Working Paper No. 580

December 2017

Determinants of power spreads in electricity futures markets: A multinational analysis

Petr Spodniak*[a,b] and Valentin Bertsch[a,b]

Abstract: The growth in variable renewable energy (vRES) and the need for flexibility in power systems go hand in hand. We study how vRES and other factors, namely the price of substitute fuels, power price volatility, structural breaks, and seasonality impact the hedgeable power spreads (profit margins) of the main dispatchable flexibility providers in the current power systems - gas and coal power plants. We particularly focus on power spreads that are hedgeable in futures markets in three European electricity markets (Germany, UK, Nordic) over the time period 2009-2016. We find that market participants who use power spreads need to pay attention to the fundamental supply and demand changes in the underlying markets (electricity, CO2, and coal/gas). Specifically, we show that the total vRES capacity installed during 2009-2016 is associated with a drop of 3-22% in hedgeable profit margins of coal and especially gas power generators. While this shows that the expansion of vRES has a significant negative effect on the hedgeable profitability of dispatchable, flexible power generators, it also suggests that the overall decline in power spreads is further driven by the price dynamics in the CO2 and fuel markets during the sample period. We also find significant persistence (and asymmetric effects) in the power spreads volatility using a univariate TGARCH model.

*Corresponding Author: petr.spodniak@esri.ie

Keywords: Financial risk management; hedging; futures markets; electricity markets
JEL Classification: Q21, Q31, Q41, L94, G13, G32.

Acknowledgements: This publication has emanated from research conducted with the financial support of Science Foundation Ireland under the SFI Strategic Partnership Programme Grant Number SFI/15/SPP/E3125

a The Economic and Social Research Institute, Dublin
b Department of Economics, Trinity College, Dublin

1 Introduction

The electric power sector is undergoing a rapid transition (Helm, 2017). This transition brings about changes to the risk profiles market participants will face, for instance related to the growth of variable renewable energy sources (vRES) in national energy mixes. In this context, the question arises whether the traditional hedging mechanisms and tradable products are still relevant and sufficient for risk management. Financial derivatives were adopted by electricity market participants relatively recently, in the 1990s, when the markets were liberalized. However, these products were designed for centralized power systems with a dispatchable generation fleet, which is not the case of the current market characterised by rapid adoption of intermittent renewable energy sources, such as wind and solar power. It is therefore essential to clearly understand the newly emerging factors shaping the risks and profits market participants face.

In electricity markets, power generators use derivatives to lock-in long-run prices to cover fixed costs, retailers use derivatives to lock-in volatile wholesale prices, and commodity traders/speculators look for profits from short-term price fluctuations. This work primarily focuses on the first group, namely power generators who typically lock-in a portion of their revenue margin in advance by selling derivatives contracts on outputs (electricity) and buying derivatives contracts on inputs (fuel and carbon) ahead of the actual delivery.

Specifically, we are interested in technologies that provide *flexibility* and *dispatchability* to the power system, meaning technologies with the capability to balance changes in power supply and demand and to provide power when vRES are not available. Coal and gas-fired power plants are flexible technologies that we focus on. This is in contrast to typical must-run baseload technologies, such as nuclear, or more variable generation, such as wind and solar. We concentrate particularly on these technologies because the outlined transformative trends, such as the increase in vRES production, increase the need for flexibility (Belderbos & Delarue, 2015). At the same time, flexibility providers in liberalized electricity markets need to recover costs and gain reasonable profits to stay in the market. We define a proxy for hedgeable profitability of a given energy technology as *power spread*.

For gas-fired assets, the differential between prices of electricity and fuel is called *spark spread*, for coal-fired assets, this differential is called *dark spread*. Because gas and coal are sources of greenhouse gases, power generators using these fuels in Europe need to acquire CO_2 emission allowances. When carbon costs are considered in spark and dark spreads, they are called *clean spark* and *clean dark spreads*.

In this work, we carry out a cross-country analysis of three different European electricity markets, namely Germany, UK and Nordics[1], and explore the drivers of hedgeable revenue margins proxied by the two clean power spreads just described. This work contrasts the incentives to provide flexibility, as manifested by the power spreads (revenue margins), with the underlying fundamental factors impacting these spreads. In addition to seasonality, fuel prices, and power price volatility, we particularly focus on the impacts of solar and wind generation, which we hypothesize decrease the clean spark and clean dark spreads.

[1] By the term Nordic we refer jointly to Norway, Sweden, Finland and Denmark.

Ultimately, the underlying issue is the energy policy trilemma, which includes the three policy objectives - environmental sustainability, reliability of supply, and economic competitiveness. The support of vRES is associated with environmental sustainability, while the question of adequate hedging mechanisms for dispatchable and flexible generation is associated with both reliability of supply and economic competitiveness. Hence, the key motivation of this work is to evaluate the impacts of current policy which promotes rapid deployment of vRES under the requirement of greater system flexibility on the one hand, with the risk management reality of flexibility providers on the other hand. If there are fundamental factors impeding risk management of flexibility providers, these have to be first identified and understood before designing new market mechanisms, such as capacity markets, aligned with the objectives of a sustainable, competitive and secure energy market. Misaligned policies may lead to consumers paying risk premia for the increased risk exposure of flexibility providers or lead to higher electricity prices because of the lack of investments into flexible capacity.

We estimate a jointed model for the mean and variance of the futures power spreads on front-month contracts in daily frequency for the period 2009-2016. Our statistical model quantifies the effects of changes in fuel futures prices (gas and coal), volatility of power futures prices, seasonality, and expected wind and solar generation on power spreads. By explicitly modelling variance (volatility) of power spreads with asymmetric threshold generalized autoregressive conditional heteroscedasticity (TGARCH), we reach two methodological benefits and contributions.

First, because volatility is a key input in option pricing formulas, which is an area typically dominated by reduced-form (stochastic) models (Cartea & Villaplana, 2008; Carmona, Coulon, & Schwarz, 2012), our econometric approach presents a practical alternative for multi-asset derivatives pricing. Simplified derivatives valuation and risk management may be appreciated especially by risk managers who often rely on complex third party software. Practicality and model agility may be highly valued to reduce cash-flow variation, especially with the growth of vRES and CO_2 prices. The second methodological benefit of explicitly modelling volatility is that our hypothesized determinants of power spreads are more robust and less prone to false sense of precision. This is because treating expected squared error terms equally at any given point (homoscedasticity) when this assumption does not hold (heteroscedasticity) leads to biased standard errors and confidence intervals, thus giving a false sense of precision (Engle R. , 2001).

Much of the econometric literature focuses on modelling determinants of commodity prices, such as weather, market tightness, or demand flexibility, in the *spot market*. This is understandable, because spot prices drive optimization decisions and physical portfolio dispatch. In contrast, the literature focusing on the *futures market* prices has mostly focused on hedging effectiveness, cashflow at risk analyses, and volatility forecasting. This is also understandable, because the uncertainty of future supply and demand factors affecting derivatives' prices is inherently high and dependent on how far on the forward curve we go. For instance, short-term futures are typically impacted by storage conditions, whereas long-term futures are impacted by the future potential energy supply (Pilipovic, 2007). We attempt to fill this gap between spot and futures commodity price research and explicitly model the determinants of the *hedgeable* profit margins in the *futures* market.

Our approach enables us to distinguish and quantify the individual factors affecting the hedgeable profit margins of flexibility providers. Such a distinction of factors may better inform policy makers and regulators in designing adequate and reliable power markets.

Additionally, by linking electricity, emissions, and fuels across three different electricity markets in Europe, we bring comprehensive empirical evidence on the evolution and determinants of hedgeable profit margins for supply-side providers of flexibility.

The paper is structured as follows. Section 2 reviews the literature on power spreads modelling and valuation. Section 3 initially outlines the main drivers of electricity supply and demand in the studied regions before proposing the main drivers of power spreads. The section continues with data and model description. Section 4 summarizes the main results which are further discussed in section 5. Section 6 concludes. In the appendix we present selected key characteristics of the three markets in the studied period.

2 Literature review

The literature on commodity spot and derivatives pricing is vast. As a starting point, the research field can be classified according to modelling approaches of electricity prices[2]. Five general modelling approaches can be identified (Weron, 2014): i) *Multi-agent* (multi-agent simulation, equilibrium, game theoretic), ii) *Fundamental* (structural), iii) *Reduced-form* (quantitative, stochastic), iv) *Statistical* (econometric, technical analysis), and v) *Computational intelligence techniques* (artificial intelligence-based, non-parametric, non-linear statistical). Next, we focus on the two most widely applied approaches in derivatives pricing – reduced-form, and statistical.

Reduced-form models, also called financial mathematical models (Möst & Keles, 2010), are dominating the electricity derivatives valuation field which focuses on the stochastic behaviour of commodity prices in one- or multi-factor models (Mahringer & Prokopczuk, 2015; Carmona, Coulon, & Schwarz, 2012; Islayev & Date, 2015; Barlow, 2002). These stochastic factors are typically mean-reversion (Brownian motion), jump diffusion (Poisson process with jump terms), and regime switching (Markov models), which undisputedly play a central role in valuing power derivatives. These models take prices as exogenous and focus on modelling the futures and volatility curves. Their main usage is in pricing financial derivatives and short term forecasting of spot and futures prices (Suren & Date, 2015). Some of the studies applying stochastic approaches particularly focus on seasonality in volatility (Fanelli, Maddalena, & Musti, 2016; Paschke & Prokopzuk, 2010; Back, Prokopzuk, & Rudolf, 2013), which is an important factor in the valuation of commodity derivatives. Reduced-form models applied to power spreads predominantly focus on the value of spread *options* (Carmona, Coulon, & Schwarz, 2012; Deng, Johnson, & Sogomonian, 2001; Mahringer & Prokopczuk, 2015; Hsu, 1998; Dempster, Medova, & Tang, 2008), which is mainly because of the versatility of options (keeping the upside while protecting the downside). Additionally, the choice of running a power plant or storage, if the operating margin between power price and the operating cost is positive, gives a rise to an option value of a power plant. The choice to run a power plant or not can then be valued as option according to option value methods, such as Black-Scholes. Option spreads are often approximated by Monte Carlo, tree methods, and partial differentiation equation (PDE) solvers (Carmono & Durrleman, 2003). A survey of reduced-form models in power futures setting is present in (Eydeland & Wolyniec, 2003; Pilipovic, 2007).

[2] Alternative classification could be along the electricity derivatives pricing approaches, namely 1) Theory of storage (Kaldor, 1939), where forward commodity contract price is equal to the spot discounted by interest rate and the storage costs; 2) Equilibrium pricing (Keynes, 1930), where futures prices are related to the expected spot prices; and 3) Stochastic pricing models (Benth & Koekabakker, 2008; Eydeland & Wolyniec, 2003), vis discussion on the reduced-form modelling.

Statistical (econometric) techniques do not solely focus on the replication of price dynamics as the reduced-form models do and they deal with stochastic processes differently (Möst & Keles, 2010). In addition to using past price characteristics to explain price fluctuations, statistical models incorporate also the current and/or past values of exogenous factors (Weron, 2014). In an electricity price modelling setting, the typical exogenous factors are, for example, electricity consumption and production, weather, and fuel prices. Statistical models thus focus on the impact of explanatory variables on the price fluctuations, which enables interpretation of the physical (fundamental) components in the analysis. Since the main purpose of this study is to explain the impacts of exogenous variables on the hedgeable profit margins, we embrace the econometric approach to price modelling.

