum and minimum average price level is more than $40 for seven of the 12 European markets. Interestingly, for the Italian GME that also yields the highest overall price levels in Europe, the intraday range is extremely high with more than $70.

For the North American markets, we obtain results quite similar to Europe. Overall, the intra-daily seasonal pattern is most dominant, followed be the annual pattern, while the weekly pattern shows relatively small variations. For the annual pattern, the difference between the month with the maximum and minimum average price level is between $7.40 and $14.34, the weekly range is between $2.12 and $9.13, while the intra-daily difference is the strongest and is between $20 and $34.

Finally, for the Asian markets, we observe very weak seasonal effects for the Russian ATS, while the effects are the strongest for the Indian IEX and the Singaporean EMC market. Interestingly, for these markets, the annual seasonal pattern is the most pronounced what is a bit surprising since Singapore does not exhibit strong weather patterns or high levels of seasonality in temperature.

Overall, our results indicate significant regular patterns on an annual basis as well as at the weekly level and throughout the day. This also confirms the necessity of estimating a long-term seasonal pattern and to account for additional weekly and intra-daily patterns as it comes to modeling the behavior of spot electricity prices, see, e.g. Weron (2006); Bierbrauer et al. (2007); Janczura et al. (2013). We also find that for the majority of the considered markets, the magnitude of the intra-daily seasonal pattern is typically the strongest, followed by the annual cycle. While the weekly pattern usually shows the smallest variation, it still yields significant changes between price levels for different days of the week.

4.1.4. *Jumps and extreme price movements*

In the next step we examine the individual markets with respect to the frequency and magnitude of jumps in spot electricity prices. Recall that we classify all price movements that exceed 30% for the applied standardized measure of difference between prices (STANDDIFF) as jumps. Overall results for all markets have been reported in Table 4 and we found the average frequency of

Table 8
Seasonal patterns listed by markets.

Region	Market	Range			Stdev		
		Months	Days	Hours	Months	Days	Hours
Australia							
	AEMO_NSW	8.26	4.05	15.85	2.42	1.47	4.11
	AEMO_QLD	4.46	4.17	17.36	1.21	1.65	4.71
	AEMO_SA	9.85	6.19	20.48	2.91	2.37	5.49
	AEMO_VIC	8.60	5.53	16.89	2.71	2.08	4.64
	IMO	14.88	8.62	32.15	4.41	3.49	11.17
Europe							
	APX_NL	11.16	18.70	43.70	3.77	7.16	13.49
	APX_UK	6.99	6.33	35.89	2.26	2.54	11.34
	BELPEX	22.38	23.25	48.38	6.92	8.79	15.13
	EPEX_CH	26.80	21.90	47.86	10.76	8.02	15.26
	EPEX_D	9.54	19.70	36.02	3.08	7.45	11.30
	EPEX_F	14.61	20.54	40.75	5.41	7.65	12.71
	EXAA	12.39	22.13	40.93	3.64	8.35	12.99
	GME	13.22	19.21	72.46	4.33	7.20	24.04
	Nordpool	11.10	3.73	6.72	3.54	1.48	2.21
	OMEL	8.64	8.04	24.77	2.75	3.03	7.68
	OPCOM	12.37	9.72	40.13	3.36	3.42	13.21
	POLPX	5.37	4.66	10.92	1.85	1.64	3.62
North America							
	AESO	10.77	6.65	32.18	3.37	2.69	10.93
	ERCOT	12.43	2.12	28.77	4.06	0.84	8.68
	ISO_NE	14.34	4.78	26.45	4.01	1.85	8.42
	MISO	9.85	9.13	28.10	3.03	3.65	9.82
	NYISO	12.01	7.32	33.79	4.19	2.91	11.21
	OIESO	7.40	7.23	20.41	2.23	2.83	7.49
	PJM	8.19	8.07	28.62	2.84	3.22	9.59
Asia							
	ATS	4.45	2.79	9.16	1.60	1.02	3.28
	EMC	30.33	6.32	26.41	9.16	2.14	8.08
	IEX	55.13	11.51	42.66	15.56	3.81	12.73
	KPX	19.48	15.22	24.42	5.67	5.58	8.40

