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The profitability of energy storage in European electricity markets

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The Profitability of Energy Storage in European Electricity Markets

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Abstract

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Keywords: Energy storage; optimization; profitability; risk analysis

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1 Introduction

Existing energy storage is dominated by hydroelectricity, but the rapid growth in generation from variable renewable energy sources (vRES) is pushing the markets to experiment with new storage technologies that could efficiently support the stability of electrical grids. Grid connected electrochemical energy storage (EES) is envisioned to potentially provide high-value energy services (Dunn, Kamath, & Tarascon, 2011). At the same time, any commercial investment into a potential energy storage project must be economically feasible, which means covering investments costs and offering a reasonable rate of return.

In this study we focus on the value of energy storage by studying temporal energy arbitrage in *electricity day-ahead markets*. We define arbitrage practiced by energy storage as an operation strategy that maximizes profits, i.e. taking advantage of electricity spot price spreads among demand hours. We are particularly interested in the fundamental drivers that explain the magnitude and dynamics of energy storage profitability. Among others, we focus on the effects of intermittent generation from wind and solar, which are changing the dynamics of electricity prices (level and volatility) and potentially affecting the value of energy storage.

The answer to the question about profitability of energy storage lies in discussing the *value of flexibility* which energy storages are creating. Heal (2016) highlights two functions that energy storages have to perform, 1. Shifting solar power produced in the daytime to the night (assuming insufficient power resources available at night), and 2. Smoothing out the variable output of renewable energy. However, Heal (2016) points out the strengths of spatial diversification of renewable energy sources as well as the power of demand-side management, which both reduce the need for energy storage. Similarly, Newbery (2018) stresses other typically cheaper sources of flexibility in contrast to EES, namely peaking generators, demand-side management, and electrical interconnectors.

Most of the current literature focuses on spatial and sizing issues of diverse energy storages while concentrating on minimization of system-wide operating costs and the cost of investments (Dvorkin, Fernández-Blanco, Pandžić, Watson, & Silva-Monroy, 2017; Panžić, Wang, Qiu, Dvorkin, & Kirschen, 2015). Other studies focus on electricity price arbitrage (Connolly, Lund, Mathiesen, & Leahy, 2011; Zafirakis, Konstantinos, Baiocchi, & Daskalakis, 2016; Bradbury, Pratson, & Patiño-Echverri, 2014) of specific energy storage technologies while using different profitability measures, such as internal rate of return. Compared to these studies, we consider a generic storage device defined only by storage capacity constraints and efficiency.

By abstracting from a specific storage technology with very different fixed and sunk cost assumptions, we can focus on the variable costs and revenues from operating an energy storage device of a particular efficiency, power and energy capacity. Therefore, in our study we measure the profitability by considering the *contribution margin,* which is defined as the difference between revenues and variable costs in the spot market. The revenues originate from the sale of electricity when the storage is discharging energy and the variable costs arise from the purchase of electricity when the storage is charging. The contribution margins therefore indicate the amount of revenues available to cover the fixed costs and company profits after variable costs. Negative or low contribution margins will indicate poor economic performance of investment into energy storage technology and vice versa.

Our motivations are threefold. First, we want to understand how the contribution margins of illustrative 1-13 MWh energy storages with maximum output of 1MW evolved during 2006 to 2016. Second, we want to understand the fundamental drivers behind the evolution of contribution margins. Third, we aim to understand what factors affect the number of charging and discharging cycles of the sampled energy storage and how the cycles are related to the development of profits.

To meet these objectives, we first build a storage optimisation model which maximises profits earned by arbitraging price differences in hourly electricity spot markets. As a case study we chose three European electricity markets, namely the UK, Germany and the Nordics[1]. Next, we estimate an econometric ARX-type model that explains the relationships between contribution margins and market fundamentals. In particular, we are interested in whether the profits change over time as the level of variable renewable energy sources (vRES) penetration increases. Similarly, we build an econometric Poisson regression model to understand the relationships between cycling frequency of the energy storage and the market fundamentals, such as vRES generation, electricity demand and fuel prices.

By using an 11 year-long sample we attempt to capture the structural changes the current power markets are going through. Despite our sole focus on Europe, the three power markets chosen for the analysis are quite diverse and offer examples to other non-European markets. Germany is the largest power system in Europe and represents an interesting case study of a system traditionally dominated by thermal generation with limited hydropower (around 6% of installed capacity), while rapidly integrating vRES. The UK is similar to Germany in the sense of being traditionally dominated by thermal generation and rapidly adopting vRES. However, the UK has much less cross-border interconnectors and has implemented different policy mechanisms (capacity markets and carbon price floor). In contrast, the Nordic electricity market has an abundance of flexible hydro generation, where Norway alone has 25 000 times as much storage in its dams than the entire British pumped hydro storage (Newbery, 2018).

Our methodological contribution is the combination of an optimisation model and econometric analysis which enables a better understanding of the drivers affecting economic viability and operation decisions of energy storages. The results presented in this study focus on the contribution margins which comprise a part of the overall investment evaluation. However, by abstracting from a technology-specific analysis of profitability, our results can be further used as inputs into capital budgeting accompanied by additional assumptions on fixed costs, capital costs, and operation and maintenance costs of a specific energy storage technology.

Finally, our study contributes towards the debate on the increasing importance of energy storage (flexibility) in the future electricity systems, which are dominated by vRES with close to zero marginal costs. Electricity markets based only on energy may not provide sufficient incentives for storage investments. Hence, they may not be sustainable in the long-run. In addition to energy, flexibility, reliability and capacity will play increasingly important roles, which need to be rewarded as such.

The paper is structured as follows. Section 2 presents the market setting of the three power markets. Section 3 first describes the storage optimisation model, which quantifies the main variables of interests (storage profits and cycles), which is followed by data summary. Section 4 specifies two econometric models and their results are presented and discussed in section 5. The work ends with conclusions in section 6.

2 Market setting

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

[1] By the term Nordic we refer jointly to the power markets in Norway, Sweden, Finland and Denmark. In the analysis, we are using the system reference price Elspot from Nord Pool market area, which has been dynamically evolving during the studied interval, i.e. expanding to the Baltic region. However, we use the explanatory fundamentals only from the Nordic region.

risks the energy storage operators face. It is therefore essential to first outline and understand the relevant local factors of electricity supply and demand[2] before proposing relevant determinants of power spreads. By the term 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 seen a rapid growth in capacity and power generation from vRES since 2008 (particularly wind and solar)[3]. 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 the market design, the UK slightly differs from the two other markets in terms of 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 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 declined since 2008 generally due to the decreasing fuel commodity prices and increasing production from vRES.

3 Data

In this section, we first present the storage optimisation model which quantifies the main variables of interests, namely profits and cycling operation of energy storages, which are used as inputs for the econometric analysis. The next subsection presents data sources and summary statistics of the main variables of interest.

3.1 Optimisation model

In this work, we consider a storage device with a 1, 4, 7, 10 and 13 MWh maximum volume (capacity), a 1MW maximum hourly discharge\charge rate (output) and 90% efficiency factor. In other words, the differently-sized storage devices represent the number of hours to store 1MW of power, i.e. 1MWh/MW stores energy worth of providing 1MW for 1h, 7MWh/MW stores 1MW for 7 hours, and so on. The main idea behind comparing differently-sized storage devices is to mimic different energy storage technologies that serve different purposes in the energy systems. For instance, an electrochemical battery (lithium-ion) has a storage capacity of around 0.5 - 1 hour (see e.g. Fortum, 2017) whereas typical daily pumped hydro storage would have storage capacity of 5-10 hours.

Next, the storage optimisation model is presented. The model describes how one would optimally utilize an electrical storage device with the objective of maximising profits, subject

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

to storage capacity constraints. Profits in the model are earned by buying electricity to store and subsequently selling it when it is discharged from storage.

The model inputs are represented by upper-case Roman letters and include the spot price time series (P_t) in addition to the storage capacity parameters. These include the maximum hourly discharge rate (*MAX_DISCHARGE*), the maximum hourly charging rate (*MAX_CHARGE*), the total storage volume (*MAX_VOL*) as well as the storage efficiency factor (*EFF*). The model decisions variables\outputs are represented by lower-case Roman letters and include the optimal amount of electricity discharged from ($g_t^{discharge}$) and charged into (g_t^{charge}) the storage device. These outputs are used to calculate profits and storage cycles, which are then used in the econometric analysis

The model is optimised over hourly time-steps for each of the years considered. It also assumes a maximum 48-hour time horizon for storage cycles, i.e., electricity charged into storage in hours 1-48 and 49-96 must be discharged by hours 48 and 96, respectively and so on. This assumption reduces the computational burden of the model significantly and, moreover, we believe it is reasonable given the relatively small storage volume considered. The following linear program describes the model:

$$\max_{g_t^{charge}, g_t^{discharge}} \sum_{t=1} P_t \times \left(EFF \times g_t^{discharge} - g_t^{charge}\right) \tag{1}$$

subject to:

$$0 \leq g_t^{charge} \leq MAX\_CHARGE, \quad \forall t, \tag{1a}$$

$$0 \leq g_t^{discharge} \leq MAX\_DISCHARGE, \quad \forall t, \tag{1b}$$

$$0 \leq \sum_{e=t'}^{t'+h-1} g_e^{charge} - g_e^{discharge} \leq MAX\_VOL, \qquad \forall t, h. \tag{1c}$$

Constraints (1a) and (1b) limit the amount of electricity that can be discharged from and charged into storage at each hour *t*, respectively. Constraint (1c) ensures that, over a 48-hour time period, the amount of electricity stored in the storage device cannot be greater than its storage capacity, less any electricity discharged. The index *h* represents the hours in the 48-hour while the index *t'* represents starting points for the storage period, i.e., 1, 49, 97, etc. Constraint (1c) also ensures, for each hour, electricity discharged from the storage device cannot exceed the amount of electricity already charged in the 48-hour time horizon.

