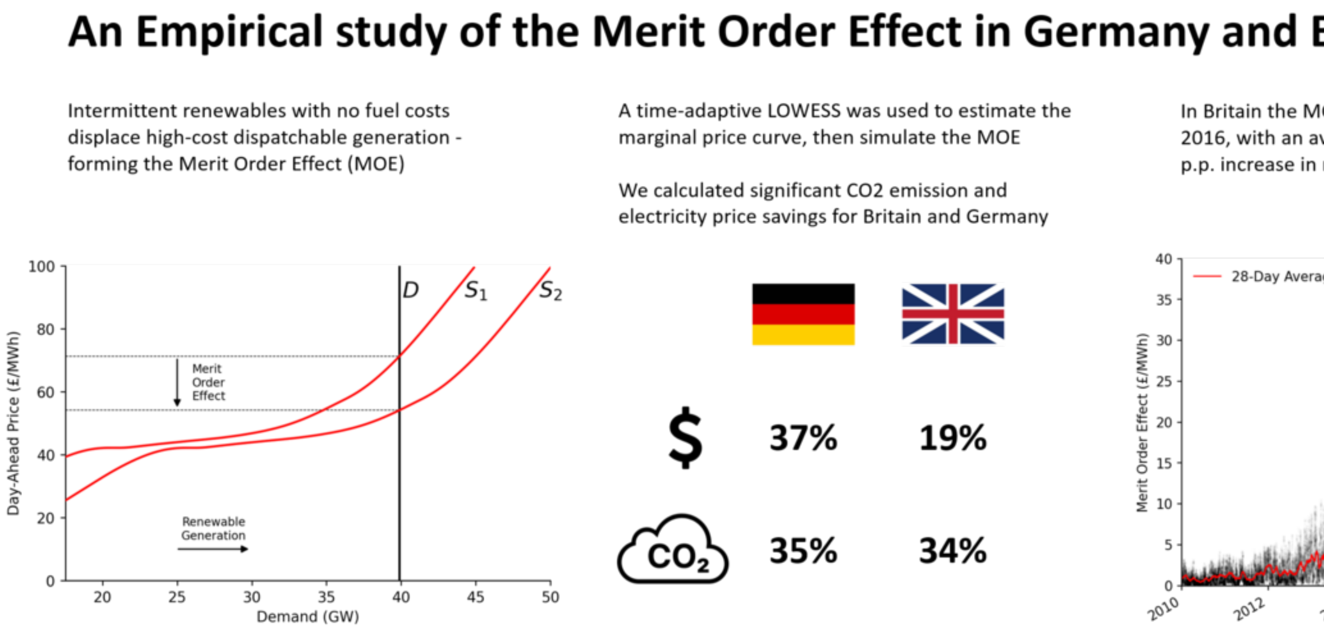
Graphical Abstract

An Empirical study of the Merit Order Effect in Germany and Britain

Bourn, Ayrton, O'Sullivan, Aidan, Agnolucci, Paolo



Highlights

An Empirical study of the Merit Order Effect in Germany and Britain

Bourn, Ayrton, O'Sullivan, Aidan, Agnolucci, Paolo

- A LOWESS estimation of the non-linear marginal price curve for dispatchable generation shows high back-casting accuracy for Germany and Britain
- The evolving Merit Order Effect (MOE) was estimated through a time-adaptive model, enabling long-term trends to be captured
- In Britain the MOE has increased sharply since 2016, with a 0.67% price reduction per p.p. increase in RES penetration
- Disaggregation of the MOE by fuel-type highlights key differences in the transition paths of Britain and Germany

An Empirical study of the Merit Order Effect in Germany and Britain

Bourn, Ayrton[a], O'Sullivan, Aidan[a], Agnolucci, Paolo[a]

[a] *UCL Energy Institute, Central House, London, WC1H, England*

Abstract

This paper presents an empirical analysis of the reduction in day-ahead market prices and CO_2 emissions due to increased renewable generation on both the British and German electricity markets. This Merit Order Effect is becoming more important as markets evolve to incorporate greater shares of renewable energy sources, driving renewable capture price cannibilisation and market volatility. However, explicitly determining its magnitude can be challenging due to the confidential nature of the data required. Existing statistical methods for inferring this effect have focused on linear parametric approaches. However, these have a number of disadvantages. In this work we propose a flexible non-parametric blended Locally Weighted Scatterplot Smoothing approach that captures the non-linear relationship between electricity price and dispatchable generation. This is the first application of this method in this context. We found the accuracy of this approach comparable to methods used in modern price back-casting literature. Our results indicate that the Merit Order Effect has increased dramatically over the time period analysed, with a sharp and continuing increase from 2016 in Britain. We found that renewables delivered total reductions equal to 318M and 442M tonnes of CO_2 and savings of €56B and £17B in Germany and Britain respectively.

Keywords: Merit Order Effect, Renewables, Electricity Markets
JEL: C22, C51, C63, Q21, Q28, Q41, Q42

1. Introduction

The power sector is at the vanguard of efforts to mitigate climate change with the decarbonisation of electricity generation a critical enabling path for decarbonising other sectors such as transport, industry and heat. There has been rapid progress in transitioning the European power sector through the installation of large capacities of wind and solar generation. These variable Renewable Energy Sources (RES) are having a significant disruptive effect on prices in electricity markets, due to their unique characteristics of having low variable costs and low price sensitivity. In electricity markets, bids are ranked by price from cheapest to most expensive (forming what is called the merit order stack) and the point at which the cumulative generation is equal to demand determines the market-clearing price. The low variable cost and price sensitivity of renewables allow them to bid into the market at a price lower than almost any other fuel type. This allows them to displace more expensive thermal generation in the merit stack (Nieta and Contreras (2020)). This mechanism is known as the Merit Order Effect (MOE) and is illustrated in Figure 1. It can be seen that renewable generation shifts the marginal price curve for dispatchable generation to the right, resulting in a lower market clearing price.

The MOE is normally expressed in terms of the average suppression of the electricity price in £/MWh, or for wider market comparison as the percentage price reduction per percentage increase in the share of RES. Further detail on the theory underpinning the MOE can be found in (Sensfuß et al. (2008)). Understanding this effect is complicated due to the same multitude of factors that affect electricity price, including the generation mix and variability in demand, however, improving our understanding is vital as the future will involve an ever larger share of renewable penetration in the generation mix and efficient market design is key to ensuring an equitable and affordable transition.

In this work we present an empirical analysis of the MOE in the British and German electricity markets between 2010-2020. These are two of the largest and most advanced electricity markets in Europe and quantifying the MOE within them has important implications for asset owners, developers and policymakers - not just in these markets but also for those earlier into their transition to a net-zero power sector. Existing research to date on the MOE has focused primarily on linear methods for modelling the merit order stack. However this approach is sub-optimal for capturing the more non-linear high/low regions of the supply curve and can lead to inaccurate estimation of the MOE magnitude. In this work a non-parametric Locally Weighted Scatterplot Smoothing (LOWESS) model is used to capture the non-linear relationship between electricity price and dispatchable generation,