This table shows the average values seasonal patterns over all available years. The seasonal patterns are based on average prices for months, days in a week, and hours in a day. The range, e.g. for month shows the difference between the month with the highest average price and the month with the lowest average price. The same holds for weekdays, and hours respectively.

jumps to be equal to 8%, with the average magnitude of an upward jump being approximately 2.59 times the average price level, while the average magnitude of a downward jump was significantly lower and around 1.16 times the average price level. Table 9 reports the results in more detail for the individual Australian, European, North American and Asian markets.

For Australia, we find that between 8% (for NSW) and 11% (for the Western Australian IMO) of price observations are classified as price jumps. We observe that roughly the same fraction of observations is classified as upward and downward jumps. However, we find that the magnitude of the price jumps for the Eastern Australian NEM markets is well above the overall level across all markets considered in this study. For the NSW, QLD and SA market upward jumps have an average magnitude of more than three times the average price levels, while the average size of downward jumps is even higher and is approximately 3.5 times the average price levels. Note that this is not an entirely surprising result, given that these markets exhibit significantly higher levels of volatility, skewness and kurtosis in comparison to most of the other markets. Also recall that in the NEM prices are determined in a constrained real-time trading mechanism, what might lead to a more volatile behavior with substantial price spikes. For the Western Australian IMO that exhibits much lower levels of volatility, skewness and kurtosis, upward and downward jumps only have a magnitude of 0.62 times the average price level in the market.

For Europe, we find substantial differences between the markets considered. For example, the Scandinavian Nordpool market has a very low frequency of extreme price movements, with slighlty less than 1% of the observations being characterized as jumps. On the other hand, for the Dutch APX NL, the Italian GME and the Romania OPCOM market, approximately 10% of the price observations are classified as jumps. For the other European markets, between 5% and 8% of observations are classified as jumps. In comparison to the Australian NEM, we find that the mean size of an upward jump is significantly smaller, typically ranging from 0.43 to 0.65 times the average price level with the exception of the Dutch APX NL, where the mean size of an upward jump is 0.94 times the average price level in the market, what is still well below the mean size of a jump in NSW, QLD, SA or VIC. The number of downward jumps for most of the considered European markets is a bit lower than the number of upward jumps, while the magnitude of positive and negative price jumps is quite similar for these markets.

For the North American markets we find that in particular the Canadian real-time markets AESO and OIESO exhibit a very high frequency of price jumps, with 22%, respectively 20% of price observations exceeding the 30% threshold based on the applied

Table 9
Jump variables listed by markets.

	Jump Up Frequency	Jump Up Mean Size	Jump Up Std	Jump Down Frequency	Jump Down Mean Size	Jump Down Std
Australia						
AEMO_NSW	0.04	3.09	11.86	0.04	−3.59	13.77
AEMO_QLD	0.05	3.05	10.61	0.05	−3.29	11.83
AEMO_SA	0.05	3.20	11.56	0.05	−3.76	13.04
AEMO_VIC	0.05	2.10	9.45	0.04	−2.46	11.34
IMO	0.05	0.62	0.52	0.05	−0.62	0.49
Europe						
APX_NL	0.05	0.94	1.13	0.04	−0.95	1.14
APX_UK	0.04	0.59	0.41	0.04	−0.60	0.45
BELPEX	0.05	0.60	1.24	0.03	−0.65	1.48
EPEX_CH	0.03	0.47	0.25	0.02	−0.50	0.28
EPEX_D	0.05	0.65	0.99	0.04	−0.68	1.08
EPEX_F	0.05	0.65	1.23	0.03	−0.72	1.42
EXAA	0.04	0.53	0.41	0.02	−0.55	0.40
GME	0.06	0.47	0.19	0.04	−0.49	0.20
Nordpool	0.02	0.42	0.12	0.01	−0.42	0.15
OMEL	0.03	0.43	0.13	0.02	−0.42	0.12
OPCOM	0.05	0.46	0.15	0.04	−0.45	0.14
POLPX	0.03	0.47	0.18	0.02	−0.46	0.15
North America						
AESO	0.11	1.52	1.66	0.11	−1.50	1.70
ERCOT	0.04	1.79	4.20	0.04	−2.00	5.09
ISO_NE	0.02	0.42	0.14	0.01	−0.42	0.15
MISO	0.06	0.48	0.16	0.05	−0.42	0.12
NYISO	0.01	0.65	0.46	0.00	−0.67	0.42
OIESO	0.10	0.70	0.73	0.10	−0.70	0.78
PJM	0.05	0.56	0.39	0.04	−0.51	0.40
Asia						
ATS	0.01	0.42	0.10	0.01	−0.39	0.10
EMC	0.03	1.07	1.63	0.03	−1.04	1.57
IEX	0.03	0.46	0.16	0.03	−0.46	0.17
KPX	0.03	0.47	0.13	0.03	−0.46	0.13