Econometric models have to address the typical and complex empirical features of (daily) electricity prices, namely extreme volatility, excess kurtosis, positive skewness, price jumps, seasonality, and conditional heteroscedasticity. Weron and Zator (2014) point out important methodological pitfalls of applying linear regression models for explaining the relationship between spot and futures electricity prices, which can be generalized to electricity prices (spreads). They mention three issues needing attention: (1) bias originating from simultaneity (endogeneity) problems, i.e. there is often a loop of causality between dependent and independent variables; (2) the effect of correlated measurement error; and (3) the impact of seasonality on regression models. We explain in detail how we address these fundamental issues in the methods section below.

The mean-reverting and seasonal behaviour of electricity prices is often modelled by autoregressive (AR-type) time series models (Weron, 2014) and volatility clustering by conditional heteroscedasticity models (ARCH). Non-linear effects, especially price-spikes, are modelled by regime-switching and authors typically combine and/or compare model performance under different specifications. For example, Karakatsani and Bunn (2008) build a fundamental regression model for intra-day electricity prices and compare its day-ahead forecasting performance to time-varying and regime-switching models. In their specification, they include multiple economic, technical, strategic, risk, behavioural and market design price effects, such as demand forecast, demand slope, demand volatility, margin (excess of generation capacity), price volatility, and seasonality. Weron and Misiorek (2008) show that AR electricity price models with system load as the exogenous variable generally perform better than pure price models. Also Kristiansen (2012) uses the Nordic demand and Danish wind power as exogenous variables in an AR model to forecast the Nordic hourly day-ahead prices. Applied directly to spot spark spreads, Woo, et al. (2012) estimate a two-step regression model applying a logistic and ARCH log linear regression using demand, wind generation and fuel prices, among others. Using European Union Allowance (EUA) future returns, Boersen and Scholtens (2014) employ a threshold GARCH model and study the impacts of natural gas, oil prices, fuel switching, electricity futures price, and weather (heating degree days) on the yearly futures carbon price.

As was briefly illustrated, most of the statistical models focus on spot prices rather than derivatives prices, which is understandable because spot prices drive optimization decisions and physical portfolio dispatch. An additional reason is that derivatives prices are not simple forecasts of expected future outcome. Instead, in addition to being a function of the basic fundamental drivers of supply and demand for the physical commodity, derivatives prices also reflect the relative risk aversion of participants, the speculative positions and the perceived cost of risk (Roques, Newbery, & Nuttall, 2004; Karakatsani & Bunn, 2008). Hence, electricity spot price modelling with econometric techniques need to capture all factors affecting the *current* supply and demand. Nonetheless, similar techniques applied to derivatives prices need to consider the *future* factors of supply and demand affecting the expected value of a derivative during its settlement period. Forecasting input factors over long horizons by, for example, exponential smoothing methods, bears obvious risks of increasing parameter uncertainty.

The uncertainty of future inputs presents the biggest challenge for applying econometric techniques to derivatives valuation. To overcome this limitation, instead of relying on point estimates, the econometric model can work with different input scenarios which establish probable boundaries. Other approaches to overcome the uncertainty of forecasted inputs include use of the nearest forward contract, such as front-month, which is convergent with the spot price because disparities between the two are quickly arbitraged away. The nearest contracts are usually the most traded and liquid representing the short-term portion of the forward curve which is often used as a spot price indicator. In fact, the influence of past spot electricity prices on the future electricity prices has been repeatedly documented (Karakatsani & Bunn, 2008; Redl, Haas, Huber, & Böhm, 2009). In such a case, the present supply and demand factors could be used to explain the nearest contract price dynamics without inherently increasing the model's uncertainty and complexity.

An additional challenge in modelling derivatives of power spreads lies in the fundamental structure of the spread itself. Power spreads, be it clean dark or clean spark, are by design cross-commodity derivatives consisting of fuel prices, electricity prices and carbon allowance prices. Each of these price series typically constitutes a separate pricing model. Nonetheless, to uncover the average price formation process of such derivatives, a joint model for all commodities is required (Carmona, Coulon, & Schwarz, 2012).

3 Material and methods

In this section, we first examine electricity supply and demand in the three European electricity markets here considered. Then, we discuss, propose and define a set of influential determinants of power spreads. Finally, we present data used in the empirical analysis and the modelling details.

3.1 Fundamentals of electricity supply and demand

This work focuses on three European electricity markets (Nordic, German, and UK) which are set in specific techno-economic environments exerting influence on the types and levels of risks the flexibility providers face. It is therefore essential to first outline and understand the relevant local factors of electricity supply and demand[3] before proposing relevant determinants of power spreads. As a reminder, by Nordic we jointly refer to Norway, Sweden, Finland, and Denmark.

On the *supply side*, the power systems in Germany and the UK have traditionally relied on thermal generation (coal, gas, nuclear). However, since the introduction of EU targets for reductions in carbon emissions and the promotion of RES, both countries have since 2008 seen a rapid growth in capacity and power generation from vRES (particularly wind and solar)[4]. On the contrary, the Nordic electricity market is a hydro-dominated system with a

[3] See (ENTSO-E, 2017) for an overview of European electricity supply and demand, and (OME, 2007) for their drivers.
[4] See Figure 4 in Appendix for a summary of yearly development of installed vRES and electricity consumption in the three studied markets.

large share of indigenous generation from biomass, making the adoption of vRES less rapid, compared to the two other cases. With respect to market design, the UK slightly differs from the two other markets due to the introduction of separate carbon price floor and capacity market mechanisms in 2013 and 2014, respectively. The UK and Nordics are generally less interconnected by cross-border transmission lines compared to Germany which is part of the highly meshed transmission grid of the Continental Europe synchronous area.

On the *demand side,* the studied markets share similarities with respect to energy intensity (mining, manufacturing, etc.), macroeconomic development (omitting the recent Brexit) and demographic structure, but differ with respect to weather characteristics and deployment of energy saving technology, such as smart metering. The peak demand in 2016 was comparable across the regions, namely 82GW, 72GW, and 70GW for Germany, Nordics, and the UK, respectively (ENTSO-E, 2017). The wholesale electricity prices in all three markets have systematically decreased since 2008 generally due to the decreasing fuel commodity prices and increasing production from vRES.

There are numerous factors that can influence the price dynamics of the four underlying markets of power spreads (coal, gas, CO_2, electricity). With the market liberalization and unbundling in many sectors, concerns about institutional aspects such as competition, strategic behaviour, and market power became evident. For example, some research focuses on the distortions of the wholesale electricity prices through horizontal market power in generation (Wolfram, 1999; Borenstein, Bushnell, & Knittel, 1999; Borenstein, Bushnell, & Wolak, 2002) while others focus on vertical market power that includes electricity retail markets (Mirza & Bergland, 2012; von der Fehr & Hansen, 2010). While institutional aspects are undoubtedly important price drivers, our focus in this paper is on the fundamental market drivers; firstly because there is less research on these drivers and, secondly, because we consider these drivers as the major sources of price dynamics during our sample period 2009-2016.

3.2 Drivers of power spreads

Next, we propose a set of potential influential drivers of power spreads, define how they are measured and provide explanations for their selection based on theoretical considerations and market intuition. The summary of proposed power spread drivers is presented in Table 1.

Market participants who use power spreads for hedging (flexibility and dispatchability providers) need to pay attention to the fundamental supply and demand changes of the underlying[5] assets (electricity, coal/gas, CO_2). As discussed in section 2 and 3.1, the effects of vRES production, especially solar and wind, on electricity prices, are well known. For this reason, we study the effect of *expected solar and wind production* (EP_{vRES}) on future power spreads. Our empirical estimation will work with front-month futures, so we need to estimate the expected solar and wind generation in the next month. We utilize the available data set on hourly PV and wind capacity factors for the EU-28 plus Norway (Pfenninger & Lain, 2016; Lain & Pfenninger, 2016) and calculate twelve long-run capacity factors ($LCF_{vRES,m,c}$) for country c and month m based on the mean capacity factors from the years 2006-2016. Then, we take the installed capacity values for wind and solar in each country during the month of

[5] Other *outputs*, such as capacity or ancillary services, and *inputs*, such as chemicals, spare parts, or labour, could be considered to affect the power spreads. However, over the near-term planning horizons, the impacts of these additional factors on cash flow uncertainty of flexibility providers are far less than that of fuel, carbon and power prices.

the underlying contract ($IC_{vRES,c,m+1}$) [6] and multiply them with the long-run capacity factors and the number of hours in the underlying month (h_{m+1}). Eq. 1 expresses the next month's expected production (GWh) of vRES technology in a country *c*.

$$EP_{vRES,c,m+1} = LCF_{vRES,c,m+1} * IC_{vRES,c,m+1} * \mathrm{h}_{\mathrm{m+1}} \tag{1}$$

Other studies also consider the impacts of installed solar and wind generation capacity on electricity spot (Rubin & Babcock, 2013) and futures (Cartea & Villaplana, 2008; Carmona & Coulon, 2014) prices. However, in an econometric setting, using installed capacities leads to high collinearity between solar and wind capacity for the considered countries, possibly biasing the results.

Price of the substitute fuel is an important driver of future (Carmona, Coulon, & Schwarz, 2012) and spot (Woo C.-K. , Horowitz, Horii, Orans, & Zarnikau, 2012) power spreads. Fuel prices also impact the cost of CO_2 (Mansanet-Betaller, Pardo, & Valor, 2007; Woo C.-K. , Horowitz, Horii, Orans, & Zarnikau, 2012) . We consider the price of the substitute fuel, meaning the price of gas in the clean dark spread model and the price of coal in the clean spark spread model. We expect to see a positive relationship between the price of fuel substitute and the power spread in question. The interpretation is that when the substitute fuel gets more expensive, using the current fuel becomes more profitable.

Volatility of power futures prices has been also shown to affect spot (Karakatsani & Bunn, 2008) and futures (Fanelli, Maddalena, & Musti, 2016) electricity prices. In our definition of power spreads (Eq.2 below), we use peak load power prices for gas and baseload power prices for coal technologies. This is because during our sample period (2009-2016) coal-fired power plants were typically run to meet continuous energy demand (baseload) and gas-fired power plants typically operated during high energy demand (peak load).[7] To keep our analysis comparable, we estimate the volatilities of power futures prices based on a five-day rolling window, defined as coefficient of variation of front-month electricity peak load price when studying clean spark spreads and front-month electricity baseload price when studying clean dark spreads. The volatility in futures power prices reflects risks for hedgers and traders, so investigating the effects on power spreads may reveal who is bearing these risks (buyers or sellers).

We further address *seasonality* in the mean of power spreads by the season-of-the-year effect, namely spring (Mar-May), summer (Jun-Aug), fall (Sep-Nov) and winter (Dec-Feb). The impact of seasonality in mean equations is typically captured by daily, monthly, and quarterly dummies (Karakatsani & Bunn, 2008), and sine/cosine-based specifications. Properly addressing seasonality in the price series nets out the average change in power spreads resulting from seasonal fluctuations. Cartea and Villaplana (2008) also show a seasonal component (summer, spring, fall, and winter) of the time-dependent volatility. We have tested the seasonal effect in volatility and have not found any significant effects, thus they are not reported.

[6] From the current trading month (m), this is the next month's installed capacity (m+1). Since the installed capacities do not drastically change month-to-month, we consider this approach realistic and reliable.

[7] These dynamics might have changed in the more recent time, i.e. 2017, especially in the UK, however, such time period is not included in our sample.

