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Asymmetric volatility in European day-ahead power markets: A comparative microeconomic analysis☆

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ABSTRACT

This paper uses high-frequency spot price data from fourteen wholesale electricity markets in Europe to analyze asymmetric volatility in European day-ahead power markets with Exponential GARCH (E-GARCH) and TARCH models. Our data set ranges from 1992 to 2015 and consists of approximately 926,000 observations. As such, this paper constitutes the most extensive and comprehensive work conducted so far on European power markets, to the best of our knowledge. Unlike most of the literature that treats price as a continuous variable and attempts to model its trajectory, this paper adopts a unique approach and regards each hour in a day a separate market. The results show, in post-2008 period, the most expensive electricity is consumed in Turkey, Ireland, and UK while the cheapest power is in Russia, Nordic countries, and Czech Republic. Russia, Poland, and Czech Republic have the least volatile markets while France, Ireland, and Portugal have the most volatile ones. Volatility has decreased in many European countries in post-2008 period. Besides, we find magnitude effect is usually larger than the leverage effect, meaning that the absolute value of price change is relatively more important than the sign of the change (*whether it is an increase or a decrease*) to explain volatility in European day-ahead power markets. Moreover, the results imply there is not a uniform inverse leverage effect in electricity prices; that is, price increases are more destabilizing in some European markets (e.g. Poland, Slovenia, Ireland, Netherlands) than comparable price decreases but vice versa also holds true in some other countries (e.g. Portugal and France). Leverage (or inverse leverage) effect in post-2008 period is relatively stronger in Portugal, France, and Ireland, but its impact is quite limited in Turkey and Germany. Furthermore, although the impact of seasonality on prices is obvious, a specific pattern cannot be identified. Finally, large changes in the volatility will affect future volatilities for a relatively longer period of time in Nordic countries, Ireland, and the UK while changes in current volatility will have less effect on future volatilities in Czech Republic, Russia, and Turkey.

1. Introduction

Until the last three decades, electricity price modeling was rarely performed due to the regulatory nature of power prices. Since the 1980s, however, the structure of electricity industry has shifted from a vertically integrated (and usually state-owned) monopoly toward unbundled (and usually privately owned) regulated utilities (Erdogdu, 2013, 2014). The popularity and importance of power price modeling grew in the late 1990s due to an increase in market risk and price volatility after deregulation. Since then, price modeling has become an important tool for regulators, electricity generators, retailers, large consumers, and those managing energy commodity portfolios.

The liberalization process has caused significant changes in electricity markets all over Europe. Electricity is no longer sold by public enterprises with fixed tariffs and now becomes a commodity traded on energy exchanges, where prices are formed on day-ahead or intraday spot markets (Erdogdu, 2011). Over the past two decades, knowledge has accumulated about the characteristics of electricity prices, including seasonality, mean-reversion, time-varying volatility, and price spikes. Some authors add other characteristics to the list like high-volatility persistence (Frömmel et al., 2014) and inverse leverage effect (Bowden and Payne, 2008), meaning that electricity price volatility tends to arise more with positive shocks than negative ones. These characteristics, usually called “*stylized facts of electricity prices*", originate from the convex supply curve, price inelastic demand in the short-run, and non-storability of electricity. As power prices follow more or less these *stylized facts*, they can be explained with deterministic functions.

In power markets, supply or demand shocks due to for instance unexpected outages of generation units or transmission constraints cannot be fully compensated in the short run. As a result, sudden jumps in prices (so-called spikes) may occur, especially when reserve capacity is limited. In fact, electricity prices are much more volatile than the prices of other commodities and, therefore, pose a huge risk for market participants, which is unknown to other commodity or financial

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markets. For instance, in a typical power market, the price can increase by 100 times or more, followed by a relatively quick return to normal levels. The literature (summarized in Section 2) on power price modeling, however, has mostly focused so far on power price forecasting, leaving behind the need for modeling price volatility in electricity markets as a separate task. This is quite surprising given the deep impact that price volatility has on market participants. This makes our work crucial as we address this issue directly by providing a simple but highly effective methodology.

This paper contributes to the literature on power price modeling in several ways. First, as mentioned above, it contributes greatly to the evolving but limited literature on modeling the asymmetric price volatility in power markets—there have been very few such studies published in the last decade. Second, this paper constitutes the most extensive and comprehensive work on European power markets, to the best of our knowledge. No study has so far used so many observations on so many power markets in Europe. Our analysis is based on fourteen European wholesale electricity markets for a period beginning in 1992 and extending through 2015 and the total number of observations is 926,227. As an additional contribution to the literature, unlike most of the literature that treats price as a continuous variable and attempts to model its trajectory, this paper adopts a unique approach and regards each hour in a day a separate market because of the reasons specified in Section 3.

Within this context, we try to answer the following research questions: (*i*) Which countries in Europe have the most/least volatile power markets? (*ii*) What is the relative importance of the absolute value of price change and its direction (an increase or a decrease) to explain volatility in European day-ahead power markets? (*iii*) Is there an inverse leverage effect in European day-ahead electricity prices? (*iv*) Which European power markets have the strongest/weakest persistence in conditional volatility; that is, in which countries volatility takes a long/short time to die out following a shock irrespective of anything happening in the market?

This paper is organized as follows. In Section 2, a literature review is presented. The data and methodology are outlined in Section 3 while the corresponding estimation procedure is described and the results are discussed in Section 4. Section 5 concludes.

2. Literature review

Modeling power prices is a complex issue and the approaches applied to model electricity prices are quite diverse. In this section, we present a glimpse of the literature on modeling of power market prices. A detailed overview of all literature is outside the scope of this paper. The interested readers may be referred to Weron (2006) and Aggarwal et al. (2009) for a wide-ranging literature review.

The methods applied to model (and sometimes, predict) electricity prices can be classified into four groups. Each of these methods has its own particular strengths and weaknesses, but a comprehensive comparison is again beyond the scope of this paper. Different methods cannot directly be compared with each other as each method has its strengths for a special task and also corresponding weaknesses.

The first group includes the simulation models (Bastian et al., 1999; Deb et al., 2000; Lin et al., 2010) that try to imitate the dispatch, the physical status of power grid, and other system necessities and constraints. These methods model electricity prices within a simulation exercise designed to optimize power flow in a grid with some system constraints. The second group of methods is related to game theory and based on some equilibrium models (e.g. Nash equilibrium, Bertrand model, Cournot model). They try to model power prices by identifying the strategies of market stakeholders and detecting optimal solutions (Pozo et al., 2011; Siriruk and Valenzuela, 2011). For instance, Boogert and Dupont (2005) evaluate the effectiveness of the anti-gaming policy between the day-ahead and real-time electricity markets in The Netherlands. Artificial intelligence techniques (e.g. artificial neural networks) constitute the third group. Methods in this group try to identify a nonlinear relationship between inputs and outputs of the power system and, and then model power prices according to this relationship (Amjady and Keynia, 2011; Catalão et al., 2007; Lin et al., 2010; Szkuta, 1999; Yamin et al., 2004).

This paper belongs to the final group of methods consisting of econometric techniques that use the past behavior of power prices and some other variables to model electricity prices. This group includes regression, autoregressive (AR) (Lucia and Schwartz, 2002; Pilipovic, 1998), moving average (MA), autoregressive moving average (ARMA) (Bowden and Payne, 2008), autoregressive integrated moving average (ARIMA) (Erdogdu, 2007, 2010), GARCH models and their variants, jump diffusion models (Clewlow and Strickland, 2000; Deng, 2000; Knittel and Roberts, 2005; Seifert and Uhrig-Homburg, 2007) and the Markov regime-switching models (Becker et al., 2007; Bierbrauer et al., 2007; Huisman and Mahieu, 2003; Kosater and Mosler, 2006). As our work clearly contributes to this line of research, more examples from it are presented below.

Christensen et al. (2009) treat price spikes as count events and attempt to build a model of the spiking process. They propose a Poisson autoregressive framework in which price spikes occur as a result of the latent arrival and survival of system stresses. Dias and Ramos (2014) compare price dynamics of electricity in the U.S. wholesale markets using a regime-switching model with mean-reversion mechanism and shows that electricity prices from the West and East coasts have different regime dynamics. Efimova and Serletis (2014) investigate the empirical properties of oil, natural gas, and electricity price volatilities using a range of univariate and multivariate GARCH models and daily data from wholesale markets in the United States for the period from 2001 to 2013. Frömmel et al. (2014) propose using Realized GARCH-type models to estimate the daily price volatility in the European Power Exchange. Similarly, Hadsell et al. (2004) examine the volatility of wholesale electricity prices for five US markets for the period from May 1996 to September 2001 using a TARCH model. They document important differences among the regional electricity markets not only with respect to wholesale price volatility and seasonal variations but also with respect to asymmetric properties and persistence of volatility.

