Energy Policy 164 (2022) 112872

Contents lists available at ScienceDirect

Energy Policy

journal homepage: www.elsevier.com/locate/enpol

Electricity storage and market power

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A R T I C L E I N F O

Keywords:
Electricity storage
Electricity market
Market power
Welfare
Consumer surplus

A B S T R A C T

Electricity storage is likely to be an important factor in balancing fluctuations in renewable generators' output, but concentrated ownership could lead to market power. We model this for short-term (daily) storage in the British electricity wholesale market, with generating companies acting as either price-takers or Cournot competitors. We discuss how competitive storage charging and discharging behaviour depends on the balance between the market price and shadow price of stored electricity. Electricity storage raises welfare, consumer surplus and renewable generators' revenues, while reducing revenues for conventional generators. Market power in storage slightly reduces the welfare gains; Cournot behaviour by generators reduces welfare but has relatively little impact on the incremental effect of storage. Market power in electricity storage is undesirable, but market power in generation is much worse. The interactions between market power in generation and in storage are complex, suggesting that predictions from one market may not apply elsewhere and context-specific modelling will be valuable.

1. Introduction

The large-scale adoption of wind and solar power is a common method of decarbonising the electricity industry but raises the challenge of dealing with variations in their output. One response is to add storage, taking in surplus electricity at times of relative abundance and releasing it when power is relatively scarce. When the prices are right, and the cost of storage is low enough, this can be socially efficient. However, electricity wholesale markets are well-known for the exercise of market power. Energy storage devices can also provide fast-acting reserves, balance short-term fluctuations in frequency and relax transmission and distribution. All these activities rely on close coordination with the network and system operators. Were those operators to argue that this coordination depended on co-ownership, the resulting concentration would enhance the potential market power of the storage operator.

This market power has already been modelled in several settings (Schill and Kemfert (2011); Sioshansi (2010, 2014)) but not in the context of the British electricity market, which now combines high levels of both wind and solar generation. Storage raises prices when it is charging and reduces them when it is discharging. The relative size of these effects depends on the efficiency of the storage units and the curvature of the generators' supply curve. Storage will be discharged when prices are high and charged when they are low; those prices depend on the amount of thermal generation, and hence on the level of demand less renewable output. The extent to which consumers are affected by these price changes depends on how storage operations are correlated with their gross demand (before subtracting wind and solar generation). Such correlations are system-specific, and so a study of the British system is needed to explain how the gains and losses from electricity storage would be distributed in this country.

We use a simulation model of the British electricity market, calibrated to "near-future" conditions. Electricity generators and storage operators can each be modelled as price-takers or as firms exploiting their market power, giving a 2×2 experimental design. The amount of storage power (GW) and energy (GWh) capacity also varies between scenarios within each design. We describe how charging and discharging by storage is related to the balance between the market price and the shadow price of stored energy, and how this shadow price only changes when storage energy capacity limits are binding.

We show that the use of electricity storage raises welfare, before taking account of its fixed costs, and market power on the part of the storage owners does not reduce these gains significantly. In our setting, overall consumer surplus increases with the amount of energy storage, whether that storage is a price-taker or exploits its market power, and whether or not generators are also raising prices above marginal costs. Market power exercised by storage owners reduces the gross gain from storage by up to 21% - the potential gain given up is greatest with large amounts of storage (in both energy and power capacity) in a market

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https://doi.org/10.1016/j.enpol.2022.112872
Received 11 May 2021; Received in revised form 2 February 2022; Accepted 21 February 2022
Available online 11 March 2022

where generators are bidding at marginal cost.

We also find that the use of energy storage raises the profits of wind and solar generators but reduces those of the conventional generators (in our model, these are mainly gas-fired plants). The loss to conventional generators is (approximately) similar in size to the gain to consumers, and between two and four and a half times greater than the gain to renewable firms.[1]

The next section of the paper reviews the relevant literature, before section 3 describes our model. Our data and optimisation algorithm are presented in section 4, along with a description of storage operation over a typical day and how this is linked to the shadow prices on stored energy and storage capacity. Section 5 presents our results, starting with how the use and profitability of storage varies with the scenario for market power. Subsection 5.2 shows its impact on price-duration curves, and subsection 5.3 reports the effects on welfare. We end with our conclusions and policy implications in section 6.

2. Literature review

Electricity storage in the form of reservoir-based hydro-electric generation has been used since the early days of the electricity industry. Rechargeable storage that does not depend on natural inflows is newer. Newbery (2018) pointed out that it is dominated by pumped storage hydro-electric stations, where water can be pumped uphill at times when power is cheap and held in a reservoir for later release when electricity (or the ability to generate it) is more valuable. The use of batteries for bulk electricity storage is a new phenomenon, held back initially by high costs, but those are now falling significantly – partly driven by, and partly driving, their rapid deployment (Schmidt et al., 2017).

Strbac et al. (2012) and Newbery (2018) both pointed out that electricity storage can fulfil multiple functions. Most of the economics literature (including this paper) concentrates on pure arbitrage, shifting electricity from cheap to higher-priced periods, but storage can also be used for balancing (offsetting short-term fluctuations in generation and load), to offset transmission constraints (moving power when the constraint is not binding) and to provide reserve.

The demand for electricity and the availability of (at least some) renewable generators vary on daily and seasonal timescales. This affects the choice of storage technology used to offset these fluctuations. When discussing the size of storage units, we must differentiate between their charging and discharging capacity (a flow of power, measured in MW), and their energy storage capacity (a stock of energy, measured in MWh). The cost per MWh of energy discharged is given by the annualised cost of energy storage capacity divided by the amount of energy discharged over the year. A 1 MWh store costing £500 per year would cost £5 per MWh stored if it discharged a total of 100 MWh over the year. This could also be expressed as £5 per (full) charge-discharge cycle. With a high cost per MWh of storage capacity, achieving a reasonable cost per MWh discharged from batteries depends on getting many cycles per year, using them to offset intra-daily fluctuations in net load. Power to gas technologies, in contrast, have a high cost per MW of charging and discharging capacity but a much lower cost per MWh of storage capacity. They would be relatively more efficient for seasonal storage.

Ambec and Crampes (2019) and Schmalensee (2019) showed in stylised models that energy storage investment and operation in a competitive market can be socially efficient. Schmalensee pointed out that this requires rational expectations and prices that reflect the true value of electricity (rising to the value of lost load at times of shortage); his model cannot exclude the possibility of an inefficient outcome as an alternative competitive equilibrium. Junge et al. (2021) used a more detailed model, including constraints on generators' ramping between periods, and also found that the welfare-maximising amount of storage exactly covers its costs in the competitive market equilibrium.

Electricity storage raises off-peak prices and reduces those at times of the peak demand on conventional generators (which in the future might be driven as much by the amount of renewable generation as by electricity demand). This creates gains and losses for consumers and generators; their size depends on how much prices respond to changes in conventional generators' output (which can vary between peak and off-peak times) and how much extra generation is needed to offset energy lost in charging and discharging. Michalski (2017) used a model calibrated for the German system and found that conventional generators and consumers can both lose from storage – consumers lose as the off-peak price increase is larger than the decrease at peak times, while the profits of storage units come at the expense of generators. Other simulations, such as Schill and Kemfert (2011), also calibrated for Germany, found that consumers gain. Sioshansi (2011) found that conventional generators and consumers both lose when energy storage is added to a simulation of the ERCOT system in Texas, but that wind generators gain.

Intuitively, these effects may depend on the curvature of the generators' supply curve. A typical convex curve might imply that price reductions per MWh from storage discharging at peak times were greater than price increases per MWh when storage recharges off-peak. This is offset by the imperfect efficiency of storage, which means more energy is used in charging than provided through discharging. The timing of storage use is also important. If discharging is mainly driven by high demand levels, prices will be reduced when this is of most benefit to consumers. Charging driven by high levels of renewable output rather than low levels of demand may be more costly for consumers, but also more beneficial for renewable generators.

Many papers consider the interaction of energy storage and market power, on the part of generators, storage owners or both. Crampes and Moreaux (2001) developed a theoretical model of thermal and hydro generation and showed that while it is welfare-maximising to equalise the marginal utility of consumption across all periods in which some water is used and the total amount available is binding, hydro owners exploiting market power would aim to equalise marginal revenue across periods. In an empirical study of the Bonneville Power Administration's potential for market power when selling to California, Bushnell (2003) assumed that it is not possible to spill water without generating, as this would be visible to regulators. This meant that a generator would sometimes have so much water that its marginal revenue would be negative and the generator would have to find the least unprofitable, rather than the most profitable, hours in which to discharge.