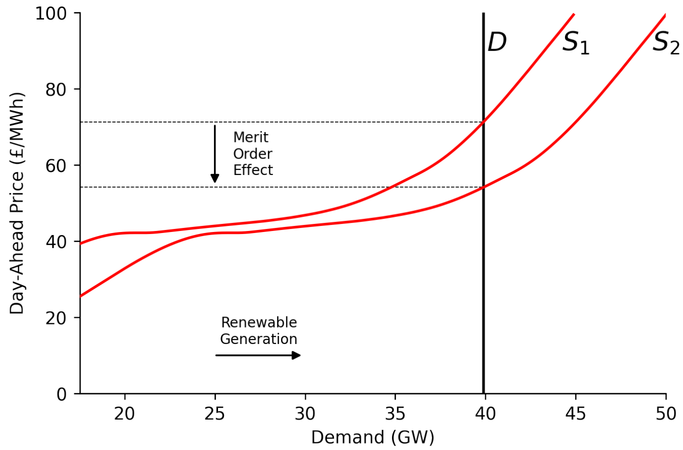


Figure 1: Example merit-order-effect cost reduction for a given demand D, where S_2 denotes the supply curve with RES generation and S_1 the counter-factual without RES generation. The marginal price curve shown is fitted using observed historical data from the GB power system during the winter of 16/17.

with historical renewable output data then used to simulate the MOE. The stationary nature of many existing methodologies means they struggle to adapt to changes in the system, such as the effect of the Covid-19 pandemic (Kirli et al. (2021)), we use a time-adaptive model to effectively address this limitation. Alongside an extension to the standard LOWESS implementation the use of a time-adaptive model significantly reduces the computational resource required.

To date the MOE has referred only to the effect seen on prices. However, the MOE can be viewed more generally as an approach to estimating the marginal effect of renewables across a range of factors including the carbon intensity of the electricity system. This framework is transferable as the fundamental drivers of both prices and carbon intensity include the types of plant making up the generation stack.

Gaining a better understanding of the carbon emissions MOE has several potential benefits, such as improved modelling for policymakers who are aiming to reduce carbon emissions. Existing approaches rely on bottom-up dispatch models which require a large number of assumptions and are often difficult to calibrate (Clancy et al. (2015), Van den Bergh et al. (2013)). Taking a more data-driven approach presents several advantages, including the ability to disaggregate the carbon savings from new renewable energy source (RES) capacity and the changing carbon intensity of the dispatchable fleet - particularly useful for policymakers evaluating net-zero pathways.

Our results show that renewables delivered reductions equal to 318M tonnes of CO_2 between 2010 and 2020, and €56B between 2015 and 2020 in Germany. In GB the reductions amounted to 442M tonnes of CO_2 and a £17B saving between 2010 and 2020. The results were similar in magnitude but generally higher than other studies from the literature, the likely reasons for which are discussed in Section 5.

The structure of the paper is as follows. Section 2 reviews recent research into the merit order effect and the methods used to quantify its magnitude. We then present in Section 3 the methodology employed in the analysis and the data required for its implementation. The results of this analysis are presented in Section 4, followed by a discussion around their implications in Section 5, before drawing some final conclusions in Section 6.

2. Review of Existing MOE Literature and Approaches

Precise determination of the MOE in any given settlement period would require access to the full list of bids and offers for that market, as well as the fuel types of the plants behind each bid/offer. One could build a counterfactual marginal price curve, after removing the bids/offers put forward by RES, so that the difference in the resulting market price can be exactly determined (Keles et al. (2013)). This approach is applied by McConnell et al. (2013) and Hildmann et al. (2015) to the Australian and German/Austrian markets. Average MOE estimates for the latter amount to 13.4-18.6 €/MWh in 2013. Direct computation is however difficult to implement as the bid/offers are not publicly available for GB or most other markets. For this reason, several methods have been explored to compute the MOE based on public data. These can be grouped into three main modelling approaches: Energy System Simulation (ESS), Renewable Penetration Regression (RPR), and Merit Stack Simulation (MSS). MOE estimates from the literature, as well as the modelling approach used to calculate them, can be seen in Table 1.

Energy System Simulation (ESS) aim to simulate the energy system through a bottom-up approach by optimising the revenues for individual plants so that they can simulate the equilibrium price with and without the

Table 1: Results overview from the MOE literature. All MOE percentages are expressed in terms of the reduction in prices relative to if renewables had not been present on the system. For ease of comparison, studies which condition the MOE on external factors (e.g. per GW of RES) have been excluded.

Study	Absolute MOE	Percentage MOE	Period	Region	Method
Sensfuss et al. (2008)	7.83€/MWh	-	2006	Germany	ESS
de Miera et al. (2008)	-	25.1%	2007	Spain	ESS
Weigt (2009)	10€/MWh	-	2006-2008	Germany	ESS
Ciarreta et al. (2014)	45€/MWh	-	2012	Spain	ESS
Bublitz et al. (2017)	5.40€/MWh	-	2011-2015	Germany	ESS
McConnell et al. (2013)	-	8.6%	2009-2010	Australia	MSS
Hildmann et al. (2015)	18.6€/MWh	-	2013	Germany and Austria	MSS
Dillig et al. (2016)	50.29€/MWh	-	2011-2013	Germany	MSS
Munksgaard and Morthorst (2008)	4€/MWh	-	2006	Denmark	RPR
Gelabert et al. (2011)	-	3.7%	2005-2012	Spain	RPR
O'Mahoney and Denny (2011)	-	12%	2009	Ireland	RPR
Woo et al. (2011)	1.53 $/MWh	-	2010	Texas	RPR
Gil et al. (2012)	9.72€/MWh	-	2007-2010	Spain	RPR
Keles et al. (2013)	5.90€/MWh	-	2006–2009	Germany	RPR
Tveten et al. (2013)	5.25€/MWh (solar)	-	2006-2011	Germany	RPR
Wurzburg et al. (2013)	-	2%	2010-2012	Germany & Austria	RPR
Cludius et al. (2014)	8€/MWh	-	2010-2012	Germany	RPR
Clo et al. (2015)	2.3€/MWh (solar) 4.2€/MWh (wind)	-	2005–2013	Italy	RPR

Continued on next page

Table 1: Results overview from the MOE literature. All MOE percentages are expressed in terms of the reduction in prices relative to if renewables had not been present on the system.

Study	Absolute MOE	Percentage MOE	Period	Region	Method
Kaufmann and Vaid (2016)	1.86 $/MWh (solar)	-	2012	Massachusetts	RPR
Bublitz et al. (2017)	6.80€/MWh	-	2011-2015	Germany	RPR

inclusion of RES. This approach can take into account fundamental price drivers such as marginal and start-up costs (Sensfuß et al. (2008), Weigt (2009)), competition Bode and Groscurth (2006), and strategic behaviour (Panos and Densing (2019), Bublitz et al. (2017)). ESS approaches can model the long-term MOE, isolating the effect to the reductions in plant operating costs (Antweiler and Muesgens (2021), Sensfuß et al. (2008)). In contrast, ESS models incorporate a large number of assumptions and significant effort is required in their calibration (Cludius et al. (2014), Halttunen et al. (2020)). For these reasons they tend to be used for modelling counterfactuals that cannot be derived from historical data alone (Weron (2014)).

Renewable Penetration Regression (RPR) and Merit Stack Simulation (MSS) models take an alternative approach whereby electricity prices are first backcasted under perfect information, then re-estimated in a sensitivity analysis around varying levels of RES generation. This is often framed as a more evidence driven procedure relative to ESS methodologies (Halttunen et al. (2020)). In contrast to ESS models, RPR and MSS consider only the instantaneous price change from adjusting RES output (Würzburg et al. (2013)).

Studies adopting the RPR technique implement empirical analysis modelling the relationship between a measure of the electricity price (sometimes using the change in price from one settlement period to the next) and a measure of generation provided by renewable sources (Hall et al. (2015), Keles et al. (2013)), while taking into account exogenous influences on price such as the overall level of generation, time of the day, day of the week, level of imports and exports and prices of fuels used by power plant such as Gelabert et al. (2011), Zipp (2017), and Halttunen et al. (2020).