Table 1 Fundamental drivers of power spreads and studies applying them in electricity futures and spot markets

Driver	Definition	Futures market	Spot market
Expected solar and wind generation	Expected next-month PV and wind productions are calculated as the product of the national long-run PV and wind capacity factors, installed capacity of solar and wind, and the number of hours in a month.	(Kristiansen, 2017)	(Woo C.-K. , Horowitz, Horii, Orans, & Zarnikau, 2012; Woo, Horowitz, & Pacheco, 2011)
Price of fuel (substitute)	Price of gas when studying clean dark spreads (CDS) and price of coal when studying clean spark spread (CSS), in EUR/unit of fuel.	(Carmona & Coulon, 2014; Carmona, Coulon, & Schwarz, 2012; Boersen & Scholtens, 2014)	(Mansanet-Bataller, Pardo, & Valor, 2007; Woo C.-K. , Horowitz, Horii, Orans, & Zarnikau, 2012)
Volatility of electricity futures price	Five-day rolling volatility of electricity futures prices, defined as coefficient of variation (standard deviation/mean) of front-month electricity peak load price when studying clean spark spreads and front-month electricity baseload price when studying clean dark spread.	(Fanelli, Maddalena, & Musti, 2016)	(Karakatsani & Bunn, 2008)
Seasonality	Season-of the year effect on the mean of power spreads, measured as dummies for spring (March-May), summer (June-August), fall (September-November), and winter (December-February), with reference to winter as the coldest and typically the most volatile season.	(Cartea & Villaplana, 2008)	(Karakatsani & Bunn, 2008)
Structural breaks	We consider two country-specific events captured by dummy variables. The first event is the introduction of carbon price floor in the UK in 2013. The second event is the announcement of the so-called nuclear moratorium by the German government, which stated a temporary* shut down of 8 out of 17 German nuclear reactors.	(Arouri, Lahiani, Lévy, & Nguyen, 2012)	(Alberola, Chevallier, & Chèze, 2008)

Note: *The temporary shut-down resulted to permanent shut down announced August 6th 2011. The affected reactors were Biblis A (1167MWe) and B (1240MWe), Brunsbüttel (771MWe), Isar 1 (878 MWe), Krümmel (1346 MWe), Neckarwestheim 1 (785 MWe), Philippsburg 1 (890 MWe) and Unterweser (1345 MWe), a total of 8422 MWe (IAEA, 2011).

Finally, we need to control for possible *structural breaks* in our time series (2009-2016). We identified two main country-specific events with possible spillover effects. The first event followed the Fukushima nuclear disaster in 11th March 2011, which led the German government to temporarily (but effectively) shut down 8 out of 17 German nuclear reactors on 15th March 2011. We hypothesize that the effect of removing over 8GW of capacity had a strong and positive impact on German power spreads. The second major event happened in the UK where a carbon price floor was introduced from the beginning of 2013. The carbon price floor started at the level of 15.70 GBP/tCO_2 and progresses by approximately 2.04 GBP/tCO_2 per year to reach 30 GBP/tCO_2 in 2020 (Sandbag, 2013). We hypothesize that the carbon price floor has negatively impacted the UK's power spreads, especially the more carbon intensive clean dark spread.

Our key modelling principles are parsimony and adequacy. By the first principle, we keep the number of coefficients in check instead of over-parametrizing the models. This is a fundamental principle in the Box-Jenkins approach. By the second principle, we verify that the main model assumptions and statistical properties of the price process are adequate. Next, we present the modelling details.

3.3 Data and model

We begin by formally defining how the power spreads are calculated. As mentioned in the introduction, clean dark and clean spark spreads represent cross-commodity derivatives consisting of fuel prices, electricity prices and carbon allowance prices. To calculate the future power spreads, we use daily closing prices of the front (prompt) month energy commodity futures contracts (electricity, gas, coal), which refer to contracts traded in the current month with a delivery in the next month. Futures power spreads represent a hedgeable payoff per unit of production from a dispatchable power plant, which is expressed in Eq. 2.

$$Cl.Spread\ (T)_t = \ (ELECTRICITY(T)_t - (\ FUEL(T)_t * ER)) - \ CO2\ (T)_t \tag{2}$$

$\mathrm{Cl.\,Spread}\ (\mathrm{T})_{\mathrm{t}}$ in Eq. (2) is the daily futures clean dark $\mathrm{CDS}\ (\mathrm{T})_{\mathrm{t}}$ or clean spark spread $\mathrm{CSS}\ (\mathrm{T})_{\mathrm{t}}$ in EUR/MWh_{el} with delivery in month T traded at day t; $ELECTRICITY(T)_t$ is the daily futures electricity price (EUR/MWh) for baseload (clean dark spread) and peak load (clean spark spread) with delivery in month T; $\mathrm{FUEL(T)}_{\mathrm{t}}$ is a daily closing monthly futures price (EUR/MWh) for natural gas (ICE UK Natural Gas for clean spark spread) or coal price (ICE Rotterdam Coal Future for clean dark spread) with delivery in month T; ER is an efficiency rate, which is the factor of how much gas (coal) is needed to produce 1 MWh of power, i.e. this considers the fuels' heating values and the efficiencies of coal and gas power plants, here assumed 36% and 50%, respectively; and $CO2(T)_t$ is the daily closing futures price of a front-month (T) EUA (ICE ECX EUA Future) carbon allowance (EUR/tCO_2) traded at time t. For the UK power spreads, the UK's carbon price floor is used from 2013 onwards as the CO_2 price, since the EUA price has stayed well below the carbon price floor, see Figure 5 in Appendix. Carbon emission intensity factor is assumed 0.41 tCO_2/MWh_{el} for clean spark spread and 0.95 tCO_2/MWh_{el} for clean dark spread. All data originates from Thomson Reuters Eikon database, except the German and Nordic monthly power futures data which originate from EEX and Nasdaq OMX, respectively. The time period covered is from the year 2009 to 2016, both included. Figure 1 and Figure 2 present the daily German, UK and Nordic clean dark (CDS) and clean spark spreads (CSS)

Because power produced from gas is typically used in times of high demand, we use the electricity peak futures in the pricing formula for clean spark spreads. Similarly, power produced from coal is, to date, considered baseload and that is why we use the electricity baseload futures in the pricing formula for clean dark spreads. *Baseload* hours are defined as 00am-12pm Mon-Sun, *peak load* hours are defined as 8am-8pm Mon- Fri, and *off-peak* hours are 8pm-8am Mon-Sun in all the studied markets.

To reach a common unit of EUR/MWh_{el} for all spreads, we did the following unit conversions. The gas futures were quoted in British pence/1000 therms and were converted to EUR/MWh_{el} (dividing the Euro converted price of natural gas by 2.93071 (1 therm = 29.3071 kilowatt hours). Coal futures were quoted in USD/tonne and were converted to EUR/MWh_{el}. Currency conversion from GBP and USD to EUR was done by using daily exchange rates from the European Central Bank, similarly as (Boersen & Scholtens, 2014; Alberola, Chevallier, & Chèze, 2008). The choice for using National Balancing Point (NBP) gas futures (ICE UK Natural Gas) is that NBP is a benchmark for natural gas trading in Britain and continental Europe (Martinéz & Torró, 2015). For the same reason, ICE Rotterdam Coal futures are used because they are settled against the API 2 index benchmark for coal imported into Norwest Europe. While the coal and gas prices differ between the three countries in terms of their absolute levels, the differences will be largely constant since they are mainly driven by (rather constant) transport costs. The underlying market dynamics, however, are generally the same.

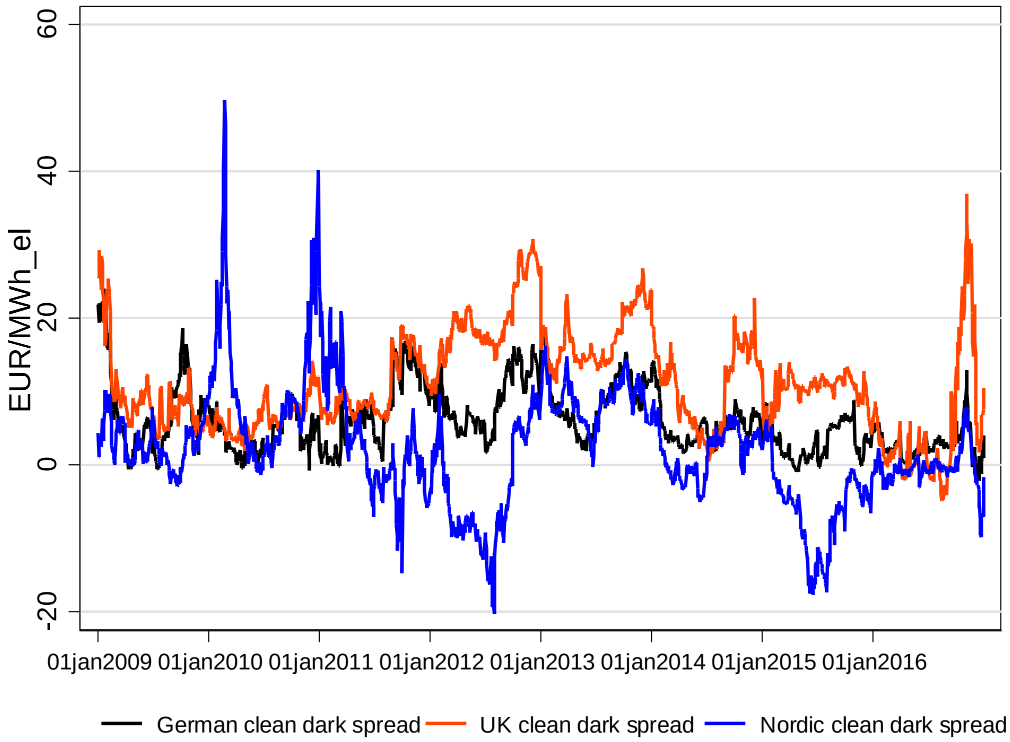

Figure 1 German, UK and Nordic daily clean dark spreads (CDS), 2009-2016

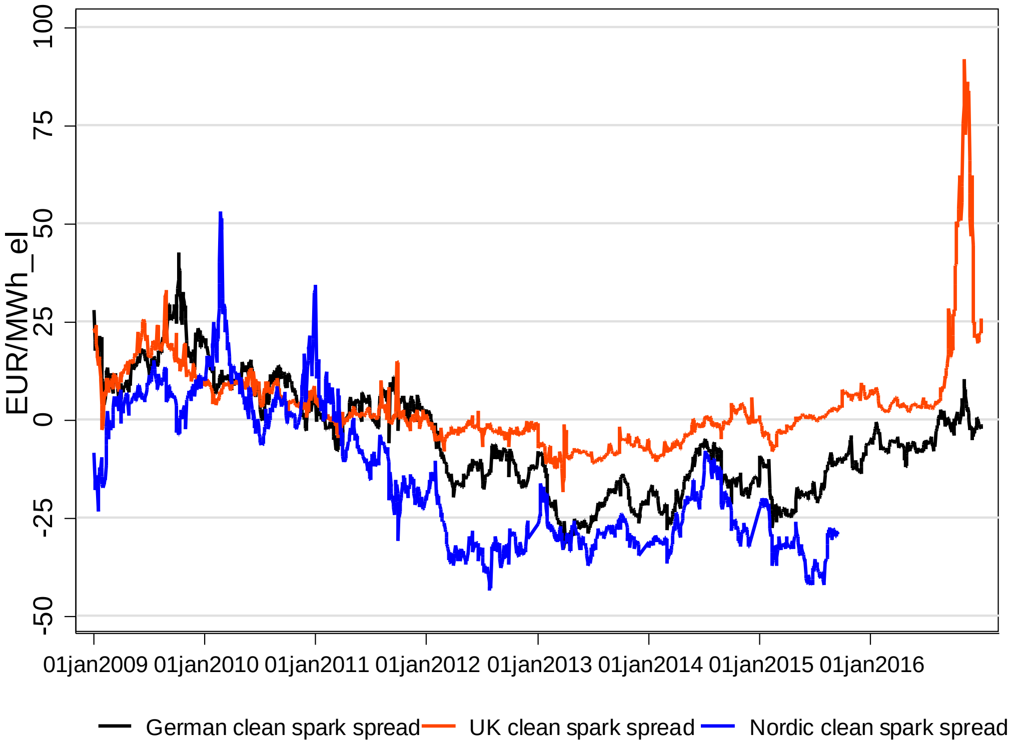

Figure 2 German, UK and Nordic daily clean spark spreads (CSS), 2009-2016

ICE ECX EUA is one of the main platforms auctioning EUA allowances since the first trading period of the EU ETS in 2005; hence the corresponding contract prices are considered representative. The UK's yearly carbon price floor was converted from GBP/tCO_2 into EUR/tCO_2 by using yearly median EUR/GBP conversion rate for each year.