This is not a problem facing batteries and other types of rechargeable storage that choose how much to charge and can ensure that the marginal cost of doing so remains below the marginal revenue from discharging. Debia et al. (2019) provided a theoretical model of this kind of storage, integrated with renewable and thermal generation, and used it to explore the impact of a carbon tax. Ekholm and Virasjoki (2020) considered the role of storage interacting with purely renewable generation, with zero marginal cost but time-varying availability, and argued that generators curtailing the overall volume of electricity available may be a greater problem than intertemporal distortions brought about by storage operators.

Sioshansi (2014) used a stylised two-period model to show that storage would not reduce welfare if added to a competitive generation market but can do so if generators have market power. This negative effect would be reduced if the storage unit also exploited any market power it had. Andrés-Cerezo and Fabra (2020), modelling the Spanish market, found that generators are likely to over-invest in storage if they are allowed to vertically integrate with it, while stand-alone storage owners with market power would under-invest and withhold capacity compared to the efficient outcome. Siddiqui et al. (2019) used a stylised model to suggest that profit-maximising merchant storage investment

[1] We have not studied the other areas in which storage would compete with conventional generators (providing reserve and balancing services) or the potential savings in network constraint costs.

might be excessive if generators are competitive, but that a merchant would invest in less capacity than a welfare maximiser if the generation sector were relatively uncompetitive.

The attractiveness of operating electricity storage over different timescales depends on market arrangements (Giulietti et al., 2018). Waterson (2017) pointed out that daily price cycles in the British market are much stronger than seasonal cycles, and that even the seven-to ten-day price forecasts that might allow for profitable (and socially valuable) arbitrage over weekly timescales are not available. For this reason, we restrict our model to intra-daily arbitrage. We also take the amount of storage capacity as given, rather than calculating equilibrium investment levels.

Our first research question is how arbitrage by electricity storage would affect time- and demand-weighted prices, and price patterns, under the conditions of the British electricity market in the 2020s. Our second is how these changes affect consumers' welfare and generators' profits. Our third question is how these results would be affected by market power, in generation, storage or both. The discussion above shows that these are empirical questions – it is possible for these variables to rise or fall, depending on the correlations between demand, renewable output and the use of storage. With a set of empirical questions, we need a numerical model, which we now describe.

3. Model

We base our model on Ward et al.'s (2019) enhanced merit order stack. This replicates the price patterns produced by the lower marginal costs of part-loaded plants, and higher costs when plants must be started to meet short-lived demand peaks, but keeps the simplicity of linear variable costs. It divides each thermal generating unit into several tranches or segments, which are independently dispatched. For each generator, some segments are assigned a variable cost below the average cost for the unit as a whole; the costs for other segments are above it. For example, the first 29% of each unit's capacity has a segment variable cost 0.45 times the unit average; the last 17% are at 2.09 times the unit average. These numbers were derived in Ward et al. (2019) to give the best overall fit to prices and outputs over this period. This allows the model to replicate the pattern of prices seen in electricity wholesale markets more accurately than the merit order stack does. While not the focus of this paper, it also improves the model's estimate of fuel shares and carbon emissions in a system like the British one, with a mix of coal and gas-fired generation. If both types of plants are needed to meet the higher levels of daily demand, it is likely that both types will produce some output overnight, reducing the next morning's start-up costs. The enhanced merit order stack replicates this behaviour, but the standard stack will often turn off all the units burning the more expensive fuel.

Nuclear output is assumed to have the lowest marginal costs, not least because of the time needed to restart a nuclear plant after each shutdown. Wind and solar output are also treated as "almost must-run", given its very low variable costs. However, wind generators can be constrained off, with their blades turned out of the wind, if the system cannot absorb their output. Whether this is economically attractive for the generator depends on the details of any subsidies it receives. The latest UK government renewable support scheme (the Contracts for Differences) can stop payments to the generator if the wholesale price falls below zero, ensuring that wind can be backed off the system if renewable and nuclear output ever exceeds the level of demand without the price needing to become negative.[2]

Storage units are limited by their charging and discharging capacity (in MW) and their energy storage capacity (in MWh). They also lose energy while charging, and can self-discharge over time, although we are studying storage operating on a daily cycle that we assume is too short for significant self-discharge. We are only studying energy arbitrage; in practice, storage can obtain revenue from several other services, including balancing short-term fluctuations, providing reserve, easing transmission constraints and participating in capacity markets (Strbac et al., 2017).

The (time-varying) demand function is

$$D_h = A_h - bp_h \tag{1}$$

where D_h is the quantity demanded in period h, A_h is the time-varying demand intercept, p_h is the price in period h and b is the (constant) slope of the demand curve. With hour-long periods, a power flow of 1 GW for one period results in an energy demand of 1 GWh, and we measure all quantities (such as D_h and A_h) in GWh. Prices are in £/MWh, and we set $b = 0.1$ (in GWh per £/MWh). With a mean price (in our scenario of competitive generators without storage) of £40.05 and a mean demand of 38 GWh per hour, this gives an average elasticity of approximately -0.1, a low value typical of electricity markets. If this value is too low, it means that we will be over-estimating the potential for market power, in a context where the welfare costs we find are already relatively small. We measure demand at the transmission level, including transmission and distribution losses.

In our base case, all market participants act competitively, as price-takers, and we solve the model to maximise social welfare. We assume firms pay the correct price for their carbon emissions, and with neither unpriced externalities nor market power, explicit welfare maximisation will result in the same market outcomes as profit maximisation by individual price-taking firms. Welfare is given by the sum of gross consumer surplus (i.e., before payment for electricity) less the variable cost of generation, summed over all hours. The full problem for this case, with constraints and the associated dual variables, is:

$$\max_{D_h, q_{ish}, R_h, s^d_{jh}, s^c_{jh}, S_{jh}} W = \sum_h \left(\int_0^{D_h} \frac{A_h - \delta}{b} d\delta - \sum_i \sum_{s \in i} c_{is} q_{ish} \right) \tag{2}$$

Subject to:

$$D_h - R_h - \sum_j s^d_{jh} + \sum_j s^c_{jh} - \sum_i \sum_{s \in i} q_{ish} = 0 \quad \forall h \quad (\lambda_h) \tag{3}$$

$$S_{jh-1} - s^d_{jh} + \eta s^c_{jh} - S_{jh} = 0 \quad \forall j, h \quad (\mu_{jh}) \tag{4}$$

$$q_{ish} \le k_{is} \ \forall i, s, h \quad (\kappa_{ish}) \tag{5}$$

$$R_h \le V_h \quad \forall h \quad (\sigma_h) \tag{6}$$

$$s^c_{jh} \le k^c_j \quad \forall j, h \quad \left(\kappa^c_{jh}\right) \tag{7}$$

$$s^d_{jh} \le k^d_j \quad \forall j, h \quad \left(\kappa^d_{jh}\right) \tag{8}$$

$$S_{jh} \le k^s_j \quad \forall j, h \quad \left(\kappa^s_{jh}\right) \tag{9}$$

$$S_{j0} = S_{jH} \quad \forall j \quad (\mu_{0j}) \tag{10}$$

$$0 \le D_h, R_h \ \forall h;\ 0 \le S_{jh},\ s^c_{jh},\ s^d_{jh} \ \forall j, h;\ 0 \le q_{ish} \ \forall i, s, h \tag{11}$$

where W is welfare (over the year as a whole) and the integral measures gross consumer surplus in period h (the amount consumers are willing to pay for each unit of electricity, up to the amount consumed). The output from segment s owned by generator i in period h is q_{ish} and its variable cost per GWh is c_{is}. We are using i to index generation companies, and one company may own segments of more than one power station. W is thus equivalent to net consumer surplus (after payment for electricity)

[2] Previous support schemes allowed generators to be backed off the system, but the system operator was effectively required to pay the generators the per-unit subsidy that they were giving up by not generating, leading to negative prices and the occasional negative news story.

plus the producer surplus (profit before fixed costs) of generators and storage units.