Note that the model does not consider uncertainty. Therefore, the contribution margins should be considered upper boundaries. However, we deliberately chose to model storage in this way as we mainly use it to provide input to the econometric analysis aimed at understanding the drivers of the contribution margins' development over time.

3.2 Data summary

All data used in this study cover the time period 2006-2016. The inputs to the optimisation model, described in detail above are the hourly day-ahead spot prices (EUR/MWh) for the

German (EPEX) and Nordic (Elspot) wholesale electricity markets. The UK's day-ahead prices (GBP/MWh) are based on APX power exchange's half-hourly prices that are first averaged to hourly prices to ensure comparability with the other markets and then used in the optimisation model. The outputs of the optimisation model are contribution margins, for simplicity called *profits*, and the number of charging and discharging *cycles*, all based on 1, 4, 7, 10 and 13 MWh energy storages. The energy storage dispatch model is in hourly resolution, but in our econometric analysis of profits and cycles (see section 4) we consider a daily resolution.

Table 1 and Table 2 present the summaries of profits and cycles, respectively, for the three markets and five storage sizes. In absolute terms, the largest mean profits and price volatility (sd) are observed in Germany, followed by the UK and Nordic markets. Similarly, the German storages cycle daily more frequently, about 20% and 40% more than in the UK and Nordic markets, respectively.

Table 1 Summary statistics of the daily storage profits, 2006-2016

	Stats	1MWh	4MWh	7MWh	10MWh	13MWh
Germany	mean	43.253	122.951	162.011	171.808	175.871
	min	-29.827	-13.968	-99.694	-245.258	-344.268
	max*	1598.826	3352.564	4006.394	4287.905	4289.253
	sd	46.573	104.611	142.991	187.713	227.063
	N	4018	4018	4018	4018	4018
UK	mean	38.413	104.465	130.933	137.607	138.92
	min	-36	-117.16	-208.663	-347.237	-487.247
	max	684.54	1468.996	1656.068	2211.869	2645.243
	sd	38.448	100.151	138.675	182.28	216.369
	N	4018	4018	4018	4018	4018
Nordic	mean	8.317	24.532	31.242	32.682	33.29
	min	-74.27	-284.63	-503.49	-652.47	-667.018
	max	294.32	753.656	962.535	1095.793	1095.793
	sd	19.856	58.169	92.948	123.345	144.344
	N	4018	4018	4018	4018	4018

Note: The table shows summary statistics of daily profits in EUR for Germany and Nordic markets, and in GBP for the UK market; the figures are based on the outputs from the optimisation model described in section 0; sd stands for standard deviation. *Due to the large price spike in the German storage profits (Thursday 27 July 2006) and potential outliers we had trimmed the top and bottom 1% of the daily profits and replaced these by the next value counting inwards from the extremes. This approach to outliers have been applied to the profits of all three markets and subsequently used in the econometric analysis.

Table 2 Summary statistics of the daily storage cycles, 2006-2016

	Stats	1MWh	4MWh	7MWh	10MWh	13MWh
Germany	mean	1.991	5.967	8.184	8.829	9.035
	min	1	3	3	3	2
	max	6	10	12	14	15
	sd	0.681	1.457	1.334	1.634	2.283
	N	4018	4018	4018	4018	4018
UK	mean	1.783	5.365	7.449	8.278	8.462
	min	1	1	2	2	0
	max	5	9	11	13	15
	sd	0.578	1.274	1.072	1.644	2.253
	N	4018	4018	4018	4018	4018
Nordic	mean	1.051	3.585	5.038	5.368	5.524
	min	0	0	0	0	0
	max	4	8	11	13	15
	sd	0.498	1.514	2.419	2.987	3.455
	N	4018	4018	4018	4018	4018

Note: The table shows summary statistics of daily storage cycles where once cycle represents either charge or discharge; the figures are based on the outputs from the optimisation model described in section 0; sd stands for standard deviation.

To shed light on our first research question, which is to understand the evolution of profit margins over 2006-2016, we present yearly summaries of the total profits and profits per MWh of storage capacity in Figure 1 and Figure 2, respectively.

Figure 1 clearly points out to the downward trend of total profits especially in Germany, but also in the UK. All the three countries exhibit large spike in profits in 2008 and slight upward trend from 2015 onwards in the Nordics and the UK. The dynamics of the Nordic total profits differs from the other two markets because of the clear seasonality showing spikes every other year (2008, 2010, 2012) until 2013 after which the pattern seems to change or weaken. The main reason behind the pronounced seasonality is the strong dependence of the Nordic power system on the hydrological conditions, namely the storage levels in hydro reservoirs and their deviations from historical values, but also the activity on cross-border interconnectors all affect the spot price dynamics. In absolute terms and for the 1MWh storages, the total profits are the highest in the UK and Germany with average of 14000 GBP/year and 15000 EUR/year respectively, followed by 3000 EUR/year in the Nordics. Even though the storage sizes are equidistant from each other (difference of 3MWh), the total profits of the largest three storage sizes (7-13MWh) are quite similar, around 62000EUR, 50000GBP and 12000EUR per year for the German, UK and Nordic storages respectively. This implies that by adding more storage hours at the upper end of our storage sample, total profits change only very little.

Figure 2 further underlines the last point by showing profits per MWh of energy storage capacity. Clearly, the smallest 1MWh storage, which stores energy worth of providing 1MW for 1 hour, captures the highest per MWh value because it typically charges and discharges only once a day during the most expensive (discharge) and the least expensive (charging) hour. The longer duration energy storages are active during more hours of the day that include not only the single most expensive and cheapest hour, making each additional MWh of capacity less valuable.

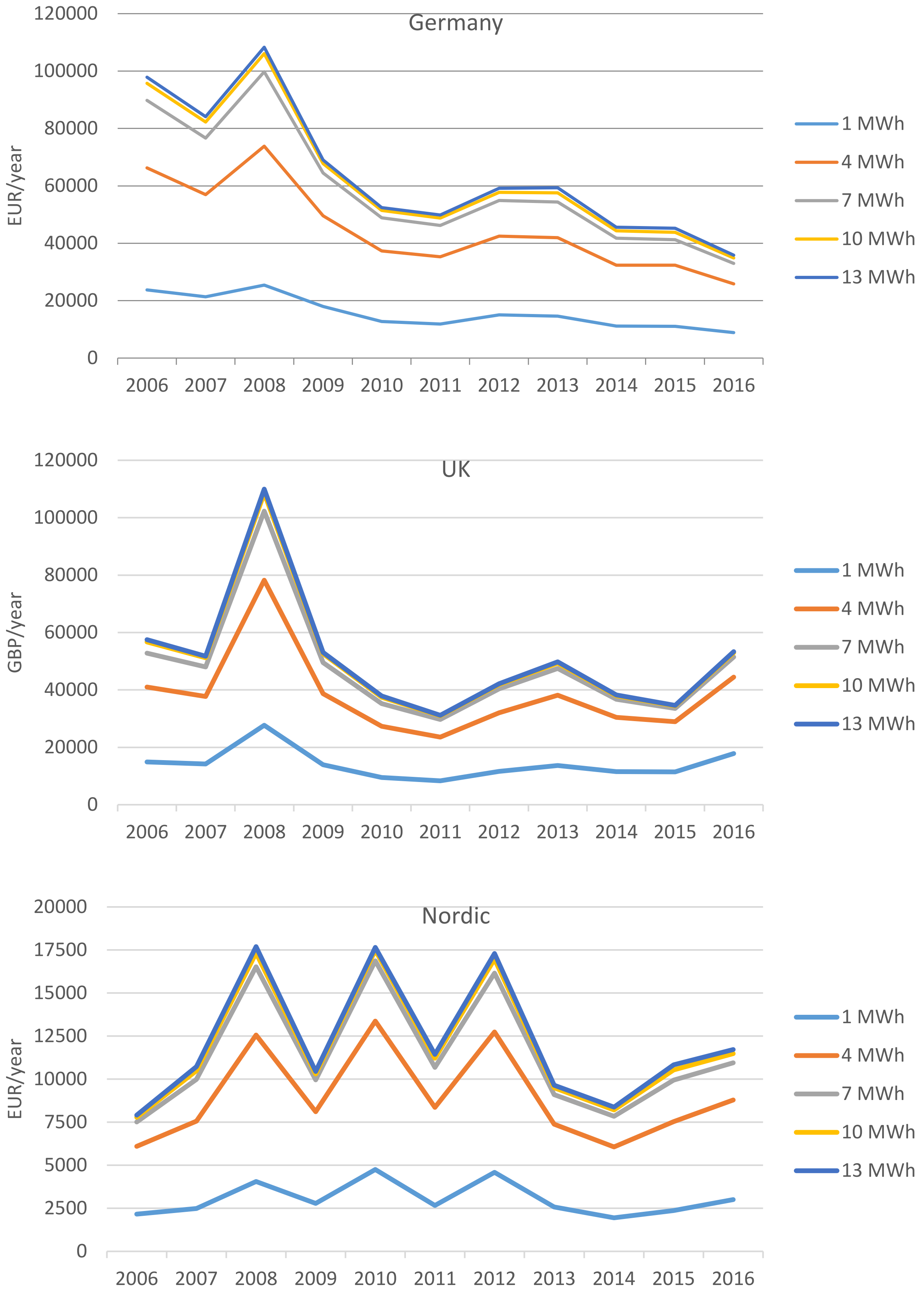

Figure 1 Total yearly profits of 1-13MWh energy storages in Germany, Nordics and the UK

