Determinants of Power Hedging Mechanisms in Liberalized Electricity Markets

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***Abstract*—This work quantifies the effect of rising variable renewable electricity production on the hedgable revenue margins of storage and conventional power generating technologies. Additional factors, namely fuel and carbon prices, power demand, and nuclear generation are investigated.**

***Index Terms*--Contracts; Financial risk management; Hedging, Futures markets**

I. INTRODUCTION

The electric power sector is undergoing a rapid transition where the share of net electricity generation in the total energy consumption is increasing globally due to digitalization [1]. The growth of electric vehicles, demand response programs, energy storage, self-generation, internet of things (IoT), and variable renewable energy sources (vRES) in national energy mixes are some factors changing the risk profiles market participants will face. In this transforming energy market environment, a 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 1990s, when the markets were liberalized. However, these products were designed for centralized power systems with dispatchable generation fleets, which is not the case in current markets characterised by a 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 market participants face and address these with adequate risk management mechanisms.

Forward electricity markets are often pure financial markets without any physical delivery obligations and they are used for risk management, speculation, and price discovery purposes. The market includes multiple participants, mainly power generators locking-in long-run prices to cover fixed costs, retailers locking-in wholesale prices, and commodity traders/speculators looking for profits from short-term fluctuations. This work primarily focuses on the first group of power generators and energy storage providers who typically lock-in a portion of their revenue margin in advance by selling derivatives contracts on outputs (electricity or storage) and buying derivatives contracts on inputs (fuel, carbon or storage costs) ahead of the actual delivery.

This work studies hedgeable risks of storage and conventional power generating technologies in Germany, UK and Nordics by exploring the drivers of hedgeable revenue margins proxied by future price spreads. Specifically, the following future price spreads are studied: 1. *peak-off peak spreads* (POS), which indicate the hedgeable revenue margin for energy storage technologies; 2. *clean dark spreads* (CDS), which indicate the hedgeable revenue margin for electricity generated from coal adjusted for price of carbon; and 3. *clean spark spreads* (CSS), which indicate the hedgeable revenue margin for electricity generated from gas adjusted for price of carbon.

We particularly focus on technologies that provide *flexibility* to the power system, meaning technologies with the capability to balance rapid changes in power supply and demand. Coal and gas-fired power plants as well as energy storage 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 focus particularly on flexibility providers, because the outlined transformative trends, such as the increase of variable RES production dependent on local weather, increase the need for flexibility [2]. However, flexibility providers in liberalized electricity markets need to recover costs and gain reasonable profits to stay in the market. We call the proxy for hedgable profitability of a given energy technology a power spread.

Explaining the dynamics and factors driving the hedgeable revenues proxied by power spreads provides knowledge on: 1. whether traditional derivatives products still work for risk management purposes in markets with increasing vRES penetration, 2. what the main drivers are behind hedgeable revenues, and 3. future directions of power derivatives design in new or established power markets. By disentangling the drivers of hedgable revenues, implications on who is bearing the risks of changing market structures can be derived – whether traditional power generators, end-consumers, or someone else.

The key motivation is to contrast the current policy which promotes rapid deployment of vRES under the requirement of greater system flexibility on the one hand, with the risk management and profit margin reality of flexibility providers on the other hand. This investigation may reveal whether a possible misalignment exists between investment signals manifested by power spreads and the actual market need for sustainable and secure energy. Power spreads provide investment signals for market participants to invest into storage and flexible power generation that can balance out fluctuating demand and intermittent power generation. However, if there are factors affecting/disturbing the reliability of such signals, new mechanisms should be in place providing signals aligned with the objectives of a sustainable and secure energy market.

This work contributes methodologically by developing an econometric model for futures spreads valuation, which is typically dominated by reduced-form (stochastic) modelling approaches [3, 4]. Specifically, we estimate the future price spreads in monthly frequency by autoregressive conditional heteroscedasticity models (ARCH) and study the significance and impacts of energy demand, price of fuels (gas and coal), price of carbon allowances (EUA), and power generation from wind, solar and nuclear energy during the period 2012-2016.

This approach enables us to distinguish individual factors affecting the profit margins of flexibility providers, which may further inform policy makers 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 evolution and determinants of profit margins for supply-side providers of flexibility. Finally, econometric modelling of multi-asset derivatives prices has a potential to simplify derivatives valuation for risk managers that often rely on complex third party software tools for valuation and risk management. Especially with the growth of vRES and CO_2 prices, practicality and model agility may be highly valued to reduce cash-flow variation.