In the constraint equations (3)–(11), R_h is the output from renewable generators (with zero variable cost) in period h, s^d_{jh} is the energy discharged by storage units owned by operator j and s^c_{jh} is the energy used in charging. The round-trip efficiency of storage is given by η. S_{jh} is the energy held in storage by operator j at the end of period h. k_{is} is the capacity of segment s of generator i and V_h is the maximum renewable generation available in period h (which depends on the installed capacity of wind and solar generators, and on the weather). k^c_j is the maximum charging capacity (GWh per hour) of energy storage owned by operator j, and k^d_j is the maximum discharge capacity. k^s_j is its energy storage capacity, in GWh.

Equation (3) is the energy balance constraint, requiring that in every period, the demand for electricity (plus storage charging) must equal generation plus storage discharging. Equation (4) is the storage balance constraint, for the amount of energy in storage (and available for future discharge) at the end of each period is equal to the amount in storage at the end of the previous period, less discharging, plus η of the energy used in charging (given our assumed round-trip efficiency). Equations (5) and (6) require that each segment of each generator is constrained to produce no more than its capacity and that wind and solar generators (considered collectively) are constrained to produce no more than their (time-varying) availability in each period. The storage operators must respect their charging, discharging and energy storage capacity limits, given in equations (7)–(9). Equation (10) ensures that the storage units end each day with the same stored energy that they had at its start. Equation (11) confirms that all variables must be non-negative. We do not include the need for reserve, or constraints on the transmission system; these are subjects for future research.

In two sets of simulations, we assume thermal generators have some market power and adopt a Cournot formulation with N symmetric generators. We set $N = 8$, which gives a value of the Herfindahl Index roughly equivalent to the state of the British market with its mix of larger and smaller generating companies. We assume that all renewable generators are either paid at fixed prices (which is effectively the case with the contracts for differences used for the more recent projects) or are owned by different companies from the thermal plants. This means that renewable output shifts the residual demand curve faced by thermal generators, but those generators do not take renewable revenues into account when maximising their profits. The profits before fixed costs, or producer surplus, of generator i (π_i) are therefore given by:

$$\pi_i = \sum_h \sum_{s\in i} (p_h - c_{is}) q_{ish} \tag{12}$$

The profits before fixed costs for storage operator j, represented by π^s_j, are equal to the market price times the energy discharged, less the market price times the energy used in charging:

$$\pi^s_j = \sum_h \left(s^d_{jh} p_h - s^c_{jh} p_h \right) \tag{13}$$

We have a four-scenario, 2 × 2 design, with and without the exploitation of market power by thermal generators and (separately) by the storage operators. In two sets of scenarios, storage acts as a price-taker when charging and discharging. In two other sets of scenarios, we assume that there are four storage operators, each attempting to maximise its profits, with no interests in generation. Each operator acts as a Cournot competitor, taking into account the slope of the demand curve while assuming constant quantities from generators and the other storage operators, whether charging or discharging. Despite assuming that the ownership of storage is twice as concentrated as generation, we will find that the effects of market power in short-term storage are much smaller than those of generators exploiting market power.

We follow (but adapt) Ekholm and Virasjoki (2020) in adding auxiliary terms to our objective function, so that it can produce first-order conditions which replicate those of generators or storage operators exploiting market power. We define β_g and β_s as the perceived (market-wide) inverse demand slopes for generators and the storage operators, respectively. If neither is attempting to exploit market power, $\beta_g = \beta_s = 0$, whereas if the generators are doing so, then $\beta_g = 1/b$, while $\beta_s = 1/b$ when the storage operators are using their market power. Our modified objective function is thus:

$$\max_{D_h, q_{ish}, R_h, s^d_{jh}, s^c_{jh}, S_{jh}} \sum_h \left(\int_0^{D_h} \frac{A_h - \delta}{b} d\delta - \sum_i \sum_{s\in i} c_{is} q_{ish} - \sum_i \frac{1}{2} \beta_g \left(\sum_{s\in i} q_{ish} \right)^2 - \sum_j \frac{1}{2} \beta_s \left(s^d_{jh} - s^c_{jh} \right)^2 \right) \tag{14}$$

subject to (3)–(11). Ekholm and Virasjoki (2020) assumed storage and generation were integrated and combined generation, charging and discharging in their auxiliary term; with separate generation and storage, we need to have separate terms. Appendix 1 gives the full Lagrangian equation for our optimisation and discusses the main first order conditions.

4. Data and optimisation

We initially calibrated our model to match conditions in 2014, which was a year of roughly average weather, compared to the last decade. Our demand originates from National Grid, which provides half-hourly demands at transmission system level. Day-ahead electricity prices were from Drax electric insights. We took fuel prices from the Office for National Statistics, and carbon prices from investing.com.

Our simulations are based on near-future conditions, with significantly more wind and solar generators. We assume 30 GW of wind and 18 GW of solar PV, up from 24 GW and 13 GW at the end of 2019. We took their load factors from the renewables.ninja website (Pfenninger and Staffell, 2016; Staffell and Pfenninger, 2016), again using 2014 weather conditions. We assumed that demand would be the same as in 2014; growth due to electrification being (approximately) offset by demand reductions due to deindustrialisation and greater energy efficiency.[3] Fossil capacity of 43 GW (mostly gas) is similar to its level at the end of 2019; renewable capacity makes only a limited contribution to security of supply. The price of gas, plus CO_2 permits and taxes[4] was £26/MWh of fuel. The efficiency of storage, η, was 0.9.

We ran our model in GAMS on standard PCs, using the CONOPT solver. A typical scenario took just over 3 min to run, modelling 183 separate days. A single day takes about 20 s, much of which is needed for data input and output.

Appendix 1 presents the Lagrangian for our optimisation and discusses the first-order conditions for each decision variable. To give an intuitive illustration of their implications, Fig. 1 shows the operation of price-taking storage in a competitive market for a typical day. The first hour of the 24-h cycle (h1, 00:00–01:00) is repeated at the right-hand end. Since generators act as price-takers, the market price is equal to marginal cost. Equations (A2) and (A3) show marginal cost equals λ_h, the shadow price on the energy balance constraint (3). In the absence of storage, those prices (the dotted line) would follow residual demand (after renewable generation). They are high in the morning and the evening, and relatively low overnight and in the early afternoon. This allows two cycles of storage use, with charging (shown by the solid

[3] While it is obviously important that our scenario is a plausible representation of the near future, the focus of this paper is on the impact of different amounts of electricity storage operated in different ways within a given future scenario, rather than on the prediction for the base-case scenario.

[4] While in the EU, generators in Great Britain had to pay a carbon tax (the Carbon Price Support) and buy permits for the EU Emissions Trading System; the EU ETS has been replaced with a UK-only carbon trading scheme.

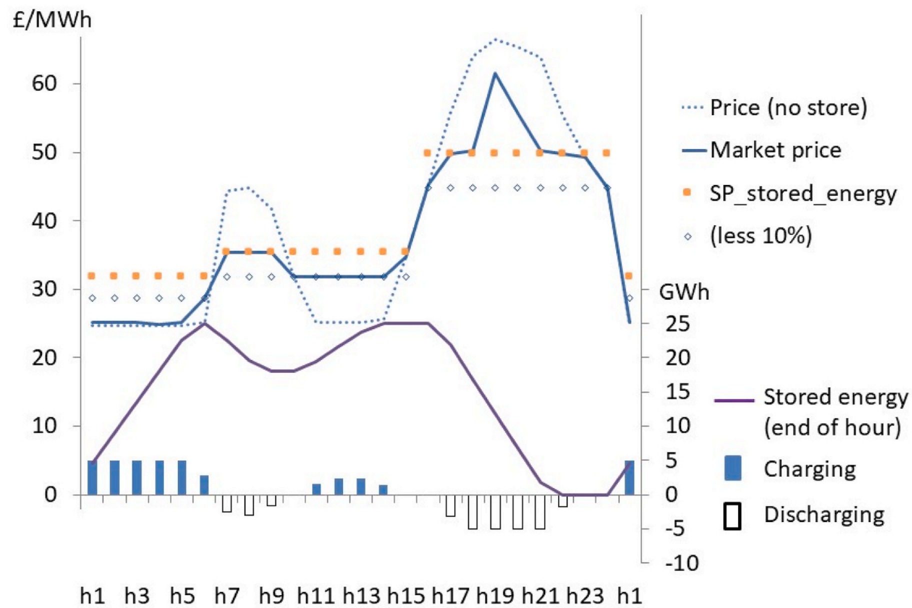

Fig. 1. Storage behaviour over a sample day.

columns) when prices are relatively low and discharging (hollow columns) when they are high. The resulting market prices, with less variation between peaks and troughs, are shown by the solid line. They still equal the marginal cost of thermal generation; the amount needed in most hours has changed.