Whilst the RPR approach is relatively easy to implement, they incorporate the assumption that the essence of a complicated mechanism such as the power market can be captured by normally a single linear equation among a relatively low number of variables (Ederer (2015), Dillig et al. (2016)). MSS approaches instead aim to explicitly replicate the merit order stack, then implement the previously described approaches of McConnell et al. (2013), Hildmann et al. (2015), and Ederer (2015) (who had access to the underlying bid/offer stacks). Dillig et al. (2016) calculates a particularly high MOE of 52.9 €/MWh for Germany using this approach, noting that the linear approximation used in other studies is responsible for a strong underestimation of the effect.

Whilst the majority of approaches to quantifying the MOE are linear, the relationship between supply and price is complex and non-linear (Gürtler and Paulsen (2018), Weron (2014)). Furthermore, the generation/price relationship cannot be easily transformed into a linear fit - though limited success has been achieved using dual-exponential transformations (Dillig et al. (2016)). Kanamura and Ohashi (2007) attempt to address this by using a structural model which is comprised of two separate linear regressions between demand and price, smoothed together using a quadratic curve. This was shown to better model periods of high prices, which is important for determination of the MOE as during these periods renewables can depress prices at a higher rate relative to when demand is in the middle of the supply curve (Dillig et al. (2016)).

A natural extension of this approach is to use Locally Weighted Scatterplot Smoothing (LOWESS), whereby multiple regressions are fitted over different regions of the data domain and then combined based on weightings linked to the distance between the prediction point and the data used to fit each of the local regressions (Cleveland (1979)). Gil et al. (2012) found that LOWESS outperformed ordinary least squares regression when assessing the relationship between wind power penetration and electricity prices. Jónsson et al. (2010) expand the exogenous variables included, finding that a LOWESS considering price, percentage share of wind, and the hour of the day is more accurate than using price and wind power alone.

Additionally, the majority of models used in the literature do not account for dynamic changes across time, an important aspect given that both the marginal costs of generators and the behaviour of consumers are continually evolving. Some of the variability, such as seasonal production/demand changes (Mosquera-López and Nursimulu (2019)), can be modelled using only the time of year as an additional input, others require additional exogenous variables such as fuel prices to explain changes in plant variable costs. Several alternative methods have been proposed which dynamically update the model coefficients rather than trying to capture the variability through exogenous factors, this both increases the generalisability of the models and enables them to account for the effect of regime shifts without increasing the number of inputs.

One approach is to train separate models based on relatively small observation periods, with the implicit assumption that the functional relationship is stable within the selected sample. As an example, Nastac and Ulmeanu (2013) found that their error increased by 50% when using a year of data compared to six months, but was negligibly affected when moving from 3 to 1½ months. Dillig et al. (2016) observes that any sample shorter than one year is unable to capture seasonal effects, however, this can be implicitly captured by allowing for the functional form to differ across periods. Another approach allows for the coefficients of linear regression to evolve across time through state-space model models estimated through a Kalman filter. Paraschiv et al. (2014) finds significantly higher performance in the case of a time-adaptive regression model. Their results showed a clear increase in the effect of wind on the MOE during early hours in the morning (Paraschiv et al. (2014)). Whilst this shows the benefits of a model that varies over time it also highlights the limitations of linear techniques, a more flexible model would be able to capture the steep decrease at the bottom of the demand curve and identify that the price reduction is most likely due to low morning demand.

MOE studies have been carried out for markets across the globe but the majority are concentrated within Europe. The only multi-market studies identified in the literature were by: Hildmann et al. (2015) who estimates the effect in 8 European countries, and Halttunen et al. (2020) who model 37 markets across a large geographic extent. Both studies note that the wide range of modelling approaches (and results) in the literature increase the need for multi-market studies for comparison purposes.

By far, the most researched market for quantification of the MOE is Germany. This is likely driven by the significant early subsidies made available to renewables, which meant it was one of the first countries to see high levels of displacement through the MOE. For this reason, as well as evaluating the MOE in Britain, the model developed in this work will also be applied to Germany so as to better benchmark it against the literature.

Four key limitations were identified in the models currently used for MOE determination:

- Prevailing methodologies fail to capture the non-linear nature of the relationship between dispatchable generation and price
- The large number of assumptions built into many of the Energy System Simulation models reduces their ability to generate accurate high-frequency estimates for MOE
- Higher dimensional multivariate regressions are less geographically generalisable, as to use them across multiple electricity markets many types of data must be collated for each region

- The energy system and its drivers are constantly evolving, meaning that models trained over long time spans often fail to account for short- and medium-term shifts in the marginal price curve

To address these limitations we develop a non-linear model which can adapt over time and requires only price, demand and RES generation time-series as inputs. To this end a LOWESS approach was selected - whereby a non-parametric regression is carried out between price and dispatchable generation - then extended so that the final estimate is derived from a local weighting over individual LOWESS fits across the time dimension. In this work the time dimension refers only to the linear progression of time (e.g. seconds from 1970), not the time of day or year. The generalisability of the model is shown by applying the modelling framework to both an alternative energy system, Germany, and a different target variable, carbon intensity. To the best knowledge of the author's this paper is the first ex-post analysis of the MOE in the British and German systems for carbon intensity. The generation of counterfactuals for the CO_2 emissions that would have been generated without renewables can in turn be used to better inform future energy policy.

3. Methodology

In this section we describe the methodology used to estimate the MOE for GB and DE electricity markets. As mentioned in the previous section, estimating the 'true' MOE for a given settlement period requires access to the full list of generator bids and offers. As this data is not publicly available for GB and DE markets so we infer the MOE using LOWESS to regress price against dispatchable generation and then calculating two prices, one at the intersection between the marginal price and total demand, the other intersecting with residual demand after intermittent RES - the difference between the two representing the price saving. We also compare the goodness-of-fit for the model between regressing the marginal price curve against dispatchable and total generation.

We begin by summarising the sources for the data used in this study and provide a high-level characterisation of the two markets in 2020. As this is the first MOE study using LOWESS, we provide a brief introduction to the LOWESS model and describe adaptations required to the specific computation of the MOE pursued here in Section 3.2. Section 3.3 will address model estimation and evaluation. Following the guidelines laid out in the 'Turing Way' (Community et al. (2019)), the analysis carried out in this work has been made available as a fully reproducible workflow, with the extended LOWESS model released as part of an open-source Python package (Bourn (2021)).

3.1. Data Sources and Market Characterisation

The GB and DE wholesale electricity markets are structured similarly - with significant volumes of electricity traded on power exchanges such as EPEXSpot and Nordpool, and through bilateral agreements between individual sellers and buyers. The majority of trades on the exchanges take place in the day-ahead market where generators bid to sell their electricity over the following day's half-hour settlement periods. While individual offers (in GBP/EUR per MWh) for each period are not publicly available, the day-ahead clearing prices and generated electricity by fuel type can be obtained. For GB half-hourly data was sourced from Electric Insights (Staffell) covering the 2009-2020 time span. For DE the price data was sourced from ENTSOE (ENTSOE) and the generation mix electricity output from Energy Charts (for Solar Energy Systems). The geographic coverage of the German market changed in 2018 to exclude Austria, but this was not found to have a significant influence on our study due to the much larger size of Germany. To match the price data the DE fuel generation time-series was aggregated to an hourly frequency, taking the average of the two half-hourly settlement periods in each hour. Hildmann et al. (2015) found that this type of aggregation does not influence the MOE result. The resulting datasets span 2010-2020, apart from the DE price data which is only available between 2015 and 2020.