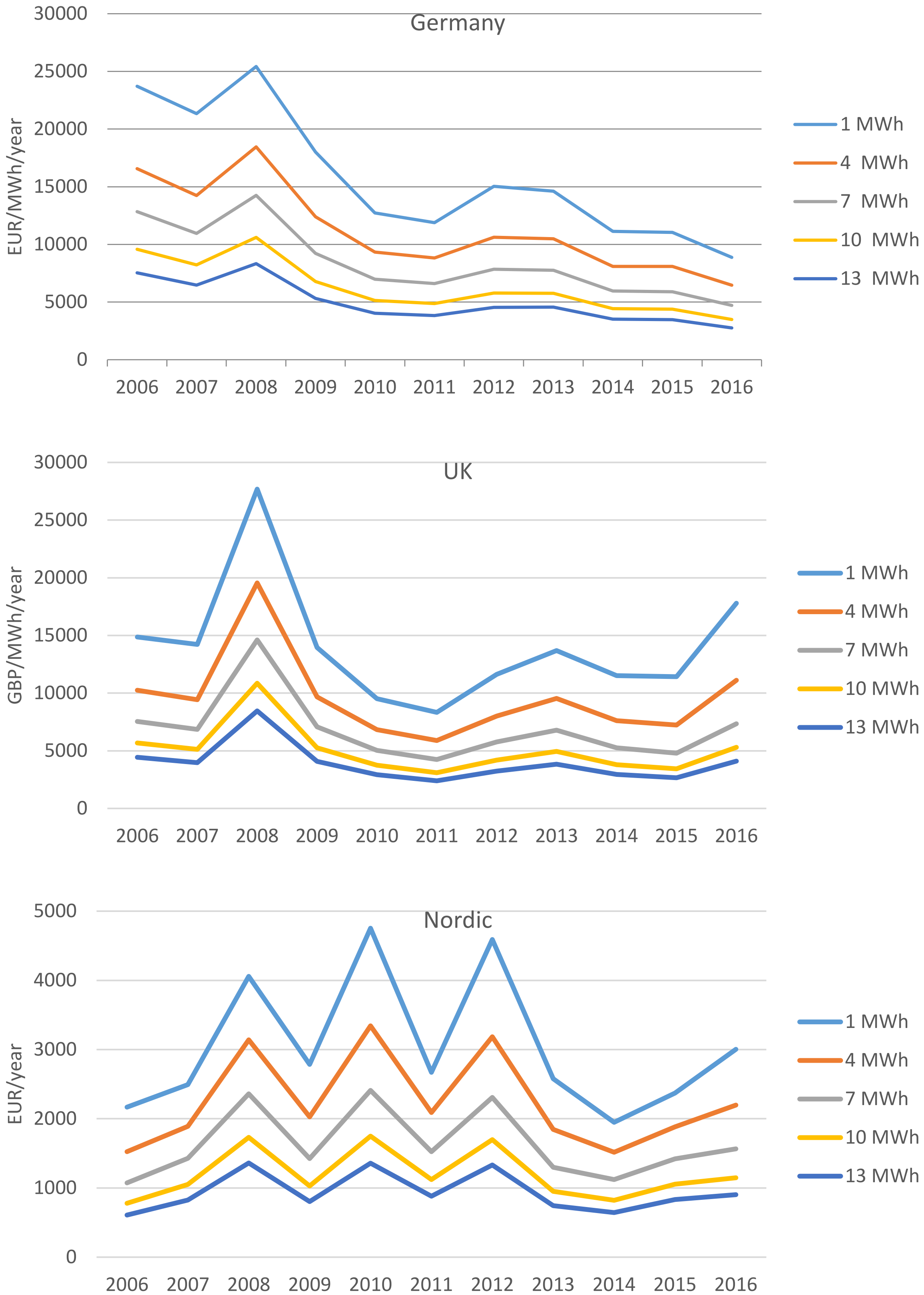

Figure 2 Yearly profits per MWh of energy storage capacity in Germany, Nordics and the UK

Figure 3 zooms into a daily operation of a 1MWh storage in Germany displaying daily storage cycles and daily profits with their respective 30-day moving averages. The figure reveals an interesting dynamics where the highly persistent yearly seasonality of the cycles diminishes after the end of the year 2010. We will use the year 2010 for sample splitting purposes as a robustness check and to control for possible structural break in our econometric exercise described in section 4.

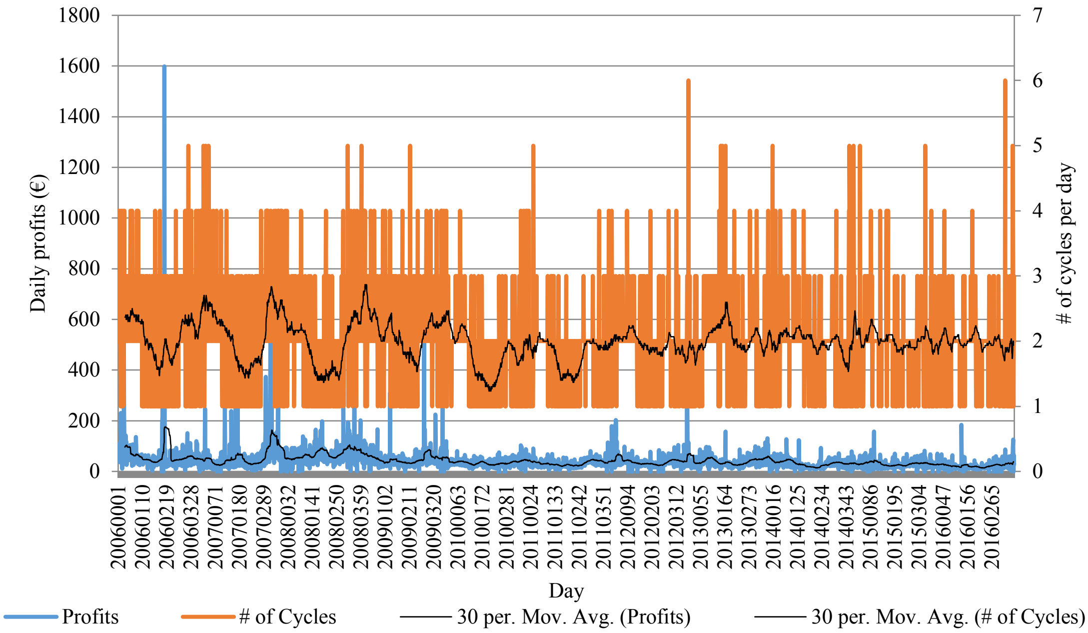

Figure 3 Daily profits and cycles of 1 MWh storage in Germany, 2006-2016

The econometric models are estimated in *daily* frequency and we use the following market and fundamental explanatory variables[4]: 1. *Electricity demand (GWh)*, which we expect to have a positive impact on profits due to the tightening of capacity margin, i.e. more high-cost marginal generation needs to run to cover the higher demand*;* 2. *Solar generation (GWh),* which we generally expect to have a negative impact on profits because the typical mid-day peak price coincides with the period when solar generation produces the most, which causes a downward pressure on the peak/off-peak spread; 3. W*ind generation (GWh),* which we hypothesize to have mostly positive effect on profits due to the lower predictability of wind production causing greater spot price volatility; 4. *Gas-coal price spread*, defined as the difference between *NBP gas price (p/therm)* and *API2 coal price (USD/t)* presented in MWh thermal, which is a unit omitting assumptions about power plants' efficiency. We expect this effect to be positive, i.e. higher spread implies higher gas prices (peak prices) relative to coal (baseload), but this will depend on the generation mix of a given power system; 5. *EUA carbon price (EUR/t)*, which we generally expect to have negative effect on profits because carbon price affects coal (baseload) more than gas (peak-load), reducing the peak/off-peak spread. However, the effect of carbon price will highly depend on the generation mix of a power system in question; 6. *Daily* spot *price volatility*, which we measure as daily standard deviation based on hourly electricity spot prices and hypothesize to have a positive impact on profits; 7. *Autoregressive (AR) terms*, which we use to control for the high persistency of the time-series; and 8. *Seasonal*

[4] The commodity and carbon prices originate from Thomson Reuters Datastream database; Electricity demand and vRES generation data are based on Open Power System Data (OPSD) and own calculations.

variables, namely yearly cycle (cosine wave) and seasonal dummies (spring, summer and fall in reference to winter) to capture annual climatic cycles. Descriptive statistics of the main fundamental variables are presented in Table 3.

Table 3 Summary statistics of the fundamental variables, daily frequency, 2006-2016

	Stats	Wind	Solar	Demand	Volatility	Spread	EUA
Germany	mean	125.963	51.086	1328.48	12.596	9.399	11.178
	min	3.869	0.367	845.494	1.946	-2.566	0.02
	max	743.792	229.71	1704.961	484.908	30.049	29.8
	sd	113.312	53.457	162.998	14.499	5.124	6.672
	N	4018	4018	4018	4018	4018	4018
UK	mean	61.997	7.306	881.194	11.312	7.478	11.178
	min	1.609	0.001	525.666	0	-1.94	0.02
	max	338.316	68.648	1228.329	185.714	20.551	29.8
	sd	53.943	12.705	127.482	10.395	4.132	6.672
	N	4018	4018	4018	4018	4018	4018
Nordic	mean	47.687	0.71	1061.024	3.589	9.491	11.178
	min	0.513	0	668.983	0.305	-2.566	0.02
	max	224.86	5.411	1583.28	75.377	33.574	29.8
	sd	39.78	1.139	188.814	3.787	5.234	6.672
	N	4018	4018	4018	4018	4018	4018

Note: The statistics are based on daily frequency data; "Wind" stands for wind generation (GWh/day), "Solar" stands for solar generation (GWh/day), "Demand" stands for daily electricity demand (GWh/day), "Volatility" stands for the standard deviation of hourly electricity spot prices in the day-ahead markets, "Spread" stands for the difference between gas and coal prices (EUR(GBP)/MWh thermal including the cost of carbon), and "EUA" is the price of carbon emission allowance (EUR/tCO2).