The solid points show μ_{jh}, the shadow price for constraint (4), reflecting the value of stored energy. With symmetric firms, this takes the same value for all of them in each hour, as do the other shadow prices we discuss. This shadow price can only change while storage is either completely full or empty (A7) and (A8). The shadow price rises when storage is full, at the end of h6 (06:00) and h15 (15:00), and falls when it is empty at the end of the day. Førsund (2015) discusses this in the context of hydro-electric generators with storage. During periods of inflow, generators are willing to sell electricity at relatively low prices to ensure that their dams do not become over-full, while during the discharge seasons, a higher price reduces demand to ensure that they do not run out of water. The increase in the shadow price of stored energy equals the value of additional energy storage capacity, κ^s_{jh}, from constraint (9). It can also be related to the change in the market price between periods of charging and discharging (A9) and (A10).

Storage will not discharge if the shadow price of stored energy is less than the market price but may discharge if these prices are equal (A5), as is the case during h7-h9 (from 06:00 to 09:00). If the shadow price exceeds the market price, storage must discharge at its maximum discharge capacity, as happens for 4 h from h17 (from 16:00 to 20:00). The difference between the shadow price of stored energy and the market price equals the shadow price on discharging capacity (κ^d_{jh}), from constraint (8).

Unlike "natural inflow" hydro, our storage units must be charged. Because energy is lost in charging, spending λ_h to buy one unit of electricity will only add energy worth $\eta\mu_{jh}$ to the amount in storage. The hollow points show this scaled shadow price, 10% lower than μ_{jh} in our case, since $\eta = 0.9$. Charging behaviour is governed by the relationship between λ_h and $\eta\mu_{jh}$, given in equation (A6). As with discharging, charging cannot take place if the market price (λ_h) is greater than the efficiency-adjusted shadow price of stored energy ($\eta\mu_{jh}$) but may take place (at any rate) if they are equal. That happens in the middle of our sample day, for example. If the market price is less than the efficiency-adjusted shadow price of stored energy, as during the first 5 h of our sample day, charging must take place at the maximum rate. The difference between the two prices gives the value of additional charging capacity, κ^c_{jh}, from constraint (7). Once storage is empty, the shadow price of stored energy can fall, as it does at the end of the day. In general, (A7) shows that the fall between μ_{jh} and μ_{jh+1} equals φ^S_{jh}, the multiplier on the non-negativity constraint (11). In our case, storage becomes empty in the final period and equation (A8) applies instead.

5. Results

Our research questions are how electricity storage would affect the level and pattern of prices, what this would imply for consumers' and generators' welfare, and how these changes would be affected by market power, in generation, storage or both. Our results have already been previewed in Fig. 1. Storage reduces market prices when it is discharging, which happens when demand is high or renewable output low, but raises them when it is charging. Since some energy is lost in the process, total generation must rise slightly, although some of this may come from a reduction in the amount of renewable energy spilled.

We now discuss how much different amounts of storage capacity are used in our various scenarios and what this implies for storage profits. We then consider the effect on the pattern of prices over the year, and their average level. Third, we show how this affects consumer surplus, generators' producer surplus and the overall level of welfare, which was our second research question. We integrate material on the impact of market power (our third question) throughout this section, to aid comparisons between scenarios.

5.1. Storage operation and profitability

Table 1 shows how the output of storage (measured by TWh discharged over the year) varies with its capacity and the scenario for market power. In each case, the first word gives the level of competition

Table 1
Storage output (TWh per year).

	5 GW, 25 GWh	5 GW, 50 GWh	10 GW, 50 GWh
Competitive, price-taker	8.44	10.43	12.81
Competitive, market power	6.42	6.94	7.30
Oligopoly, price-taker	8.73	10.93	13.43
Oligopoly, market power	6.95	7.72	8.33

Table 2
Storage constraints.

	Power Capacity			Energy Capacity		
	5 GW, 25 GWh	5 GW, 50 GWh	10 GW, 50 GWh	5 GW, 25 GWh	5 GW, 50 GWh	10 GW, 50 GWh
Competitive, price-taker	11.6%	20.0%	2.3%	10.7%	49 GWh	3.0%
Competitive, market power	2.4%	5.1%	0.0%	3.9%	44 GWh	0.3%
Oligopoly, price-taker	13.6%	22.2%	2.8%	14.2%	0.0%	4.1%
Oligopoly, market power	3.5%	7.5%	0.1%	4.6%	47 GWh	0.5%

Percentages show the proportion of hours in which storage is constrained by power and or energy capacity (measured by charging/discharging at maximum rate, or store either full or empty on days during which it was energy-constrained). Figures in GWh give the maximum capacity used in the cases when storage was not energy-constrained.

between generators and the second pair relates to storage behaviour. Adding either power or energy capacity increases the amount of electricity stored and discharged, but doubling the size of the store does not double its usage. This is particularly noticeable for storage operated strategically, as most of the opportunities available to a storage operator with market power can be exploited with the smallest size we model.

Oligopoly behaviour on the part of generators raises the difference between peak and off-peak prices, and creates slightly more opportunities for profitable storage use, whether or not the storage operator is exploiting its own market power. Unsurprisingly, a storage operator exploiting market power runs much less than a price-taker.

Table 2 shows how often storage is constrained by its capacity, either to charge and discharge, or to hold more energy. Energy constraints are proxied by the number of hours in which the storage unit is either full or empty; in some of those periods, prices would not have made additional charging or discharging profitable, anyway. In a few cases, an energy storage capacity of 50 GWh is not binding, and the maximum capacity used is given instead. Adding storage power capacity naturally reduces the number of hours in which storage is power-constrained but raises the importance of energy constraints. Adding energy capacity has the opposite effect. A strategic operator almost never exhausts the capacity of 10 GW and 50 GWh of storage. This is in line with the data of Table 1, in which an increase in capacity brings about a much less than proportionate increase in discharging.

Table 3 confirms that the (collective) profits of price-taking storage operators fall as capacity is added, even before taking account of fixed costs. This is natural – the more storage is used, the smaller the gap between peak and off-peak prices, and hence the arbitrage profits. A storage operator exploiting its market power would make sure that adding capacity does not reduce its (own) profits, of course, but the corollary (seen above) is that additional capacity is not used very much and is unlikely to be an attractive investment. Even for the lowest capacities we study, the profits before fixed costs of Table 3 would be inadequate to cover the fixed cost of battery storage.[5] The additional revenue streams from balancing and reserve services would make a significant difference, however, and are an important topic for further research.

Table 3
Storage operators' profits before fixed costs (£m per year).

	5 GW, 25 GWh	5 GW, 50 GWh	10 GW, 50 GWh
Competitive, price-taker	105.7	99.1	62.6
Competitive, market power	123.3	128.0	134.2
Oligopoly, price-taker	139.2	130.7	82.2
Oligopoly, market power	161.2	167.5	174.7

5.2. The impact of storage on prices

To get an overview of how storage affects prices over the year as a whole, we use price-duration curves, in which the prices are ranked from highest to lowest over the year. Although the hour with (e.g.) the 500th-highest price in one scenario may well not have the 500th-highest price in a different scenario, in which the pattern of charging and discharging (and possibly generator behaviour) is different, these curves can still show the overall impact of storage on the market.

Fig. 2 presents results for the case in which the power system is a fully competitive market, with all participants acting as price-takers. The left-hand panel shows the whole year, while the right-hand panel repeats the highest-priced 10% of hours for more clarity. The solid black line shows the price-duration curve when there is no storage; the presence of storage reduces peak prices and raises off-peak prices, on average. 5 GW and 25 GWh of storage is enough to have a noticeable impact on the pattern of prices, shown with the dotted line. Adding either storage or charging capacity has little additional impact, except in some of the highest- and lowest-priced hours.

Fig. 3 shows the impact of storage exploiting market power when generators are competitive. The black line (no storage) is of course the same as in Fig. 2; there are two key differences in the lines for storage. The first is obvious within the figure – the price-duration curves with storage are very similar. Table 1 already showed that additional storage capacity beyond 5 GW or 25 GWh is hardly used when the operators exploit market power. The extra capacity would change prices in some hours, but the annual patterns are practically identical. The second difference requires a comparison of Figs. 2 and 3; since storage is used less when there is market power, the price-duration curves with storage are closer to the one without. Peak prices are reduced by less, and the lowest prices raised by less. The impact of storage when generators are exploiting market power is qualitatively similar and Appendix 2 has the price-duration curves for the two cases we consider.