This table shows the average values of the jump variables for each market over all years. Jumps are classified when the standardized differences (see 1) exceed 30% up or down. Mean size and standard deviation of the jumps depend on the standardized differences measure as well.

standardized measure of difference between prices. Thus, roughly one in five prices exhibits a substantial price movement in these markets. For AESO we also find a large magnitude for the observed upward and downward jumps (1.50 and −1.50), what provides further evidence for the more volatile behavior of real-time markets. The lowest number of jumps can be found for the US ISO NE market that contains the states of Connecticut, Maine, Massachusetts, New Hampshire, Rhode Island and Vermont as well as the New York NYISO market. For these markets, also the magnitude of the observed jumps is rather low. Price jumps with the highest magnitude are observed for the ERCOT market in Texas, where the mean size of upward and downward jumps is 1.79, respectively 2.00 times the average price level. This 'spiky' behavior also explains the high level of kurtosis for spot electricity prices in the market.

We find typically lower frequencies of price jumps for the Asian markets, ranging from 0.01 in the Russian ATS up to 0.06 in the Singaporean EMC and Indian IEX exchange. For Singapore, the spikes are also of relatively large magnitude with the average size of both upward and downward jumps being greater than 100% of average price levels. Recall that Singapore is also the market with the overall highest average price level of $108.20, such that the average jump size in this market is above $100 and quite substantial. Thus, spot electricity prices in this market also exhibit extreme kurtosis, almost as high as for the Eastern Australian real-time markets.

4.2. Tests & regressions

As shown in Section 4.1, the power markets around the world show different price behavior. Some are prone to a high variation, both in prices as well as in returns, others are more exposed to extreme price movements and have a high frequency, or height of price jumps or spikes. As the power markets and thus their prices are exposed to a multitude of influences, e.g. demand and supply fluctuations, the structure of the merit order, the market design, as well as limitations in the power grid, the sources for differences in price and return variation across the markets are not easy to determine. This section analyzes key factors that help to characterize the different markets as well as the relation between price variations and market design.

4.2.1. Classification of the markets

In the following we try to classify the $N = 28$ markets based on the analyzed key characteristics, using principal component analysis (PCA). PCA is a statistical method that applies orthogonal transformation to a set of observations of typically correlated variables to convert the data into a set of values of linearly uncorrelated variables, the so-called *principal components*. Generally, the objective of PCA is dimension reduction in order to describe the variation in a set of usually high-dimensional variables through those experienced by a small set of factors. Hereby, observed variables are assumed to be linear combinations of the unobserved factors, with the factors being characterized up to scale and rotation transformations. In an orthogonal K-factor model an observable J-dimensional random vector of observations $X_i = (Y_{i,1}, \ldots, Y_{i,J})$ for each market $i = 1, \ldots, 28$ can be represented as

$$Y_{i,j} = Z_{i,1}m_{1,j} + \cdots + Z_{i,K}m_{K,j} + \varepsilon_{i,j} \,, \tag{2}$$

where $Z_{i,k}$ are (unobservable) principal components or latent factors, the coefficients $m_{i,j}$ are factor loadings and $\varepsilon_{i,j}$ are errors. [21]