Hadsell and Shawky (2006) examine the volatility characteristics of the NYISO day-ahead and real time electricity markets for peak hours from January 2001 to June 2004. They use GARCH to study the differences in volatility across zones and find that price volatility is higher but less persistent in the real time market than in the day-ahead market. Haugom and Ullrich (2012) use high-frequency real-time spot prices and day-ahead forward prices from the Pennsylvania–New Jersey–Maryland wholesale electricity market to calculate, describe, and forecast spot price volatility. Hellström et al. (2012) empirically explore the possible causes behind electricity price jumps in the Nordic electricity market, Nord Pool. A time-series model (a mixed GARCH–EARJI jump model) capturing the common statistical features of electricity prices is used to identify price jumps. They conclude that the structure of the market plays an important role in whether shocks in the demand and supply for electricity translate into price jumps. Hickey et al. (2012) estimate and evaluate the forecasting performance of four ARMAX–GARCH models for five MISO pricing hubs (Cinergy, First Energy, Illinois, Michigan, and Minnesota) using hourly data from June 1, 2006 to October 6, 2007. Their results reveal (a) electricity price volatility is regional and the optimum volatility model depends in part on the hub location, the forecast horizon, and regulated versus unregulated status of the market; (b) the APARCH model performs well in hubs in deregulated states; and (c) volatility dynamics in regulated states are better captured by a simple GARCH model and thus are less complex.

Higgs (2009) and Higgs and Worthington (2005, 2008) examine the electricity prices in four regional electricity markets in the Australian National Electricity Market (NEM). Le Pen and Sévi (2010) estimate a VAR-BEKK model using daily data from March 2001 to June 2005 and find evidence of return and volatility spillovers between the German, the Dutch, and the British forward electricity markets. Liu and Shi (2013) apply various ARMA–GARCH models, along with their modified forms, ARMA–GARCH-in-mean to model and forecast hourly ahead electricity prices. Paraschiv et al. (2015) propose a novel regime-switching approach for electricity prices in which simulated and forecasted prices are consistent with currently observed forward prices. Schlueter (2010) introduces a new stochastic long-term/short-term model for short-term electricity prices and applies it to four major European indices, namely, to the German, Dutch, UK, and Nordic one. Finally, Ziel et al. (2015) introduce an econometric model for the hourly time series of electricity prices of the European Power Exchange which incorporates specific features like renewable energy.

3. Data and methodology

Our data set is based on 14 European wholesale electricity markets for a period beginning in 1992 and extending through 2015. Details of electricity markets in our data set are available in Table 1. Due to data availability, the data length differs throughout markets. Our data set, for instance, covers more than 22-year data for Nordpool while it has slightly less than 5-year data on Slovenia's electricity market. Data beginning and ending dates for each electricity market represent the earliest and the last dates for which data were available at the time the research is conducted. The European markets included into our sample are also determined by data availability. In this study, the term “European” is used as inclusive as possible, so Russia and Turkey are regarded as “European” countries in this paper. The total number of observations is 926,227 (see Table 2).

Time-series models assume that the information set is updated by moving from one observation to the next in time (Huisman et al., 2007). This assumption is not valid for power markets that do not allow for continuous trading. In a typical day-ahead electricity market, the quoted prices for each of the 24 hours are determined simultaneously through the daily auction, with the physical delivery arranged at each specific hour on the next day. That is, day-ahead electricity wholesale markets are structured such that agents submit their bids and offers for delivery of electricity in all hours in the next day before a certain market closing time. In short, hourly prices for next-day delivery are determined at the same time. In this paper, therefore, hourly prices are not seen as a pure time series process. The information set used for setting the price of delivery in, say, hour 21, is the same as the information set used to set the price for delivery in, say, hour 2. Therefore, each of the 24 hours is regarded as a separate market in this paper. To sum up, unlike most of the literature that treats price as a continuous variable and attempts to model its trajectory, this paper regards each hour in a day a separate market because the notion of modeling price as a continuous variable in time appears to be at odds with the way in which an electricity market functions and, therefore, applying directly a time-series approach is not sound from a methodological perspective.

Data collection, classification, transformation, and methodology development in the paper are carried out as follows. First of all, day-ahead prices for Turkish wholesale electricity market are obtained from PMUM (2015), and the data on day-ahead prices for all other wholesale markets are taken from Datastream (2015). The data on UK (APX-UK) and Ireland (SEMO) markets have half-hourly frequency; that is, each day consists of 48 observations. To ensure conformity with other data, half-hourly prices are converted into hourly prices by taking their arithmetic mean. The data from Datastream (2015) do not cover weekends; so, to ensure conformity throughout the data set, observations on weekends are removed from the data obtained from PMUM (2015). Therefore, our analysis is based on working days.

Second, in order to carry out a meaningful analysis, nominal prices in our data set need to be converted into real prices to remove the effects of general price level changes (inflation) over time. Using monthly consumer price indices provided by OECD (2015), we transformed all nominal prices into real prices using June 2010 as the reference month (or base month). Besides, we divide observations in two groups: before and after September 1, 2008; since when negative price bids have been allowed at the German power exchange. The year 2008 is also a turning point due to Global Financial Crisis (also called “2008 financial crisis”), which has been the worst financial crisis since the Great Depression of the 1930s. It threatened the collapse of large financial institutions, which was prevented by the bailout of banks by national governments, but stock markets still dropped worldwide. The 2008 crisis played a significant role in the failure of key businesses, declines in consumer wealth estimated in trillions of U.S. dollars, and a downturn in economic activity leading to the 2008–2012 global recession and contributing to the European sovereign-debt crisis. Because of these two incidents, we identify a structural break in our data set at 1.9.2008. So, for each country we divide the observations into two and estimate them separately. Since our data set does not have any observation on Czech Republic, Russia, Turkey, and Slovenia for pre-1.9.2008 period, we cannot estimate models for these countries representing pre-2008 period. In total, we have 24 $(10 \times 2 + 4)$ “country–time period” pairs in this analysis (see Table 2). Since we carry out a separate analysis for each hour of each market and focus on volatility of prices (not on prices themselves), we do not need to convert different national currencies into a common one. Since we regard each of the 24 hours a separate market and consider 24 different “country–time period” pairs, we analyze a total of 576 (24×24) micro-markets in this paper. Summary statistics for each micro-market is provided in Online Appendix A.

At this point, it is necessary to explain how the issue of negative prices is tackled in the paper. We have 926,227 observations in total and only 235 of them are negative prices, meaning that only 0.03% of total observations belong to negative prices. In fact, negative prices can be removed from data set and regressions may be carried out without them. Since negative prices represent extremely small portion of our data set, our results would probably not change significantly if such an approach was adopted. Actually, the generators bidding negative prices are not willing to generate power at prevailing prices (that

Table 1
European wholesale electricity markets analyzed in the study.

Country	Market	Unit	Data starts on	Data ends on	Data length (years)
Nordic countries	Nordpool	NOK per MWh	04.05.1992	30.01.2015	22.8
Spain	OMEL	EUR per MWh	01.01.1998	30.01.2015	17.1
Netherlands	APX-NL	EUR per MWh	26.05.1999	30.01.2015	15.7
Germany	EEX	EUR per MWh	16.06.2000	30.01.2015	14.6
UK	APX-UK	GBP per MWh	27.03.2001	30.01.2015	13.9
France	Powernext	EUR per MWh	23.06.2004	30.01.2015	10.6
Romania	OPCOM	EUR per MWh	01.07.2005	30.01.2015	9.6
Poland	POLPX	Zloty per MWh	01.01.2007	30.01.2015	8.1
Portugal	OMEL	EUR per MWh	02.07.2007	30.01.2015	7.6
Ireland	SEMO	EUR per MWh	02.11.2007	30.01.2015	7.2
Czech Republic	OTE	EUR per MWh	01.09.2009	30.01.2015	5.4
Russia	ATS	Rouble per MWh	22.09.2009	30.01.2015	5.4
Turkey	PMUM	TL per MWh	01.12.2009	30.01.2015	5.2
Slovenia	SRE	EUR per MWh	26.03.2010	30.01.2015	4.9

Table 2
Summary statistics (daily averages, in Euros per MWh at June 2010 prices).