Table 4 Correlation matrix of the fundamental variables, example of Germany 1MWh energy storage, 2006-2016

	Profits	Cycles	Wind	Solar	Demand	Volatility	Spread	EUA
Profits	1							
Cycles	0.203*	1						
Wind	-0.009	0.174*	1					
Solar	-0.316*	-0.03	-0.004	1				
Demand	0.157*	-0.192*	0.084*	-0.189*	1			
Volatility	0.423*	0.038	-0.051*	-0.227*	0.160*	1		
Spread	0.108*	0.083*	0.103*	0.183*	0.110*	0.079*	1	
EUA	0.316*	-0.053*	-0.216*	-0.452*	0.039	0.239*	-0.216*	1

Note: Correlation coefficients marked with * indicate statistical significance at the 1% level or better.

Table 4 presents correlation coefficients of the main variables for a sample 1MWh storage in Germany. Profits are positively correlated with the price of carbon (EUA) and negatively correlated with solar generation. Also solar generation and EUA appear to have relatively high negative and statistically significant correlation[5]. One of the highest and statistically significant

[5] During the model estimation part of our work we have estimated multiple collinearity diagnostic measures, such as tolerance, eigenvalues, condition index, and R-squared, without identifying a collinearity issue.

positive correlation is between profits and volatility, which is expected and desirable from the modelling perspective which is discussed next.

4 Econometric models

In this section we specify two econometric models which we use to explain the variations in *profits* (contribution margins) and the number of storage *cycles* per day over the sample period 2006-2016. We also split the total time period into periods before year 2011 (2006-2010) and after (2011-2016) to better capture the rapid growth of vRES and also to provide a robustness check of our models.

In the first model, we take the daily profits ($Profits_t$) from the optimisation model as the dependent variable and estimate a time-series model using the explanatory variables defined in Section 3. This relationship is expressed in Eq.2, which also controls for the high persistence in profits by including the first (AR_{t-1}) and seventh (AR_{t-7}) lagged autoregressive terms. The lag of the autoregressive terms were identified from the autocorrelations and partial-autocorrelation functions of the daily profits. Such model types are typically called ARX-type models (Weron, 2014) which capture the autoregressive structure while relying on fundamental exogenous regressors.

$$\begin{aligned} Profits_t = {} & c + \beta_1 WindProd_t + \beta_2 SolarProd_t + \beta_3 ElDemand_t \\ & + \beta_4 SpotPriceVola_t \\ & + + \beta_5 GasCoalSpread + \beta_6 CarbonPrice_t + \beta_8 \text{Seasons} \\ & + \beta_8 \text{YearCycle} + \theta_1 AR_{t-1} + \theta_2 AR_{t-7} + \varepsilon_t \end{aligned} \tag{2}$$

In the second econometric model we are interested in knowing the relationship between the number of storage cycles per day, as determined by the optimisation model, and the same explanatory variables as in the previous model except the autoregressive terms, as defined in Section 3. Because the dependent variable is a count variable, i.e. number of cycles per day (y_i), we first estimate a standard Poisson regression as a benchmark model, defined in Eq.3

$$f(y_i; \theta_i) = \frac{\theta_i^{y_i} e^{-\theta_i}}{y_i!},\ y_i = 0, 1, 2, \dots,\ \theta_i > 0 \tag{3}$$

where $\theta_i = \exp(x_i \beta)$ with x_i covariate vector and β vector of regression parameters to be estimated. The main model assumptions are that the observations are independent, that the distribution of counts follows a Poisson distribution, and that the mean and variance of the model are identical (equidispersion). In our benchmark model, we use robust (heteroscedasticity-consistent) standard errors which are recommended to control for mild violation of the underlying assumptions (Cameron & Trivedi, 1986).

However, the assumption of equal variance and mean in Poisson distribution is frequently violated in empirical work where over-/underdispersion is commonly present (Ridout & Besbeas, 2004; Winkelmann, 1995). Our dependent count variable, the number of storage cycles, have signs of underdispersion, as indicated by the variance-mean ratios between 0.2-0.6 for differently sized storages. Not controlling for the underdispersion of the data could lead to overestimated standard errors and misleading inference (Winkelmann, 2015; Harris, Yang, & Hardin, 2012). There are several alternative approaches to standard Poisson regression that allow modelling overdispersion (variance greater than mean), such as negative binominal (Yang, Hardin, & Vuong, 2007) or generalised Poisson model (Winkelmann & Zimmermann, 1994), which also addresses underdispersion. More broadly, count models should be regarded as approximations of the truth and the results treated as approximate effects (Winkelmann, 2015).

In order to control for the lower variance in storage cycles as compared to the mean as well as to provide a robustness check (see Table 12) to the benchmark Poisson regression model, we turn to the generalised Poisson (GP) regression, which has an additional dispersion parameter δ. In the GP setting, the probability mass function of the response variable Y_i is described in Eq.4:

$$f(y_i;\theta_i;\delta) = \frac{\theta_i(\theta_i+\delta y_i)^{y_i-1}e^{-\theta_i-\delta y_i}}{y_i!},\ y_i = 0,1,2,\dots,\ \theta_i > 0 \tag{4}$$

where δ is the dispersion parameter with $\max(-1, -\theta_i/4) < \delta < 1$. When $\delta = 0$, the generalised Poisson distribution reduces to Poisson distribution; when $\delta > 0$, the model accounts for overdispersion; and when $\delta < 0$, there is underdispersion present. Covariates are introduced into the model via the following relationship (Consul & Famoye, 1992) described in Eq.5:

$$log\frac{\theta_i}{1-\delta} = \sum_{r=1}^{p} x_{ir}\beta_r \tag{5}$$

where x_{ir} is the *i*th observation of the *r*th covariate, p is the number of covariates in the model, and βr is the *r*th regression parameter, see also (Harris, Yang, & Hardin, 2012).

In the results sections below we focus on the marginal effects of key variables of interest, namely the change in daily storage cycles with respect to changes in vRES generation. As the population mean of both the Poisson and generalized Poisson (GP) distributions is given by the parameter θ_i the marginal effect of an attribute change is given by Eq. 6:

$$\frac{\partial E(\theta_i)}{\partial x_{ir}} = \theta_i\beta_r \tag{6}$$

In sum, the three models presented above give us tools to answering our three objectives. First, the optimisation model provides us with estimates of daily profits and cycles of illustrative 1-13 MWh energy storages during 2006-2016. The ARX-type time series model gives insights into the fundamental drivers behind storage profits. Finally, the Poisson model enables us to understand the fundamental drivers of energy storage operation. Next, we present and discuss the results.

5 Results

In this section, we present the results of the two econometric models as discussed above. In order to focus on the big picture first, we present a simplified version of the results in Table 5. This table shows the direction of the main effects on profits and cycles, positive (+) and negative (-) with their respective significance (*) insignificance (0) levels, for the three countries and five storage sizes. Table 5 omits the effects of the seasonal and autoregressive variables, which are all included with further details in the Appendix.

Electricity demand positively contributes to the profitability of storages in all three markets and across storage sizes. This finding confirms our expectation that with increasing electricity demand higher marginal cost units have to be switched on, which leads to the increase of peak prices from which energy storages benefit. The effect of electricity demand on storage cycles is rather mixed, being systematically positive in the Nordics and UK (for larger storages 10-13MWh), but being negative in Germany for smaller storages (1-7MWh) and positive for the larger ones. The *volatility* of day-ahead spot prices is the largest positive driver of storage profits and cycles across the three markets and storage sizes. This is unsurprising given the objective of energy storages to arbitrage hourly price differences as defined in our model. Nonetheless, it is useful to quantify the effect of price volatility on profits and cycles, as seen from the coefficients in the Appendix and from the figures below. For example, increasing the standard deviation by 1 GBP/MWh in the UK would increase the profits of 1 MWh storage by 2.60 GBP/day, which is close to 7% increase in the average daily profits. Interestingly, volatility seems not to affect the storage cycles of smaller storages (1 and 4 MWh) in the UK. At the same time, volatility is the key driver of storage operation in the Nordic market.

Gas-coal spread has a strong positive effect on daily profits especially in Germany and partially in the UK, whereas it is insignificant in the Nordic market. This result is intuitive since the German electricity generation mix is a blend of baseload coal power plants and peaking gas power plants in which the relative fuel price dynamics highly impacts the marginal electricity prices and thus energy storage profits. Similar argument holds for the UK market, but the coal-fired power generation is a bit more limited as compared to the German market, so the overall effects of gas-coal spread on profits is not as persistent there. The intuition is that as gas gets more expensive relative to coal, the input costs for peaking technology increase so do also the peak prices during which energy storages discharge their stored energy. Conversely, when the gas-coal price spread decreases, this means that the baseload technology input costs (coal) is getting more expensive relative to gas, and the profits of energy storages decline because the charging costs increase. See Figure 8 and Figure 9 in Appendix for gas-coal price dynamics in EUR/MWh and GBP/MWh respectively.

Carbon emission prices (EUA) affect the storage profits negatively in the Nordic market but positively in Germany and the UK. The positive effect of carbon price on the profits may be caused by the already relatively large shares of vRES in the German and the UK power systems, which shift the traditional coal-fired baseload generation to the right on the merit-order curve. This means that the disproportionally stronger negative effect of carbon price on coal (high carbon intensity) relative to gas (lower carbon intensive) does not affect the off-peak prices (storage charging) so much while still increasing the peak-prices via the increased variable cost of gas-fired power plants. This allows energy storages to be "spared" from the impact of EUA on off-peak prices during charging while still benefiting from the higher peak-prices during discharging. This positive effect holds also for the number of storage cycles in Germany and the UK. In the Nordic electricity market, this does not seem to hold and increase in carbon price is associated with lower energy storage profits and cycles. This result underlines the differences between power system fundamentals that need to be considered prior to generalizing the findings to other markets.