Fig. 4 compares prices across the four market power scenarios, showing the largest storage capacity (10 GW, 50 GWh) to maximise the impact of differences in its behaviour. Generators exploiting market power raise the price-duration curve throughout its length. When storage takes the impact of its behaviour on market prices into account, the price-duration curve pivots slightly, giving higher peak prices and lower prices off-peak. The impact on time-weighted average prices is not obvious *a priori*, and while demand-weighted prices would fall if storage were mostly discharged at times of high demand, this might not be the case if variations in renewable output were both the main driver of storage behaviour and uncorrelated with demand.

Table 4 shows these average prices. The most noticeable feature is that prices are around 25% higher under oligopoly. The impact of storage on time-weighted average prices is small, and not monotonic in its capacity. Additional power and energy capacity allow storage to have greater price effects in many different hours, and in each hour, the effect depends on the price-sensitivity of demand and the other generators' supply at that time. The demand-weighted prices change more as storage expands (although the relationship is still not monotonic), showing that renewable output is less important than demand in driving its

[5] Schmidt et al. (2017) project costs of $280–400 per kWh of capacity for battery storage. At an exchange rate of $1.40 = £1, a lifetime of 13 years and an 8% cost of capital, the lower end of the range gives an annualised cost of £25/kWh of capacity. This is four times the annual profit before fixed cost of the lowest capacity we study in the case with generator and storage market power.

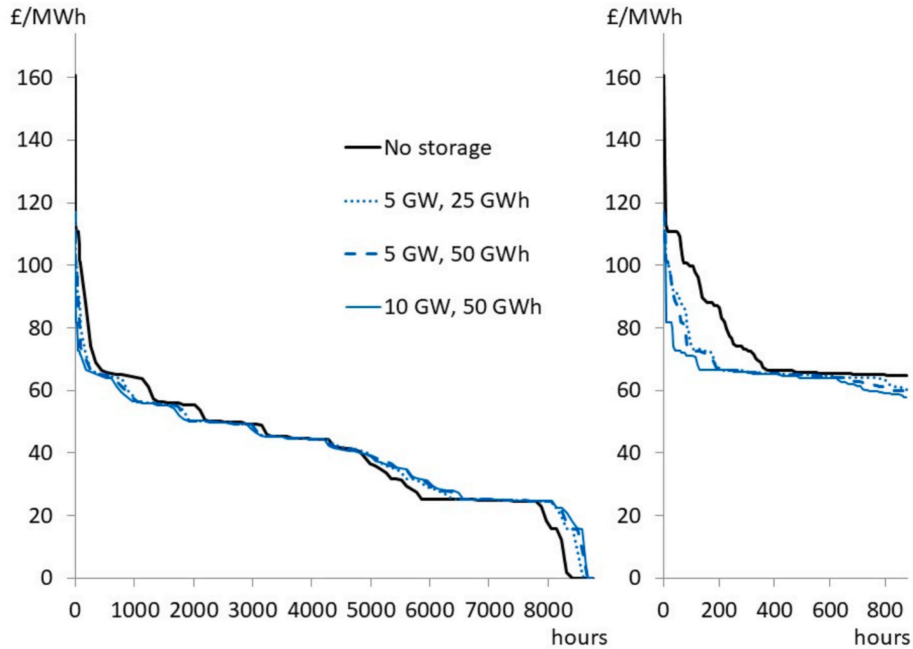

Fig. 2. Price-duration curves with competitive generators and price-taking storage.

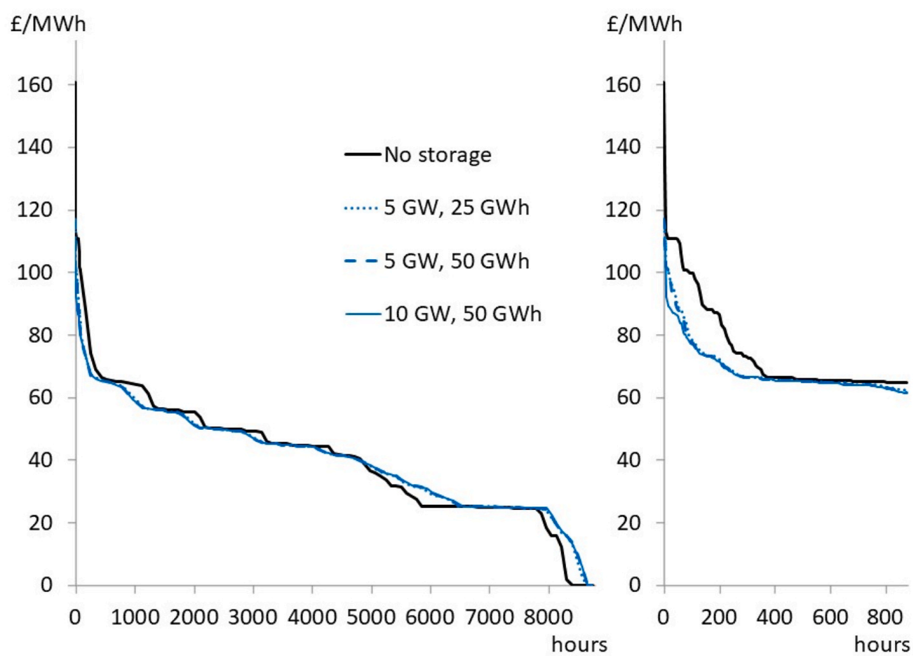

Fig. 3. Price-duration curves with competitive generators and storage using market power.

behaviour. When storage is a price-taker, its effects depend more on its charging/discharging capacity than on its energy capacity.

5.3. Consumer and generator welfare

We now consider our second research question, the impact of these changing prices on consumer surplus and generators' profits before fixed costs (producer surplus). Starting with the former, Table 5 shows that the use of energy storage raises consumer surplus. We provide all our surplus and profit estimates relative to the case of competitive behaviour by generators and no storage, thus avoiding the need to calculate generators' fixed costs or the shape of the upper part of the demand curve. To put the numbers in context, the turnover of the (wholesale) generation market is around £13 billion in this base case.

Electricity storage is clearly good for consumer surplus, even if storage operators are exploiting market power. Among the scenarios tested here, the power capacity has more impact than energy capacity on the gains, and the impact of the first 5 GW is greater than that of the

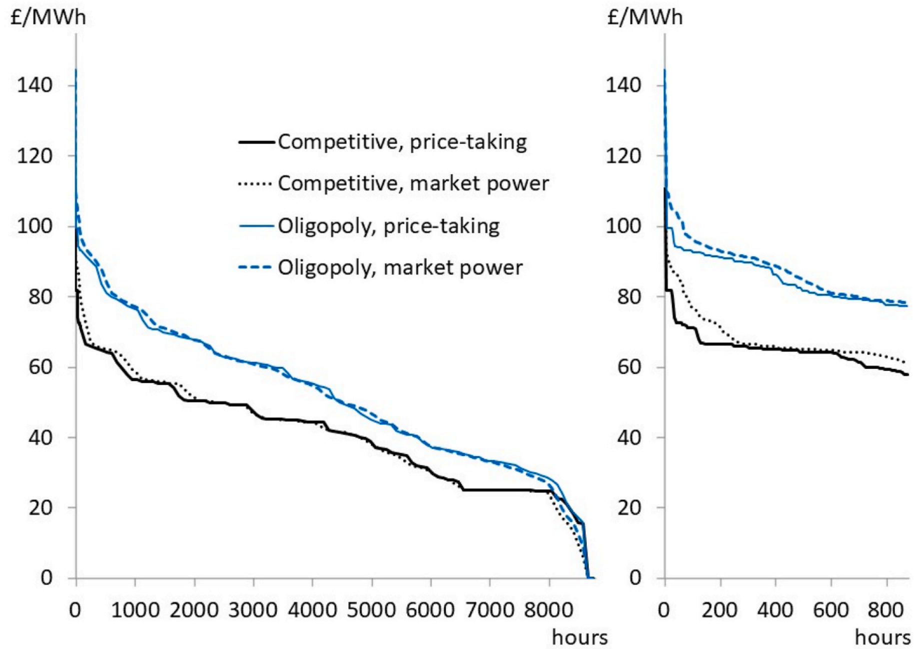

Fig. 4. Price duration curves for different market scenarios, with 10 GW and 50 GWh of storage.