In the following, factors and loadings are estimated using PCA on a set of 13 characteristics of the markets. In particular, we consider the following variables: the mean price level of the market as well as the three price based measures, StDev Price, Skewness Price and Kurtosis Price (see Table 5); three return based measures, namely the variation, skewness and kurtosis of returns (see Table 6) based on the return measure defined in Equation (1); three seasonality based measures, Range Months, Range Days and Range Hours (see Table 8); and three jump-based measures, Std Jumps, Jump Up Size, Jump Down Size (see Table 9). Thus, for each of the $i = 1, \ldots, 28$ markets we consider $j = 1, \ldots, 13$ characteristics and identify principal components that explain a maximum of the variation between the markets with respect to the considered variables. Note that PCA is typically conducted using a data matrix X with column-wise zero empirical mean and unit variance for each variable. Therefore, the sample mean of each column has been shifted to zero and we also scale each variable to have unit variance.

To derive the loadings $m_{k,j}$ and latent factors $Z_{i,k}$, a PCA seeks an orthogonal matrix M which yields a linear transformation $MX = Z$ of the matrix of characteristics for all markets X and latent factors Z, such that the maximum variance is extracted from the variables. The matrix M is constructed using an eigenvector decomposition. Assume

$$X = M_K Z, \tag{3}$$

where M_K consists of the first K columns of M and Z is the $K \times N$-dimensional matrix of factors $Z_{K,i}$. Let Σ denote the $N \times N$ covariance matrix of X, that can be decomposed as

$$\Sigma = M \Lambda M', \tag{4}$$

where the diagonal elements of $\Lambda = \text{diag}\,(\lambda_1, \ldots, \lambda_K)$ are the eigenvalues, and the columns of M are the eigenvectors. Eigenvalues and eigenvectors are both arranged in decreasing order of the eigenvalues. Denoting the K largest eigenvalues as $\lambda_1, \ldots, \lambda_K$ and the associated eigenvectors by $M_K = [m_1, \ldots, m_K]$, the first K principal components (or factors) $Z = [z_{1,N}, \ldots, z_{K,N}]$ are then defined by $z_{k,i} = M_k' X_i$. Hereby, X_i is a J-dimensional vector of the characteristics for market i.

Applying a PCA to extract the latent factors allows for a data-driven selection of the number of K factors. We decide to use the first three latent factors, since these factors have eigenvalues greater than 1. Hereby, the first principal component yields an eigenvalue of $\lambda_1 = 7.83$ and explains approximately 60% of the variation in the considered variables across the markets; the second component yields $\lambda_2 = 1.60$, explaining roughly 12%; and the third component yields $\lambda_3 = 1.27$, explaining approximately 10% of the variation. Thus, for the considered markets, the first three principal components are already sufficient to explain more than 80% of the variation in the key characteristics of the spot price behavior across the considered 28 markets. Further details on the results of the conducted PCA are provided in Tables 10 and 11 and will be discussed in the following.

Table 10 provides the loadings $m_{k,j}$ of the considered variables on the first three principal components. We find that the first component $K = 1$, explaining approximately 60% of the variance in the data, captures the price dispersion measured by the variables StDev Price, Skewness Price and Kurtosis Price, the return dispersion measured by variation, skewness and kurtosis of returns and the jump-based measures, Std Jumps, Jump Up Size, Jump Down Size. Each of these nine variables has a loading with magnitude greater than 0.25 on the first component, indicated by bold letters in Table 10. The second principal component $K = 2$ that explains roughly 12% of the variance captures mainly the weekly and intra-daily seasonality, indicated by the high loadings $m_{RangeDays,2} = 0.72$ and $m_{RangeHours,2} = 0.65$ for these variables, while the loadings for all other variables are below 0.20. Finally, the third component, explaining approximately 10% of the variation, captures the overall price level of the markets, the kurtosis of returns and the annual seasonality measures by the variable Range Months. As pointed out above, the first three principal components explain more than 80% of the variance for the considered market characteristics. Overall the extracted factors can be interpreted as a *dispersion factor* ($K = 1$), a *weekly and daily seasonality factor*, ($K = 2$), and a *price level and annual seasonality factor* ($K = 3$).