Table 2 presents a high-level summary of the data for both markets in 2019 - due to Covid-19 2020 was deemed non-indicative of the long-term market characteristics. It can be seen that the DE market is larger, cheaper and more carbon intensive the the UK market despite a lower penetration of renewable electricity in the latter.

The carbon intensity of each fuel type was sourced from Volker-Quaschning (Volker-Quaschning (2015)) for DE. In the case of GB, the estimates for coal and gas were taken from DUKES (of National Statistics and Department for Business (2020)), and the interconnectors and biomass from Electric Insights (Staffell). The effect of storage was not taken into account. All renewables

Table 2: Markets overview for 2019

	Germany	Great Britain
Average Solar/Wind Generation (%)	32.52	24.71
Average Demand (GW)	59.05	32.58
Average Price ([EUR,GBP]/MWh)	37.67	41.81
Minimum Price ([EUR,GBP]/MWh)	-90.01	-72.84
Maximum Price ([EUR,GBP]/MWh)	121.46	152.00
Average Carbon Intensity (gCO_2/kWh)	163.22	105.55

including run-of-river hydro, wind and solar were defined as having a carbon intensity of 0.

3.2. LOWESS Model Formulation

LOWESS is a non-parametric regression method that extends the least squares approach by fitting multiple regressions across the data domain - see Chambers et al. (1990); Loader (1999) for a full description of the LOWESS. These 'local' regressions are then combined using a weighting function based on their distance to the point being predicted. The standard weighting function used is the tri-cubic function shown below:

$$w(d) = \begin{cases} (1-|d|^3)^3 & \text{for } |d| < 1 \\ 0 & \text{for } |d| \geq 1 \end{cases} \tag{1}$$

Where d is the distance between a data point, x, and the center of one of the local regressions. Greater weight is placed on data points nearest the point of estimation. The distance is normalised between 0 and 1, where points with a distance of 1 represent those at the edge of the subset considered within a single local regression. The fraction of data considered in each local regression is specified by the model bandwidth β.

The standard loss function λ when fitting N local regressions is formulated as:

$$\lambda(x) = \frac{1}{N} \sum_{k=1}^{N} W_k(x) \left(y - \sum_{j=0}^{p} \beta_{kj} x^j \right)^2 \tag{2}$$

where the nested summation $\sum_{j=0}^{p} \beta_{kj} x^j$ represents the p order polynomials used in the local regressions, W_k represents the vector of weights associated with each of the N local regressions and N is the number of data points.

In our application we chose a first order polynomial since it was found to perform well.

LOWESS is highly flexible and able to model complex functions delivering continuous smoothing, therefore removing the discrete changes associated with regime switching models, whilst being able to incorporate large changes when they do occur. However, it is both computationally and data intensive due to the need to estimate N local regressions. To address some of these shortcomings we adapted the LOWESS approach through adjustments to the distribution of regression locations and the formulation of the weighting function.

In the original implementation of the LOWESS model the computational complexity scales to the square of the number of data points, $\mathcal{O}(N^2)$, so it becomes infeasible to use this approach for the almost 200,000 half-hour periods in the GB dataset. For this reason, we adapt the LOWESS model to fit local regressions at K pre-specified locations in the dataset (instead of being fit at each data point), based on the procedure laid out in Cleveland et al. (1988). It should be noted that we used evenly spaced locations rather than concentrating them within denser regions to ensure that the regression locations are consistent across the dataset. This necessitates the introduction of another hyperparameter, called the interval (φ), specifying the distance between subsequent weight distributions $w(d)$ - visualised in the case of a single dimension in Figure 2, so that the computational complexity scales linearly with the number of data points and regression locations, $\mathcal{O}(K.N)$.

We further extend the traditional LOWESS model by considering time as a third dimension in the weighting of the data points used for each local regression. Here the time dimension relates to the linear progression of time (e.g. seconds from 1970), not the time of day or year. This approach, described in detail in Hastie et al. (2001), has the additional benefit of reducing errors at the boundary of the data domain compared to including time as an additional variable in the regression itself.

Separate bandwidths, β, and intervals, φ, must be specified for the dispatchable generation and time dimensions, denoted using *dgen* and *time* respectively. The final model is tuned through identification of the optimal values of β_{dgen}, β_{time}, φ_{dgen}, and φ_{time} which minimise $\lambda(x)$ as described in equation 3.

$$\lambda\left(x\right) = \frac{1}{T \cdot K} \sum_{t=1}^{T} \sum_{k=1}^{K} W_t(x) W_k(x) \left(y - \sum_{j=0}^{p} \beta_{kj} x^j\right)^2 \tag{3}$$

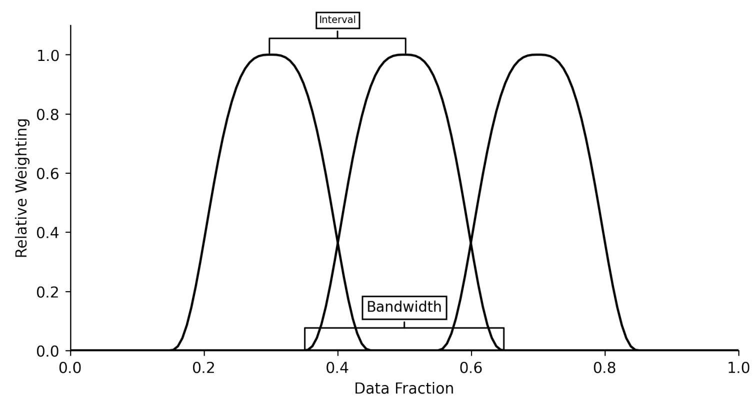


Figure 2: Rather than fit a local regression at each data point we introduce the interval hyperparameter and fit models at specific locations in state space as shown here with 3 overlapping regions.

3.3. Model Estimation and Evaluation

As discussed above, there are four hyper-parameters : β_{dgen}, β_{time}, φ_{dgen}, and φ_{time} that we tune through through Bayesian optimisation. We used Gaussian Process Regression (GPR) to build a probabilistic model of the objective function over the hyper-parameters so that this function surface can be considered as an approximation of the accuracy for the LOWESS model regression surface. By generating probabilistic estimates of the objective function the model is able to capture the increased uncertainty of its predictions in regions of the parameter space that have not yet been explored as extensively.

In this work the *skopt* Python package was used to carry out the hyper-parameter optimisation. The robustness of the optimisation process was validated by confirming that multiple runs reached the same local minimum region. Uniform priors were selected to reflect the prior uncertainty around the optimal parameters. We selected the squared exponential kernel due to its generalisability and relative ease to implement (Wilson and Adams (2013), Kanagawa et al. (2018)), as well as its performance in the electricity demand forecasting literature (Yang et al. (2018)).

Model evaluation was based on the mean absolute error (MAE), the average width of the 68% prediction interval, and the average width of the 95% confidence interval. The MAE was used as the metric to be minimised by the optimisation model, as it is most commonly used to compare the accuracy of electricity price forecasting models (Weron (2014)). A 68% prediction interval was also calculated while the confidence around the LOWESS estimate was determined through bootstrapping of the data and then repeatedly fitting LOWESS regressions on each subset. In this work 1000 runs were fitted for each model, this quantity of runs has previously been shown to be robust for MOE confidence interval estimation (Maciejowska (2020)). The 95% confidence limit was then calculated by calculating the difference between the 2.5 and 97.5 percentiles of the LOWESS estimates at each point in the marginal price curve.