The paper is structured as follows. Section II presents background on risk management and hedging in electricity markets and briefly introduces the three power markets studied. Section III presents methods applied and describes the data used. Section IV presents the main findings and the paper ends with conclusions in section V.

II. BACKGROUND

Firms pursue many objectives in managing risks, such as earnings, taxable income, operating cash flow, and equity value [5]. Derivatives and non-derivatives based strategies are employed by firms to manage hedgable (price) and unhedgable (quantity) risks. The risk management strategies are non-exclusive and energy firms embrace a variety of strategies adequate to their needs, size, and risk appetite. Non-derivatives based strategies in electric power sector typically involve changes in operating decisions, such as adjusting production, or integrating diverse energy systems which jointly reduce cash flow volatility.

A derivatives-based strategy involves a derivative asset, which is a security whose value is explicitly dependent on the exogenously given value of some underlying primitive asset on which the financial contract is written [6]. Financial derivatives are typically used for non-speculative risk management purposes [7], but speculation and price discovery are also essential. Derivatives can be structured into two categories, 1. Vanilla derivatives, such as forwards, futures, and options, which are common, standardized, and relatively simple derivative contracts; and 2. Custom or exotic derivatives, which are more complex derivatives because of their elaborate payoffs and/or underlying structures. The number of derivative instruments available for trade is limited or impeded by market frictions so market participants sometimes prefer proxy hedging strategies via delivery-period or locational mismatch [8].

Firms operate in a broader techno-economic environment which also affects their risk management strategies. This paper focuses on three liberalized electricity markets, namely Germany, UK and the Nordics. The three markets have in common that they are all part of the single European electricity market, however the structure of the main drivers of electricity supply and demand differs [9]. On the supply side, Germany and UK power systems traditionally relied on thermal generation (coal, gas, nuclear), however since the introduction of RES subsidies, both countries have seen a rapid growth in capacity and power generation from vRES (particularly wind and solar). On the contrary, the Nordic electricity market is a hydro-dominated system with a 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, UK slightly differs from the two cases due to the introduction of separate capacity market and carbon price floor mechanism. The UK and Nordics are generally less interconnected by cross-border transmission lines compared to Germany which is a part of the highly meshed power grid of the Continental Europe synchronous area.

On the demand side, the considered markets share similarities with respect to energy intensity (mining, manufacturing, etc.), macroeconomic development and demographic structure, but differ with respect to weather characteristics and deployment of energy saving technologies, such as smart metering. The wholesale electricity prices in all the three markets have systematically decreased since 2008 due to the near zero-marginal cost of vRES, which push marginally more expensive production off the merit order curve [10]. In the following section we present methodological details and background to data.

III. METHOD AND DATA

Clean dark and clean spark spreads represent a cross-commodity derivative consisting of fuel prices, electricity prices and carbon allowance prices. For pricing such derivatives, a joint model for all commodities is required [4]. Peak – off peak spread is a single commodity derivative represented by electricity prices only. Two general approaches have been applied to analysing prices of commodity derivatives, namely reduced-form (stochastic) models and statistical (econometric) models.

Reduced-form models, also called financial mathematical models [11], are dominating the electricity derivatives valuation field which focuses on the stochastic behavior of commodity prices (mean-reversion, Brownian motion, jump-diffusion) in one- or multi-factor models [12, 4, 13, 14]. 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 [11]. In addition to using past price characteristics to explain price fluctuations, statistical models incorporate also the current and/or past values of exogenous factors [15].

Since the main purpose of this study is to explain the impacts of exogenous variables on the hedgable profit margins, we embrace the econometric approach to price modelling. In this work, we estimate autoregressive conditional heteroscedasticity models (ARCH) which address the unique statistical properties of electricity price (spreads), namely seasonality and volatility. This method has been widely applied in the day-ahead electricity price forecasting literature [15]. The seasonal and mean-reverting behavior of electricity prices is modelled by autoregressive (AR) processes and volatility clustering by conditional heteroscedasticity (ARCH) terms. Additional exogenous fundamental variables can be assessed in the mean or variance equations of ARCH-type models.

For instance, [16] show that AR models with system load as the exogenous variable generally perform better than pure price models. Also [17] 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, [18] estimate a twostep regression model applying a logistic and ARCH log linear regression using demand, wind generation and fuel prices, among others. Finally, [19] point out important methodological pitfalls of applying linear regression models for explaining the relationship between spot and futures electricity prices, which is generalizable to electricity price (spreads). They mention three issues needing attention: (1) bias originating from simultaneity (endogeneity) problem, that is typically loop of causality between dependent and independent variables; (2) the effect of correlated measurement error; and (3) the impact of seasonality on regression models.