Table 11 provides the estimated factor scores for the individual markets with respect to the identified three principal components. We find that for the fist principal component, the highly volatile Australian markets in NSW, QLD, SA and VIC as well as the ERCOT market yield the highest factor scores (marked by bold letters in Table 11), identifying them as markets with extreme price volatility, return dispersion and significant jumps. Typically these markets do not yield high factor scores for the second and third principal

[21] Please note that the terms factor and principal component are used interchangeably throughout this analysis.

Table 10
Loadings for the first three Principal Components.

		PC_1	PC_2	PC_3
		$\lambda_1 = 7.83$	$\lambda_2 = 1.60$	$\lambda_3 = 1.27$
Price-Based Measures	Mean Price	−0.15	0.02	**0.59**
	Std Dev Price	**0.33**	0.00	0.06
	Skewness Price	**0.34**	0.05	0.14
	Kurtosis Price	**0.32**	0.10	0.21
Return-Based Measures	Ret Var	**0.35**	−0.01	−0.08
	Ret Skew	**−0.28**	0.07	0.14
	Ret Kurt	**0.29**	0.17	**0.28**
Seasonality Measures	Range Months	0.03	−0.03	**0.65**
	Range Days	−0.05	**0.72**	0.05
	Range Hours	0.04	**0.65**	−0.19
Jump Based Measures	Jump Std	**0.35**	−0.03	−0.06
	Jump Up Size	**0.34**	−0.07	−0.08
	Jump Down Size	**−0.35**	0.06	0.07

Loadings of the considered variables on the first three principal components. The first principal component *(the dispersion factor)* explains approximately 60% of the variation in the considered variables, the second principal component *(the weekly and daily seasonality factor)* explains roughly 12% and the third component *(price level and annual seasonality factor))* explains approximately 10%. Variables with loadings on a principal component of magnitude greater than 0.25 are highlighted in bold.

Table 11
Factor scores for the individual markets for the first three Principal Components.

Market		Scores PC_1	Scores PC_2	Scores PC_3
Australia				
	AEMO NSW	**6.47**	−0.57	−0.11
	AEMO QLD	**5.99**	−0.26	−1.06
	AEMO SA	**6.15**	−0.20	−0.24
	AEMO VIC	**6.23**	0.63	0.59
	IMO	−1.27	0.48	−0.08
Europe				
	APX NL	−0.75	1.72	−0.55
	APX UK	−1.36	−1.05	−0.69
	BELPEX	0.43	2.22	1.84
	EPEX CH	−1.77	0.93	1.02
	EPEX D	−0.74	2.16	−0.13
	EPEX F	−0.36	2.23	0.63
	EXAA	−1.73	1.92	−0.24
	GME	−1.83	0.77	−0.04
	Nordpool	*−1.64*	*−2.20*	0.36
	OMEL	−1.82	−0.52	−0.83
	OPCOM	−1.74	0.12	−0.54
	POLPX	*−1.77*	*−1.49*	−1.15
US				
	AESO	0.29	−0.92	−0.69
	ERCOT	**3.05**	−0.44	−0.47
	ISO NE	*−1.76*	*−1.33*	−0.01
	MISO	−1.66	1.08	−0.81
	NYISO	−1.74	−0.52	−0.44
	OIESO	−0.54	−0.19	−0.86
	PJM	−1.37	0.38	−1.02
Asia				
	ATS	*−1.77*	*−1.20*	−1.31
	EMC	0.63	−1.82	3.01
	IEX	*−1.64*	*−0.90*	3.19
	KPX	*−1.98*	*−1.01*	0.64