Table 2 further presents detailed descriptive statistics for the power spreads during the studied period 2009-2016. It must be first noted that futures contracts are traded only during the business (trading) days, which excludes weekends and bank holidays, which further vary across the different exchanges and markets. Our sample size of this eight-year long sample for each of the markets is approximately 2000 observations (approximately 21 trading days/month). The sample size slightly varies across the market/spread combinations, because in some cases, the power spreads could not be calculated if one or more of the commodity future prices weren't available. The Nordic CSS is an exception with a sample size of 1624 due to the missing access to the Nordic power peak futures contracts that we possess only until 27th May 2015.

The mean *spread* (P_t) is significantly higher for CDS than CSS, mainly due to the higher gas fuel prices. The changing fuel price dynamics, see Figure 5 in Appendix, are observable on the power spread levels, especially on the convergence between German CDS and CSS from 2014 to 2016. In general, the highest mean (median) CDS and CSS spreads are in the UK and the lowest in the Nordics, with Germany scoring in between. CSS spreads are more volatile (standard deviation) than CDS spreads while both exhibiting positive skewness.

Log transformation is a typical approach to limit and stabilize price volatility in electricity price modelling studies (Möst & Keles, 2010). In the presence of negative spreads, we apply a common method (Sewalt & De Jong, 2003; Knittel & Roberts, 2005) and add a small constant *log(x + constant)*, where *min(x + constant)* is equal to 0.1. To preserve the sign of the spread, the log of the constant is further subtracted, making the full transformation equal to *log(x + constant) – log (constant)*. Transforming the daily power spreads by *natural logarithm* (lnP_t) shows the stabilization and normalization effects on the distribution, as shown by reduced values of standard deviation, skewness, and kurtosis.

The visual inspection of the power spreads in Figure 1 and Figure 2 implies that the time series may not be stationary, which is further confirmed by the traditional unit-root tests (KPSS, ADF, and DFGLS). Using nonstationary time series for estimation would lead to spurious regression, hence we calculate *daily spread changes* (P_t-P_{t-1}), and *daily log spread returns* (lnP_t-lnP_{t-1}). Log-returns are widely used in energy research (Boersen & Scholtens, 2014; Pilipovic, 2007; Mansanet-Bataller, Pardo, & Valor, 2007) because they are more likely to result in stationarity and represent continuously compounded price changes. Also, when both the left hand side and the right hand side variables in a regression equation are in logs, the coefficients are interpreted as elasticities. We will use this property in our model described in detail further below.

The daily log returns (*lnPt-lnPt-1*) in Table 2 exhibit mostly positive skewness, which implies long right tails possibly caused by positive outliers, and excessive kurtosis, which often exceed value 3, a benchmark for normal distribution in financial econometrics. High kurtosis values imply that more frequent extreme (positive and negative) returns can be expected (fat-tails). All of the mean and median log returns are close to zero or slightly negative, which implies the negative tendency of power spread returns. The standard deviation of log returns also points out to high volatility, which is the highest for UK CDS (0.083), which translates into 132% annualized volatility[8].

Next, we test whether the daily log returns contain a time dependent volatility using the ARCH Lagrange multiplier (LM) test. Residuals from a simple regression of log return spreads on a constant are tested for the presence of autoregressive conditional heteroscedasticity (ARCH) and in all cases the null hypothesis of no volatility clustering is rejected. Hence ARCH-type models are appropriate in this modelling context. As outlined above, the distribution of log returns is fat-tailed, as implied by large kurtosis values, which may be better described by a t-distribution than a Gaussian distribution. In the model selection process, we compared normal and t-distribution alternatives with the latter leading to a better goodness of fit (AIC, BIC, LL). The thickness of the tails of the error distribution is confirmed by the degrees of freedom (values of around 2) under the t-distribution assumption, which are far from the value 30 which would imply normal distribution. Specifically, we have tested one symmetric GARCH(1,1) and two asymmetric SAARCH(1,1), and TGARCH(1,1) ARCH-type models with normal and t-distributions.

[8] This is calculated by multiplying the square root of 252 (the number of trading days in a year) by the standard deviation.

Table 2 Summary statistics for German, Nordic, and UK daily power spreads, 2009-2016

		Variable	N	mean	med	min	max	sd	Skew	kurt
Clean dark spread (CDS)	Germany	P_t	2010	5.983	5.158	-2.090	24.044	4.394	0.991	3.789
		P_t-P_{t-1}	2010	-0.008	-0.026	-5.821	8.575	0.922	1.333	19.254
		lnP_t	2010	0.353	0.333	-0.175	1.045	0.218	0.467	2.746
		lnP_t-lnP_{t-1}	2010	0.000	-0.001	-0.310	0.447	0.049	1.106	18.076
	Nordic	P_t	1989	2.130	1.756	-20.276	49.613	7.972	0.834	6.947
		P_t-P_{t-1}	1989	-0.005	0.013	-17.868	10.627	1.379	-1.222	32.651
		lnP_t	1989	0.034	0.043	-0.709	0.808	0.190	-0.322	4.766
		lnP_t-lnP_{t-1}	1989	0.000	0.000	-0.232	0.353	0.031	1.257	25.237
	UK	P_t	2036	11.012	10.303	-4.890	36.920	6.833	0.514	3.055
		P_t-P_{t-1}	2036	-0.007	-0.034	-11.304	8.297	1.155	-0.391	21.584
		lnP_t	2036	1.056	1.120	-3.910	2.128	0.516	-1.720	11.835
		lnP_t-lnP_{t-1}	2036	0.000	-0.002	-0.584	0.594	0.083	0.499	14.423
Clean spark spread (CSS)	Germany	P_t	1998	-5.026	-6.971	-33.069	42.428	13.712	0.360	2.486
		P_t-P_{t-1}	1998	-0.010	-0.026	-10.448	14.571	1.491	0.444	16.350
		lnP_t	1998	-0.314	-0.236	-5.804	0.824	0.607	-1.379	8.435
		lnP_t-lnP_{t-1}	1998	0.000	-0.001	-0.523	0.532	0.070	0.343	14.876
	Nordic	P_t	1624	-14.652	-19.419	-43.440	52.991	17.795	0.534	2.371
		P_t-P_{t-1}	1624	-0.012	-0.013	-19.620	12.680	1.920	-0.937	20.553
		lnP_t	1624	-0.553	-0.540	-2.715	0.760	0.618	-0.323	2.348
		lnP_t-lnP_{t-1}	1624	-0.002	0.000	-0.506	0.487	0.077	-0.447	10.588
	UK	P_t	2021	3.423	1.122	-18.372	92.018	11.938	3.227	19.295
		P_t-P_{t-1}	2021	0.001	-0.014	-19.797	15.255	1.662	-0.280	36.959
		lnP_t	2021	0.063	0.059	-5.219	1.789	0.458	-0.489	12.699
		lnP_t-lnP_{t-1}	2021	0.000	-0.001	-0.593	0.521	0.066	0.135	21.092

Note: This table shows descriptive statistics for the daily spread (P_t), daily log spread (lnP_t), daily spread change (P_t-P_{t-1}), and daily log returns (lnP_t-lnP_{t-1}) of power spreads - clean dark spread (CDS) and clean spark spread (CSS). Outliers in the log returns series, defined as log returns greater 0.6 (60%), were substituted by the nearby past log return. The following numbers of log returns were affected: 12 UK CDS, 3 Nordic CSS, 3 UK CSS, 6 DE CSS.

Our baseline model is the symmetric GARCH(1,1) model, which is frequently used for volatility forecasting and in the derivatives literature (Hull, 2012). The first asymmetric GARCH is simple asymmetry ARCH (SAARCH(1,1)) first proposed by Engle (1990). The asymmetric term γ accounts for the leverage effect of volatility. In the SAARCH model, the sign of γ is expected to be negative, implying the greater impact of negative news on volatility than positive news. The asymmetric term γ in the threshold GARCH (TGARCH(1,1)), first introduced by (Zakoian, 1994), is expected to be negative, because this coefficient loads only the absolute positive innovations, which should have a smaller (negative) impact on variance rather than the negative news. TGARCH(1,1) with t-distribution has systematically outperformed other specifications and is selected as the best-fitting model for further estimation. In Table 3 we present the model selection summary for the German CDS exemplarily, however, the results are systematically similar for the other country-spread combinations.

Table 3 Model selection, example of German CDS daily log returns

	GARCH	GARCH(t)	SAARCH	SAARCH(t)	TGARCH	TGARCH(t)
Constant	-0.001	-0.001*	-0.001	-0.001**	-0.003***	-0.001**
	(-0.53)	(-1.93)	(-1.32)	(-2.17)	(-5.16)	(-2.27)
ARCH(-1)	0.392**	0.026**	0.383**	0.027***	0.344**	0.106***
	(2.24)	(2.46)	(2.25)	(2.94)	(2.57)	(4.64)
GARCH(-1)	0.127	0.962***	0.094	0.957***	0.381*	0.939***
	(1.02)	(66.94)	(1.04)	(77.97)	(1.90)	(73.15)
Leverage effect γ	-	-	-0.007	-0.003**	-0.078	-0.068***
	-	-	(-1.04)	(-2.42)	(-0.43)	(-2.68)
Constant	0.001***	0.000	0.002***	0.000**	0.021**	0.001**
	(4.75)	(1.52)	(5.54)	(2.11)	(2.34)	(2.57)
Log degrees of freedom (t-dist.)	-	-0.680**	-	-0.713***	-	-0.670**
	-	(-2.50)	-	(-2.65)	-	(-2.47)
Akaike Information Criterion	-6572.14	-7517.15	-6576.45	-7525.11	-6613.97	-7570.87
Bayesian Information Criterion	-6549.72	-7489.13	-6548.43	-7491.48	-6585.94	-7537.24
Log likelihood	3290.071	3763.576	3293.227	3768.555	3311.985	3791.437
Degrees of freedom		2.506		2.490		2.512
N	2009	2009	2009	2009	2009	2009

Note: Significance levels are *p< 0.10, **p< 0.05, *** p<0.01; Z-statistics based on Bollerslev-Woodridge robust standard errors in parentheses; The table displays model selection with different volatility specifications (GARCH(1,1), SAARCH(1,1), and TGARCH(1,1)) and distribution assumptions (t-distribution, indicated by symbol (t)). The best fitting model that captures the time dependence structure of the series is selected based on the information criteria and log likelihood statistics.