Finally, we turn to the results of *vRES*. In Germany, *solar power generation* is persistently associated with a significantly negative effect on daily profits but significantly positive effect on the number of daily storage cycles. This interesting finding implies that despite the greater number of storage cycles associated with the growth of solar PV generation in Germany the operators of storages are able to capture lower profit margins. The increased frequency of energy storage cycles and reduced profits results from the fact that the typical mid-day peak demand coincides with the period when solar generation produces the most. This causes a downward pressure on the peak/off-peak spread which depresses profits but at the same time the PV generation creates two smaller mid-day peaks in residual demand which increases storage cycles. Unsurprisingly, solar PV generation does not affect either storage profits or cycles in the Nordic markets but it does positively affect both in the UK. This highlights the fundamental difference between the UK and the German markets, where the adoption of vRES in the UK did not result in as strong "merit order effect" as in Germany and the UK's price levels, peak/off-peak spreads and price volatility have preserved their dynamics.

Table 5 Overall effects (2006-2016) of fundamental variables on 1-13 MWh storages in Germany, UK and Nordic markets

		DE		UK		Nordic	
Storage	Effect	Profits	Cycles	Profits	Cycles	Profits	Cycles
1 MWh	Wind	+***	+***	-***	0	0	0
4 MWh		+***	+*	+***	-**	+*	+***
7 MWh		0	0	+***	-***	0	+***
10 MWh		0	0	+***	-***	0	0
13 MWh		0	-**	+***	-***	0	0
1 MWh	Solar	-***	+***	+***	+***	0	0
4 MWh		-***	+***	+***	+***	0	0
7 MWh		-***	+***	0	+***	0	0
10 MWh		-***	+***	0	+***	0	0
13 MWh		-***	+***	0	+***	0	0
1 MWh	Demand	0	-***	+*	0	+***	+***
4 MWh		+***	-***	+***	0	+***	+***
7 MWh		+***	-***	+***	0	+***	+***
10 MWh		+***	+***	+***	+***	+***	+***
13 MWh		+***	+***	+***	+***	+***	+***
1 MWh	Vola	+***	+***	+***	0	+***	+***
4 MWh		+***	0	+***	0	+***	+***
7 MWh		+***	+***	+***	+***	+***	+***
10 MWh		+***	+***	+***	+***	+***	+***
13 MWh		+***	+	+***	+***	+***	+***
1 MWh	Spread	+***	0	+***	-**	0	-***
4 MWh		+***	0	+***	0	0	-***
7 MWh		+***	0	+***	-**	0	-***
10 MWh		+***	0	0	-***	0	-***
13 MWh		+***	0	0	-***	0	-**
1 MWh	EUA	+***	+**	+***	+***	-***	-***
4 MWh		+***	+**	+***	+***	0	-***
7 MWh		+***	+*	+***	+**	-***	-***
10 MWh		+***	0	+***	0	-***	-***
13 MWh		+***	-**	0	-**	-***	-***

Note: + (-) indicates positive (negative) significant effect of a regressor on the dependent variable (profits or cycles) at the significance levels *p< 0.10, **p< 0.05, *** p<0.001; 0 indicates statistical insignificance (p>10%). The full model also includes seasons of the year (spring, summer, fall), yearly cycle, and two autoregressive terms (AR1 and AR7) but the effects are not displayed here.

Wind power generation drives positively profit margins of all energy storage sizes in the UK except the 1MWh (negative effect) and positively the smaller storages (1-4 MWh) in Germany. The positive effect of wind power generation is driven by its uncertainty and volatility which is reflected in spot price dynamics that creates a profit opportunity to energy storages. Wind power generation is mostly insignificant for energy storage profits and cycles in the Nordic electricity market, which is already dominated by flexible hydro generation. Wind power generation is associated with a positive effect on storage cycles of smaller storages 1-4MWh in Germany which implies that these need to cycle more frequently in order to capture the higher profits. Nonetheless, in the UK wind power generation affects the storage cycles negatively, while still being associated with increasing profits. This implies that wind generation in the UK creates high enough volatility that is sufficient to increase profits with less frequent operation of the storage device. Finally, the *seasonal* and *autoregressive* effects are relevant and significant factors of storage profitability and operation, but we do not focus here on their impacts and treat them as controls.

Another way to study the effects of fundamental variables on the profitability of energy storages is to plot the point estimates from our ARX models with their respective 95% confidence intervals. Here we also check whether the point estimates were significantly different between the periods prior to the rapid adoption of vRES and afterwards, defined by the year 2011. The sample splitting allows us to control for a possible structural change as well as it provides a robustness check for our model. Figure 4 plots the estimation results of the effects of fundamental variables on the profits of a sample 1MWh storage in Germany for three different time periods. Interestingly, for example the solar generation has an overall negative effect on profits which was even stronger in the pre-2011 period, however, this effect is opposite in the post-2011 period. This can be explained by the fact that in the pre-2011 period solar PV had the typical merit order effect on wholesale prices, but did not actually change the profile of residual demand. This has changed in the post-2011 period, when large share of PV generation coincides with typical mid-day peak, creating two smaller peaks, which can be captured by energy storages with positive effects on their profits.

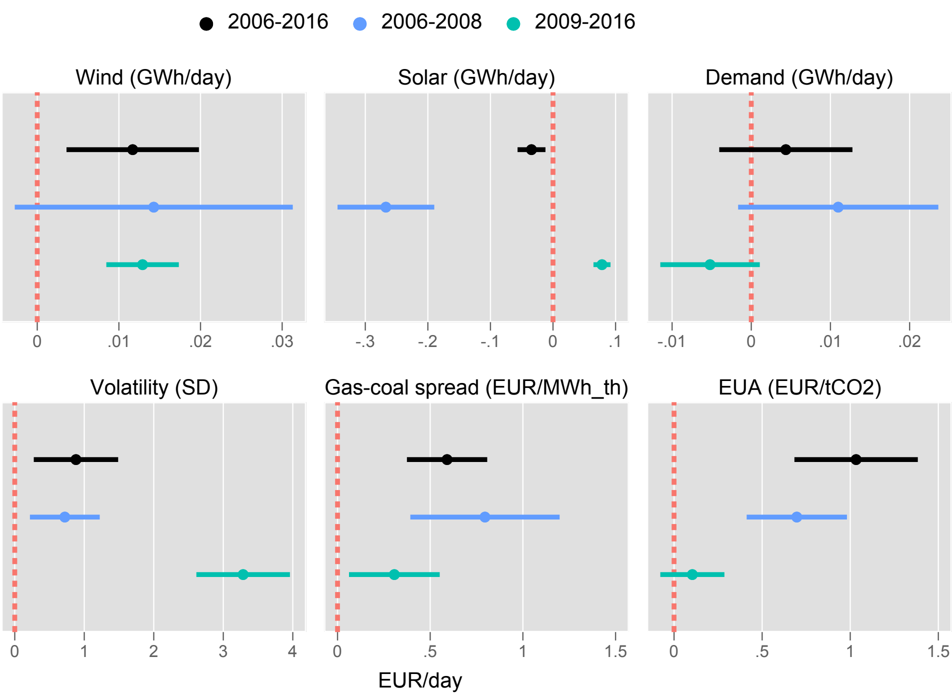

Figure 4 Point estimates and 95% confidence intervals for the profits of 1MWh storage in Germany

Note: To interpret the figure, use one unit change of the independent variable (units in brackets) and see the expected change in daily profits (EUR/day). The red reference line at zero shows which coefficients are significantly different from zero, i.e. these whose confidence intervals do not intersect the reference line.

Similarly, we can plot the expected mean cycles per day with respect to changes in the covariates of our fundamental variables. These plots effectively show the conditional expectations of number of cycles per day to marginal changes in the covariates. Figure 5 plots exactly this relationship using the estimation results of the Poisson regression for a sample 1 MWh energy storage in Germany. The 95% confidence intervals are the narrowest around the mean value of the fundamental variables and increasing when moving away from this value. For instance, if we increase both solar and wind generation by 200 GWh/day from their mean values, we could expect around 0.5 cycle/day more, holding everything else constant.

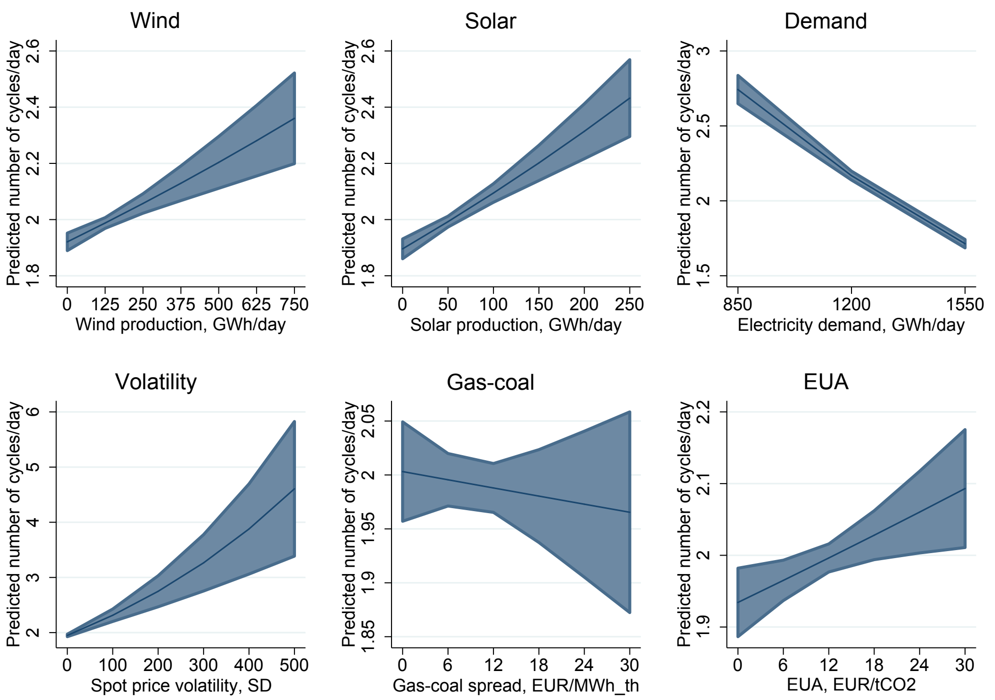

Figure 5 Marginal effects of fundamental variables on 1MWh storage cycles in Germany with 95% confidence intervals, 2006-2016

Finally, Figure 6 shows the predicted number of cycles per day for all storage sizes in Germany. The predictions are made at the mean values of the fundamental variables. We can see that the estimated number of cycles are very close to the observed cycles, which justifies the usage of Poisson regression and confirms a good model fit. This is in addition to the cross-validation of the model to the generalized Poisson regression which controls for the significant underdispersion, as showed in Table 12. To keep this work concise, we do not report all the results for all the countries and storage sizes, but include all the model results in Appendix.