Table 4
Average electricity prices.

£/MWh	time-weighted price				demand-weighted price			
	no storage	5 GW, 25 GWh	5 GW, 50 GWh	10 GW 50 GWh	no storage	5 GW, 25 GWh	5 GW, 50 GWh	10 GW 50 GWh
Competitive, price-taker	40.45	40.45	40.58	40.46	42.45	41.76	41.77	41.29
Competitive, market power		40.42	40.44	40.42		41.94	41.94	41.88
Oligopoly, price-taker	51.29	51.31	51.44	51.43	53.42	52.67	52.64	52.21
Oligopoly, market power		51.29	51.36	51.33		52.87	52.91	52.80

Table 5
Changes in consumer surplus (£m, annual).

Relative to base case:	No storage	5 GW, 25 GWh	5 GW, 50 GWh	10 GW, 50 GWh
Competitive, price-taker	Base case	210	218	339
Competitive, market power		164	169	187
Oligopoly, price-taker	- 2522	- 2282	- 2263	- 2148
Oligopoly, market power		- 2331	- 2330	- 2298
Relative to Oligopoly without storage				
Oligopoly, price-taker	–	240	259	374
Oligopoly, market power		191	192	224

Table 6
Change in generators' producer surplus (profits before fixed costs).

	No storage	5 GW, 25 GWh	5 GW, 50 GWh	10 GW, 50 GWh
Conventional Generators				
Competitive, price-taker	Base case	−192	−207	−272
Competitive, market power		−168	−179	−194
Oligopoly, price-taker	1365	1112	1085	1018
Oligopoly, market power		1132	1116	1085
Relative to Oligopoly without storage				
Oligopoly, price-taker	–	−253	−279	−347
Oligopoly, market power		−233	−249	−279
Renewable Generators				
Competitive, price-taker	–	58	92	115
Competitive, market power		47	60	65
Oligopoly, price-taker	1071	1129	1165	1209
Oligopoly, market power		1127	1150	1163
Relative to Oligopoly without storage				
Oligopoly, price-taker	–	58	94	138
Oligopoly, market power		56	80	92

second increment. The middle rows of the table show that an oligopoly in generation reduces consumer surplus by around £2.5 billion a year, compared to a competitive generation market. To isolate the effect of storage, the two bottom rows give its impact relative to the case of oligopoly generators without storage, which is slightly greater than with competitive generators. Gains to consumers of £164–374 million a year are noticeable, but only 1–3% of the wholesale market's turnover.

The upper part of Table 6 shows that storage reduces the profits of conventional generators (including nuclear stations), in the same way that it reduces demand-weighted average prices. At the same time, however, it raises those of variable renewable generators (wind and solar) (shown in the lower part of the table). Whenever their output is above-average, it is likely to have an above-average effect in reducing prices, driving the so-called value capture effect (Halttunen et al., 2020). While the profits of both groups of generators are much higher under oligopoly, the marginal impacts of storage (shown in the second and fourth blocks of the table) are reasonably close. The biggest difference is that while increasing the amount of storage (power or energy) capacity generally raises the profits of renewable generators by larger amounts, storage exploiting market power in a competitive generation market has an effect that becomes smaller as its capacity increases. It is worth noting that many renewable generators have long-term fixed-price contracts and so higher market prices for their output give a gain to the contract counterparties: where the contracts are part of the government's subsidy scheme, the ultimate counterparties are electricity consumers.

Changes in carbon emissions are also relevant, but small (less than 1 million tonnes of CO_2 a year). Emissions increase, because the impact of fewer renewable curtailments (by about 1 TWh a year) is more than offset by the increased gas generation needed to overcome the inefficiency penalty of the charging cycle. Generators' costs include the price of emissions permits and the UK carbon tax; increased emissions produce a gain to the UK government, of about £90 per tonne of CO_2 at the time of writing. Even if these revenues were identical to the cost of the additional emissions, there would be distributional impacts between countries and generations. It is unlikely that helping future taxpayers by paying down debt, or increasing foreign aid, would offset those impacts. We can simplify the social welfare function that we use if we are willing to neglect distributional impacts and assume that the UK carbon prices are at the right level, following the principle that a properly taxed externality is internalised. Since the changes in emissions are small, those assumptions would have to be very wrong for them to have a large impact on overall welfare.

Table 7 shows the overall impact of the changes in consumer surplus, generator surplus and storage earnings (before fixed costs). When generation is competitive and storage is price-taking, 5 GW and 25 GWh of storage raises welfare by around £180 million. More capacity increases the gain (before taking account of its cost); power capacity matters more than energy capacity. Storage exploiting market power produces a smaller gain which grows less with the amount of capacity; the gross welfare gain from the largest size of storage is reduced by one-fifth.

Rows 3 and 4 show the welfare impact of oligopoly generators and different levels of storage, relative to the base case of competitive storage and no storage. To see the impact of moving from competitive to oligopoly generators across the scenarios, consider rows 7 and 8, which give a cost of between £68 million and £87 million. (Row 7 is equal to row 3 minus row 1.) The cost of a generation oligopoly is slightly smaller when storage is also exploiting market power.

The impact of storage with a generation oligopoly is shown in rows 5 and 6, which give figures relative to the case of an oligopoly without storage (so £87 million is added to all the figures in rows 3 and 4). The gross gains from price-taking storage are very similar to those with competitive generators, and the gains from storage that exploits market power (compared to no storage) are slightly greater. This implies that the loss from storage exploiting market power is slightly smaller when generation is an oligopoly. That loss is shown directly in rows 9 and 10 (row 9 subtracts row 2 from row 1). Peak prices rise more than off-peak prices with a generation oligopoly, creating a stronger incentive to use storage than with competitive generators. Capacity constraints have a greater impact on the ability of the price-taking storage operator to respond to this than for storage exploiting market power, and this may explain the difference between the two rows. Comparing rows 1 and 5 with rows 9 and 10, a storage operator that exploits its market power reduces the gross welfare gains from having storage by up to one-fifth.

Table 7
Annual changes in welfare (£m).

	No storage	5 GW, 25 GWh	5 GW, 50 GWh	10 GW, 50 GWh
Competitive, price-taker (1)	Base case	181	201	243
Competitive, market power (2)		167	178	192
Oligopoly, price-taker (3)	- 87	98	118	161
Oligopoly, market power (4)		89	103	125
The impact of storage relative to oligopoly without storage:				
Price-taking storage (5)	–	185	204	247
Storage with market power (6)		176	190	211
The impact of oligopoly relative to competitive generation				
Price-taking storage (7)	- 87	- 83	- 83	- 83
Storage with market power (8)		- 78	- 74	- 68
The impact of storage with market power relative to price-taking storage:				
Competitive generators (9)		- 14	- 23	- 52
Oligopoly generators (10)		- 9	- 15	- 36

Rows 5 and 6 give the values in rows 3 and 4, relative to that in the left-hand cell of row 3. Rows 7 and 8 compare rows 1 and 3, and 2 and 4, respectively. Row 9 compares rows 1 and 2, and row 10 compares rows 3 and 4.

6. Conclusions and policy implications

In the conditions of the near-future British electricity market, large-scale use of short-term electricity storage would reduce demand-weighted prices while having very little impact on time-weighted prices (our first research question). This arbitrage would be good for consumers and renewable generators, but would reduce revenues for conventional generators. We needed a calibrated model to answer this second research question, since the effects on each group depend on the correlation between storage use and its own output or consumption. As is often the case, the transfers between groups are much larger than the overall change in welfare, but the overall effect of arbitrage by storage is positive in every case we study. These effects are reduced if storage operators exploit their market power (our third question), but the balance remains positive. We do not study the other services that storage can provide, such as reserve and short-term balancing, or the costs of providing it.

When there are welfare gains overall, the government, regulators and the electricity industry should take steps to encourage large-scale storage deployment. One key question concerns licensing, and whether network operators should be allowed to own storage to get more benefits from the reserve and frequency response services that storage can provide. This might improve coordination, but since networks are a natural monopoly, integrating networks and storage could be a source of market power. We model an extreme case of this so as to provide an upper limit on its likely costs in practice.