After defining the log returns and identifying the best fitting model (TGARCH with t-distribution), we jointly estimate the mean and variance equations for log power spread returns by the method of conditional maximum likelihood. The mean equation is expressed in Eq.3 and the conditional variance in Eq. 4.

$$\Delta R(T)_t = c + \Delta\beta_1 SolarProduction(T) + \Delta\beta_2 WindProduction(T) + \Delta\beta_3 SubstituteFuel(t) + \Delta\beta_4 PowerPriceVolatility(t) + \Delta\beta_5 StructuralBreaks(t) + \Delta\beta_6 Seasons(t) + \epsilon_t \tag{3}$$

$$\sigma_t = \alpha_0 + \alpha_i|\varepsilon_{t-1}| + \gamma_i|\varepsilon_{t-1}|I(\varepsilon_{t-1} > 0) + \beta_7\sigma_{t-1} \tag{4}$$

In Eq.3, $R(T)_t$ refers to the daily log return of the power spread for the delivery in month *T* traded during time *t; Solar* and *Wind production* refers to the expected generation of the respective technology in the next month T at time *t; SubstituteFuel* stands for the daily futures price of the substitute fuel, which is coal (ICE Rotterdam Coal Future) for the clean spark spread equation and gas (ICE UK Natural Gas) for the clean dark spread equation*; PowerPriceVolatility* stands for a five-day rolling volatility of electricity futures prices, defined as coefficient of variation of front-month electricity peak load price for the clean spark spread and front-month electricity baseload price for the clean dark spread; *StructuralBreaks* are two dummy variables referring to the German nuclear moratorium (15March2011) and the introduction of the carbon price floor in the UK (since year 2013)*; Seasons* stands for spring (March-May), summer (June-August) and fall (September-November) seasonal dummies of the trading time *t*, where winter (December-February) is the reference season. Similar to the dependent variables (power spreads), all the independent variables are transformed by the natural logarithm and first differenced, which maintains the property of coefficients representing elasticities.

In Eq.4, σ_t denotes conditional variance, α_i accounts for the symmetric impact of innovations (lagged squared errors) irrespective of their sign, and γ_i accounts for the leverage effect by loading only positive innovations (I(.) is an indicator function, equalling 1 when true, otherwise 0). As discussed above, the coefficient γ_i is expected to be negative because positive news typically have a smaller impact on the variance than negative news; finally β_j is a coefficient of the lagged conditional variance addressing the heteroscedasticity effect.

In sum, we have first defined power spreads and investigated their statistical properties, such as skewness, kurtosis and volatility. Then, we identified volatility clustering and selected a best fitting model (TGARCH with t-distribution). Finally, we propose a statistical model that in its mean equation accounts for the supply and demand effects in power spreads, while the variance equation accounts for the volatility clustering. Next, we present the estimation results.

4 Results

In this section, we first present the estimation results for the mean and variance models of the German, Nordic, and UK clean dark (CDS) and clean spark (CSS) spreads for the period 2009-2016 (section 4.1). Subsequently, we present the model's fit and performance measures (section 4.2).

4.1 Empirical results

We begin by presenting the results from the mean equation and move to the results from the variance equation afterwards. Table 4 summarizes the entire results for clean dark spreads and Table 5 for clean spark spreads. As a reminder, both the left hand side and the right hand side variables are log-differenced, representing a log-log regression model where the coefficients in the mean equation represent marginal effects (elasticities).

The expected wind production only seems to have a significant, negative effect on the German CSS (at 1% significance level). It also has a negative effect on the German CDS, but at a 20% significance level only. The interpretation is that 1% increase in monthly wind production reduces the German CSS by 0.42% and the German CDS by 0.22%. To put this into an installed capacity perspective, the monthly average wind production in Germany was approximately 6000GWh/month in 2016. To produce an extra 60GWh/month (1%) approximately 410MW of additional installed wind capacity would be needed[9]. Converting to euros[10], holding everything else constant, an additional 1GW of installed wind capacity reduces the German CSS by 0.051 EUR/MWh$_{el}$ and the German CDS by 0.032 EUR/MWh$_{el}$. The values may seem rather small, however, considering that there were 22 GW of new installed wind capacity added in Germany during our sample period (2009-2016), the total negative effect for the German CSS is 1.122 EUR/MWh$_{el}$ (-22.3%) and 0.704 EUR/MWh$_{el}$ (-11.8%) for the German CDS.

[9] Here we assume average 20% wind capacity factor, 13% PV capacity factor, and average of 730 hours/month.
[10] Here we use the mean daily clean spark and clean dark spread values over 2009-2016, see Table 2.

The effect of expected PV production on CSS and CDS is more systematic, with negative and highly significant coefficients across the three markets. The coefficients of the PV generation, however, are much smaller than those for wind, implying a smaller negative impact. PV has the strongest negative effect on the German CSS (0.24%) and CDS (0.17%) followed by the impacts on the Nordic CSS (0.046%) and CDS (0.037%), and the UK's CSS (0.024%). Again, to put this into installed capacity perspective, the monthly average PV production was approximately 3800 GWh in Germany, 1000 GWh in the UK, and 72 GWh in the Nordics in 2016. To increase the monthly generation values by 1%, approximately 400 MW in Germany, 105 MW in the UK, and 8 MW in the Nordics would be needed[8]. In Euro values[9] and holding everything else constant, an additional 1 GW of PV capacity would reduce the German CSS by 0.030 EUR/MWh$_{el}$, the German CDS by 0.026 EUR/MWh$_{el}$, the Nordic CSS by 0.889 EUR/MWh$_{el}$, the Nordic CDS by 0.105 EUR/MWh$_{el}$, and the UK's CSS by 0.008 EUR/MWh$_{el}$. Again, the values may seem rather small, however, considering that there were around 32 GW of new installed PV capacity added in Germany during our sample period (2009-2016), the total negative effect for the German CSS is 0.962 EUR/MWh$_{el}$ (-19.1%) and 0.815 EUR/MWh$_{el}$ (-13.6%) for the German CDS. Similarly, approximately 11 GW of new solar PV capacity was built in the UK during the studied period. Effectively, the new PV capacity is associated with a 0.088 EUR/MWh$_{el}$ drop in the UK's CSS, which is approximately 2.6% of the UK's average CSS during the studied period. For the Nordic market, the mentioned 1GW increase in solar PV capacity would mean more than doubling its total capacity, because only approximately 900 MW of solar PV capacity was added during 2009-2016. Hence, the total effect of solar PV on the Nordic CSS has been 0.800 EUR/MWh$_{el}$ (-5.5%) and on the Nordic CDS 0.094 EUR/MWh$_{el}$ (-4.4%) over the studied period 2009-2016.

The effect of the substitute fuel, i.e. gas in the CDS and coal in the CSS, is found to be significant only for the CDS, especially in the UK. The estimated elasticities of the CDS for the substitute fuel (gas) are 1.69% for UK, 0.16% for Germany, and 0.05% for the Nordics. In Euro perspective, 1% increase in gas price would increase the UK CDS by 0.186 EUR/MWh$_{el}$, the German CDS by 0.011 EUR/MWh$_{el}$ and the Nordic CDS by 0.001 EUR/MWh$_{el}$. Given the domination of flexible hydro-generation in the Nordic power system, we would not expect a very strong effect of changes in gas price on the Nordic power spreads. However, Germany's and the UK's power systems are much more reliant on gas generation, which explains the stronger effects.

The volatility of power futures contracts has small but significant positive effects on the CDS in Germany and the UK. The increased volatility in baseload power futures contracts used in the CDS seems to allow market participants to capture a small positive risk premium. This premium may represent a compensation for coal power generators facing the increased uncertainty around the futures power price.

The two structural events studied in this work, namely the UK carbon price floor and the nuclear moratorium in Germany, both significantly affected the clean dark and clean spark spreads in the affected markets. Specifically, the carbon price floor had a more negative effect on the UK CDS than the CSS, which is to be expected given the greater carbon intensity of coal. Also, the German nuclear moratorium, that led to a large and sudden drop in generation capacity, has had a positive and significant impact on the German CSS and more so on the German CDS. The sudden drop in German capacity was largely substituted by coal generators, who have, temporarily, seen an increase in their hedgeable profits. Since these events represent binary variables that are not log-transformed, we can take the exponential of the coefficient to find out the exact percentage difference between the pre- and post-event. Holding everything else fixed, we can say that after the introduction of the UK carbon price floor in 2013, we would expect a 55% drop in UK's CDS and a 38% drop in UK's CSS, as compared to the pre-carbon price floor period. Similarly, after the German nuclear moratorium and holding everything else fixed, we would expect a 56% increase in the German CDS and a 36% increase in the German CSS in comparison to the pre-moratorium period.

Our final results from the mean equation refer to the seasonality (spring, summer, fall), which is referenced to the winter season. We have found significant and negative seasonality especially in the German power spreads. Taking the exponential of the seasonality coefficients, we find that in the non-winter seasons, the mean German CDS and CSS are approximately 16% and 20% lower, respectively. We also find a significantly negative effect of summer (7%) and fall (7%) on the Nordic CDS and a significantly negative effect of fall (9%) on the Nordic CSS, holding everything else constant.

In the variance equation, we find significant leverage effects in the CDS and CSS volatility, specifically for the CDS in the UK and Germany, and the CSS in the Nordics and Germany. This means that positive news has a lower impact on the volatility of the mentioned power spreads than negative news. Also, the sum of ARCH and GARCH terms is close to unity, indicating that the volatility is also highly persistent.

Behind the general decline in power spreads (see Figure 1and Figure 2) are a multitude of fundamental and market risk factors that jointly contributed towards this downward trend in the hedgable profits. The fact that the expansion of vRES capacity is only associated with a drop of 3-22% of hedgeable profit margins suggests that the overall decline in power spreads is also driven by the price dynamics in the CO_2 and fuel markets during the sample period.

Table 4 Estimation results of TGARCH model for German, Nordic, and UK clean dark spreads (CDS), 2009-2016

	DE CDS	NORD CDS	UK CDS
Mean equation			
Expected Wind Production (GWh/month)	-0.2145	0.0067	0.056
	(-1.21)	(0.08)	(1.18)
Expected Solar Production (GWh/month)	-0.1704***	-0.0373***	0.0179
	(-3.63)	(-5.22)	(1.27)
Gas price (EUR/MWh)	0.1621***	0.0446*	1.6911***
	(6.51)	(1.66)	(28.42)
Base power futures price volatility	0.0036**	-0.0013	0.0039**
	(2.25)	(-0.84)	(2.46)
German nuclear moratorium(15March2011)	0.4460***	-	-
	(67.85)	-	-
UK Carbon floor (y2013)	-	-	-0.4386***
	-	-	(-29.25)
Spring	-0.1624***	-0.0033	0.0063
	(-3.03)	(-0.21)	(0.31)
Summer	-0.1193**	-0.0645***	-0.0185
	(-2.17)	(-3.72)	(-1.20)
Fall	-0.1518***	-0.0635***	-0.007
	(-3.77)	(-9.83)	(-0.63)
Constant	-0.0008	-0.0002	0.0002
	(-1.34)	(-0.29)	(0.30)
Variance equation			
ARCH(-1)	0.0907***	0.1103***	0.3934***
	(4.88)	(5.70)	(5.76)
ARCH(-2)	-	-	-0.2880***
	-	-	(-4.29)
Leverage effect γ	-0.0859***	0.0103	-0.0786***
	(-3.83)	(0.44)	(-3.29)
GARCH(-1)	0.9563***	0.8950***	0.9588***
	(68.91)	(55.14)	(129.14)
Constant	0.0008**	0.0007***	0.0002*
	(1.98)	(3.30)	(1.83)
Akaike Information Criterion	-7671.0118	-9271.1837	-7025.506
Bayesian Information Criterion	-7592.6834	-9198.5882	-6935.78
Log likelihood	3849.5059	4648.5918	3528.753
Degrees of freedom	2.6994	3.6766	2.6185
Durbin-Watson statistic	2.0477	1.9646	2.1411
N	1988	1967	2014
Time interval	5Jan2009-28Nov2016		

Note: Significance levels are *p< 0.10, **p< 0.05, *** p<0.01; Z-statistics based on Bollerslev-Woodridge robust standard errors in parentheses; the table shows estimation results of TGARCH(1,1) model (DE & NORD CDS) and TGARCH(2,1) model (UK CDS) with t-distribution on daily log returns. All the explanatory variables are also log-differenced, therefore the coefficients of this log-log regression model represent marginal effects (elasticities).