Factor scores for the individual markets based on the first three identified principal components that explain more than 80% of the variance of the data based on the considered characteristics of the markets.

component, indicating that, while being extremely volatile, this group of markets do not exhibit strong seasonality or high price levels throughout the sample period. With respect to the second principal component that measures mainly weekly and intra-daily seasonality, the APX NL, the BELPEX, the EPEX in Germany and France as well as the Austrian EXAA are classified as a group of markets with extreme seasonality throughout the week and on an intra-daily scale. Based on the conducted PCA, we can also identify a third group of markets with very low price and return dispersion levels and also low levels for weekly and intra-daily seasonality

Table 12
Test statistics of real-time and day-ahead markets variation.

	Day-ahead	Real-time	Difference	p-value	t-value
	n = 195	n = 94			
Price Stdev	2.98	4.25	−1.27	<0.0001	−12.97
Return Variation	−1.84	0.35	−2.19	<0.0001	−17.73
Jump Frequency	−3.38	−2.37	−1.00	<0.0001	−7.81
Jump Size Std	−0.48	1.52	−2.00	<0.0001	−16.08

This table shows test results, based on the difference of mean levels of different variation variables for the group of day-ahead and the group of real-time markets. All variables are log-transformed. A Welch-test on the difference with H_0: *difference* ≥ 0 and H_1: *difference* < 0 is performed and results are shown in column 5 and 6. All variables are log-transformed.

Table 13
Test statistics of variation between day-ahead and real-time markets in the US.

	Day-ahead	Real-time	Difference	p-value	t-value
	n = 43	n = 44			
Price Stdev	3.08	3.41	−0.33	<0.0001	−3.64
Return Variation	−1.82	−0.71	−1.12	<0.0001	−8.86
Jump Frequency	−3.18	−1.79	−1.39	<0.0001	−8.57
Jump Size Std	−0.67	0.16	−0.83	<0.0001	−6.49

This table shows test results, based on the difference of mean levels of different variation variables for the markets in the United States of America, where both (day-ahead and real-time) types of trading is performed. All variables are log-transformed. A Welch-test on the difference with H_0: *difference* ≥ 0 and H_1: *difference* < 0 is performed and results are shown in column 5 and 6. All variables are log-transformed.

(marked by *italic* letters in Table 11), namely the Nordpool, the Polish POLPX, the ISO NE in the United States as well as three markets in Asia, the ATS in Russia, the IEX in India and the KPX in Korea. Finally, we observe a group of markets with high factor scores for the third principal component, indicating high price levels in combination with either high levels of kurtosis or annual seasonality. The conducted analysis identifies in particular the Belgian BELPEX as well as the two Asian markets EMC in Singapore and IEX in India. These markets yield high factor scores for the third principal component.

Overall, the analysis illustrates that a high fraction of the variation in the key characteristics for the considered markets, and, therefore a classification of the markets, can be conducted using the identified *dispersion factor*, a *weekly and intra-daily seasonality factor* and a *price level and annual seasonality factor*. The analysis also illustrates that five of the eight markets, where power trading is organized as a real-time market, exhibit either very high scores for the dispersion factor that refers to price volatility, skewness, kurtosis, return dispersion and price jumps (NSW, QLD, SA, VIC) or high scores for the price level factor (EMC). These results reiterate the specific spot price behavior of exchanges with a real-time market design that was also illustrated in Section 4.1. This motivates us to more thoroughly compare the differences between real-time and day-ahead electricity markets.