Country (time period)	Number of obs.	Mean	Min.	Max.	Std. dev.	Variance	Skewness	Kurtosis
Czech Republic (after 1.9.2008)	33,936	42.79	0.25	92.70	12.04	149.08	−0.07	4.46
France (after 1.9.2008)	40,200	48.58	5.83	673.07	27.76	1407.40	6.84	200.69
France (before 1.9.2008)	26,232	53.86	9.87	547.29	32.85	1473.71	4.86	83.87
Germany (after 1.9.2008)	40,200	45.34	2.60	163.10	15.74	264.78	1.40	12.23
Germany (before 1.9.2008)	51,384	42.52	0.95	556.09	27.79	1109.48	4.88	87.71
Ireland (after 1.9.2008)	40,200	57.04	18.45	267.23	22.84	677.78	2.73	29.38
Ireland (before 1.9.2008)	5,184	74.92	30.80	220.36	23.92	704.69	2.83	25.32
Netherlands (after 1.9.2008)	40,200	48.56	13.08	136.67	13.87	206.85	1.53	8.99
Netherlands (before 1.9.2008)	58,032	53.73	0.75	989.58	52.31	4322.35	6.41	117.17
Nordic countries (after 1.9.2008)	40,200	41.46	6.04	148.70	15.01	1798.38	0.19	1.32
Nordic countries (before 1.9.2008)	102,240	29.87	1.36	149.50	15.05	1784.04	0.16	1.03
Poland (after 1.9.2008)	40,200	43.92	17.57	125.92	11.04	629.83	0.37	2.83
Poland (before 1.9.2008)	10,440	39.23	19.40	99.13	11.43	586.26	0.30	1.44
Portugal (after 1.9.2008)	40,200	44.83	0.03	342.23	18.16	461.71	3.77	139.92
Portugal (before 1.9.2008)	7,320	63.62	36.64	105.36	13.95	199.19	0.09	2.25
Romania (after 1.9.2008)	40,200	46.58	1.03	102.04	16.37	271.72	0.31	3.20
Romania (before 1.9.2008)	19,824	95.31	3.60	230.58	52.77	2858.63	0.39	2.01
Russia (after 1.9.2008)	33,576	23.44	8.37	40.22	3.37	452.88	0.00	0.18
Slovenia (after 1.9.2008)	30,384	49.33	0.93	144.21	14.69	228.38	0.82	7.34
Spain (after 1.9.2008)	40,200	44.21	0.05	130.91	13.97	196.02	0.22	15.12
Spain (before 1.9.2008)	66,768	45.39	2.92	142.46	16.69	294.18	0.98	4.66
Turkey (after 1.9.2008)	32,371	65.00	9.53	203.27	15.31	466.29	0.92	18.50
UK (after 1.9.2008)	40,200	53.50	25.00	245.60	18.04	336.51	3.97	31.77
UK (before 1.9.2008)	46,536	41.17	11.76	299.99	27.38	741.75	2.98	16.89
Total:	*926,227*							

is, their actual bid may be regarded as very close to zero), but they still bid negative prices as the costs of shutting down and ramping up a power plant unit exceed the loss for accepting negative prices. Taking into account this idea, we convert negative prices in our data set into positive but very low figures, by linear interpolation, ranging from 0.1 and 0.2, representing the lowest and highest negative prices respectively. For instance, a negative bid of -75 EUR per MWh is converted into 0.17 EUR per MWh while another one of -140 EUR per MWh is converted into 0.14 EUR per MWh. Thanks to this approach; we keep price signals coming from negative prices while removing problems related to negative prices from our analysis.

Having collected the data and converted them into real terms, as a third task, we need to test for a unit root, which should always be an essential part of time series analysis. Indeed no time series study in economics and other disciplines that use time series observations should ignore the crucial issue of non-stationarity caused by a unit root. Non-stationary data, as a rule, are unpredictable and cannot be modeled or forecasted. The results obtained by using non-stationary time series may be spurious in that they may indicate a relationship between two variables where one does not exist. In order to receive consistent, reliable results, the non-stationary data needs to be transformed into stationary data. In contrast to the non-stationary process that has a variable variance and a mean that does not remain near, or returns to a long-run mean over time, the stationary process reverts around a constant long-term mean and has a constant variance independent of time. Augmented Dickey–Fuller (ADF) test is applied to test for a unit root in 576 micro-markets analyzed in this paper, the results of which are available in Online Appendix B. ADF test is an augmented version of the Dickey–Fuller test for a larger and more complicated set of time series models. The ADF statistic, used in the test, is a negative number. The more negative it is, the stronger is the rejection of the hypothesis that there is a unit root at some level of confidence. The ADF test results in Online Appendix B indicate that 98.4% (567 out of 576) of series in our data set are stationary. Further details of stationarity, unit root, and ADF test are outside the scope of the present paper but available from Wooldridge (2009).

The fourth, and final, task is to select an appropriate method to measure asymmetric volatility. The GARCH (Bollerslev, 1986) family of models assume that the market conditions its expectation of market variance on both past conditional market variance and past market variables (price, output, and so on). Bollerslev (1986) proposed an extension of the ARCH type models in order to allow longer memory and a more flexible lag structure. Thus, Generalized Auto Regressive Conditional Heteroskedasticity (GARCH) type models were born. A GARCH (p,q) process is given by

$$R_t = \alpha_0 + \sum_{i=1}^{k} \beta_i X_i + \sum_{j=1}^{h} \psi_j R_{t-j} + \epsilon_t \tag{1}$$

where $\epsilon_t | \Omega_{t-1} \sim \mathrm{N}(0, \mathrm{h}_t)$

$$\mathrm{h}_t = \alpha + \sum_{i=1}^{p} \beta_i \mathrm{h}_{t-i} + \sum_{j=1}^{q} \theta_i \epsilon_{t-j}{}^2 \tag{2}$$

where $\mathrm{h}_t = \sigma_t^2 | \Omega_{t-1}$ (conditional variance dependent on the information set 'Ω_{t-1}') With the following conditions:

$\mathrm{p} \geq 0, \mathrm{q} > 0$

$\alpha \geq 0, \theta \geq 0, \beta \geq 0$

and ϵ_t is the residual of the mean equation, R_t denotes dependent variable at time t, and X's are explanatory variables. Eq. (1) is called the mean equation while Eq. (2) is called the equation for the conditional variance. It can be clearly seen that the GARCH (p,q) models the conditional variance as the function of both the squared market values and its own past values. However, it is important to note that this equation restricts the parameters to be strictly non-negative in order to satisfy the condition of a positive variance. This means that the regular GARCH type models only capture the magnitude of the shocks and tend to neglect its sign. In order to capture asymmetric volatility, we need a model that does not impose a non-negativity constraint on market variance and allows for conditional variance to respond asymmetrically to price spikes of different signs.

To answer such a problem of not capturing signs, Nelson (1991) modified the GARCH which led to the Exponential GARCH (E-GARCH) model. By modifying ϵ_t or the residuals of the mean equation such that

$$\frac{\epsilon_t}{\sqrt{\mathrm{h}_t}} = z_t \tag{3}$$

where z_t~iid (0,1) and is called the standardized residuals. The E-GARCH model is given by

$$\ln(\mathrm{h}_t) = \alpha_i + \sum_{k=1}^{\infty} \beta_k g(z_{t-k}), \beta \leq 1 \tag{4}$$

where $g(z_t) = \theta z_t + \gamma[|z_t| - \mathrm{E}|z_t|]$. Upon simplification, the EGARCH variance equation becomes

$$\ln(\sigma_t^2|\Omega_{t-1}) = \alpha_i + \sum_{j=1}^{q} \boldsymbol{\gamma}_j[|z_{t-j}| - E|z_{t-j}|] + \sum_{j=1}^{q} \boldsymbol{\theta}_j z_{t-j} + \sum_{i=1}^{p} \Delta_i \ln(\sigma_{t-i}^2|\Omega_{t-i-1}) \tag{5}$$

Eq. (4) employs the natural logarithm of the conditional variance in order to ensure that the conditional variance remains non-negative. This is in contrast to the previous approach of GARCH-type models which impose conditions that the variables must be strictly positive so that a linear combination of such will also be positive. Given this freedom, $g(z_t)$ will now be able to accommodate asymmetric volatility.

The notion that negative shocks have stronger effect on variance than positive shocks is called "leverage effect". In Eq. (5), the parameter denoted by "**θ**" is called the asymmetry or the leverage effect. This is the parameter of importance for this study as it lets E-GARCH model test for asymmetries. A negative "**θ**" indicates the existence of leverage effect. A positive "**θ**" implies "inverse leverage effect," meaning that unanticipated price increases are more destabilizing than unanticipated price decreases. If "**θ**" equals to zero, then the model is symmetric. The parameter denoted by "**γ**" is called the symmetry or the magnitude effect (or "GARCH" effect) and it captures the impact of the change in variable with its long run average. Finally, the parameter "Δ" represents the persistence in conditional volatility irrespective of anything happening in the market. When it is relatively large, then volatility takes a long time to die out following a shock in the market.

To check robustness of the results and improve the credibility of the study, a TARCH (threshold ARCH) model is also estimated. This model is sometimes called GJR-GARCH and may indicate a leverage effect as well. A TARCH(p,q) model is represented by

$$\sigma_t^2 = \alpha_i + \sum_{i=1}^{p} \omega_i \mu_{t-i}^2 + \sum_{i=1}^{\gamma} \gamma_j \mu_{t-i}^2 d_{t-i} + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 \tag{6}$$

where $d_{t-i} = \begin{cases} 1, & \text{if } \mu_{t-i} \geq 0 \\ 0, & \text{if } \mu_{t-i} < 0 \end{cases}$

The TARCH model in Eq. (6) specifies that the ARCH effect depends on whether the error is positive or negative. If the error is negative, the effect is ω; if it is positive, the full effect is $\omega + \boldsymbol{\gamma}$. In this specification, ω represents ARCH effect while **γ** denotes TARCH effect. If there is a leverage effect, **γ** must be both statistically significant and negative. The existence of a statistically significant but positive **γ** implies inverse leverage effect.