4. Results

In this section we describe the results of applying our model to data from the GB and DE markets, by estimating the MOE impact on day-ahead market price and carbon emissions, each used as the dependent variable. We implement two formulations of the LOWESS methodology, one incorporating total generation as the independent variable, and the other using dispatchable generation.

4.1. Hyper-Parameter Optimisation

The hyper-parameter optimisation was able to successfully converge on a minima for MAE, identifying a dispatchable generation bandwidth of 30% and a time dimension bandwidth of 12 weeks as optimal for modelling the GB day-ahead market. The identified hyper-parameters were relatively consistent across the two countries for both dependent variables, carbon emissions and day-ahead price, with the carbon model requiring a larger dispatchable generation bandwidth but similar date smoothing bandwidth to the latter.

As can be seen in Figure 3 the dispatchable generation bandwidth was found to have a relatively small effect on the size of the MAE. In contrast, the choice of the time dimension bandwidth has a strong impact on the MAE. The optimisation routine concluded that the dispatchable generation band-

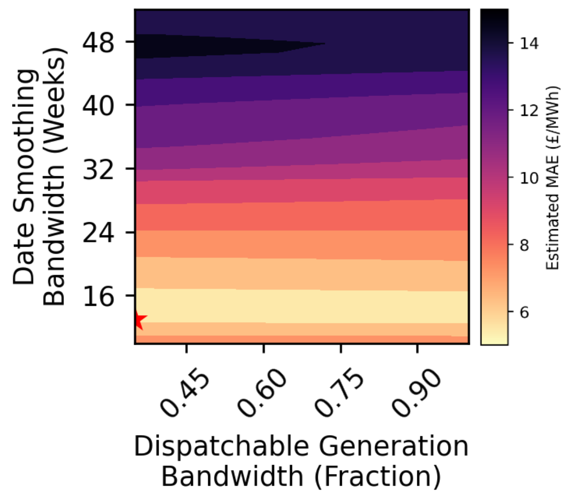


Figure 3: Surface of objective function in the hyper-parameter optimisation. The time dimension bandwidth was found to have a strong and convex relationship with the model accuracy, whereas a far weaker effect was observed with changes to the dispatchable generation bandwidth.

width benefited from being as small as possible[1] whilst the time dimension bandwidth had a minimum at 12 weeks.

4.2. Model Accuracy

The average MAE between the estimated and observed marginal prices were reduced by 22% for the UK when using the amount of generation supplied by dispatchable sources rather than total generation. A further 1.4% reduction in MAE could be achieved by regressing against the median rather than average price values, the results are summarised in Table 3. As well as being more accurate, the median regression approach was selected as it tends to be robust against outliers (Hagfors et al. (2016)).

For Germany the MAE reduction when using dispatchable rather than total generation was even greater, 68%, so much that the estimated marginal

[1]The lower bounds of the hyper-parameter optimisation were constrained by data availability, as when the bandwidth becomes too small it is not possible to fit a local regression model for each region of the marginal price curve

price curve is difficult to interpret when RES volumes are included. This result was found to be consistent across time, highlighting the benefit in using the dispatchable generation instead of total generation when forecasting the price of electricity. An example of this can be seen in Figure 4. Across both countries the MAEs were found to revert to a long-term trend of around £6.6/MWh for GB and 5.9 €/MWh in Germany.

Table 3: Price forecasting model mean absolute error when regressing against dispatchable and total generation for GB and DE.

	Germany	Great Britain
Dispatchable Load	5.9	6.6
Total Load	18.3	8.4

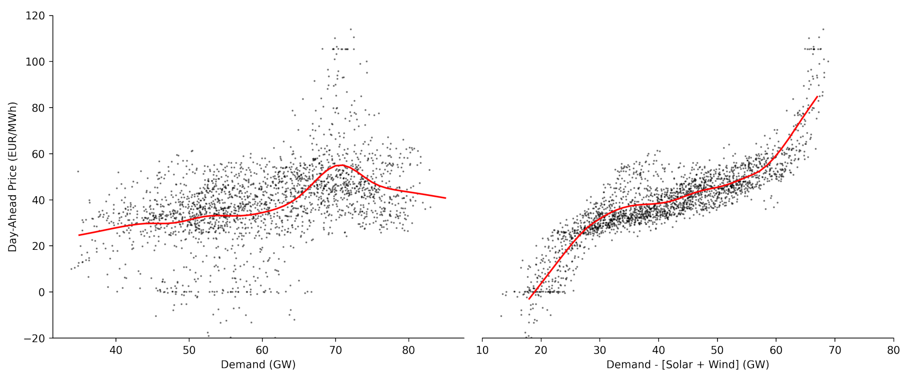


Figure 4: LOWESS fit using total generation (left) and dispatchable generation (right) for Germany, highlighting the importance of using the latter in tasks such as electricity price forecasting. The time period covered in this regression ranges from October 2020 to December 2020.

The LOWESS regressions were shown to have a high degree of precision, with an average 95% confidence interval of 1.69 €/MWh for DE and £1.04/MWh in GB. The model runs were found to diverge more towards the limits of the observed dispatchable generation, capturing the increased uncertainty in regions containing less historical data. The 68% prediction interval had an average width of 13.79 €/MWh for Germany and 16.32 £/MWh in GB. Examples of each interval type can be seen in Figure 5.

Whilst many studies report their estimates for MOE, far fewer indicate the accuracy of the underlying price forecasting model. The recent paper by

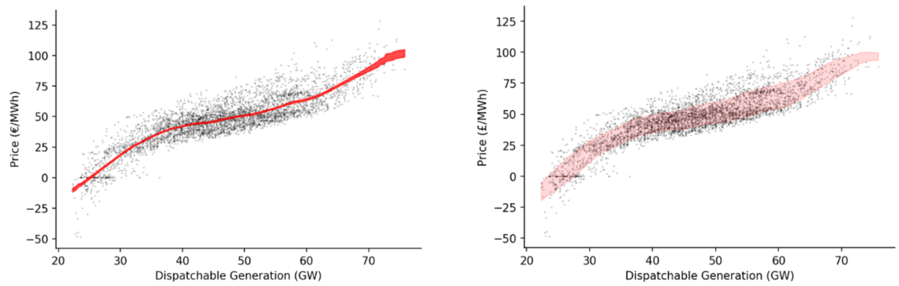


Figure 5: Example 95% confidence interval showing the increasing uncertainty towards the extents (left), and equivalent standard deviation or 68% prediction interval (right) for a single LOWESS regression.

Halttunen et al. (2020) stands out as it provides an R^2 score for both Germany (0.73) and Britain (0.45) using an RPR approach, closely comparable to the results in this work (0.72/0.46).

Extending the LOWESS model weighting to adapt over time was found to greatly enhance the accuracy. When regressing the day-ahead price for a single year the MAE shrank by more than 50% when using the time adaptable model for both GB and DE. This enabled the model to capture both cyclical effects such as seasonality and non-repeating events such as depressed prices over the winter of 15/16 and the high prices seen in 2018. Figure 6 shows the LOWESS regressions for the marginal price curve visualised as heatmap surfaces, highlighting the seasonal and non-cyclical changes over time.