4.2.2. Real-time vs. day-ahead

One inherent difference between power markets are their different market designs, that appear in various forms and features. One of these features is the market trading, that can either occur day-ahead, usually in auctions, or on a continuous basis[22] in real-time. The market sample consists of 8 pure real-time markets with a total of 94 market years of data, and 20 markets where the major trading is conducted in a day-ahead market (with 195 market years of data). In the following we examine whether there are significant differences between real-time and day-ahead power exchanges with respect to the standard deviation of prices, the defined return variation measure as well as measures related to the frequency and size of price jumps.

Table 12 shows the result of a Welch test on the difference of mean values between day-ahead and real-time markets for the variables price standard deviation, return variation, the frequency of jumps and the standard deviation of the magnitude of price jumps. The test is performed with the null hypotheses that the difference is positive, i.e. that day-ahead markets yield higher values for price standard deviation, return variation, jump frequency and magnitude. The conducted Welch tests indicate that the null hypotheses can be rejected for all variables, while the obtained p-values ($p < 0.0001$) for all variables suggest that the test statistics are highly significant. Thus, the real-time markets in our sample of power exchanges show a significantly higher standard deviation of prices, return variation, jump frequency, as well as standard deviation of the jump sizes than day-ahead markets.

As these differences may be related to other market characteristics, we also perform the same test on markets with both, day-ahead and real-time trading. Therefore, we use the markets in the United States, where under the standard market design both types are applied. For the 5 US markets we have 43 calendar year observations for day-ahead, and 44 observations for real-time prices. The test results are shown in Table 13 and confirm the observations of the previous test. Real-time markets exhibit significantly higher

[22] For example, trading in the AEMO region in Australia takes place on basis of 5 min intervals in a so-called constrained real-time spot market, see e.g. Clements et al. (2016); Ignatieva and Trück (2016). For example, the power that is traded for the interval 9:00–9:05 takes place at 8:50, for the interval 9:05–9:10 at 8:55, and so on. The half-hourly prices we use in this study are arithmetic averages over these 5 min intervals.

standard deviation of prices, return variation, jump frequency and standard deviation of jump size in comparison to the day-ahead markets.

Overall, these results confirm the special behavior of power exchanges that are organized as real-time markets. Given the significantly higher volatility and price dispersion in these markets as well as the higher frequency and uncertainty about the magnitude of price jumps, most likely retailers and large customers with direct access to these exchanges will be required to more thoroughly hedge their risks. Given that in particular retailers typically supply most of their customers with electricity for prices that are fixed, or time-varying only to a limited extend, in real-time markets these retailers face the difficult task to manage the risk of highly volatile input prices, while supplying an output with a more or less fixed price.

5. Conclusion

In this paper, we have examined hourly spot electricity prices of 28 different power markets across Asia, Australia, Europe and North America. In our analysis we considered the most extensive database in the literature so far, comprising electricity exchanges from 19 different countries around the world for a sample period ranging from 1999 to 2012. We focus on market characteristics such as price levels, volatility, skewness, seasonal behavior and price jumps, and relate these characteristics to specific features of the markets such as electricity generation, trading and fuel sources.

Our findings suggest significant differences between the markets. While Australian markets, throughout the sample period, were typically characterized by a low price level and relatively low levels of annual, weekly and intra-daily seasonality, they were by far the most volatile markets considered in this study. On the other hand, European markets in Belgium, Switzerland and Italy as well as the Asian markets in Singapore, India and South Korea exhibited the highest average price levels among all 28 markets. We also find that almost all markets, with the exception of the Russian ATS and the Scandinavian Nordpool market, exhibit frequent price jumps or spikes.

We also conduct a principal component analysis (PCA) based on the identified market characteristics to further investigate the differences between the considered markets. Our results illustrate that more than 80% of the variance in the data can be explained by three principal components, that, based on their loadings can be interpreted as a *dispersion factor*, a *weekly and intra-daily seasonality factor* and a *price level and annual seasonality factor*. Based on these three factors, we are also able to classify the considered markets into different groups of price behavior.