In this study we attempt to avoid the above-mentioned pitfalls. Before we specify the final ARCH model, we define our dependent variables as:

$$Cl.Spread\,(T)_t = (ELECTRICITY(T)_t - (\,FUEL(T)_t * EF)) - CO2_t \qquad (1)$$

$\mathrm{Cl.Spread}\,(\mathrm{T})_t$ in eq. (1) is the monthly futures clean dark CDS $(\mathrm{T})_t$ or clean spark spread CSS $(\mathrm{T})_t$ with delivery in month T traded in time t; $ELECTRICITY(T)_t$ is the monthly futures electricity price[1] (EUR/MWh) with delivery in month T ; $\mathrm{FUEL(T)}_t$ is a monthly average of the closing futures price (EUR/MWh) of natural gas ((ICE UK Natural Gas for clean spread) or coal price (ICE Rotterdam Coal Future for dark spread) with delivery in month T; EF is the efficiency of electricity generation by a power plant burning coal or gas, assuming 36% and 50%, respectively; and $\mathrm{CO2}_t$ is the monthly average of closing futures price of EUA (ICE ECX EUA Future) carbon allowance (EUR/MWh). Additionally, we define the future peak-off peak spread:

$$POS\,(T)_t = \,ELECTRICITY\;Peak(T)_t - \;ELECTRICITY\;Off\;Peak(T)_t \qquad (2)$$

$POS\,(T)_t$ in eq. (2) is the peak-off peak spread in time t for delivery month $T;$ $ELECTRICITY\;Peak(T)_t$ is a monthly electricity futures contract for electricity consumed during the peak hours of 8am-8pm; and $ELECTRICITY\;Off\;Peak(T)_t$ is a monthly electricity futures contract for electricity consumed during the off-peak hours of 8pm-8am.

To create monthly series, we use the front (prompt) month when calculating our dependent variables clean dark spread (CDS), clean spark spread (CSS), or peak-off peak spread (POS). We define the front-month as a monthly futures contract with the nearest delivery time. Front month futures contracts thus refer to a contract traded in the current month with a delivery in the next month.

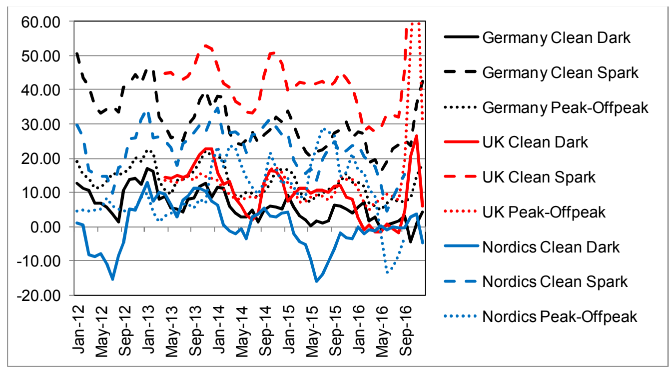

Figure 1. Monthly futures spreads. *(EUR/MWh)*

Figure I. summarizes the three types of spreads for the three power markets of interest. Three points can be mentioned. First, there is a general downward trend in monthly futures spreads during the studied interval of 2012-2016, most prominent in Germany. Second, seasonality of especially peak-off peak spreads is visible, taking lower values in summer where loads are typically lower and solar generation is higher. Third, the Nordic power market dominated by flexible hydro generation does not send any investment signals to new flexible baseload generation (coal), as showed by the mostly negative clean dark spreads for the Nordics. Note, that the clean spreads for German and Nordic markets reflect the price of EUA allowance whereas the clean spreads for the UK reflect the price of UK carbon price floor [20].

The visual inspection of the futures monthly spreads implies that the time series may not be stationary, which is confirmed by all traditional unit-root tests (KPSS, ADF, and DFGLS). For this reason we turn to natural logarithmic transformation of all spreads and calculate their returns as $\ln(\frac{fut.spread_t}{fut.spread_{t-1}})$. Additionally, by taking natural logs of the explanatory variables, the coefficients of the log-log regression model are interpreted as marginal effects. A similar approach was developed by [18] who estimate positive payoffs for spot spark spreads by the same exogenous variables as in this paper but for the ERCOT electricity

[1] The monthly power futures data originate from the following power exchanges: EEX (Germany), Nasdaq OMX (Nordic), and ICE UK Futures (UK).