4. Empirical analysis and discussion of the results

Our analysis is based on estimation of E-GARCH(1,1) and TARCH(1,1) models for 576 micro-markets in our data set. In order to capture the impact of seasonality on power prices, we regard spring as the base season and include three dummy variables representing summer, autumn, and winter. Hansen and Lunde (2005) tested 330 different volatility model specifications and concluded that no specification could be shown to significantly outperform the GARCH(1,1). Similarly, Andersen and Bollerslev (1998) and Wang and Wu (2012) argue that simple models of the GARCH(1,1) remain very useful because they converge much faster to a local maximum in quasi-maximum likelihood estimation while delivering very competitive forecasting performance. In the same way, we tested E-GARCH(1,2), E-GARCH(2,1), and E-GARCH(2,2) specifications and found that E-GARCH(1,1) performs much better in modeling volatility. Online Appendix B presents estimation results.[1]

Each micro-market is unique, and therefore, E-GARCH and TARCH model estimation results for a specific market should be evaluated independently within its own context; however, for practical considerations, we provide and analyze four different indicators for each market. The first indicator is the average of statistically significant coefficients representing day time hours (06:00–17:00); the second denotes the average of statistically significant coefficients for peak time hours (17:00–22:00); the third one is for night time (22:00–06:00), and the final one is the daily average of statistically significant coefficients representing 24 hours in a day. This clustering is taken from the well-established practice, called Time of Use Pricing (TOU), in many European power markets, which lets consumers shift their electricity consumption to hours where electricity costs the least and thereby lower their total bill. Under TOU pricing, there are three different prices for three different periods: day time (06:00–17:00), peak time (17:00–22:00), and night time (22:00–06:00). In this paper, we follow this well-established tradition to cluster significant coefficients for practical reasons. Interested readers may cluster coefficients in many other different ways and see the results using data in Online Appendix B. Without clustering, it is very difficult, if not impossible, to interpret the results due to large number of models estimated during our analysis.

Before analyzing the estimation results, we would like to focus on the summary statistics as it may provide very useful insights into our study. Table 2 presents daily averages of summary statistics given in Online Appendix A. It is important to note that all prices in Table 2 are expressed in Euros[2] at June 2010 prices to let readers compare the prices while the data in Online Appendix A is in national currencies. The data in Table 2 indicate that in post-2008 period, the most expensive electricity is consumed in Turkey, Ireland, and UK, while the cheapest power is in Russia, Nordic countries, and Czech Republic.

The main focus of this paper is volatility and it is closely related to concepts of "variance" and "standard deviation." The standard deviation is a measure that is used to quantify the amount of variation or dispersion of a set of data values. A standard deviation close to 0 indicates that the data points tend to be very close to the mean (also called the expected value) of the set, while a high standard deviation indicates that the data points are spread out over a wider range of values. The standard deviation of a data set is the square root of its variance. A useful property of the standard deviation is that, unlike the variance, it is expressed in the same units as the data, and hence is comparable to deviations from the mean. Fig. 1 presents standard deviation in European day-ahead electricity markets by four different time periods.

In terms of day-time volatility in post-2008 period; Russia, Poland, and Czech Republic have the least volatile markets. On the other hand, France, Ireland, and Portugal have the most volatile day-time electricity markets. For peak hours, the least volatile markets seem to be in Russia, Czech Republic, and Portugal while the most volatile ones are in Ireland, the UK, and France. During night hours, Russia, Poland, and the UK have the least volatile markets; Turkey, Portugal, and Romania have the most volatile ones. Overall, our data set clearly indicates that Russia, Poland, and Czech Republic have the least volatile markets while France, Ireland, and Portugal have the most volatile ones in post-2008 period. It should also be noted that volatility decreased in many European countries in post-2008 period.

Skewness is a measure of the asymmetry of the distribution of a data set about its mean. The skewness value can be positive or negative. Negative skew indicates that the tail of the data set is longer or fatter on the

[1] Throughout the paper, model estimations are carried out and cross-checked by Stata 13 and Eviews 8. Stata data and command files are available in Online Appendix C and D, respectively.

[2] As of 15 June 2010, 1 EUR = 0.832 GBP = 7.8515 NOK = 38.48 Ruble = 1.9316 TL = 4.0734 Zloty (*Source*: *https://sdw.ecb.europa.eu/curConverter.do*).

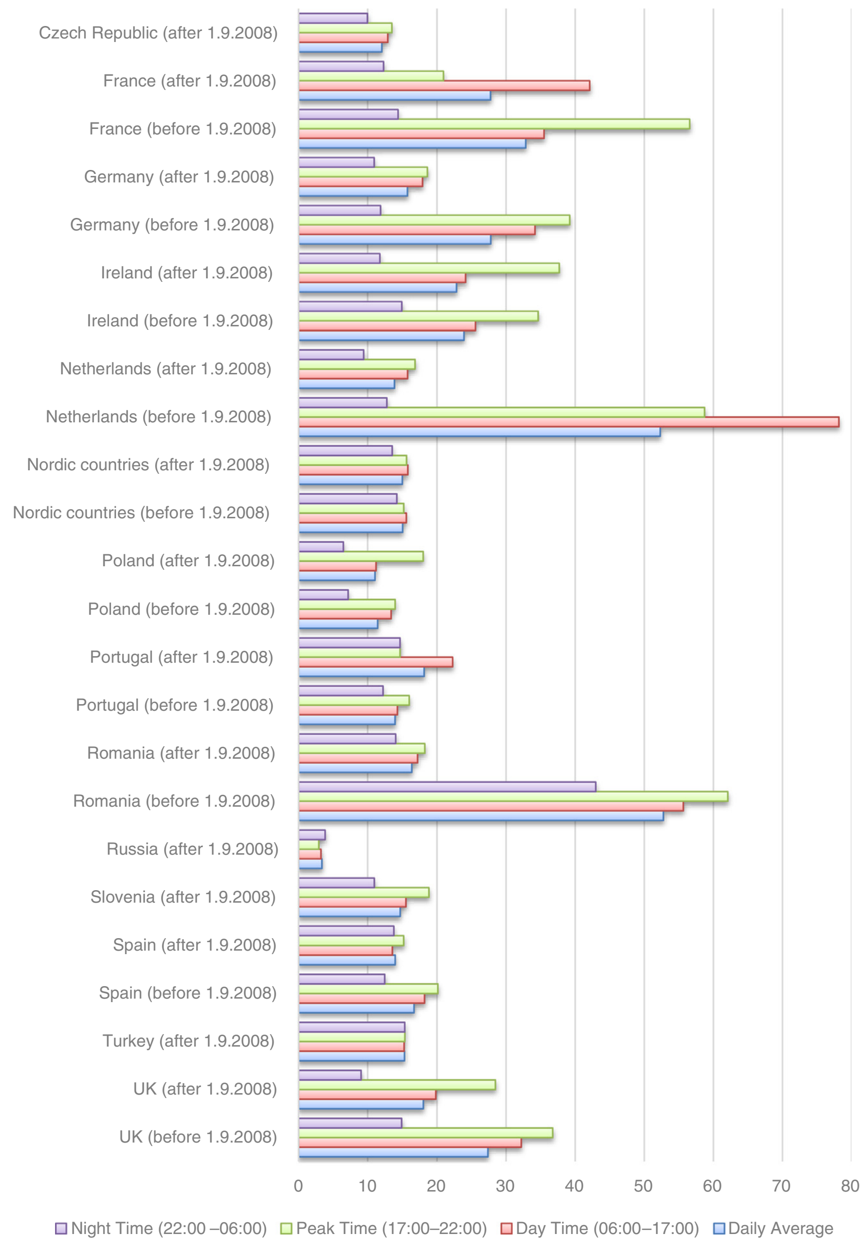


Fig. 1. Standard deviation in European day-ahead electricity markets.

left side of the distribution than the right side. Conversely, positive skew indicates that the tail on the right side is longer or fatter than the left side. In our sample, the tails of post-2008 day-ahead electricity price series for France (S: 6.84) and the UK (S: 3.97) on the right side seem to be relatively longer or fatter than the left side. Moreover, kurtosis is a measure of the "peakedness" of the distribution of a data set. In a similar way to the concept of skewness, kurtosis is a descriptor of the shape of a distribution. Higher kurtosis means more of the variance is the result of infrequent extreme deviations, as opposed to frequent modestly sized deviations. Our data indicate that more of the variance in France (K: 200.7) and Portugal (K: 139.9) is the result of relatively infrequent extreme deviations in post-2008 period.

Table 3 summarizes GARCH(1,1) estimation results. At first look, magnitude effect seems to be usually larger than the leverage effect, meaning that the absolute value of price change is relatively more important than the sign of the change (whether it is an increase or a decrease) to explain volatility in European day-ahead power markets. However, there are some exceptions. For instance, in Ireland (pre-2008 period), day-time volatility is explained more by inverse leverage effect than by magnitude effect, meaning that unanticipated price increases are more destabilizing than price decreases and this impact is stronger than the size of the price shock. Besides, although the findings imply that asymmetric volatility is an important component of overall volatility in European day-ahead power markets; unlike Bowden and Payne (2008) who detect an inverse leverage effect in electricity prices, a specific pattern cannot be identified in our analysis, that is, in post-2008 period, price increases are more destabilizing in some European markets (e.g. Poland, Slovenia, Ireland, Netherlands) than comparable price decreases but *vice versa* also holds true in some other countries (e.g. Portugal and France). Besides, in terms of leverage effect, pre- and post-2008 periods differ enormously for some countries (e.g. Spain) while they are almost the same for some others (e.g. Nordic countries).

To check robustness of the results, we also estimate TARCH(1,1) models and the results are shown in Table 4. As we mentioned before, there are 24 "country–time period" pairs and 4 different time period

Table 3
Summary of GARCH(1,1) estimation results (averages).