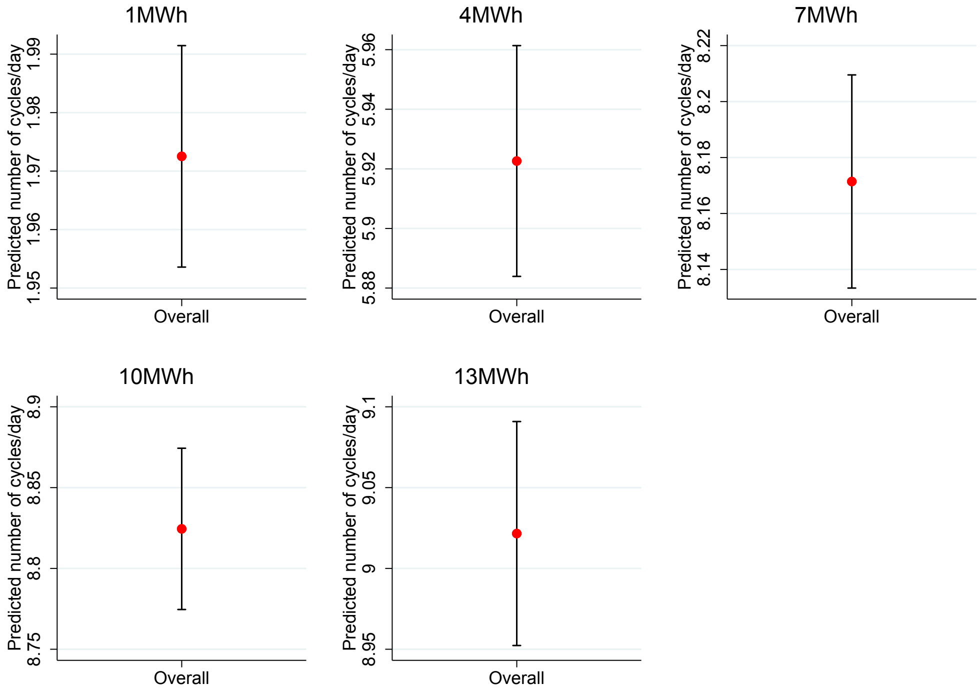

Figure 6 Predicted number of cycles per day for German 1-13MWh energy storages at the mean values of fundamental variables with 95% confidence intervals, 2006-2016

6 Conclusions

In this work, we have opened up the question of profitability of energy storages operating in the German, Nordic and UK electricity day-ahead markets during 2006-2016. We were particularly interested in energy storages as one source of flexibility and the value it can create. We have been able to avoid working with large number of techno-economic assumptions behind specific energy storages and instead focused on abstract but fundamentally relevant profit margins of generic energy storages with different capacity. The aim of our empirical work was to quantify ex-post the profitability and operation of generic storages and disentangle their main fundamental drivers.

We have empirically shown that the profits expressed as contribution margins have been declining over the studied period in Germany and the UK and exhibit high seasonality in the Nordics. Interestingly, the pronounced seasonal structure of profits and number of storage cycles in Germany has steadily disappeared after 2011, coinciding with the rapid adoption of vRES. Electricity spot price volatility and electricity demand are the main positive drivers of profits and storage cycles across the studied markets and storage sizes. Carbon emission price appears to positively affect storage profits in the markets with increasing share of vRES (Germany and the UK) but negatively in the hydro-dominated Nordic market.

We have found that wind generation is associated with increasing profits and number of cycles, which we argue is due to the innate nature of variability and lower predictability of wind production. Interestingly, we found that the solar power generation in Germany is associated with negative effect on daily profits but positive effect on the number of daily storage cycles. This finding implies that despite the greater number of storage cycles associated with the growth of solar PV generation in Germany the operators of storages gain lower profits. We have argued this is due to the coincidence of the typical mid-day peak demand with peak PV generation, which reduces the peak/off-peak spread (lower profits) but creates two smaller mid-day peaks in the residual demand (higher cycles). In the UK, the solar PV generation is associated with positive effect on profits and cycles, highlighting the different power market structure. During the studied period, with have found no effect of vRES on the profitability of operation of Nordic energy storages.

By conducting cross-country comparison over a relatively long time period, we have highlight the importance of controlling for market-specific conditions where the same fundamentals may have different effects. Nevertheless, future work could focus on better capturing the limited flexibility of power plants, such as their start & stop costs, which could provide further insights into the price setting mechanics and volatility, which all affect the profitability of energy storages and other flexibility providers.

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8 Appendix

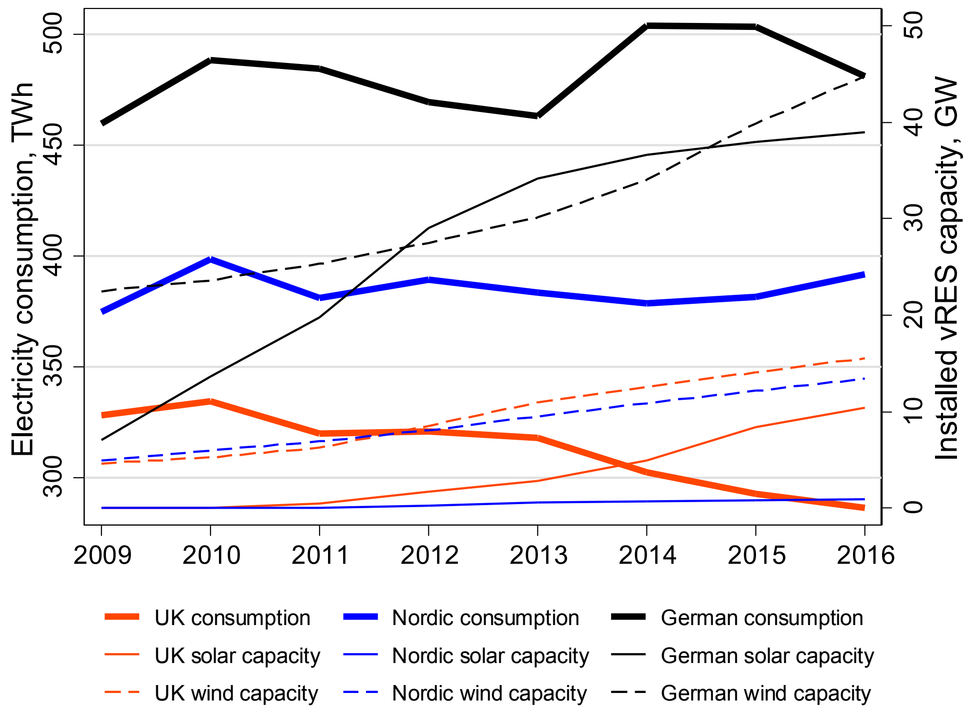

Figure 7 Electricity consumption and installed vRES capacity in Germany, UK and Nordic