market. Since we are now estimating the log returns, our main concern is to address the potential time-varying volatility. Hence, we estimate the following ARCH model:

$$\begin{aligned} &ln.Future\ spread\ return\ (T)_t \\ &= \alpha + \beta_1 ln.Consumption(T) + \beta_2 ln.Wind\ Generation(T) \\ &+ \beta_2 ln.Solar\ Generation + \beta_3 ln.Fuel\ prices(T) \\ &+ \beta_4 ln.Nuclear\ gneration(T) + \beta_4\ ln.EUA\ price(T) + u_t \end{aligned} \quad (3)$$

$$u_t = z_t h_t \quad (4)$$

$$h_t = \gamma_{0+} \sum_{j=1}^{q} \gamma_j u_{t-j}^2 \quad (5)$$

$\mathrm{ln.Future\ spread\ return(T)_t}$ in eq. (3) is the natural log return of one of our three dependent variables - clean dark spread (CDS), clean spark spread (CSS), or peak-off peak spread (POS), with delivery in month T traded in time t; $\mathrm{ln.Consumption(T)}$ is the natural log of monthly consumption (MWh) in delivery month T ; ln.solar, ln.wind and ln.nuclear generation are natural logs of power generations from the respective energy sources (MWh) in delivery month T; $\mathrm{ln.Fuel\ prices(T)}$ are natural logs of monthly average of closing futures prices of coal (ICE Rotterdam Coal Future) and gas (ICE UK Natural Gas); $\mathrm{ln.EUA\ price(T)}$ is the natural log of monthly average closing futures price of EUA (ICE ECX EUA Future) carbon allowance (EUR/MWh); $\mathrm{u_t}$ in eq. (4) is the error term comprised of time dependent variance h_t and white noise term z_t; γ_j in eq. (5) is the estimated ARCH coefficient of the lagged squared errors u_{t-j}^2. We test for the presence of ARCH effects in the residuals by ARCH LM test and if insignificant, we estimate OLS with Newey-West standard errors.

IV. Results and Discussion

Intuition behind the price returns in futures spreads is as follows. Spreads can increase (or decrease) for two reasons. For storage spreads (peak – off peak), they can go up if peak prices increase (for the reasons of higher expected scarcity) or off peak prices decrease (e.g., owing to expected oversupply of low cost generation). The clean dark spread can increase (or decrease) if electricity baseload price go up (due to expected increased demand, economic activity, etc.) or operating costs go down (e.g., owing to expected decrease in coal futures). Finally, the clean spark spread can increase (or decrease) if electricity peak price increase (for the reasons of higher expected scarcity) or decreased operating costs (e.g., expected price of natural gas goes down).

Table I. below presents the final regression results according to eq. (3). All explanatory variables are in monthly frequency and transformed by natural logarithm. Our three dependent variables, namely clean dark (CDS), clean spark (CSS) and peak-off peak (POS) spreads are in log returns. As mentioned earlier, the coefficients in log-log regression model can now be interpreted as marginal effects (elasticities).

The most intuitive as well as statistically significant results are presented in the German regression models. Firstly, according to expectation, a 1% increase in the price of coal decreases the clean dark spread (CDS) by over 2%. Also, one percent increase in the price of coal's substitute, gas, increases CDS by almost 0.9%. Surprisingly, the opposite relationship holds for clean spark spreads (CSS) where a percentage increase in the price of gas leads to a significant increase in CSS by 0.25%. Also, if the price of coal, as gas's potential substitute, increases by one percent CSS reduces by almost 0.4%. More intuitive results with respect to the marginal effects of fuels on spread is visible in the peak-off peak spread (POS) where the cost increase of coal as baseload fuel leads to drop of 0.6% in POS. Further, one percentage increase in gas price leads to 0.5% increase in POS hedgable margins, which means that by making gas production, as another provider of flexibility, more expensive the hedgable revenue of storage increases.

Less intuitive results are the effects of consumption on spreads. The typical hypothesis [18] is that consumption tends to increase electricity prices and therefore the theoretical margins. However, we find mostly negative and statistically significant coefficients, suggesting that increase in monthly electricity consumption decreases e.g. CDS in Germany by almost 2%. The only significant and positive coefficient for consumption impact on CDS was found in the Nordic market. The other counterintuitive effects include the positive and statistically significant coefficients of EUA in CDS and CSS models. This would again imply that by increasing the operational costs of gas and coal generators, their hedgable profit margins increase by 0.2% and 1% respectively. Nonetheless, the positive EUA coefficient in the POS model is intuitive, since making the conventional generators more expensive increases the value of storage.