Country (time period)	Day time (06:00–17:00)			Peak time (17:00–22:00)			Night time (22:00–06:00)			Daily average		
	LE	ME	PiCV	LE	ME	PiCV	LE	ME	PiCV	LE	ME	PiCV
Czech Republic (after 1.9.2008)	−0.10	0.90	0.72	−0.13	1.05	0.79	0.12	0.91	0.78	0.00	0.94	0.75
France (after 1.9.2008)	−1.61	2.06	0.80	−0.28	1.31	0.85	0.15	0.93	0.80	−0.51	1.63	0.81
France (before 1.9.2008)	0.18	1.31	0.93	−1.35	2.81	0.92	0.19	1.02	0.95	−0.23	1.61	0.94
Germany (after 1.9.2008)	−0.09	1.00	0.81	−0.09	1.00	0.89	0.12	0.88	0.80	−0.02	0.97	0.83
Germany (before 1.9.2008)	0.24	1.11	0.86	−0.06	1.84	0.76	0.25	1.03	0.80	0.12	1.35	0.83
Ireland (after 1.9.2008)	0.14	0.45	1.10	0.15	0.56	0.90	0.09	0.38	0.59	0.13	0.45	0.87
Ireland (before 1.9.2008)	0.35	0.30	0.43	0.10	0.50	0.50	−0.25	1.49	0.56	−0.02	0.80	0.49
Netherlands (after 1.9.2008)	0.07	1.02	0.82	*NSC*	1.13	0.83	0.14	0.86	0.87	0.12	0.98	0.84
Netherlands (before 1.9.2008)	−0.02	1.42	0.89	−0.43	2.22	0.88	−0.03	1.48	0.93	−0.11	1.61	0.89
Nordic countries (after 1.9.2008)	−0.13	1.64	0.95	−0.17	1.89	0.93	*NSC*	1.71	0.95	−0.15	1.73	0.95
Nordic countries (before 1.9.2008)	−0.16	1.97	0.94	−0.17	1.99	0.95	−0.13	1.99	0.96	−0.15	1.98	0.95
Poland (after 1.9.2008)	−0.10	1.34	0.88	0.58	1.68	0.81	0.14	1.59	0.85	0.16	1.55	0.84
Poland (before 1.9.2008)	−0.36	2.52	0.87	*NSC*	2.06	0.98	0.26	0.97	1.01	0.11	1.95	0.93
Portugal (after 1.9.2008)	−0.94	2.11	0.81	−0.10	1.01	0.95	*NSC*	1.01	0.74	−0.52	1.56	0.85
Portugal (before 1.9.2008)	*NSC*	1.05	0.89	*NSC*	1.28	0.93	*NSC*	1.43	0.93	*NSC*	1.25	0.92
Romania (after 1.9.2008)	0.07	0.83	0.81	*NSC*	0.88	0.82	0.11	0.60	0.84	0.09	0.74	0.82
Romania (before 1.9.2008)	*NSC*	1.43	0.90	*NSC*	1.54	0.97	0.25	1.14	0.90	0.25	1.34	0.91
Russia (after 1.9.2008)	*NSC*	1.12	0.76	*NSC*	1.16	0.76	−0.11	0.97	0.82	−0.11	1.08	0.78
Slovenia (after 1.9.2008)	−0.10	1.00	0.90	*NSC*	1.05	0.85	0.19	0.97	0.80	0.14	1.00	0.86
Spain (after 1.9.2008)	−0.10	1.09	0.83	−0.27	1.22	0.88	−0.12	0.83	0.79	−0.16	0.96	0.81
Spain (before 1.9.2008)	0.11	1.09	0.85	*NSC*	1.07	0.86	0.10	1.24	0.88	0.11	1.14	0.87
Turkey (after 1.9.2008)	−0.07	1.08	0.74	*NSC*	0.82	0.73	0.10	0.86	0.87	0.01	0.96	0.80
UK (after 1.9.2008)	0.15	0.79	0.87	−0.04	1.30	0.86	0.10	0.90	0.85	0.09	0.92	0.86
UK (before 1.9.2008)	0.17	1.51	0.84	0.14	1.65	0.85	0.13	1.67	0.89	0.15	1.61	0.86

LE: *leverage effect*, *ME*: *magnitude effect*, *PiCV*: *persistence in conditional volatility*, *NSC*: *no significant coefficient is available.*

Table 4
Summary of TARCH(1,1) estimation results (averages).

Country (time period)	Day time (06:00–17:00)			Peak time (17:00–22:00)			Night time (22:00–06:00)			Daily average		
	A	T	A + T	A	T	A + T	A	T	A + T	A	T	A + T
Czech Republic (after 1.9.2008)	0.82	−0.24	0.58	0.87	−0.32	0.56	0.56	0.13	0.69	0.74	−0.05	0.70
France (after 1.9.2008)	0.85	1.30	2.15	0.88	0.48	1.36	0.55	0.32	0.87	0.75	0.74	1.49
France (before 1.9.2008)	0.65	0.38	1.03	0.95	0.76	1.72	0.54	0.30	0.84	0.68	0.42	1.10
Germany (after 1.9.2008)	0.78	−0.19	0.59	0.72	*NSC*		0.52	0.26	0.78	0.68	0.19	0.87
Germany (before 1.9.2008)	0.69	0.47	1.16	0.89	0.45	1.34	0.45	0.33	0.78	0.64	0.39	1.03
Ireland (after 1.9.2008)	0.27	0.18	0.45	0.40	0.07	0.47	0.21	0.05	0.26	0.29	0.12	0.41
Ireland (before 1.9.2008)	0.70	0.32	1.02	0.89	−0.84	0.05	0.53	−0.14	0.39	0.67	−0.08	0.58
Netherlands (after 1.9.2008)	0.68	0.23	0.91	0.75	*NSC*		0.49	0.26	0.76	0.63	0.25	0.88
Netherlands (before 1.9.2008)	9.23	−7.97	1.25	1.30	0.18	1.48	0.74	0.39	1.12	4.34	−3.82	0.52
Nordic countries (after 1.9.2008)	1.03	0.01	1.03	1.07	*NSC*		1.00	*NSC*		1.03	0.01	1.03
Nordic countries (before 1.9.2008)	1.07	0.00	1.07	1.05	*NSC*		1.15	−0.22	0.94	1.10	−0.11	0.99
Poland (after 1.9.2008)	1.20	−0.29	0.91	1.68	−0.92	0.76	0.92	0.20	1.12	1.21	−0.46	0.75
Poland (before 1.9.2008)	1.88	−1.04	0.85	0.77	*NSC*		0.46	0.37	0.82	1.47	−0.62	0.85
Portugal (after 1.9.2008)	2.25	−1.92	0.33	0.92	−0.31	0.61	0.84	−0.48	0.37	1.51	−1.19	0.31
Portugal (before 1.9.2008)	0.74	*NSC*		0.71	*NSC*		1.03	*NSC*		0.85	*NSC*	
Romania (after 1.9.2008)	0.50	0.18	0.68	0.54	*NSC*		0.27	0.24	0.51	0.43	0.21	0.64
Romania (before 1.9.2008)	0.92	*NSC*		0.98	−0.34	0.64	0.70	0.42	1.12	0.86	0.04	0.90
Russia (after 1.9.2008)	0.80	0.18	0.98	0.82	0.22	1.04	0.80	−0.24	0.56	0.81	0.05	0.85
Slovenia (after 1.9.2008)	0.75	0.29	1.04	0.76	*NSC*		0.52	0.49	1.01	0.67	0.46	1.14
Spain (after 1.9.2008)	0.89	−0.24	0.65	1.21	−0.66	0.55	0.83	−1.18	−0.35	0.93	−0.49	0.45
Spain (before 1.9.2008)	0.62	0.23	0.85	0.67	0.20	0.88	0.65	0.22	0.87	0.64	0.23	0.87
Turkey (after 1.9.2008)	0.98	0.17	1.15	0.92	0.14	1.06	0.53	0.26	0.80	0.82	0.19	1.01
UK (after 1.9.2008)	0.42	0.52	0.94	0.55	0.79	1.34	0.57	0.19	0.76	0.50	0.51	1.00
UK (before 1.9.2008)	0.57	0.87	1.44	0.70	0.60	1.30	0.79	0.30	1.09	0.69	0.70	1.39

A: *arch effect*, *T*: *tarch effect*, *NSC*: *no significant coefficient is available.*

indicators in this study, so in total there are 96 (24 × 4) specific models for the leverage effect. Out of 96 models, the results from GARCH and TARCH models indicate a similar relationship (i.e. the existence of leverage effect or inverse leverage effect) for 68 models (70.8%). Table 5 compares the results from two models.

Table 6 provides magnitude/leverage effect ratio in absolute terms. The higher this ratio is, the stronger magnitude effect becomes. It is clearly seen in Table 6 that leverage effect in post-2008 period is relatively stronger in Portugal, France, and Ireland, but its impact is quite limited in Turkey and Germany.