Our results also suggest that electricity markets organized as day-ahead markets typically exhibit a significantly lower overall price variation in comparison to markets with real-time trading. These differences exist in a cross-market observation, as well as for markets that feature both trading schemes. These results suggest that in particular in real-time electricity markets, retailers and large customers with direct access to these exchanges will be required to more thoroughly hedge their risks. They face the difficult task to manage the risk of highly volatile input prices, while they will most likely not be able to pass through these costs to their customers, at least not in the short term.

Overall, our results provide important information for market participants by classifying the considered markets with respect to associated price and volatility risks.

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Appendix

Appendix A. Definition of variables

Variable	Description
Price Variables	
Mean Price	Average price of electric power. Based on US Dollar price data.
Stdev Price	Hourly standard deviation of the power prices. Based on power prices that are aggregated to hourly data and converted into US Dollar on daily exchange rates.
Skewness Price	Skewness of hourly US Dollar power prices.
Kurtosis Price	Kurtosis of hourly US Dollar power prices.
Seasonal Patterns	
Intraday Spread	Difference between the price of the hour with the highest prices and the hour with the lowest prices of an average day.
Weekly spread	Difference between the average price of the weekday with the highest prices and the weekday with the lowest prices of an average week.
Monthly spread	Difference between the average price of the month with the highest prices and the month with the lowest prices.
Intraday Stdev	Standard deviation of the prices of an average day.

(*continued on next page*)

Variable	Description
Weekly Stdev	Standard deviation of the average day prices in an average week.
Monthly Stdev	Standard deviation of the average month price levels.
Return Variables	
Return Variation	Standard deviation of the standardized differences of hourly electricity prices. Standardized differences are defined as $d = \frac{p_t - p_{t-1}}{average(p)}$.
Jump Variables	
Jump Frequency	Frequency of jumps, either up or down, in the respective market. All hours, for which the standardized differences *d*, in absolute terms, are above a certain threshold are classified as jumps.
Jump Up Frequency	Frequency of positive jumps. All hours, for which the standardized differences *d* are above a certain threshold are classified as upside jumps.
Jump Down Frequency	Frequency of negative jumps. All hours, for which the standardized differences *d* are below the negative threshold are classified as downside jumps.
Mean Size Up	Average size of the positive jumps. Average of all standardized differences above the threshold.
Mean Size Down	Average size of the negative jumps. Average of all standardized differences above the threshold.
No Jump Stdev	Standard deviation of the standardized differences that are not classified as jumps.
Jump Stdev	Standard deviation of the standardized differences that are classified as jumps.
Abs. Jumps	Average absolute jump returns, multiplied by the jump frequency.
Jump Stdev (weighted)	Standard deviation of the jump returns, multiplied by the jump frequency.
Power market characteristics	
Stochastic capacity	Share of non-dispatchable power plants in the corresponding market, i.e. the share of wind and solar capacities. Source: Own calculations based on the *Platts WEPP* database.
Wind capacity	Share of wind power plants on the total capacity of the corresponding market. Source: Own calculations based on the *Platts WEPP* database.
Solar capacity	Share of solar power plants on the total capacity of the corresponding market. Source: Own calculations based on the *Platts WEPP* database.
Hydro capacity	Share of hydro power plants on the total capacity of the corresponding market. Source: Own calculations based on the *Platts WEPP* database.
Wind capacity (SA)	Share of wind power plants on the total capacity of the corresponding market. Source: Own calculations based on data of various statistic agencies and data providers (*EIA, Statistics Canada, NEM-Review*).
Wind generation	Share of wind power production in the corresponding year in percentage of total production. Source: Own calculations based on data of various statistic agencies and data providers (*EIA, Statistics Canada, Eurostat, Statistics Norway*).
Market size	Total power generation in the market in GW. Source: Own calculations based on data of various statistic agencies and data providers (*EIA, Statistics Canada, Eurostat, Statistics Norway*)
Market age	Time since deregulation of the market in years.

Appendix B. Supplementary data

Supplementary data related to this article can be found at https://doi.org/10.1016/j.jcomm.2018.02.001.

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