Table 5 Estimation results of TGARCH model for German, Nordic, and UK clean spark spreads (CSS), 2009-2016

	DE CSS	NORD CSS	UK CSS
Mean equation			
Expected Wind Production (GWh/month)	-0.4185***	0.0936	0.0221
	(-11.44)	(0.91)	(0.72)
Expected Solar Production (GWh/month)	-0.2395***	-0.0460**	-0.0236**
	(-23.42)	(-2.26)	(-2.53)
Coal price (EUR/MWh)	-0.3013	-0.2126	0.0428
	(.)	(-1.17)	(0.74)
Peak power futures price volatility	0.0017	-0.0051	-0.0029
	(1.07)	(-1.28)	(-1.36)
German nuclear moratorium(15March2011)	0.3101***	-	-
	(49.06)	-	-
UK Carbon floor (y2013)	-	-	-0.3193***
	-	-	(-20.10)
Spring	-0.2103***	-0.023	0.0157**
	(-312.07)	(-0.74)	(2.06)
Summer	-0.1565***	-0.0369	0.0107
	(-13.95)	(-0.90)	(0.92)
Fall	-0.1805***	-0.0835***	-0.0182
	(-11.16)	(-2.77)	(-1.39)
Constant	-0.0008	-0.0008	-0.0003
	(-1.26)	(-0.65)	(-0.37)
Variance equation			
ARCH(-1)	0.1380***	0.1946***	0.4708***
	(5.50)	(3.85)	(5.84)
ARCH(-2)	-	-	-0.3343***
	-	-	(-4.46)
Leverage effect γ	-0.1163***	-0.0761**	-0.0346
	(-5.22)	(-2.44)	(-0.94)
GARCH(-1)	0.9428***	0.8832***	0.9271***
	(74.88)	(24.58)	(54.94)
Constant	0.0006**	0.0011*	0.0010**
	(2.56)	(1.77)	(2.39)
Akaike Information Criterion	-6548.9012	-4628.1019	-7013.5527
Bayesian Information Criterion	-6481.8291	-4558.2481	-6929.5392
Log likelihood	3286.4506	2327.051	3521.7764
Degrees of freedom	2.8010	3.2198	2.3953
Durbin-Watson statistic	2.0594	1.4515	1.4550
N	1977	1593	2000
Time interval	5Jan2009-30Nov2016*		

Note: Significance levels are *p< 0.10, **p< 0.05, *** p<0.01; Z-statistics based on Bollerslev-Woodridge robust standard errors in parentheses; the table shows estimation results of TGARCH(1,1) model (DE & NORD CSS) and TGARCH(2,1) model (UK CSS) model with t-distribution on daily log returns; All the explanatory variables are also log-differenced, therefore the coefficients of this log-log regression model represent marginal effects (elasticities). *NORD CSS estimation sample is 5Jan2009-28Aug2015.

4.2 Model fit and performance

Next, we present a summary of the model fit and performance. After each model was estimated, we have tested for the presence of autocorrelation in the standardized residuals with portmanteau Q test, which was rejected at 10% level of significance in all models. The test is applied to evaluate whether the residuals are free of systematic variation and are normally distributed. Additionally, the ARCH Lagrange multiplier test was applied on the standardized residuals to check for the presence of heteroscedasticity, which was again rejected for various lags.

As a visual summary of the model fit, we present multiple diagnostics of standardized residuals, namely their distribution against time, histogram, autocorrelation and partial-autocorrelation functions, as displayed in Figure 3. We present these diagnostics for the German CDS model only; however, the results for the remaining models are very similar.

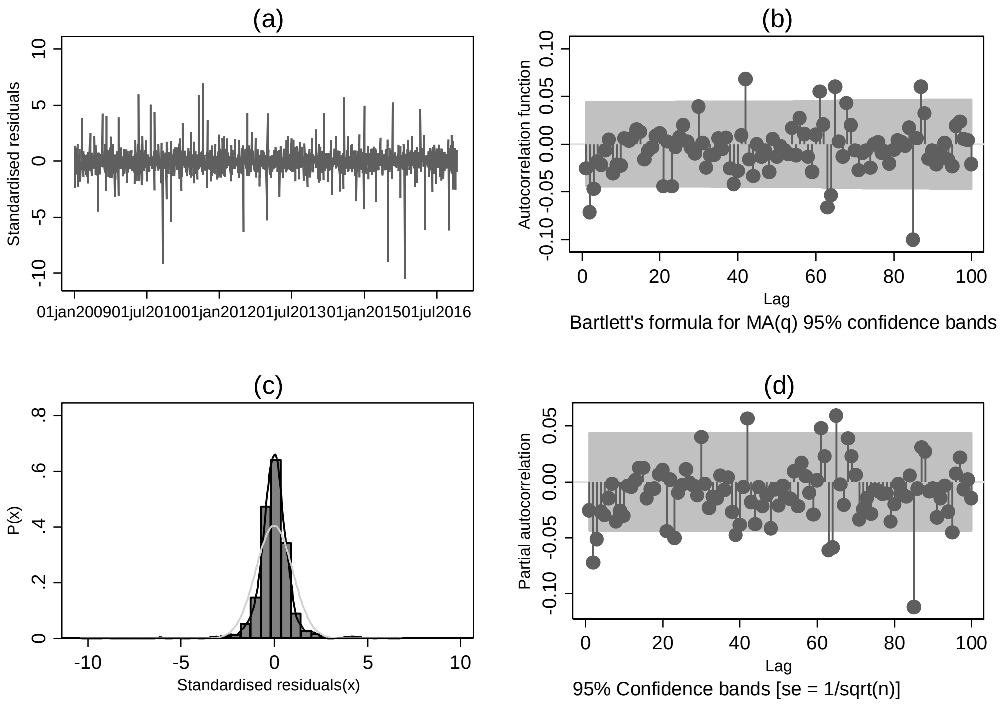

Figure 3 Diagnostics for German clean dark spreads (CDS) with TGARCH model specified in Eq.(3-4): (a) Daily standardized residuals against time. (b) Autocorrelation function of standardized residuals against lag in days. (c) Histogram with normal and kernel distribution of standardized residuals. (d) Partial autocorrelation function of standardized residuals against lag in days.

The efficient market hypothesis postulates that returns follow a martingale process and thus cannot be predicted. Within our model specification, we can explicitly forecast the volatility of power spread returns, and thus measure the model's performance. We do this by in-sample one-step ahead (one trading day ahead) volatility forecast and reporting four different loss functions (Degiannakis & Floros, 2016). Specifically, these functions are root mean square error (RMSE), mean-absolute error (MAE), mean heteroscedasticity adjusted absolute error (HMAE), and mean heteroscedasticity adjusted squared error (HMSE), as defined in Eq. (5-8).

$$MSE = 1/(n)\sum_{t=1}^{n}(\hat{\sigma}_t^2 - \sigma_t^2)^2 \tag{5}$$

$$MAE = 1/(n)\sum_{t=1}^{n}|\hat{\sigma}_t^2 - \sigma_t^2| \tag{6}$$

$$HMSE = 1/(n)\sum_{t=1}^{n}(1 - \sigma_t^2/\hat{\sigma}_t^2)^2 \tag{7}$$

$$HMAE = 1/(n)\sum_{t=1}^{n}|1 - \sigma_t^2/\hat{\sigma}_t^2| \tag{8}$$

where σ_t^2 is the actual volatility and $\hat{\sigma}_t^2$ is the predicted volatility at day *t*. The in-sample prediction provides only the historical performance of the model, which is sufficient given the main purpose of the paper focusing on the determinants of power spreads. The out-of-sample hedging effectiveness and out-of-sample forecasting of the power spreads volatility are natural extensions, as shown earlier on crack spreads (Wang & Wu, 2012). Table 6 summarizes the forecast evaluation statistics showing good in-sample performance and fit.

Table 6 Comparison of in-sample forecasting performance of volatility models for power spreads,

Loss function	DE CDS	UK CDS	NORD CDS	DE CSS	UK CSS	NORD CSS
MSE	4.50E-06	0.00075	0.000032	0.00079	0.01356	0.002268
MAE	0.0031	0.00827	0.001134	0.00614	0.00739	0.007707
HMSE	22.08326	120.047	12.55427	12.24601	11.0894	11.91409
HMAE	-0.07084	-0.58742	-0.105445	0.02459	0.27927	0.022787

*Note: RMSE refers to root mean square error, MAE refers to mean absolute error, HMSE and HMAE refer to heteroscedasticity adjusted MSE and MAE, respectively, as defined in Eq. (5-8).

5 Discussion

In this section, we discuss the results in the context of the motivation for the paper. We focus on the energy policy trilemma, which includes the high-level policy objectives environmental sustainability, reliability of supply, and economic competitiveness. The promotion of vRES is associated with environmental sustainability, while the question of adequate hedging mechanisms for dispatchable and flexible generation is associated with both reliability of supply and economic competitiveness. To jointly study these policies, we have focused on the risk management reality of dispatchable flexibility providers (coal and gas power generators) and the fundamental factors impacting the risk management, proxied by hedgeable power spreads. Below, we first deepen the discussion around some of the main results and then follow with broader implications that span beyond the country-specific drivers of hedgeable profit margins.

First, the finding of negative effects of vRES on hedgeable power spreads concurs with studies on spot markets. This suggests that the risk management of flexible conventional generation becomes more challenging with the growth in vRES. The statistical significance (insignificance) of the vRES effects on some hedgeable power spreads can be mostly explained by the structure of a power generation fleet in a given country. Germany has seen the largest increase in solar PV and wind capacity, where especially the latter substituted the conventional generation (coal, lignite, nuclear and natural gas) in the daily operation. The stronger negative effect of wind generation on the CSS rather than the CDS can be explained by the structure of the merit order curve: gas generation is typically dispatched after coal. The close-to-zero marginal variable costs of vRES push gas off the merit order curve first, making the negative effect stronger for the CSS than for the CDS. In the UK, the share of coal-fired power generation in the overall electricity supply has been steadily declining and the major drop in the UK's CDS seems to be explained by the carbon price floor rather than by vRES. The UK's CSS is negatively impacted by solar PV generation mostly because the day-time peak demand typically coincides with peak solar PV generation which pushes the peaking gas generators off the merit order curve. With respect to the Nordic market, it may seem surprising that the limited solar PV generation has significantly negative impacts on both the CDS and the CSS. Despite the fact that the Nordic electricity market is a hydro-dominated system with natural access to flexibility, there are national differences which may be confounding some of the estimated effects. Disaggregation of the individual Nordic countries, which would need to take into consideration futures zonal prices of the individual countries[11], could reveal more nuanced relationships between hedgeable power spreads and vRES. Perhaps more interesting for the Nordic market, a study of hedgeable peak/off-peak spreads could reveal the hedging dynamics of hydro-generating power plants which also function as energy storage.