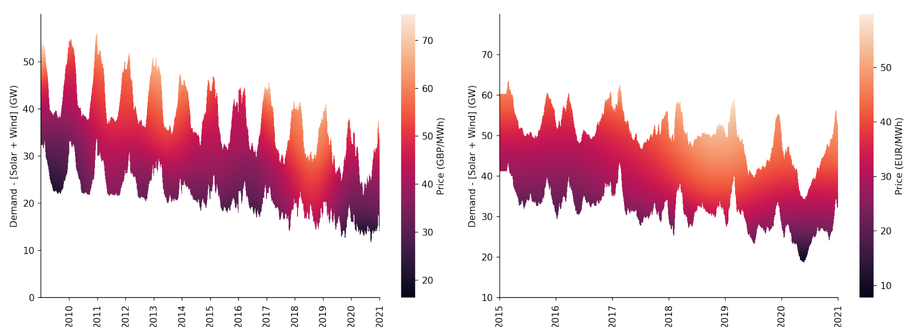


Figure 6: Surface fit over LOWESS marginal price curve estimates for GB (left) and DE (right). A mask has been applied where the residual demand after RES is outside the range of 99% of the data.

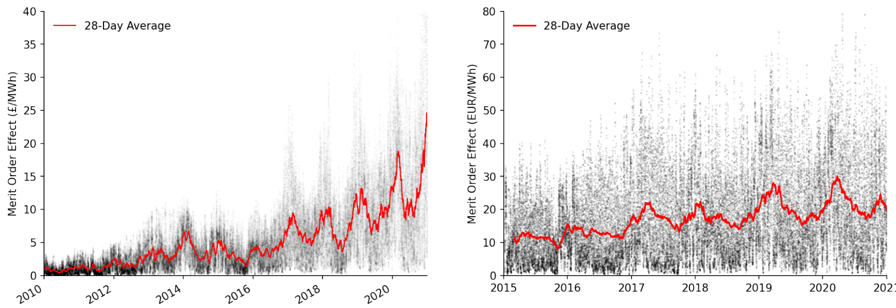


Figure 7: Increasing MOE for price in Britain (left) and Germany (right).

Table 4: Merit Order Effect results overview for 2019 (weighted by volume). Price reduction is expressed in terms of the percentage decrease relative to the counter-factual price that would have occurred with RES generation

	Germany	Great Britain
Price ([EUR,GBP]/MWh)	20.53	9.80
Price Reduction (%)	36.70	19.30
Carbon (Tonnes/h)	5085.92	1637.20
Carbon Reduction (%)	34.88	33.53

4.3. The Merit Order Effect

Price and carbon MOE for GB and DE have both increased and become more variable, as can be seen in Figure 7. Within GB the price MOE has increased from an average of £0.9/MWh in 2010 to £13.9/MWh in 2020. For Germany a two-fold rise was seen over the observed period, averaging EUR 22.1/MWh in 2020. An overview of the results can be seen in Table 4.

With regards to carbon intensity, a total of 221M tonnes of CO_2 has been displaced due to renewables in GB over the last decade, whilst 318M tonnes have been displaced in DE over the same period. In 2020 the reduction represented a reduction in carbon emissions of about 40% compared to a counterfactual with no renewable electricity in the grid.

Within GB and DE a seasonal effect was observed across the carbon intensity and price MOE, driven by the annual cycles in wind/solar resource. The effect was disaggregated by RES technology based on their relative output for each half-hour the MOE was simulated. In both countries the greatest share of MOE reductions was attributed to wind rather than solar, which is why the MOE tended to be higher during winter months - driven in part by predominately higher winter prices. The impact of the MOE on price across time for wind and solar can be seen in Figure 8. For GB the higher wind/solar capacity ratio further exacerbates this seasonal effect, increasing the uncertainty around prices during these periods.

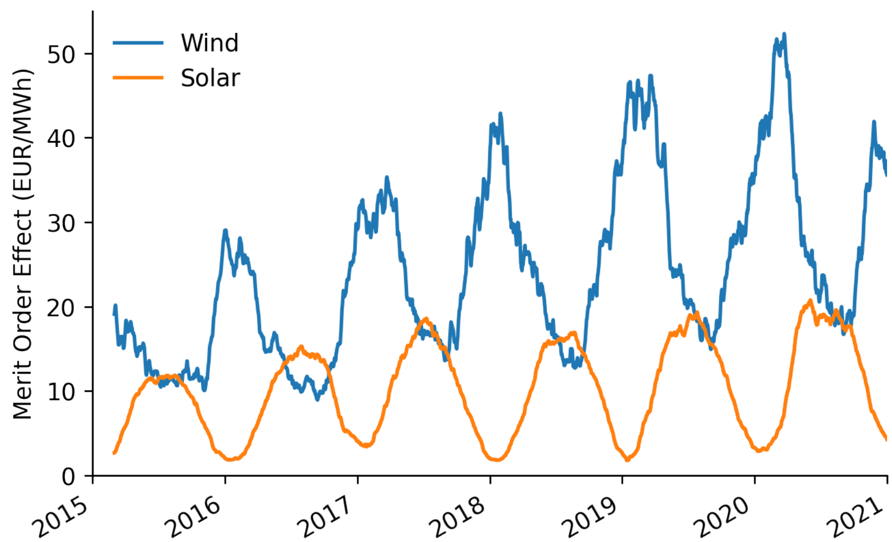


Figure 8: Seasonal trend for the German price MOE, disaggregated into the contributing RES technologies.

5. Discussion

The results presented in the previous section provide several insights into both the efficacy of our methodology and the evolution of the MOE over time in both markets. As outlined in Section 2 direct estimation of the MOE is generally not possible due to the confidential nature of bids and offer data. Thus, the results obtained are estimates of the MOE from publicly available aggregate data on price and generation mix. Comparison with results in the literature, see Table 1, reveals that our results are relatively consistent with the literature, but tended to be higher. This comparison is complicated by the diversity in markets, time periods, metrics and methodology used to estimate the MOE across the literature. However, our estimate of 22.17 €/MWh for Germany in 2020 was remarkably close to the 20 €/MWh MOE prediction for the same year made by Traber and Kemfert (2009) in 2011.

The marginal MOE (per percentage penetration of RES) was 17% higher than the most recent study for Germany in the same time period (Halttunen et al. (2020)). We estimated a higher MOE than the majority of the literature, likely due to the ability of our methodology to capture non-linear functional forms. A similar observation was made by Dillig et al who also used non-linear methods, however, our results are more in line with the rest of the literature relative to their 'astonishingly high' estimate (Dillig et al. (2016)). Our results provide further evidence of the importance of capturing the non-linear nature of the marginal price curve when measuring the MOE.

Our adapted LOWESS approach showed accuracy comparable to modern research in price back-casting, achieving MAEs of €5.85/MWh and £6.56/MWh (DE/GB) whilst requiring fewer independent variables and assumptions. This was particularly pronounced when using dispatchable generation instead of total generation (visualised in Figure 4). The implications of which are particularly important for MOE studies using the popular Renewable Penetration Regression (RPR) approach. As well as in the quantification of the MOE this finding is highly relevant to the wider field of electricity price forecasting.

By regressing CO_2 emissions against dispatchable generation additional insights can be gained into the changing carbon intensity of the fleet. In Figure 9 it can be seen how over the last decade the British fleet has been able to lower its carbon intensity for a given demand of dispatchable generation, primarily due to the coal-to-gas switch (Wilson and Staffell (2018)). In contrast, for Germany the carbon intensity of the dispatchable fleet has increased slightly, this is likely due to the decommissioning of low-carbon base-load generation. For policy-makers this provides a useful tool to disaggregate carbon savings between increased renewable output and less carbon intensive thermal generation.