Finally, it is interesting to see that wind has a significant negative effect on the hedgeable profit margins of conventional generators (CDS and CSS) as well as storages (POS), while solar generation negatively affects conventional peak generation (CSS) and storages (POS) in Germany. This finding concurs with studies on spot markets. It is interesting because it suggests that the futures market does not provide any investment signal for more flexible conventional generation (gas) or flexible storages, both of which are frequently discussed as important complements of an increasing amount of variable renewables. At the same time, the transmission system operators call for new flexible gas power plants to run the system reliably [21]. Our findings, however, suggest that hedging becomes more challenging for flexibility providers and investors – particularly in the absence of other market mechanisms remunerating capacity and flexibility.

Critically reflecting our findings, we wish to emphasize that the results need to be interpreted with some caution. While the model seems to represent the German market rather well, much less significant results are found for the other markets. This may indicate that relevant country-specific drivers for these markets are missing, which needs to be investigated in future research. Moreover, the time horizon for the analysis can be extended for future analyses.

V. Conclusions

This work quantified the effects of rising variable renewable electricity production on the hedgable revenue margins of storage and conventional power generating technologies. Additional factors, namely fuel and carbon prices, power demand, and nuclear generation were

TABLE I. REGRESSION RESULTS ON MONTHLY LOG RETURNS OF FUTURE CLEAN DARK (CDS), CLEAN SPARK (CSS) AND PEAK-OFF PEAK SPREADS (POS)

	Germany			Nordic			UK		
	CDS	CSS	POS	CDS	CSS	POS	CDS	CSS	POS
ln consumption (MWh)	-1.995*	-0.714	-1.211	1.521*	-0.909**	-1.677***	-0.096	-0.159	0.089
	(-1.054)	(-0.48)	(-0.778)	(-0.82)	(-0.373)	(-0.194	(-0.288)	(-0.154)	(-0.401)
ln future coal price (EUR/MWh)	-2.065***	-0.391**	-0.624**	1.278	0.486	-0.312	-0.129	0.084	0.062
	(-0.553)	(-0.192)	(-0.311)	(-0.928)	(-0.452)	(-0.572)	(-0.382)	(-0.24)	(-0.697)
ln future gas price (EUR/MWh)	0.870**	0.246*	0.468**	-0.355	-0.177	0.403	0.177	0.051	0.056
	(-0.35)	(-0.135)	(-0.237)	(-0.548)	(-0.224)	(-0.311)	(-0.197)	(-0.125)	(-0.374)
ln future EUA contract price (EUR/MWh)	1.028***	0.200**	0.334**	-0.393	0.008	-0.108	0.067	0.073	0.23
	(-0.311)	(-0.086)	(-0.131)	(-0.363)	(-0.188)	(-0.096)	(-0.115)	(-0.054)	(-0.215)
ln wind production (MWh)	-0.374**	-0.154**	-0.268***	0.203	0.175	0.733***	-0.073	-0.044	-0.206
	(-0.152)	(-0.067)	(-0.099)	(-0.404)	(-0.196)	(-0.128)	(-0.06)	(-0.032)	(-0.155)
ln solar generation (MWh)	-0.022	-0.119***	-0.212***						
	(-0.114)	-0.043	-0.057						
ln nuclear generation (MWh)	1.354**	-0.153	-0.374	-2.558***	0.828**	0.305	-0.264*	2.445*	-0.031
	(-0.591)	(-0.208)	(-0.321)	(-0.719)	(-0.337)	(-0.259)	(-0.153)	(-1.47)	(-0.268)
L.arch	2.691***					3.048***			
	(-0.84)					(-0.81)			
Constant	18.28	13.245***	23.434***	2.231	-0.498	8.823***	3.439	2.445*	8.980*
	(-13.634)	(-5.118)	(-7.288)	(-8.216)	(-2.344)	(-2.512)	(-2.675)	(-1.47)	(-4.82)
Sigma2	0.029	0.011***	0.023***	0.521***	0.052***	0	0.008***	0.003***	0.028***
	(-0.03)	(-0.003)	(-0.006)	(-0.093)	(-0.009)	(-0.002)	(-0.002)	(-0.001)	(-0.007)
Observations	51	51	51	66	56	55	40	40	40
Sample	2012m1 - 2016m3			2010m1 - 2016m9	2012m1 - 2016m9	2012m2 - 2016m9	2013m5 - 2016m8		

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

investigated. The results show that despite the current policy of complementing rapid deployment of variable renewable energy sources with flexibility generation and storage, risk management for providers of flexibility becomes more challenging. Hence, in order to provide market participants with adequate investment signals, different risk-mitigating mechanisms may be needed in future.

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