Second, we find a systematic effect of gas, as a substitute fuel, on the clean dark spread. Depending on the power generating fleet in a given market, we typically expect a stronger impact of the substitute fuel on the CDS than the CSS. This is because in the past, coal was typically a cheaper fuel than gas, which means that coal-fired power plants (depending on their efficiency) would be dispatched before gas-fired power plants. Consequently, when gas-fired power plants are needed to cover the demand, they set the power price and gas prices would therefore drive the clean dark spread. On the contrary, increasing coal prices would not drive the clean spark spread to the same extent. These dynamics, though, may be also changing in the future. For example, Ofgem (2016) highlights a wholesale market situation in May 2016 when CCGTs pushed all coal off the merit order curve for four hours. Increasing coal prices, increasing efficiencies of gas-fired power plants, and higher carbon prices are just some factors behind the changing dynamics between CDS and CSS.

Third, the large negative impact of the UK's carbon price floor on power spreads reveals the following issues. The increased cost of carbon was not fully passed through to power prices, so the externality was paid for by the polluters rather than the end-users. This may be explained by increasing electricity imports into the UK following the introduction of the carbon price floor since the floor was introduced in the UK only. This shows that, as opposed to a continent-wide or global policy on carbon, a single-country policy may lead to carbon leakage. In the case of EU and the UK, the UK's carbon emitting power generators faced approximately four times higher costs for carbon than their European counterparts. Inside the single electricity market with cross-border transmission connections, the more expensive

[11] This would involve combining the Nordic baseload and peak load power futures with electricity area price differential (EPAD) contracts.

generators are easily substituted by less expensive imports, irrespective of their carbon intensity.

Now, we may move towards broader implications of the results. First, many countries currently have an overcapacity in their power systems so the negative or low power spreads are sending "correct" market signals to not invest into new flexible generation. However, the exit of large-scale nuclear power plants and decommissioning of old dispatchable units puts pressure on the transmission system operators (TSO) to run the system reliably already in the short-term.[12] The design of efficient, market-based solutions to promote adequate risk management of existing assets or, if needed, investments into new flexible capacity is therefore an important challenge.

Second, given the acclaimed role of natural gas as a transition fuel, it is interesting to see that vRES seems to have a stronger negative impact on the CSS than on the CDS. With the shut-down of coal-fired power plants in the medium term and continuous adoption of vRES, gas-fired power plants may find economic challenges, particularly when relying on energy-only markets exclusively. New markets rewarding capacity, reliability or flexibility may be needed to enable flexibility providers to stay in or enter the market.

Third, the effects of vRES on hedgeable power spreads may change with the change in subsidy-based economics of vRES. Moving towards a subsidy-free vRES market, wholesale power prices may start to reflect scarcity and under the assumption of sufficiently high price caps, power prices may again start sending investment signals into flexible generation and storage, if these are needed. The current prolonged downward pressure on electricity prices has led to the introduction of regulatory-driven solutions, such as capacity markets or capacity payment mechanisms. Depending on the further development of vRES subsidies, and the development of commodity and CO_2 prices all jointly impacting the power prices, capacity markets may offer advantages for reliable risk management. However, in addition to the security of supply as the core purpose of capacity markets, the regulatory and cost burden should be also accounted for when justifying their existence.

The results of our work need to be interpreted with some caution. Our main focus is on market fundamentals. We have made this research decision consciously. While we acknowledge that institutional aspects and market organisation affect power spread dynamics as well, we see the consideration of fundamental drivers both as more novel and more important for the studied period 2009-2016. Nonetheless, enlarging future research of power spreads by market power indicators, such as concentration ratios, may add depth and dynamics to the analysis. Additionally, the price dynamics of power spreads as cross-commodity derivatives is complex and there may be a multitude of additional fundamental and market risk factors that jointly determine the hedgable profits of flexible and dispatchable power plants. Future research could explore the effects of changes in transmission networks and model market events more dynamically by vector error correction, for example.

[12] For instance, the German TSO's have been calling for new flexible gas power plants to run the transmission system reliably (Frankfurter Allgemeine Zeitung, 2017).

6 Conclusions

This work has studied the impacts of power market fundamentals on risk management of technologies that provide flexibility and dispatchability to the power system. By explicitly studying the relationships between fundamentals and hedgeable power spreads, we have revealed important dynamics. Methodologically, we have attempted to bridge a gap between the spot and futures pricing models and empirically quantify the impacts of fundamentals on the futures market.

We find that the growth in variable renewable energy generation and capacity reduces the possibility of coal and especially gas power plants to manage risk ahead of actual operation. In particular, the total vRES capacity installed during the studied period 2009-2016 is associated with a decline of 3-22% in power spreads. This suggests that the overall decrease of power spreads is further driven by the CO_2 and fuel market price dynamics during the sample period. This finding is especially relevant for markets that do not have an abundance of flexible renewable generation, such as the hydro-based Nordic power market. Moreover, this finding is particularly relevant for market places where the futures markets for electricity, fuel and CO_2 are the main markets for risk management (e.g., Germany), i.e. where there is no capacity market such as in the UK.

The time period analysed here captured the transition period in which traditional business models and risk management strategies designed for the centralized power system are ceasing to work. This effect is manifested by the increasing challenge to secure profit margins by traditional hedging methods. Great emphasis has been put on the environmental sustainability as one policy of the energy trilemma. However, without addressing the remaining two energy policies of the energy trilemma, issues such as lack of investment in flexible and dispatchable generation, and high electricity prices may become more pronounced in the near future. New hedging strategies and hedging products, portfolios of integrated energy technologies, and the possibility to participate in multiple marketplaces may aid smoothing the transition.

Acknowledgement

This publication has emanated from research conducted with the financial support of Science Foundation Ireland under the SFI Strategic Partnership Programme Grant Number SFI/15/SPP/E3125. We are thankful for the useful comments by Seán Lyons, the participants of the 2nd ESRI-UCD Energy Policy Research Workshop in Dublin and the 3rd Applied Financial Modelling Conference in Kampar, especially Ivan Diaz-Rainey. Valentin Bertsch acknowledges funding from the ESRI's Energy Policy Research Centre. All omissions and errors are our own.

Appendix

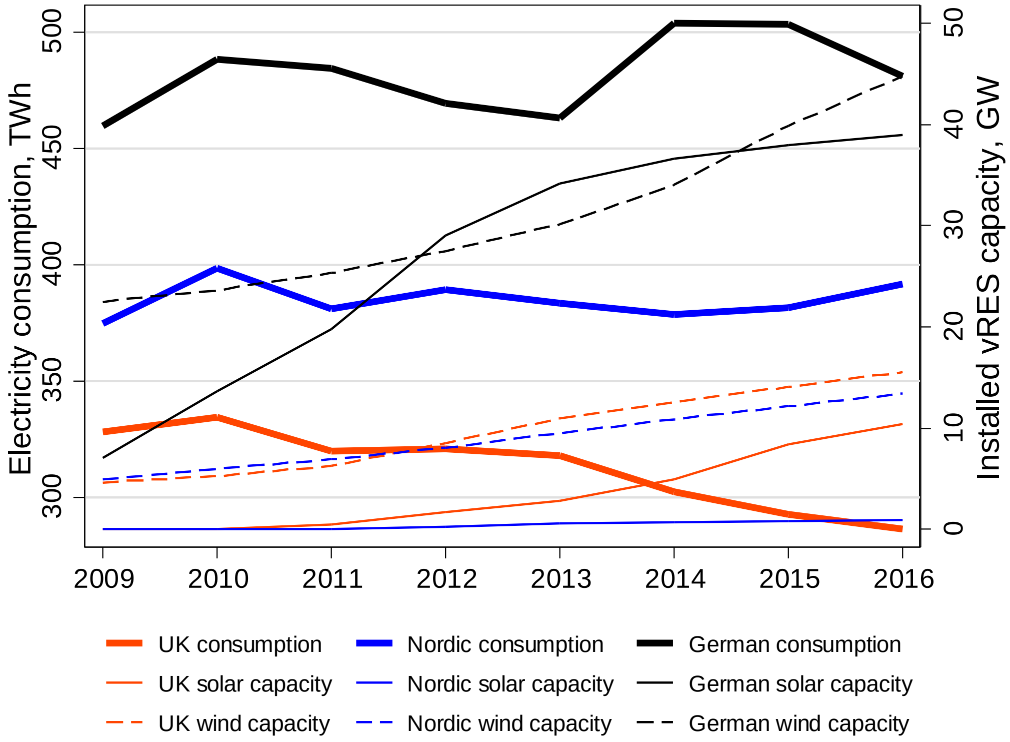

Figure 4 Electricity consumption and installed vRES capacity in Germany, UK and Nordic

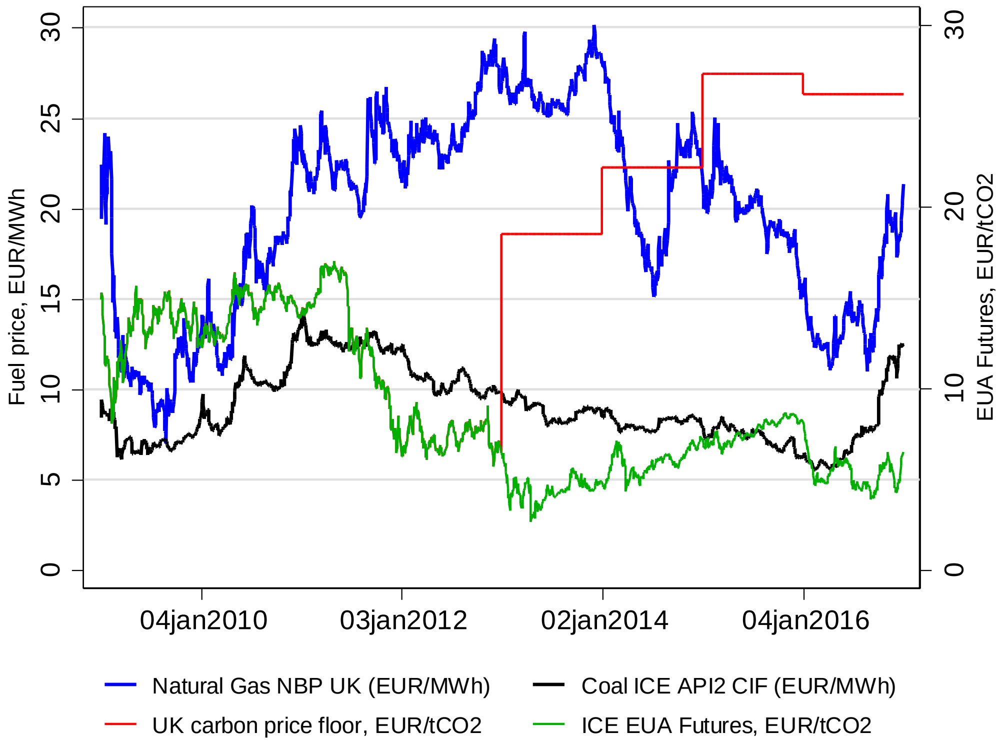

Figure 5 Fuel, EU ETS and UK carbon price floor prices

Bibliography

Alberola, E., Chevallier, J., & Chèze, B. (2008). Price drivers and structural breaks in European carbon prices 2005–2007. *Energy Policy, 36*(2), 787-797.