In terms of the long-term trend (excluding 2020) each percentage point increase in the share of intermittent renewables meeting demand has led to a 0.67% decrease in the price of electricity for Great Britain, shown in Figure 10. Renewable developers will have to account for this increasing effect in order to better understand how the MOE will cannibalise the returns of their assets (Prol et al. (2020), Halttunen et al. (2020)). In 2030 variable RES is expected to reach 68% of the generation mix under the National Grid's 'System Transformation' scenario (Grid (2020)), which our results suggest would lead to a 46% reduction in the market price (relative to a grid without RES). For Germany, the smaller number of available years made it difficult

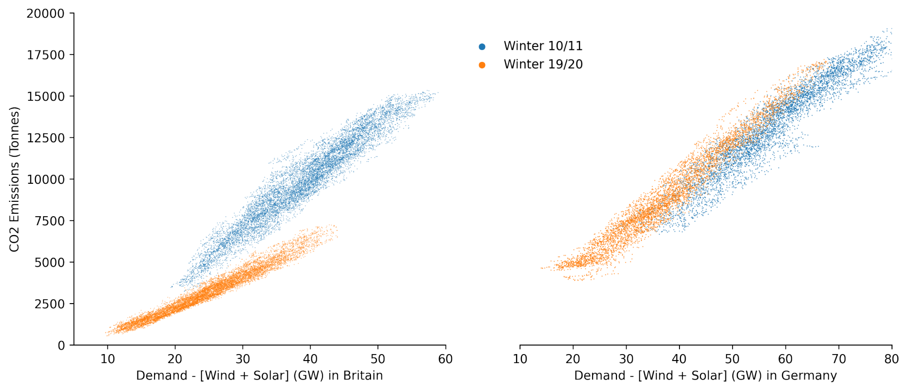


Figure 9: Comparison between the changes in the carbon merit stacks of Germany and Britain over the last decade.

to carry out a similar estimation.

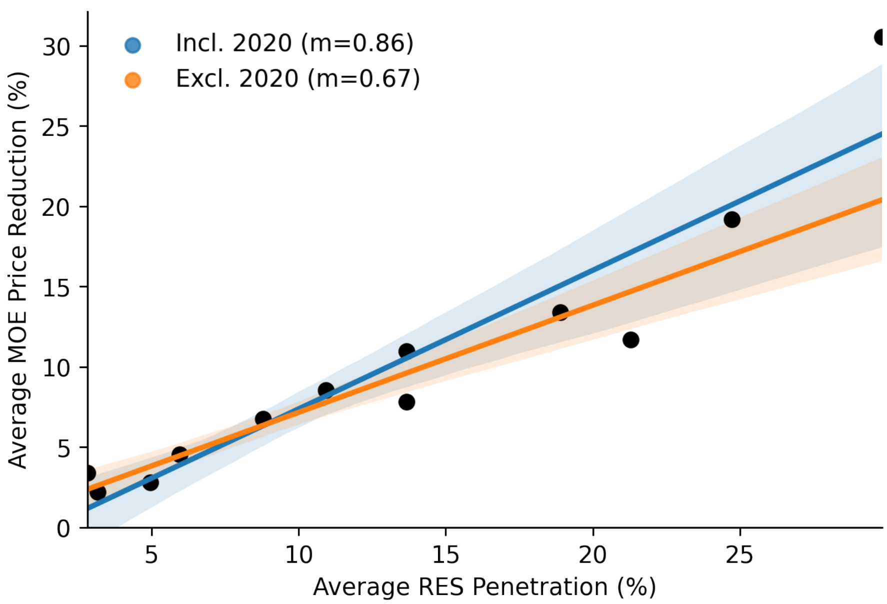


Figure 10: Relationship between the annual day-ahead price suppression due to the MOE and the percentage penetration of RES in Britain. The regression including 2020 has a standard error that's 50% higher than when its excluded.

The Bayesian hyper-parameter optimisation yielded several insights. The dispatchable generation bandwidth was found to have a relatively small influence on model accuracy, and its optimum was found at the edge of the hyper-parameter domain extent - constrained by data availability. The optimum for the time dimension bandwidth was identified as 12 weeks, representing a trade-off between more relevant data which are closer in time to the estimation point and the sample size required for a robust fit. As the trade-off included data availability it was surprising that the DE model (which used half the number of data points within the same time-span) was found to have a similar optimum bandwidth as the GB model. Likely this is due to adjacent half-hour settlement periods clearing at similar prices and utilising a similar generation fleet.

A core assumption in the determination of the MOE in this work was that RES always bids below the market clearing price. In some countries with very high renewable penetration it is becoming apparent that this may not always be the case (ENTSOE), however these events are rare and their effect on the final result likely to be minimal. Additionally, GB wind farms can offer negative bids as the price they ultimately receive for generation comes from government subsidies (ROCs & CfDs), incentivising them to continue to bid below market clearing prices as long as they are negative for no more than 6 consecutive hours[2] (Baringa (2015)).

6. Conclusion

In this paper we present an approach for estimating the MOE for price and carbon emissions from aggregate price and generation mix data using a flexible non-parametric data driven model. The extended LOWESS framework presented has a number of advantages over previous methods for estimating MOE in that it requires relatively few assumptions and a minimal number of variables, enabling relative ease in application across different geographies and power system phenomena. The modifications implemented here and described in Section 3 significantly reduced the computational cost of the approach, a key barrier in previous research.

Our results show broad agreement with the literature for the magnitude of the MOE price but tended to be higher, a feature of our methods ability to

[2]This has since changed for the 4th allocation round of the GB CfD scheme, with no subsidies to be provided for periods of negative pricing. However, there remains a large volume of existing CfD contracts that will continue without this amendment till 2030.

better model the higher non-linear portion of the price curve. The MOE savings from RES in terms of financial cost and tonnes of CO_2 were calculated. For DE, renewables were found to reduce 318M tonnes of CO_2 between 2010 and 2020, as well as €56B between 2015 and 2020. Whilst in GB a reduction of 442M tonnes of CO_2 was seen between 2010 and 2020, with a £17B price saving observed between 2010 and 2020.

For policymakers the significant impact of the price MOE in high RES penetration power systems should be reflected as an additional benefit to most RES support schemes, though the high seasonality in GB presents new challenges around increasing annual variability of power prices. For countries earlier into the transition to net-zero these findings suggest that a more balanced RES portfolio could significantly reduce the high cannibalisation seen in the capture prices of specific fuel types such as wind.

For RES asset-owners (and policymakers assessing CfDs) the MOE is reflected as an increased cost - one which has risen sharply over recent years in GB and likely to continue rising given increased government deployment targets. Finally for developers, these findings present additional considerations in wind farm siting, where locating them in areas with dissimilar wind yield patterns to the national fleet could result in higher market capture prices (Meus et al. (2021), Eising et al. (2020)) - a form of analysis greatly aided by high-frequency MOE estimates such as developed in this work.

References

Antweiler, W., Muesgens, F., 2021. On the long-term merit order effect of renewable energies. Energy Economics 99, 105275. URL: https://www.sciencedirect.com/science/article/pii/S0140988321001808, doi:https://doi.org/10.1016/j.eneco.2021.105275.

Baringa, 2015. Negative pricing in the GB wholesale electricity market .

Van den Bergh, K., Delarue, E., D'haeseleer, W., 2013. Impact of renewables deployment on the CO2 price and the CO2 emissions in the European electricity sector. Energy Policy 63, 1021–1031. URL: http://dx.doi.org/10.1016/j.enpol.2013.09.003, doi:10.1016/j.enpol.2013.09.003. publisher: Elsevier.

Bode, S., Groscurth, H.M., 2006. The Effect of the German Renewable Energy Act (EEG) on ?the Electricity Price? .

Bourn, A., 2021. moepy. URL: https://ayrtonb.github.io/Merit-Order-Effect/. 10.5281/zenodo.4642896.