Table 7 summarizes the results from GARCH and TARCH models related to the impact of seasonality on power prices. All coefficients in Table 7 are expressed in Euros[3] at June 2010 prices to let readers compare the results while the data in Online Appendix B is in national currencies. Since spring is taken as the base season, there are 3 coefficients representing summer, autumn, and winter in each model, and

[3] As of 15 June 2010, 1 EUR = 0.832 GBP = 7.8515 NOK = 38.48 Ruble = 1.9316 TL = 4.0734 Zloty (*Source*: https://sdw.ecb.europa.eu/curConverter.do).

Table 5
Comparison of GARACH(1,1) and TARCH(1,1) results on leverage effect.

Country (time period)	Day time (06:00–17:00)		Peak time (17:00–22:00)		Night time (22:00–06:00)		Daily average	
	GARCH(1,1)	TARCH(1,1)	GARCH(1,1)	TARCH(1,1)	GARCH(1,1)	TARCH(1,1)	GARCH(1,1)	TARCH(1,1)
Czech Republic (after 1.9.2008)	LE	LE	LE	LE	Inv. LE	Inv. LE	LE	LE
France (after 1.9.2008)	LE	Inv. LE	LE	Inv. LE	Inv. LE	Inv. LE	LE	Inv. LE
France (before 1.9.2008)	Inv. LE	Inv. LE	LE	Inv. LE	Inv. LE	Inv. LE	LE	Inv. LE
Germany (after 1.9.2008)	LE	LE	LE	No LE	Inv. LE	Inv. LE	LE	Inv. LE
Germany (before 1.9.2008)	Inv. LE	Inv. LE	LE	Inv. LE	Inv. LE	Inv. LE	Inv. LE	Inv. LE
Ireland (after 1.9.2008)	Inv. LE	Inv. LE	Inv. LE	Inv. LE	Inv. LE	Inv. LE	Inv. LE	Inv. LE
Ireland (before 1.9.2008)	Inv. LE	Inv. LE	Inv. LE	LE	LE	LE	LE	LE
Netherlands (after 1.9.2008)	Inv. LE	Inv. LE	No LE	No LE	Inv. LE	Inv. LE	Inv. LE	Inv. LE
Netherlands (before 1.9.2008)	LE	LE	LE	Inv. LE	LE	Inv. LE	LE	LE
Nordic countries (after 1.9.2008)	LE	Inv. LE	LE	No LE	No LE	No LE	LE	Inv. LE
Nordic countries (before 1.9.2008)	LE	LE	LE	No LE	LE	LE	LE	LE
Poland (after 1.9.2008)	LE	LE	Inv. LE	LE	Inv. LE	Inv. LE	Inv. LE	LE
Poland (before 1.9.2008)	LE	LE	No LE	No LE	Inv. LE	Inv. LE	Inv. LE	LE
Portugal (after 1.9.2008)	LE	LE	LE	LE	No LE	LE	LE	LE
Portugal (before 1.9.2008)	No LE	No LE	No LE	No LE	No LE	No LE	No LE	No LE
Romania (after 1.9.2008)	Inv. LE	Inv. LE	No LE	No LE	Inv. LE	Inv. LE	Inv. LE	Inv. LE
Romania (before 1.9.2008)	No LE	No LE	No LE	LE	Inv. LE	Inv. LE	Inv. LE	Inv. LE
Russia (after 1.9.2008)	No LE	Inv. LE	No LE	Inv. LE	LE	LE	LE	Inv. LE
Slovenia (after 1.9.2008)	LE	Inv. LE	No LE	No LE	Inv. LE	Inv. LE	Inv. LE	Inv. LE
Spain (after 1.9.2008)	LE	LE	LE	LE	LE	LE	LE	LE
Spain (before 1.9.2008)	Inv. LE	Inv. LE	No LE	Inv. LE	Inv. LE	Inv. LE	Inv. LE	Inv. LE
Turkey (after 1.9.2008)	LE	Inv. LE	No LE	Inv. LE	Inv. LE	Inv. LE	Inv. LE	Inv. LE
UK (after 1.9.2008)	Inv. LE	Inv. LE	LE	Inv. LE	Inv. LE	Inv. LE	Inv. LE	Inv. LE
UK (before 1.9.2008)	Inv. LE	Inv. LE	Inv. LE	Inv. LE	Inv. LE	Inv. LE	Inv. LE	Inv. LE

LE: leverage effect, Inv. LE: inverse leverage effect, No LE: no leverage effect.

they show the difference of each specific season from spring season. As usual, there are 24 “country-time period” pairs and 4 different time period indicators, so in total, there are 288 ($3 \times 24 \times 4$) specific models for the impact of seasonality on power prices. Out of these 288 models, 258 of them (89.6%) imply a relationship in the same direction with both GARCH and TARCH specification. Although the impact of seasonality on prices is obvious, a specific pattern cannot be identified. For instance, in post-2008 period, the results from both models imply that power prices decline in Nordic countries and France during summer by 2.3–4.3 Euros per MWh at June 2010 prices; however, they increase in Turkey, Spain, and Portugal during the same period by 4.3–12.3 Euros per MWh.

The final information coming from our analysis on European day-ahead power markets relates to the persistence in conditional volatility. When the persistence in conditional volatility is relatively large, then volatility takes a long time to die out following a shock irrespective of anything happening in the market. As can be seen in Fig. 2, our results imply that large changes in the volatility will affect future volatilities for a relatively longer period of time in Nordic countries, Ireland, and the UK in post-2008 period since the decay is slower in these countries. On the other hand, changes in current volatility have less effect on future volatilities in Czech Republic, Russia, and Turkey as volatility takes a relatively shorter time to die out following a shock in the market in these countries.

Table 6
The absolute value of magnitude/leverage effect ratio.

Country (time period)	Day time (06:00–17:00)	Peak time (17:00–22:00)	Night time (22:00–06:00)	Daily average
Czech Republic (after 1.9.2008)	9.38	8.15	7.68	–
France (after 1.9.2008)	1.28	4.59	6.37	3.18
France (before 1.9.2008)	7.29	2.09	5.23	7.02
Germany (after 1.9.2008)	11.50	11.60	7.63	50.33
Germany (before 1.9.2008)	4.62	29.00	4.08	11.23
Ireland (after 1.9.2008)	3.23	3.87	4.38	3.47
Ireland (before 1.9.2008)	0.85	5.03	5.87	47.57
Netherlands (after 1.9.2008)	14.54	–	6.36	7.87
Netherlands (before 1.9.2008)	86.60	5.22	49.17	14.60
Nordic countries (after 1.9.2008)	12.70	11.34	–	11.90
Nordic countries (before 1.9.2008)	12.56	11.98	14.98	13.17
Poland (after 1.9.2008)	12.84	2.91	11.29	9.48
Poland (before 1.9.2008)	7.03	–	3.67	18.01
Portugal (after 1.9.2008)	2.24	10.07	–	2.99
Portugal (before 1.9.2008)	–	–	–	–
Romania (after 1.9.2008)	11.83	–	5.32	7.90
Romania (before 1.9.2008)	–	–	4.48	5.25
Russia (after 1.9.2008)	–	–	8.81	9.77
Slovenia (after 1.9.2008)	10.46	–	4.98	7.32
Spain (after 1.9.2008)	11.12	4.47	6.95	5.88
Spain (before 1.9.2008)	9.66	–	12.16	10.61
Turkey (after 1.9.2008)	15.08	–	8.47	64.28
UK (after 1.9.2008)	5.35	30.58	9.09	10.58
UK (before 1.9.2008)	9.10	11.78	12.45	10.64

Table 7
The impact of seasonality on power prices (in Euros per MWh at June 2010 prices).