Arouri, M. E., Lahiani, A., Lévy, A., & Nguyen, D. K. (2012). Forecasting the conditional volatility of oil spot and futures prices with structural breaks and long memory models. *Energy Economics, 34*(1), 283-293.

Back, J., Prokopzuk, M., & Rudolf, M. (2013). Seasonality and the valuation of commodity options. *Journal of Banking & Finance*, *2*, 37.

Barlow, M. T. (2002). A diffusion model for electricity prices. *Mathematical Finance, 12*(4), 287-298.

Belderbos, A., & Delarue, E. (2015). Accounting for flexibility in power system planning with renewables. *International Journal of Electrical Power & Energy Systems, 71*, 33-41.

Benth, H. E., & Koekabakker, S. (2008). Stochastic modelling of financial electricity contracts. *Energy Economics*, *30*(3), 1116-1157.

Boersen, A., & Scholtens, B. (2014). The relationship between European electricity markets and emission allowance futures prices in phase II of the EU (European Union) emission trading scheme. *Energy, 74*, 585-594.

Borenstein, S., Bushnell, J. B., & Wolak, F. A. (2002). Measuring Market Inefficiencies in California's Restructured Wholesale Electricity Market. *The Americal Economic Review, 92*(5), 1376-1405.

Borenstein, S., Bushnell, J., & Knittel, C. R. (1999). Market Power in Electricity Markets: Beyond Concentration Measures. *The Energy Journal, 20*(4), 65-88.

Carmona, R., & Coulon, M. (2014). A survey of commodity markets and structural models for electricity prices. In F. E. Benth, V. Kholodnyi, & P. Laurence, *Quantitative energy finance: modeling, pricing, and hedging in energy and commodity markets* (pp. 41-83). Springer.

Carmona, R., Coulon, M., & Schwarz, D. (2012). The valuation of clean spread options: linking electricity, emissions and fuels. *Quantitative Finance, 12*, 1951-1965.

Carmono, R., & Durrleman, V. (2003). Pricing and Hedging Spread Options. *SIAM Review, 45*(4), 627-685.

Cartea, Á., & Villaplana, P. (2008). Spot price modeling and the valuation of electricity forward contracts: The role of demand and capacity. *Journal of Banking & Finance, 32*(12), 2502-2519.

Degiannakis, S., & Floros, C. (2016). *Modelling and forecasting high frequency financial data.* Springer.

Dempster, M. A., Medova, E., & Tang, K. (2008). Long term spread option valuation and hedging. *Journal of Banking & Finance, 32*, 2530-2540.

Deng, S.-J., Johnson, B., & Sogomonian, A. (2001). Exotic electricity options and the valuation of electricity generation and transmission assets. *Decission Support Systems, 30*, 383-392.

Engle, R. (2001). GARCH 101: The use of ARCH/GARCH models in applied econometrics. *Journal of Economic Perspectives, 15*(4), 157-168.

Engle, R. F. (1990). Discussion: Stock volatility and the crash of '97. *Review of Financial Studies, 3*, 103-106.

ENTSO-E. (2017). *Statistical Factsheet 2016.* Brussels: ENTSO-E.

Eydeland, A., & Wolyniec, K. (2003). *Energy and Power Risk Management: New Developments in Modeling, Pricing, and Hedging.* Hoboken: Wiley.

Fanelli, V., Maddalena, L., & Musti, S. (2016). Modelling electricity futures prices using seasonal path-dependent volatility. *Applied Energy, 173*, 92-102.

Frankfurter Allgemeine Zeitung. (2017). Süddeutschland braucht neue Gaskraftwerke. Frankfurt am Main. Retrieved from http://www.faz.net/-gqe-8v72q

Helm, D. (2017). *Burn Out: The Endgame for Fossil Fuels.* Padstow: Yale University Press.

Hsu, M. (1998). Spark Spread Options Are Hot! *The Electricity Journal, 11*(2), 28-39.

Hull, J. C. (2012). *Options, Futures, and other Derivatives.* Boston: Prentice Hall.

IAEA. (2011). *Power Reactor Information System (PRIS).* Retrieved August 22, 2017, from International Atomic Energy Agency (IAEA): https://www.iaea.org/PRIS/home.aspx

Islayev, S., & Date, P. (2015). Electricty futures price models: Calibration and forecasting. *European Journal of Operational Research, 247*, 144-154.

Kaldor, N. (1939). Speculation and ecoomic stabilitiy. *The Review of Economic Studies, 7*, 1-27.

Karakatsani, N. V., & Bunn, D. W. (2008). Intra-day and regime-switching dynamics in electricity price formation. *Energy Economics, 30*, 1776-1797.

Keynes, J. M. (1930). *Treatise on Money.* London: McMilllan.

Knittel, C., & Roberts, M. (2005). An empirical examination of restructured electricity prices. *Energy Economics, 27*(5), 791-817.

Kristiansen, T. (2012). Forecasting Nord Pool Day-ahead Prices with an Autoregressive Model. *Energy Policy, 49*, 328-332.

Kristiansen, T. (2017). Fundamental indexation: An application to the Nordic wholesale electricity market. *Energy Strategy Reviews, 17*, 1-5.

Lain, S., & Pfenninger, S. (2016). Using bias-corrected reanalysi to simulate current and future wind power output. *Energy, 114*, 1224-1239.

Mahringer, S., & Prokopczuk, M. (2015). An empirical model comparison for valuing crack spread options. *Energy Economics, 51*, 177-187.

Mansanet-Bataller, M., Pardo, A., & Valor, E. (2007). CO2 prices, energy and weather. *Energy Journal, 28*(3), 73-92.

Mansanet-Betaller, M., Pardo, A., & Valor, E. (2007). CO2 prices, energy and weather. *The Energy Journal*, *28*(3), 73-89.

Martinéz, B., & Torró, H. (2015). European natural gas seasonal effects on futures hedging. *Energy Economics, 50,* 154-168.

Mirza, F. M., & Bergland, O. (2012). Pass-through of wholesale price to the end user retail price in the Norwegian electricity market. *Energy Economics, 34*(6), 2003-2012.

Möst, D., & Keles, D. (2010). A survey of stochastic modelling approaches for liberalised electricity markets. *European Journal of Operational Research, 207*, 543–556.

Ofgem. (2016). *Wholesale Energy Markets in 2016.* London: Ofgem.

OME. (2007). *Cost Assesment of Sustainable Energy Systems - The Drivers of Electricity Supply and Demand.* Observatoire Méditerranéen de l' Energie (OME).

Paschke, R., & Prokopzuk, M. (2010). Commodity derivatives valuation with autoregressive and moving average components in the price dynamics. *Journal of Banking & Finance, 34*, 2742–2752.

Pfenninger, S., & Lain, S. (2016). Long-term patterns of European PV output using 30 years of validated hourly reanalysis and satlite data. *Energy, 114*, 1251-1265.

Pilipovic, D. (2007). *Energy risk: valuing and managing energy derivatives.* New York: McGraw-Hill.

Redl, C., Haas, R., Huber, C., & Böhm, B. (2009). Price formation in electricity forward markets and the relevance of systematic forecast errors. *Energy Economics, 31*, 356-364.

Roques, F., Newbery, D. M., & Nuttall, W. J. (2004). *Generation Adequacy and Investment Incentives in Britain: from the Pool to NETA.* Cambridge: University of Cambridge.

Rubin, O. D., & Babcock, B. A. (2013). The impact of expansion of wind power capacity and pricing methods on the efficiency of deregulated electricity markets. *Energy, 59*(15), 676-688.

Sandbag. (2013). *The UK Carbon Floor Price.* London: Sandbag.

Sewalt, M., & De Jong, C. (2003). Negative Prices in Electricity Markets. *Commodities Now, June*, 74-77.

Suren, I., & Date, P. (2015). Electricity futures price models: Calibration and forecasting. *European Journal of Operational Research*, *247*, 144-154.

von der Fehr, N.-H. M., & Hansen, P. V. (2010). Electricity Retailing in Norway. *The Energy Journal*, *31*(1), 25-45.

Wang, Y., & Wu, C. (2012). Forecasting energy market volatility using GARCH models: Can multivariate models beat univariate models? *Energy Economics, 34,* 2167-2181.

Weron, R. (2014). Electricity price forecasting: A review of the state-of-the-art with a look into the future. *International Journal of Forecasting, 30*, 1030-1081.

Weron, R., & Misiorek, A. (2008). Forecasting Spot Electricity Prices: A Comparison of Parametric and Semiparametric Time Series Models. *International Journal of Forecasting, 24*, 744-763.

Weron, R., & Zator, M. (2014). Revisiting the Relationship between Spot and Futures Prices in the Nord Pool Electricity Market. *Energy Economics, 44*, 178-190.

Wolfram, C. (1999). Measuring duopoloy power in the British electricity spot market. *American Economic Review, 89*, 805-826.

Woo, C. K., Horowitz, L. C., & Pacheco, A. (2011). The impact of wind generation on the electricity spot-market price level and variance: the Texas experience. *Energy Policy, 39*(7), 3928-3938.

Woo, C.-K., Horowitz, I., Horii, B., Orans, R., & Zarnikau, J. (2012). Blowing in the Wind: Vanishing Payoffs of a Tolling Agreement for Natural-gas-fired Generation of Electricity in Texas. *The Energy Journal, 31*(1), 207-229.

Zakoian, J. M. (1994). Threshold heteroskedastic models. *Journal of Economic Dynamics and Control, 2*, 107-131.

Year	Number	Title/Author(s)
2017		
	578	Anglers' views on stock conservation: Sea Bass angling in Ireland *Gianluca Grilli, John Curtis, Stephen Hynes and Paul O'Reilly*
	576	Determinants of residential heating system choice: an analysis of Irish households *John Curtis, Daire McCoy, Claudia Novielli*
	575	Estimating, and interpreting, retirement income replacement rates *Alan Barrett and Sanna Nivakoski*
	574	Sea bass angling in Ireland: A structural equation model of catch and effort *Gianluca Grilli, John Curtis, Stephen Hynes and Paul O'Reilly*
	573	Ireland's international trade and transport connections *Martina Lawless and Edgar Morgenroth*
	572	Do youth access control policies stop young people smoking? Evidence from Ireland *Michael Savage*
	571	The impact of investment in innovation on productivity: firm level evidence from Ireland *Mattia Di Ubaldo and Iulia Siedschlag*
	570	The value of tourist angling: a travel cost method estimation of demand for two destination salmon rivers in Ireland *Gianluca Grilli, John Curtis, Stephen Hynes and Gavin Landgraf*
	569	Advertising and investment spillovers in the diffusion of residential energy efficiency renovations *Matthew Collins and John Curtis*
	568	Working at a different level? Curriculum differentiation in Irish lower secondary education *Emer Smyth*
	567	Identifying rent pressures in your neighbourhood: a new model of Irish regional rent indicators *Martina Lawless, Kieran McQuinn and John R. Walsh*

For earlier Working Papers see http://ww.esri.ie