Market power in electricity storage would be undesirable, but its costs in the British context would be significantly less than those of market power in generation. In line with Ekholm and Virasjoki (2020), we therefore suggest that regulators should primarily concentrate on keeping generation competitive.

A market with electricity storage would have higher consumer and producer surplus (before fixed costs) than one without, whether that storage is operated to maximise welfare or the owner's profits, and whether or not generators are attempting to exploit their own market power. The gross benefits of storage range from £181 million a year to £247 million a year if operated as a price-taker. The cost of market power in storage is between £9 million a year and £52 million a year. In the context of a wholesale market with turnover of £13 billion a year, those numbers are small, although it is worth remembering that this is true of many estimates of the short-term cost of market power, dating right back to Harberger (1954). The interactions between market power in generation and in storage are complex, suggesting that predictions from one market may not apply elsewhere and context-specific modelling will be valuable.

The transfers between generators are greater than the net benefits of storage – conventional generators lose and renewable generators gain from storage, which helps offset the fall in the relative value of renewable output as its share increases (Hirth, 2013). We do not consider the impact of transmission constraints, which could increase the amount of renewable generation that has to be constrained-off. Under the current market rules, generators are fully compensated for the lost output; using storage to absorb this generation would thus help the transmission system operator (and the customers who ultimately pay the cost of running the system) rather than the generators. If the market rules changed so that generators were no longer compensated (which would increase the incentive to avoid transmission-constrained areas), then their gains from storage would increase. However, this would require the storage unit to be located relatively close to the generator (on the same side of the transmission constraint) and might suggest co-ownership. Whether combining (some) generation and storage would worsen the effect of market power is a topic for further research. The effects of storage on balancing and reserve, and the impact of market power on these, are another important area for future study.

We have modelled the British electricity market while storage is useful, but not essential, in accommodating large amounts of variable renewable generation. If the share of wind and solar power continues to rise, then electricity storage and other means of coping with variable supplies will become essential in balancing the system. The amount of stored energy required to deal with week-long periods of low wind speeds, or the 3:1 imbalance between summer and winter production of solar power, would be much greater than that studied here. However, the argument for integrating long-duration storage with networks is weaker than for short-duration batteries, as the fast response times of the latter allow them to offer a wider range of ancillary services. Given the larger volumes, the cost of market power would be greater with long-duration than with short-duration storage. The government should therefore encourage the entry of competing providers as this market develops. The cost of market power in short-duration storage in the scenarios modelled here is small, but past experience shows that it is better to prevent market power emerging in electricity wholesale markets than to deal with its effects once it has become disruptive.

CRediT authorship contribution statement

Olayinka Williams: Conceptualization, modelling and writing up the results of this study. **Richard Green:** Conceptualization, modelling and writing up the results of this study.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

Acknowledgements

Funding from the Engineering and Physical Science Research Council, under Grand Challenge grant EP/K002252/1 Energy *Storage for Low-Carbon Grids*, is gratefully acknowledged.

Appendix 1. Mathematical derivation of the results in section 4

We can write the constrained optimisation problem in this paper as a Lagrangian equation, directly incorporating all the constraints (3)–(11) alongside the function to be maximised (14):

$$\Lambda = \sum_h \left(\int_0^{D_h} \frac{A_h - \delta}{b} d\delta - \sum_i \sum_{s \in i} c_{is} q_{ish} - \sum_i \frac{1}{2} \beta_g \left(\sum_{s \in i} q_{ish} \right)^2 - \frac{1}{2} \beta_s \sum_j \left(s_{jh}^d - s_{jh}^c \right)^2 + \lambda_h \left(\sum_i \sum_{s \in i} q_{ish} + R_h + \sum_j s_{jh}^d - D_h - \sum_j s_{jh}^c \right) + \sum_i \sum_{s \in i} \kappa_{ish} (k_{ish} - q_{ish}) \right.$$
$$\left. + \sigma_h (V_h - R_h) + \sum_j \kappa_{jh}^c \left(k^c - s_{jh}^c \right) + \sum_j \kappa_{jh}^d \left(k^d - s_{jh}^d \right) + \sum_j \kappa_{jh}^s \left(k^s - S_{jh} \right) + \varphi_h^D D_h + \varphi_h^R R_h + \sum_i \sum_s \varphi_{ish} q_{ish} + \sum_j \varphi_{jh}^c s_{jh}^c + \sum_j \varphi_{jh}^d s_{jh}^d + \sum_j \varphi_{jh}^S S_{jh} \right)$$
$$+ \sum_j \mu_{j1} \left(S_{jH} - s_{j1}^d + \eta s_{j1}^c - S_{j1} \right) + \sum_j \sum_{h=2}^{H} \mu_{jh} \left(S_{jh-1} - s_{jh}^d + \eta s_{jh}^c - S_{jh} \right) \quad \text{(A1)}$$

The notation is the same as in the main body of the paper, with the addition of φ_h^D, φ_h^R, φ_{ish}, φ_{jh}^c, φ_{jh}^d and φ_{jh}^S for the multipliers on the constraints that demand, renewable generation, conventional generation, charging, discharging and the amount of stored energy are non-negative. We are following Junge et al. (2021), except that we insert S_{jH} directly into the constraint for the change in stored energy during period 1. We can interpret the derivatives with respect to decision variables as follows:

$$\frac{\partial \Lambda}{\partial D_h} = \frac{A_h - D_h}{b} - \lambda_h + \varphi_h^D \quad \forall h \quad \text{(A2)}$$

The first term in (A2) gives the market price in terms of the level of demand. If that demand is positive, that price (and the consumers' marginal willingness to pay) is equal to λ_h, the shadow price on the constraint that demand plus charging must equal generation plus discharging. The final term, the shadow price on the constraint that demand must be positive, is unlikely to be binding.

$$\frac{\partial \Lambda}{\partial q_{ish}} = \lambda_h - \beta_g \sum_{s' \in i} q_{is'h} - c_{is} - \kappa_{ish} + \varphi_{ish} \quad \forall h,\ i,\ s \quad \text{(A3)}$$

The first pair of terms in (A3) gives the marginal revenue perceived by generators. If they are competitive and β_g is zero, marginal revenue equals the market price, λ_h; otherwise it is reduced to take account of the impact of additional output on existing sales by all of the segments owned by firm i, and oligopoly generators perceive a marginal revenue below the market price. In either case, marginal revenue equals the marginal cost (c_{is}) of any generator producing some output but at less than full capacity. Generators with lower marginal costs should produce at full capacity, and κ_{ish} shows how much additional capacity would be worth. The amount that marginal revenue would have to rise before a non-operating generator was turned on is given by φ_{ish}.

$$\frac{\partial \Lambda}{\partial R_h} = \lambda_h - \sigma_h + \varphi_h^R \quad \forall h \tag{A4}$$

Renewable generators should produce at full availability if the market price is positive, given the assumption that their marginal costs are zero. While the available output may equal zero, it is unlikely that the constraint that output must be non-negative would ever bind.

$$\frac{\partial \Lambda}{\partial s_{jh}^d} = \lambda_h - \beta_s\left(s_{jh}^d - s_{jh}^c\right) - \mu_{jh} - \kappa_{jh}^d + \varphi_{jh}^d \quad \forall j,h \tag{A5}$$

Each storage operator decides discharging by comparing its marginal revenue (the first two terms of (A5)) with its shadow price of stored energy, μ_{jh}. It is suboptimal to waste energy by simultaneously charging and discharging, and so whenever discharging is taking place, the term in brackets is simply equal to s_{jh}^d. If marginal revenue exceeds the shadow price of stored energy, the full discharging capacity should be used, and κ_{jh}^d is the value of having a greater capacity. No discharging should take place when marginal revenue is less than the value of stored energy, and $\varphi_{jh}^d + \beta_s s_{jh}^c$ shows how much the price would have to rise before discharging was optimal. If the storage operator is not exerting market power, $\beta_s = 0$ and the marginal revenue equals the market price.

$$\frac{\partial \Lambda}{\partial s_{jh}^c} = \eta\mu_{jh} - \lambda_h - \beta_s\left(s_{jh}^c - s_{jh}^d\right) - \kappa_{jh}^c + \varphi_{jh}^c \quad \forall j,h \tag{A6}$$