Country (time period)	Day time (06:00–17:00)						Peak time (17:00–22:00)						Night time (22:00–06:00)						Daily average					
	GARCH			TARCH			GARCH			TARCH			GARCH			TARCH			GARCH			TARCH		
	S	A	W	S	A	W	S	A	W	S	A	W	S	A	W	S	A	W	S	A	W	S	A	W
Czech Republic (after 1.9.2008)	5.1	8.8	5.3	5.4	9.1	6.9	−2.3	6.7	4.3	0.1	7.4	7.0	−1.0	−2.0	1.2	1.4	−1.2	−0.9	2.1	6.1	4.4	3.1	5.9	4.9
France (after 1.9.2008)	−3.2	8.6	6.1	−0.6	7.1	5.7	−1.9	12.7	12.1	−1.8	11.7	11.3	−6.0	0.6	7.1	−4.5	3.3	7.1	−3.6	8.2	7.7	−2.3	7.3	7.4
France (before 1.9.2008)	−2.2	1.9	5.2	1.9	2.5	2.7	4.4	12.7	12.4	2.1	11.5	13.1	−3.4	−1.4	4.5	−4.1	−2.4	2.4	−1.3	4.1	7.2	−0.1	3.3	4.9
Germany (after 1.9.2008)	1.4	8.5	6.4	1.4	7.7	5.9	0.9	10.4	14.8	−0.1	9.3	9.3	0.1	2.5	3.1	−0.1	1.7	3.3	1.1	8.7	7.7	0.7	6.9	5.7
Germany (before 1.9.2008)	6.0	4.1	3.3	1.9	3.9	4.0	0.9	5.3	26.4	−1.0	6.2	7.3	−2.8	0.0	0.8	−3.3	−0.5	1.6	3.0	4.5	13.3	−0.6	3.3	3.6
Ireland (after 1.9.2008)	5.6	5.1	−0.8	2.1	−2.5	−5.1	−8.2	12.7	21.5	−8.5	12.6	21.0	−2.9	−3.2	−1.4	−2.6	−3.0	−2.2	0.4	3.9	5.2	−1.6	1.4	3.4
Ireland (before 1.9.2008)	15.3	−20.0	−15.1	16.7	−13.8	−9.2	3.2	1.5	14.3	11.2	63.3	89.3	6.4	−20.1	−2.9	7.3	−17.3	−7.7	11.0	−14.7	−5.5	14.3	−5.0	3.4
Netherlands (after 1.9.2008)	2.1	5.4	4.9	3.3	6.4	5.2	2.0	10.9	13.9	2.0	9.1	10.9	−1.1	2.2	2.6	−0.4	2.0	2.7	1.0	5.6	5.9	1.8	5.5	5.6
Netherlands (before 1.9.2008)	7.0	10.5	2.2	0.2	16.8	5.6	0.3	28.9	26.0	−1.7	11.4	13.3	−1.6	−1.7	0.0	−2.5	0.4	1.3	3.6	11.9	8.4	−1.1	11.6	5.4
Nordic countries (after 1.9.2008)	−4.6	−1.7	7.8	−4.1	−2.0	−0.7	−3.4	−2.0	−1.4	−2.1	−0.8	0.1	−4.9	−3.1	−3.1	−3.0	−1.0	−0.8	−4.3	−2.2	2.5	−3.2	−1.4	−0.6
Nordic countries (before 1.9.2008)	1.5	3.0	7.3	1.3	1.4	6.2	1.7	0.8	4.9	0.4	0.9	4.6	−0.1	4.2	4.8	0.0	5.0	4.9	1.1	3.1	6.1	0.6	2.9	5.5
Poland (after 1.9.2008)	3.2	6.6	3.3	2.5	6.0	2.0	0.0	6.0	4.1	0.7	10.1	7.5	3.3	1.4	−1.3	3.2	1.5	−0.2	2.3	4.8	2.5	2.4	5.4	3.1
Poland (before 1.9.2008)	10.3	−6.3	−2.2	0.7	−2.9	1.1	4.9	−15.4	−3.7	−0.4	−0.3	−0.4	−1.4	−1.6	−0.8	−2.1	−1.6	0.0	5.2	−6.2	−2.0	0.0	−2.5	0.9
Portugal (after 1.9.2008)	2.9	0.5	4.1	6.8	7.6	7.0	5.2	10.7	12.7	5.6	11.7	13.1	7.2	4.7	1.1	6.9	4.6	3.6	4.3	4.8	7.0	6.6	7.4	7.3
Portugal (before 1.9.2008)	−2.4	−18.1	16.0	5.0	−18.7	15.6	4.3	−9.9	21.5	0.3	−14.8	20.5	4.9	−18.2	20.7	3.2	−17.8	9.8	2.3	−14.6	19.5	3.0	−17.8	14.5
Romania (after 1.9.2008)	0.5	9.2	7.3	0.1	9.5	8.1	−6.6	16.2	9.6	−2.5	15.1	12.2	3.8	5.2	−4.0	3.5	4.9	−3.7	0.7	8.7	2.8	0.7	9.1	4.9
Romania (before 1.9.2008)	−39.2	35.7	28.7	−58.7	25.0	24.3	−55.3	26.3	51.1	−69.1	11.2	52.2	9.4	17.8	3.6	4.0	26.3	14.6	−23.0	26.7	24.9	−39.3	23.4	25.7
Russia (after 1.9.2008)	2.7	1.5	0.3	2.9	1.3	0.6	2.6	1.5	0.6	2.3	1.7	0.3	2.4	−1.1	−1.6	3.2	−1.1	−1.6	2.5	0.8	−0.4	2.8	0.9	−0.5
Slovenia (after 1.9.2008)	5.7	5.3	8.7	3.3	5.4	7.4	1.1	9.3	13.8	−1.0	10.1	12.5	1.8	1.3	0.4	1.8	0.4	−1.0	3.6	5.6	7.0	1.8	5.9	6.3
Spain (after 1.9.2008)	8.6	8.8	7.3	6.8	7.1	5.7	5.8	14.8	24.5	6.0	12.2	17.7	7.2	4.3	4.7	7.3	4.8	9.7	7.6	6.9	8.5	6.8	7.4	9.5
Spain (before 1.9.2008)	10.0	5.5	0.6	7.5	5.5	0.6	7.9	10.2	13.8	9.4	10.3	9.6	−0.4	−0.1	2.0	−0.4	−0.5	−0.7	5.7	4.5	4.1	5.3	4.5	2.6
Turkey (after 1.9.2008)	9.8	7.1	9.7	10.8	8.1	8.1	14.5	9.8	7.7	14.8	13.8	13.1	14.1	6.7	7.3	13.7	7.4	7.9	12.3	7.1	8.6	12.7	9.1	9.2
UK (after 1.9.2008)	0.0	0.0	−0.3	0.6	0.5	0.9	−3.0	3.1	3.7	−−3.5	2.3	4.0	−1.2	1.9	1.9	−0.6	1.1	1.4	−0.8	1.2	1.2	−0.6	1.0	1.7
UK (before 1.9.2008)	3.3	3.8	3.1	2.9	1.6	3.4	1.2	6.7	14.3	1.9	6.2	10.6	−0.1	3.2	3.2	−0.6	1.9	2.5	1.3	4.1	4.6	1.6	3.0	5.5

S: *summer*, *A*: *autumn*, *W*: *winter*, *NSC*: *no significant soefficient is available.*

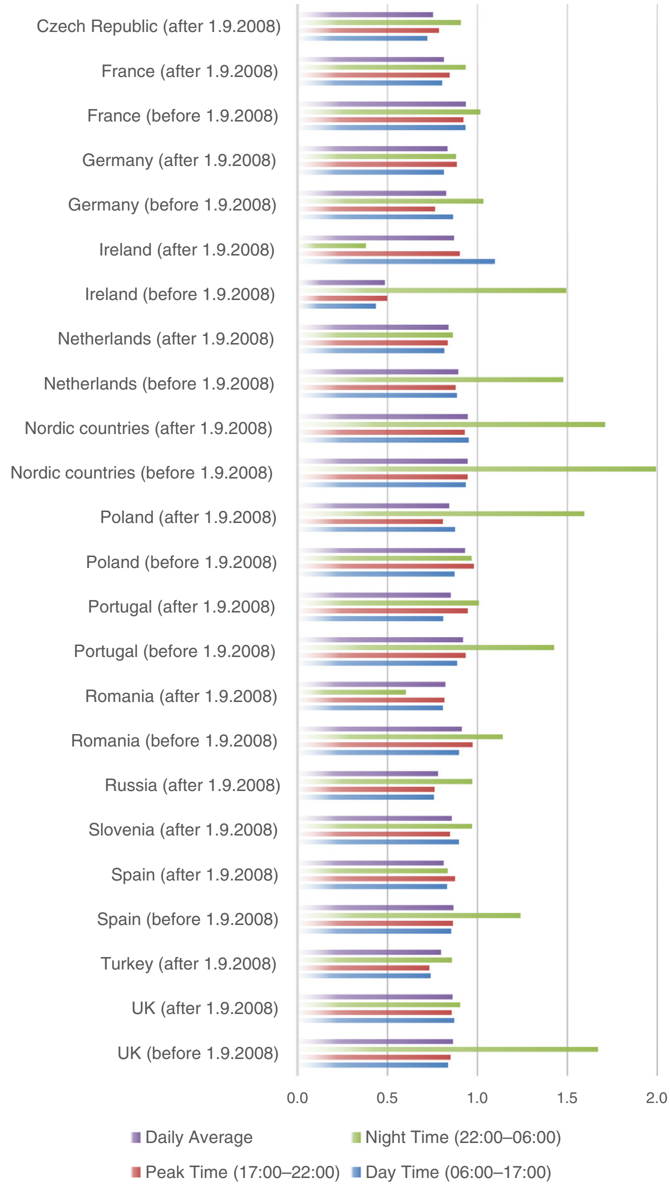


Fig. 2. Persistence in conditional volatility.