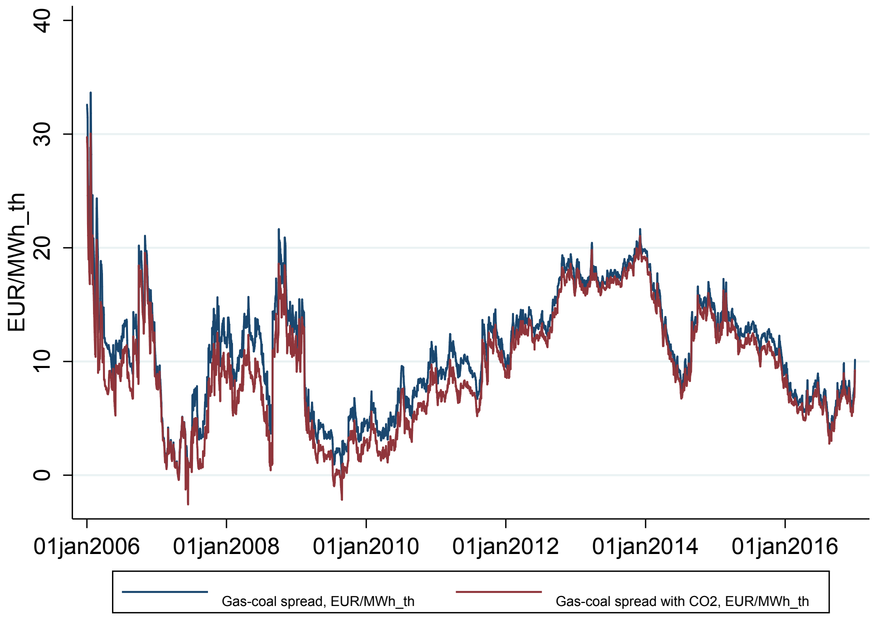

Figure 8 Gas coal spread in EUR/MWh thermal

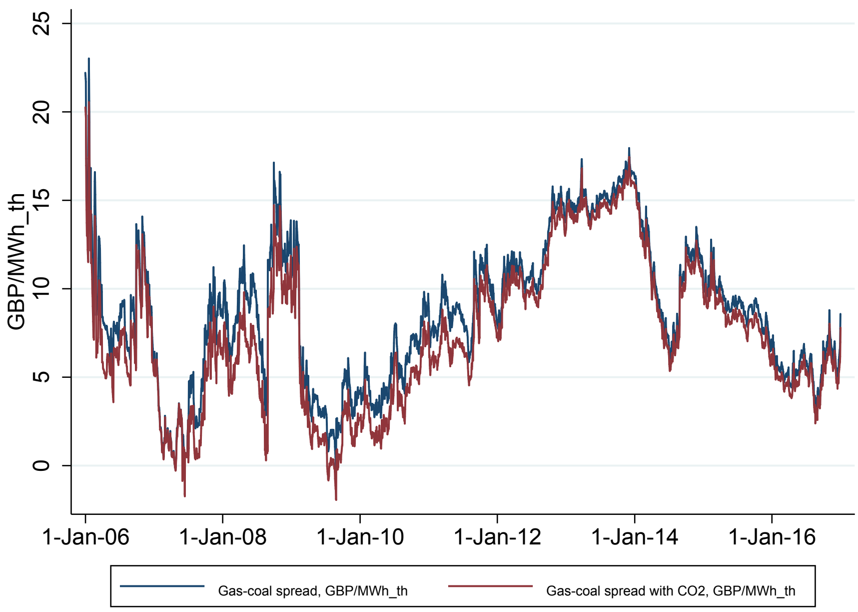

Figure 9 Gas coal spread in GBP/MWh thermal

Table 6 Results of the German profit model, 1-13 MWh (EUR), 2006-2016

Variables	1 MWh	4 MWh	7 MWh	10 MWh	13 MWh
Wind production(GWh)	0.0117***	0.0431***	0.0173	-0.003	-0.017
	(2.83)	(4.15)	(1.42)	(-0.26)	(-1.20)
Solar production (GWh)	-0.0344***	-0.0798**	-0.3659***	-0.4065***	-0.4131***
	(-3.02)	(-2.01)	(-8.03)	(-6.90)	(-6.62)
El. demand (GWh)	0.0044	0.0554***	0.1237***	0.1652***	0.2197***
	(1.02)	(4.71)	(6.29)	(11.93)	(14.26)
Spot price volatility (SD)	0.8809***	1.8012***	3.3458**	5.0702***	5.7245***
	(2.84)	(2.75)	(2.51)	(4.20)	(4.62)

Gas-coal spread (EUR/MWh_th)	0.5910***	1.7264***	3.0318***	2.9187***	2.8021***
	(5.35)	(5.25)	(7.20)	(6.53)	(5.84)
EUA carbon price (EUR/t)	1.0334***	3.1677***	3.5503***	2.8813***	2.4544***
	(5.78)	(8.15)	(5.53)	(5.25)	(4.24)
Spring	4.4446***	7.5228	-2.1515	-8.8495*	-10.8088*
	(2.66)	(1.57)	(-0.42)	(-1.86)	(-1.88)
Summer	3.9442*	8.1791	-2.121	-12.0208*	-15.1235*
	(1.76)	(1.29)	(-0.29)	(-1.82)	(-1.90)
Fall	4.8782***	13.470***	6.6448	-0.9179	-4.3545
	(2.99)	(2.87)	(1.38)	(-0.22)	(-0.87)
Yearly cycle (cosine wave)	4.7957***	4.2861	-14.626***	-22.9429***	-29.0911***
	(3.43)	(1.03)	(-3.35)	(-5.39)	(-5.89)
Constant	4.6075	-36.9797**	-100.34***	-147.820***	-213.996***
	(0.89)	(-2.55)	(-4.81)	(-10.34)	(-12.33)
AR(1)	0.1217*	0.2657***	-0.0104	-0.3759***	-0.4490***
	(1.71)	(4.99)	(-0.17)	(-8.41)	(-11.04)
AR(7)	0.1686***	0.2676***	0.0676	-0.2317***	-0.2448***
	(3.97)	(6.44)	(1.07)	(-5.78)	(-7.59)
Sigma Constant	20.2449***	46.0805***	77.1760***	112.7405***	141.1175***
	(23.70)	(24.02)	(18.93)	(17.70)	(22.40)
Akaike Information Criterion	35602.3691	42212.242	46355.7936	49401.9916	51206.3269
Bayesian Information Criterion	35690.5486	42300.422	46443.9731	49490.1712	51294.5065
Log Likelihood	-17787.185	-21092.121	-23163.897	-24686.9958	-25589.1635
N	4018	4018	4017	4018	4018

Table 7 Results of the German storage cycles model, 1-13 MWh, 2006-2016

Variables	1 MWh	4 MWh	7 MWh	10 MWh	13 MWh
Wind production(GWh)	0.0003***	0.0001*	0	0	-0.0001**
	(5.00)	(1.70)	(1.03)	(-0.82)	(-2.31)
Solar production (GWh)	0.0010***	0.0022***	0.0011***	0.0004***	0.0002*
	(6.84)	(22.16)	(15.07)	(4.31)	(1.92)
El. demand (GWh)	-0.0007***	-0.0004***	-0.0001***	0.0001***	0.0003***
	(-19.92)	(-16.43)	(-2.90)	(5.62)	(10.63)
Spot price volatility (SD)	0.0017***	0.0002	0.0004***	0.0009***	0.0011***
	(6.22)	(0.77)	(4.43)	(2.95)	(2.70)
Gas-coal spread (EUR/MWh_th)	-0.0006	-0.0004	-0.0003	0.0003	0.0002
	(-0.55)	(-0.55)	(-0.47)	(0.42)	(0.20)
EUA carbon price (EUR/t)	0.0026**	0.0013**	0.0008*	-0.0002	-0.0014*
	(2.54)	(2.13)	(1.92)	(-0.37)	(-1.95)
Spring	0.0600***	0.0844***	0.0493***	0.0218*	0.0125
	(3.05)	(5.78)	(4.57)	(1.75)	(0.76)
Summer	-0.0116	-0.0501**	-0.0295*	-0.0123	-0.0133
	(-0.40)	(-2.38)	(-1.92)	(-0.67)	(-0.55)
Fall	0.0301	0.0422***	0.0184**	0.0081	0.0032
	(1.64)	(3.49)	(2.22)	(0.82)	(0.23)
Yearly cycle (cosine wave)	0.1869***	0.1148***	0.0294***	0.0115	-0.006
	(10.83)	(9.83)	(3.50)	(1.14)	(-0.44)
Constant	1.4211***	2.1464***	2.0911***	1.9839***	1.7992***
	(28.64)	(61.99)	(77.78)	(62.58)	(42.92)
Akaike Information Criterion	11068.6657	15664.9585	16653.1227	17383.9994	18446.9475
Bayesian Information Criterion	11137.9496	15734.2425	16722.4066	17453.2833	18516.2314
Log Likelihood	-5523.3329	-7821.4793	-8315.5613	-8680.9997	-9212.4737
N	4018	4018	4018	4018	4018

Table 8 Results of the UK profit model, 1-13 MWh (GBP)

Variables	1 MWh	4 MWh	7 MWh	10 MWh	13 MWh
Wind production(GWh)	-0.0150***	0.0292**	0.0936***	0.1084***	0.1291***
	(-2.65)	(2.26)	(5.34)	(5.03)	(4.82)
Solar production (GWh)	0.2064***	0.2481***	0.0372	0.0621	0.1552*
	(9.59)	(4.52)	(0.62)	(0.89)	(1.79)
El. demand (GWh)	0.0032	0.0392***	0.0944***	0.1582***	0.2213***
	(0.58)	(2.72)	(6.58)	(10.16)	(11.99)
Spot price volatility (SD)	2.6392***	7.2592***	9.8167***	10.816***	11.3666***
	(16.57)	(15.67)	(22.26)	(26.66)	(28.71)
Gas-coal spread (GBP /MWh_th)	0.2375***	0.6855***	0.5724***	0.1922	-0.1033
	(2.95)	(3.26)	(2.77)	(0.84)	(-0.38)
EUA carbon price (EUR/t)	0.2242***	0.7580***	1.0035***	0.6535***	0.1803
	(2.82)	(3.59)	(4.60)	(2.92)	(0.73)
Spring	4.7200***	-0.066	-9.5896***	-13.437***	-14.327***
	(4.50)	(-0.03)	(-4.02)	(-4.22)	(-3.38)
Summer	4.9830***	0.5777	-7.7133**	-9.8930**	-10.8074*
	(3.98)	(0.22)	(-2.34)	(-2.26)	(-1.83)
Fall	6.9947***	8.1248***	0.7398	-0.858	0.3895
	(7.38)	(3.75)	(0.32)	(-0.30)	(0.11)
Yearly cycle (cosine wave)	8.3375***	-0.9978	-20.629***	-31.725***	-40.934***
	(9.56)	(-0.49)	(-8.76)	(-10.55)	(-10.43)
Constant	-4.0295	-33.538***	-82.993***	-136.87***	-191.97***
	(-0.81)	(-2.62)	(-6.26)	(-9.37)	(-11.00)
AR(1)	-0.1475***	-0.0986**	-0.3924***	-0.5539***	-0.5788***
	(-4.41)	(-2.53)	(-8.41)	(-18.33)	(-27.62)
AR(7)	0.0654*	0.0509	-0.1962***	-0.2499***	-0.2339***
	(1.79)	(0.97)	(-3.25)	(-7.71)	(-11.39)
Sigma Constant	14.6786***	32.8532***	54.6024***	78.808***	102.614***
	(16.16)	(11.14)	(16.61)	(29.40)	(45.06)
Akaike Information Criterion	33018.4524	39492.7584	43575.6783	46525.0162	48646.2302
Bayesian Information Criterion	33106.632	39580.938	43663.8579	46613.1958	48734.4098
Log Likelihood	-16495.2262	-19732.3792	-21773.8392	-23248.508	-24309.115
N	4018	4018	4018	4018	4018