Charging decisions are governed by (A6). Storage operators take the efficiency of charging into account when comparing their marginal payment for additional energy (the second and third terms) with the shadow price of the additional energy stored, $\eta\mu_{jh}$. If the marginal payment is less than this, κ_{jh}^c is the value of additional charging capacity. $\varphi_{jh}^c + \beta_s s_{jh}^d$ is the amount by which a high price would have to fall for charging to become optimal.

$$\frac{\partial \Lambda}{\partial S_{jh}} = \mu_{jh+1} - \mu_{jh} - \kappa_{jh}^S + \varphi_{jh}^S \, for \; h = 1 \ldots H-1 \; \forall j \tag{A7}$$

Equation (A7) shows that the shadow price of stored energy cannot change from period to period unless storage is either full or empty. If storage is full, the shadow price of stored energy will rise by κ_{jh}^S, the shadow price of having additional capacity to store energy. If storage is empty, the shadow price of stored energy falls by φ_{jh}^S.

$$\frac{\partial \Lambda}{\partial S_{jH}} = \mu_{j1} - \mu_{jH} - \kappa_{jH}^S + \varphi_{jH}^S \; \forall j \tag{A8}$$

Equation (A8) has the same interpretation as equation (A7), linking the shadow prices of energy stored at the end and at the start of our operating period, since we require storage to hold the same amount of energy at the end of period H as at the start of period 1. Over the entire cycle from the start period 1 to the end of period H, since the shadow price of stored energy returns to its starting value, the sum of κ_{jh}^S equals the sum of φ_{jh}^S.

We can also relate changes in the shadow price of stored energy to changes in the market price (or the marginal revenue from discharging, in the case in which a storage operator is exploiting market power). Consider an interval during which storage moves from empty to full, at the end of which the shadow price of stored energy will rise. If this interval contains a period, c, in which there was some charging but neither the charging nor the stored energy capacity limit was binding, we know that $\eta\mu_{jc} = \lambda_c$, or $\mu_{jc} = \lambda_c/\eta$. If, before storage becomes empty again, there is a period, d, in which there is discharging with neither the discharging capacity nor the zero stored energy limit binding, we have $\mu_{jd} = \lambda_d$. This gives us an exact expression for the change in the shadow price of stored energy while storage is full:

$$\mu_{jd} - \mu_{jc} = \lambda_d - \lambda_c/\eta \tag{A9}$$

If no capacity constraints are binding during (some) charging and discharging, the increase in the shadow price of stored energy is equal to the difference between the price at which it will be discharged and the efficiency-adjusted price of charging. It is possible that storage only charged (or discharged) at its full charging (or discharging) limit or became full (empty) in the only period in which these limits were not binding. In this case, use hc as the highest-price period in which storage was charged, and ld as the lowest-price period in which it was discharged. We now have $\mu_{jhc} \geq \lambda_{hc}/\eta$ and $\mu_{jld} \leq \lambda_{ld}$. This gives us $(\mu_{jhc} - \lambda_{hc}/\eta) \geq 0 \geq (\mu_{jld} - \lambda_{ld})$ or:

$$\mu_{jld} - \mu_{jhc} \leq \lambda_{ld} - \lambda_{hc}/\eta \tag{A10}$$

If one or more capacity constraints binds whenever charging or discharging takes place, the difference between the lowest price during discharging and the highest efficiency-adjusted price during charging becomes the upper bound on the increase in the shadow price of stored energy while storage is full. The same logic and expressions apply to the reduction in the shadow price of stored energy while storage is empty. This derivation applies to the cumulative difference between periods in which charging and discharging actually take place, which need not be adjacent. Junge et al. (2021, Appendix A) derive upper bounds for the change in the shadow price of stored energy between adjacent periods when storage is full, for each possible combination of charging, discharging or doing neither.

Appendix 2. Price-duration curves

Figure A1 shows the situation when generators are exploiting market power and storage acts as a price-taker. The impact of storage is qualitatively similar when generators are price-takers, but the price-duration curves are at a higher level.

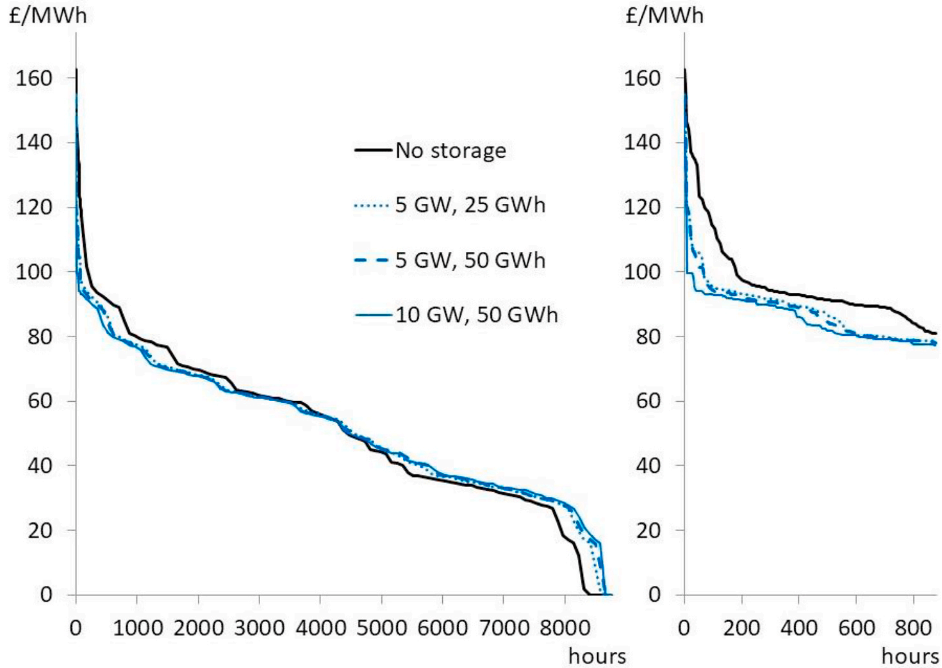

Fig. A1. Price-duration curves with oligopoly generators and price-taking storage

Figure A2 shows the outcome with oligopoly generators and different levels of storage exploiting market power. In contrast to Fig. 3, it is (just) possible to tell the curves with different levels of storage power capacity apart, although expanding the energy capacity of 5 GW of power-capacity storage from 25 GWh to 50 GWh has very little effect on prices.

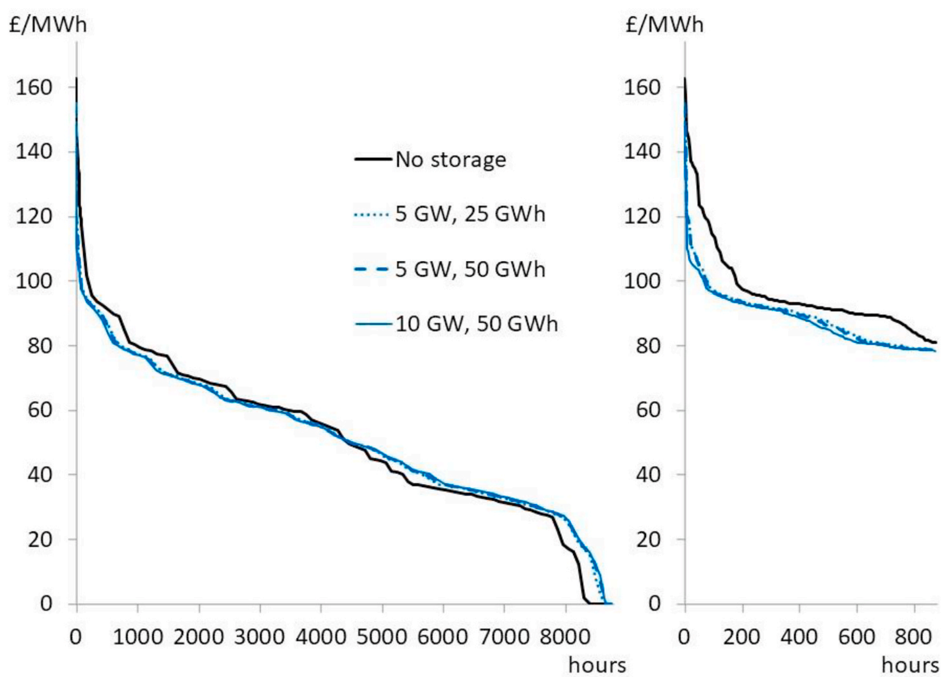

Fig. A2. Price-duration curves with oligopoly generators and storage using market power

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