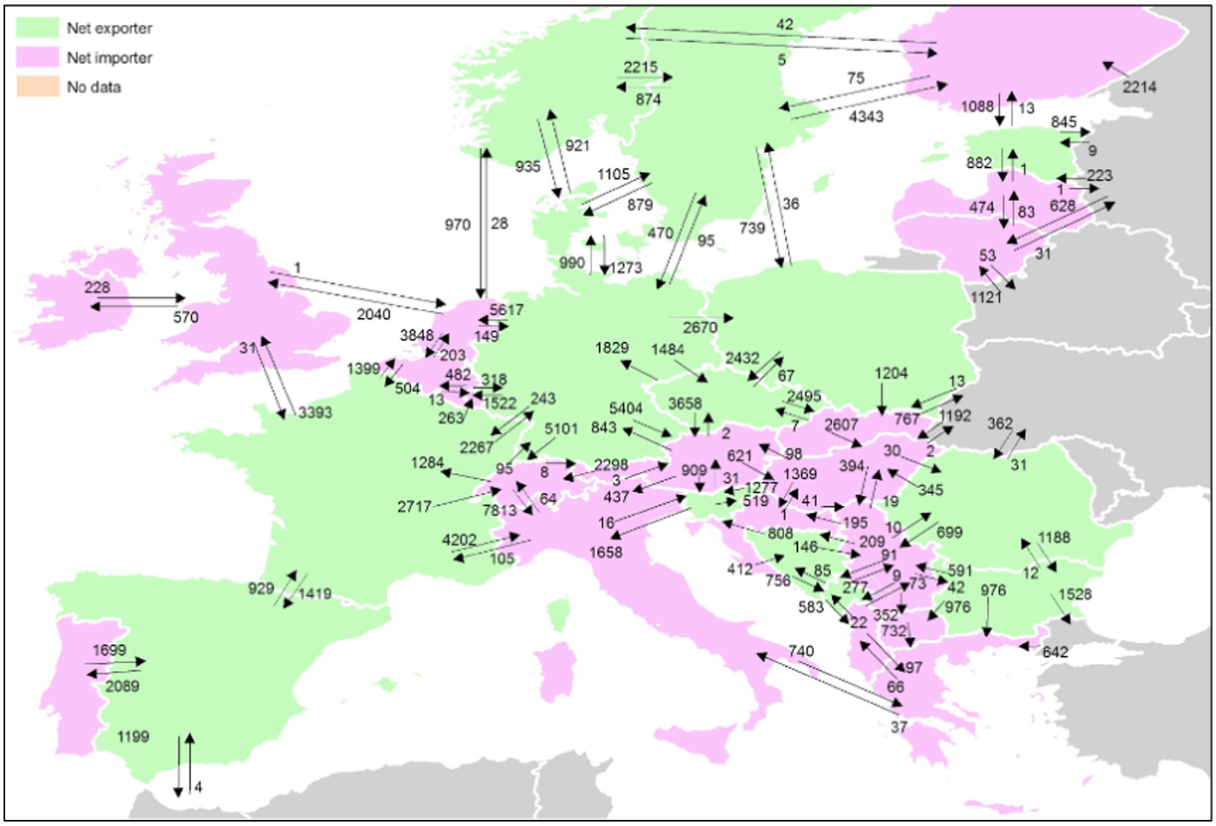
5. Conclusion

In this concluding section, we discuss whether we have answered the research questions asked in the introductory section. Then, we mention main policy repercussions of the results. The third part of the section mentions possible limitations of the research. The final part discusses what we have done and what still needs to be done.

Let us start by discussing whether we have answered all research questions we asked in Section 1. The first question was *which countries in Europe have the most/least volatile power markets*? The analysis in the paper shows that Russia, Poland, and Czech Republic have the least volatile markets while France, Ireland, and Portugal have the most volatile ones in post-2008 period. The second question was *what is the relative importance of the absolute value of price change and its direction* (*an increase or a decrease*) *to explain volatility in European day-ahead power markets*? In the course of the analysis, we find that magnitude effect is usually larger than the leverage effect, meaning that the absolute value of price change is relatively more important than the sign of the change (whether it is an increase or a decrease) to explain volatility in European day-ahead power markets. The third question was *is there an inverse leverage effect in European day-ahead electricity prices*? The results from the paper show that there is not a uniform inverse leverage effect in electricity prices; that is, price increases are more destabilizing in some European markets (e.g. Poland, Slovenia, Ireland, Netherlands) than comparable price decreases but vice versa also holds true in some other countries (e.g. Portugal, France). The final question was *which European power markets have the strongest/weakest persistence in conditional volatility*? Our empirical findings suggest that large changes in the volatility will affect future volatilities for a relatively longer period of time in Nordic countries, Ireland, and the UK in post-2008 period while changes in current volatility will have less effect on future volatilities in Czech Republic, Russia, and Turkey.

Since this is an all-encompassing study in which hundreds of models are estimated with hundred thousands of observations, the results and their policy repercussions are numerous. In this and previous sections, we just provide a glimpse of the results. Interested readers may refer to Online Appendices to get much more detailed results. Within this context, regulators may benefit from our results to measure market efficiency and to assess market design and exercise of market power. The analysis in this paper has identified relatively more and less volatile European wholesale markets, but the investigation of reasons for being more/less volatile is outside the scope of present paper. Regulators should explore the reasons for why some markets are relatively more volatile than the others. Possible reasons for frequent and extreme volatility in the market may include abuse of market power, higher-than-expected demand, unexpected capacity bottlenecks, plant outages, poorly developed transmission networks, changes in purchasing and contracting behavior, fluctuant renewable electricity generation, inappropriately designed market mechanisms and information asymmetries. A satisfactory explanation of price volatility in any electricity market is required from a regulatory perspective and should be able to accommodate remarkable empirical price regularities and irregularities. Regulators should also investigate the issue of the persistence in conditional volatility. An answer is required to the question *why do some markets have relatively larger persistence in conditional volatility*; *that is, why does volatility in some markets take a longer time to die out following a shock regardless of anything happening in the market*? Moreover, power generators may utilize our results to optimize the terms of bilateral contracts and to participate efficiently in the day-ahead and real-time markets. A power generator that wishes to secure a stable flow of income may prefer to avoid concluding contracts for volatile hours. The findings of this study also let retailers and large consumers create an optimal bidding strategy. Risk averse retailers and large consumers may choose to buy their electricity by bilateral contracts rather than from spot markets if prices in the latter are highly volatile. Similarly, for those managing energy commodity portfolios, information about volatilities is required and value-at-risk calculations benefit from a comprehensive knowledge of price variance.

The research presented in this paper may have a number of limitations that we acknowledge. In fact, we have no reason to believe that any of these limitations should undermine our analyses but cannot of course rule them out. The limited nature of our data set, the lack of exogenous variables, and inter-/cross-market dependency constitute three potential limitations of the analysis presented in this paper. The first shortcoming may originate from the limited nature of our data set. Our sample is composed of fourteen European wholesale electricity markets for which we could obtain data. There will be sample selection bias if the countries making these data available have differing results for volatility than those which do not make data available. Moreover, different countries may have different classifications and reporting conventions, so observations in a given data series may not have the same meaning across all countries. Taken together, any measurement error and omission of explanatory variables may bias estimates of coefficients in the models. Second, due to lack of data, we could not properly account for the impact of some other variables (e.g. regulatory practices, market power, demand structure, capacity constraints, share



Source: EC (2015)

Fig. 3. Commercial electricity flows in GWh in December 2014–February 2015 *Source*: EC (2015).

of renewable power, market structure) on volatility. Given the significance of understanding power price volatility and the fact that the literature has only begun to explore these issues, a comprehensive investigation of volatility with additional variables may be a useful contribution to the subject. Finally, as can be seen in Fig. 3 (EC, 2015), which shows the map of commercial power flows between neighboring European power markets, there is huge cross-border power trade in Europe. Besides, through coordinated calculation of prices and flows between countries, the European Union tries to optimize the allocation process of cross-border capacities, called *market coupling*. The most important step of European power market integration took place on 4 February 2014, when price coupling in North Western Europe (NWE) went live. Since the launch of NWE, two extensions have taken place. In May 2014, Spain and Portugal joined; in February 2015, Italy coupled with France, Austria, and Slovenia. As a result, the coupled area is called Multi-Regional Coupling and now covers 19 countries, standing for about 85% of European power consumption. Cross-border trade and market coupling in Europe have the potential to influence volatilities in individual European markets. Due to space limitations, we could not investigate this potentially important topic.

In this paper, we tried to model asymmetric volatility in European day-ahead power markets using a simple but highly effective methodology. However, even with the results from this paper, the present econometric evidence on the volatility in European power markets is still limited. The hope is that future research will continue developing econometric models to analyze electricity price volatility. We suggest the following for future research. First of all, we focus on measurement of the volatility rather than its optimal level. However, there is a definite need for identifying optimal or excess volatility levels based on well-defined criteria. So, future research on electricity markets should focus on identifying what optimal level of volatility is and developing new tools to measure it. Second, we investigate the volatility in day-ahead power markets only. These are just one dimension of power markets. There is clearly a need for further analysis regarding volatility in other sections of the power markets like real-time electricity markets and derivative markets, including exchange-traded contracts such as futures and options, and over-the-counter (i.e., privately negotiated) derivatives such as forwards, swaps, and options. Third, although there are some academic work on the social cost-benefit analysis of power price volatility, they mostly use data from one country or few countries and deal with a single dimension only (usually, redistribution of wealth from consumers to power producers/traders). However, what is needed is a comprehensive social-cost benefit analysis that takes into account as many countries as possible and all implications of volatility. The fourth task for future research should be the extension of the data set in terms of number of countries, time period, and number (and quality) of variables. The final extension may be realized by taking into account the fact that electricity markets are a part of wider economy in general and energy market in particular. In this research, we did not take into account possible spill-over effects from or to volatility of other energy (natural gas, oil etc.) and non-energy sectors but inter-market volatility relationship is clearly an important research area open to exploration.

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Online Appendices

Online Appendices to this article can be found online at http://dx.doi.org/10.1016/j.eneco.2016.04.002.

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