Table 9 Results of the UK storage cycles model, 1-13 MWh, 2006-2016

Variables	1 MWh	4 MWh	7 MWh	10 MWh	13 MWh
Wind production(GWh)	-0.0001	-0.0002**	-0.0002***	-0.0003***	-0.0003***
	(-0.76)	(-2.43)	(-2.89)	(-3.87)	(-3.26)
Solar production (GWh)	0.0065***	0.0064***	0.0028***	0.0011***	0.0012***
	(13.30)	(18.45)	(10.39)	(3.15)	(3.02)
El. demand (GWh)	0	-0.0001	0	0.0001***	0.0003***
	(0.23)	(-1.62)	(0.89)	(2.93)	(5.11)
Spot price volatility (SD)	0.0005	0	0.0015***	0.0037***	0.0049***
	(0.88)	(-0.10)	(6.61)	(8.79)	(8.31)
Gas-coal spread (GBP/MWh_th)	-0.0030**	0.0013	-0.0012**	-0.0038***	-0.0047***
	(-2.19)	(1.40)	(-2.06)	(-4.69)	(-4.30)
EUA carbon price (EUR/t)	0.0037***	0.0026***	0.0008**	-0.0003	-0.0015**
	(3.93)	(4.13)	(2.06)	(-0.56)	(-1.98)
Spring	0.0414**	0.0949***	0.0269***	-0.0144	-0.0199
	(2.02)	(5.88)	(2.58)	(-1.09)	(-1.13)
Summer	-0.0973***	-0.0374*	-0.0249*	-0.0307	-0.0306
	(-3.14)	(-1.72)	(-1.79)	(-1.62)	(-1.19)
Fall	0.0608***	0.0721***	0.0238***	-0.004	0.0012
	(3.54)	(5.73)	(3.05)	(-0.37)	(0.08)
Yearly cycle (cosine wave)	0.0789***	0.1012***	0.0252***	0.0006	-0.0198
	(4.05)	(7.75)	(3.00)	(0.05)	(-1.25)

Constant	0.4910***	1.6407***	1.9492***	2.0120***	1.8900***
	(7.24)	(33.79)	(63.01)	(47.14)	(33.68)
Akaike Information Criterion	10611.4359	15147.49	16090.06	17175.9175	18205.84
Bayesian Information Criterion	10680.7198	15216.77	16159.35	17245.2014	18275.12
Log Likelihood	-5294.7179	-7562.74	-8034.03	-8576.9588	-9091.92
N	4018	4018	4018	4018	4018

Table 10 Results of the Nordic profit model, 1-13MWh (EUR), 2006-2016

Variables	1 MWh	4 MWh	7 MWh	10 MWh	13 MWh
Wind production(GWh)	-0.0021	0.0160*	0.0137	-0.0077	-0.0213
	(-0.72)	(1.71)	(0.88)	(-0.37)	(-0.81)
Solar production (GWh)	-0.0697	-0.446	-0.3411	0.0619	0.3691
	(-0.58)	(-1.17)	(-0.60)	(0.09)	(0.42)
El. demand (GWh)	0.0106***	0.0347***	0.0839***	0.1310***	0.1663***
	(4.26)	(4.85)	(8.38)	(10.52)	(10.98)
Spot price volatility (SD)	2.4251***	7.3927***	10.3571***	11.8255***	12.6286***
	(13.81)	(13.41)	(14.90)	(18.06)	(19.01)
Gas-coal spread (EUR/MWh_th)	-0.0039	-0.005	0.0142	0.0405	0.0428
	(-0.15)	(-0.07)	(0.13)	(0.29)	(0.25)
EUA carbon price (EUR/t)	-0.0569**	-0.0927	-0.2036**	-0.3712***	-0.5310***
	(-2.57)	(-1.38)	(-2.04)	(-2.87)	(-3.40)
Spring	-1.0237	-3.5374*	-6.6349**	-7.8743**	-8.2448**
	(-1.53)	(-1.86)	(-2.41)	(-2.31)	(-2.06)
Summer	-1.1746	-4.2960*	-5.3715	-5.1258	-3.582
	(-1.52)	(-1.95)	(-1.58)	(-1.14)	(-0.66)
Fall	-0.4557	-0.0025	3.1443	6.8760**	10.4286***
	(-0.97)	(-0.00)	(1.58)	(2.55)	(3.13)
Yearly cycle (cosine wave)	-3.1141***	-13.849***	-27.845***	-38.561***	-46.237***
	(-3.81)	(-5.63)	(-7.95)	(-9.09)	(-9.16)
Constant	-10.539***	-36.907***	-91.568***	-143.33***	-182.26***
	(-4.43)	(-5.50)	(-9.43)	(-11.18)	(-11.43)
AR(1)	-0.4599***	-0.5211***	-0.5676***	-0.5915***	-0.5900***
	(-13.96)	(-17.30)	(-25.24)	(-31.25)	(-32.48)
AR(7)	-0.0654**	-0.0815***	-0.1532***	-0.1767***	-0.1696***
	(-2.42)	(-3.52)	(-8.43)	(-12.10)	(-12.77)
Sigma Constant	10.9162***	33.7379***	55.4638***	75.1355***	91.6340***
	(31.09)	(29.84)	(38.54)	(50.38)	(53.72)
Akaike Information Criterion	30638.9248	39706.591	43701.6753	46141.2594	47736.4423
Bayesian Information Criterion	30727.1044	39794.7705	43789.8548	46229.439	47824.6218
Log Likelihood	-15305.4624	-19839.2955	-21836.8376	-23056.63	-23854.221
N	4018	4018	4018	4018	4018

Table 11 Results of the Nordic storage cycles model, 1-13 MWh, 2006-2016

Variables	1 MWh	4 MWh	7 MWh	10 MWh	13 MWh
Wind production(GWh)	-0.0003	0.0005***	0.0006***	0.0002	0
	(-1.39)	(2.87)	(3.24)	(0.95)	(0.10)
Solar production (GWh)	0.0022	-0.0069	-0.0068	0.0003	0.0044
	(0.29)	(-1.12)	(-0.98)	(0.04)	(0.43)
El. demand (GWh)	0.0003***	0.0005***	0.0008***	0.0011***	0.0013***
	(2.93)	(4.48)	(7.51)	(8.33)	(9.18)
Spot price volatility (SD)	0.0282***	0.0275***	0.0287***	0.0292***	0.0290***
	(7.62)	(7.70)	(7.33)	(6.97)	(6.70)
Gas-coal spread (GBP/MWh_th)	-0.0041***	-0.0037***	-0.0051***	-0.0046***	-0.0041**
	(-2.76)	(-2.78)	(-3.48)	(-2.68)	(-2.11)

EUA carbon price (EUR/t)	-0.0079***	-0.0102***	-0.0123***	-0.0127***	-0.0136***
	(-5.50)	(-8.19)	(-9.13)	(-8.32)	(-7.88)
Spring	-0.1080***	-0.1284***	-0.2188***	-0.2448***	-0.2535***
	(-2.84)	(-3.64)	(-5.79)	(-5.79)	(-5.52)
Summer	-0.1182**	-0.0614	-0.0616	-0.0591	-0.058
	(-2.57)	(-1.49)	(-1.36)	(-1.12)	(-0.98)
Fall	0.0332	0.0815***	0.1104***	0.1253***	0.1396***
	(1.32)	(3.47)	(4.02)	(3.85)	(3.80)
Yearly cycle (cosine wave)	-0.1742***	-0.2591***	-0.4102***	-0.4548***	-0.5062***
	(-4.80)	(-7.75)	(-10.82)	(-10.29)	(-10.25)
Constant	-0.2265*	0.8421***	0.8097***	0.6367***	0.4325***
	(-1.85)	(7.59)	(6.65)	(4.52)	(2.79)
Akaike Information Criterion	8745.2029	15129.4964	18435.8294	20287.3372	21813.1101
Bayesian Information Criterion	8814.4868	15198.7803	18505.1133	20356.6211	21882.394
Log Likelihood	-4361.6014	-7553.7482	-9206.9147	-10132.6686	-10895.5551
N	4018	4018	4018	4018	4018

Table 12 Robustness checks for storage cycles in Germany using generalized Poisson regression, 2006-2016

Variables	1 MWh	4MWh	10MWh	13MWh
Wind production(GWh)	0.0002***	0.0001**	0	-0.0001**
	(3.38)	(2.07)	(-0.10)	(-2.09)
Solar production (GWh)	-0.0005***	0.0021***	0.0004***	0.0002*
	(-3.25)	(21.23)	(5.45)	(1.91)
El. demand (GWh)	-0.0007***	-0.0004***	0.0001***	0.0003***
	(-16.15)	(-18.81)	(4.01)	(10.28)
Spot price volatility (SD)	0.0019***	0.0001	0.0010***	0.0012***
	(4.20)	(0.59)	(2.85)	(2.67)
Gas-coal spread (EUR/MWh_th)	0.0025*	-0.0001	0.0004	0.0002
	(1.85)	(-0.09)	(0.64)	(0.22)
EUA carbon price (EUR/t)	-0.0042***	0.0008	-0.0002	-0.0015**
	(-4.10)	(1.23)	(-0.38)	(-2.11)
Spring	0.0021	0.0762***	0.0236**	0.0104
	(0.08)	(5.66)	(2.00)	(0.63)
Summer	0.042	-0.0457**	-0.0107	-0.0129
	(1.10)	(-2.27)	(-0.61)	(-0.53)
Fall	-0.0272	0.0364***	0.008	0.0013
	(-1.25)	(3.09)	(0.86)	(0.10)
Yearly cycle (cosine wave)	0.1688***	0.1140***	0.0128	-0.0068
	(8.14)	(9.89)	(1.33)	(-0.50)
Constant	1.5598***	2.1964***	2.0286***	1.8157***
	(24.47)	(66.59)	(68.23)	(43.67)
Delta	-0.8628***	-1.5243***	-1.3358***	-0.3551***
	(-36.78)	(-13.27)	(-15.53)	(-24.79)
Akaike Information Criterion	8436.8399	13262.8869	15210.8804	17862.5796
Bayesian Information Criterion	8512.4223	13338.4693	15286.4628	17938.162
Log Likelihood	-4206.4199	-6619.4434	-7593.4402	-8919.2898
N	4018	4018	4018	4018

Note: Delta is the dispersion parameter, as defined in the section 0. The 7MWh storage cycle model had issues with convergence and is thus not reported here.

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