Bublitz, A., Keles, D., Fichtner, W., 2017. An analysis of the decline of electricity spot prices in Europe: Who is to blame? Energy Policy 107, 323–336. URL: https://EconPapers.repec.org/RePEc:eee:enepol:v:107:y:2017:i:c:p:323-336.

Chambers, J., Hastie, T., Pregibon, D., 1990. Statistical Models in S, in: Momirović, K., Mildner, V. (Eds.), Compstat, Physica-Verlag HD, Heidelberg. Chapter 6.

Clancy, J.M., Gaffney, F., Deane, J.P., Curtis, J., Ó Gallachóir, B.P., 2015. Fossil fuel and CO2 emissions savings on a high renewable electricity system - A single year case study for Ireland. Energy Policy 83, 151–164. URL: http://dx.doi.org/10.1016/j.enpol.2015.04.011, doi:10.1016/j.enpol.2015.04.011. publisher: Elsevier.

Cleveland, W.S., 1979. Robust locally weighted regression and smoothing scatterplots. Journal of the American Statistical Association 74, 829–836. doi:10.1080/01621459.1979.10481038.

Cleveland, W.S., Devlin, S.J., Grosse, E., 1988. Regression by local fitting: Methods, properties, and computational algorithms. Journal of Econometrics 37, 87–114. URL: https://www.sciencedirect.com/science/article/pii/0304407688900772, doi:https://doi.org/10.1016/0304-4076(88)90077-2.

Cludius, J., Hermann, H., Matthes, F.C., Graichen, V., 2014. The merit order effect of wind and photovoltaic electricity generation in Germany 2008–2016: Estimation and distributional implications. Energy Economics 44, 302–313. URL: https://linkinghub.elsevier.com/retrieve/pii/S0140988314001042, doi:10.1016/j.eneco.2014.04.020.

Community, T.T.W., Arnold, B., Bowler, L., Gibson, S., Herterich, P., Higman, R., Krystalli, A., Morley, A., O'Reilly, M., Whitaker, K., 2019. The Turing Way: A Handbook for Reproducible Data Science. URL: https://doi.org/10.5281/zenodo.3233986, doi:10.5281/zenodo.3233986.

Dillig, M., Jung, M., Karl, J., 2016. The impact of renewables on electricity prices in Germany – An estimation based on historic spot prices in the years 2011–2013. Renewable and Sustainable Energy Reviews 57, 7–15. URL: https://EconPapers.repec.org/RePEc:eee:rensus:v:57:y:2016:i:c:p:7-15.

Ederer, N., 2015. The market value and impact of offshore wind on the electricity spot market: Evidence from Germany. Applied Energy 154, 805–814. URL: https://linkinghub.elsevier.com/retrieve/pii/S0306261915006431, doi:10.1016/j.apenergy.2015.05.033.

Eising, M., Hobbie, H., Möst, D., 2020. Future wind and solar power market values in Germany — Evidence of spatial and technological dependencies? Energy Economics 86, 104638. URL: https://www.sciencedirect.com/science/article/pii/S0140988319304359, doi:https://doi.org/10.1016/j.eneco.2019.104638.

ENTSOE, . ENTSOE Transparency Platform. URL: https://transparency.entsoe.eu/.

Gelabert, L., Labandeira, X., Linares, P., 2011. An ex-post analysis of the effect of renewables and cogeneration on Spanish electricity prices. Energy Economics 33, S59–S65. URL: http://dx.doi.org/10.1016/j.

eneco.2011.07.027, doi:10.1016/j.eneco.2011.07.027. publisher: Elsevier B.V.

Gil, H.A., Gomez-Quiles, C., Riquelme, J., 2012. Large-scale wind power integration and wholesale electricity trading benefits: Estimation via an ex post approach. Energy Policy 41, 849–859. URL: http://dx.doi.org/10.1016/j.enpol.2011.11.067, doi:10.1016/j.enpol.2011.11.067. publisher: Elsevier.

Grid, N., 2020. Future Energy Scenarios. Technical Report. URL: https://www.nationalgrideso.com/future-energy/future-energy-scenarios/fes-2020-documents.

Gürtler, M., Paulsen, T., 2018. The effect of wind and solar power forecasts on day-ahead and intraday electricity prices in Germany. Energy Economics 75, 150–162. URL: https://www.sciencedirect.com/science/article/pii/S0140988318302512, doi:https://doi.org/10.1016/j.eneco.2018.07.006.

Hagfors, L.I., Bunn, D., Kristoffersen, E., Staver, T.T., Westgaard, S., 2016. Modeling the UK electricity price distributions using quantile regression. Energy 102, 231–243. URL: https://www.sciencedirect.com/science/article/pii/S0360544216300688, doi:https://doi.org/10.1016/j.energy.2016.02.025.

Hall, L.M., Buckley, A., Mawyin, J., 2015. Estimating the Impact of Wind Generation in the UK. _eprint: 1510.05854.

Halttunen, K., Staffell, I., Slade, R., Green, R., Saint-Drenan, Y.M., Jansen, M., 2020. Global Assessment of the Merit-Order Effect and Revenue Cannibalisation for Variable Renewable Energy. SSRN Electronic Journal URL: https://www.ssrn.com/abstract=3741232, doi:10.2139/ssrn.3741232.

Hastie, T., Tibshirani, R., Friedman, J., 2001. The Elements of Statistical Learning. Springer Series in Statistics, Springer New York Inc., New York, NY, USA.

Hildmann, M., Ulbig, A., Andersson, G., 2015. Empirical Analysis of the Merit-Order Effect and the Missing Money Problem in Power Markets with

High RES Shares. IEEE Transactions on Power Systems 30, 1560–1570. doi:10.1109/TPWRS.2015.2412376.

Jónsson, T., Pinson, P., Madsen, H., 2010. On the market impact of wind energy forecasts. Energy Economics 32, 313–320. URL: https://linkinghub.elsevier.com/retrieve/pii/S0140988309002011, doi:10.1016/j.eneco.2009.10.018.

Kanagawa, M., Hennig, P., Sejdinovic, D., Sriperumbudur, B.K., 2018. Gaussian Processes and Kernel Methods: A Review on Connections and Equivalences , 1–64URL: http://arxiv.org/abs/1807.02582. _eprint: 1807.02582.

Kanamura, T., Ohashi, K., 2007. A structural model for electricity prices with spikes: Measurement of spike risk and optimal policies for hydropower plant operation. Energy Economics 29, 1010–1032. doi:10.1016/j.eneco.2006.05.012.

Keles, D., Genoese, M., Möst, D., Ortlieb, S., Fichtner, W., 2013. A combined modeling approach for wind power feed-in and electricity spot prices. Energy Policy 59, 213–225. URL: https://linkinghub.elsevier.com/retrieve/pii/S0301421513001821, doi:10.1016/j.enpol.2013.03.028.

Kirli, D., Parzen, M., Kiprakis, A., 2021. Impact of the COVID-19 Lockdown on the Electricity System of Great Britain: A Study on Energy Demand, Generation, Pricing and Grid Stability. Energies 14. URL: https://www.mdpi.com/1996-1073/14/3/635, doi:10.3390/en14030635.

Loader, C., 1999. Local Regression and Likelihood. Springer-Verlag New York.

Maciejowska, K., 2020. Assessing the impact of renewable energy sources on the electricity price level and variability – A quantile regression approach. Energy Economics 85, 104532. URL: https://www.sciencedirect.com/science/article/pii/S0140988319303275, doi:https://doi.org/10.1016/j.eneco.2019.104532.

McConnell, D., Hearps, P., Eales, D., Sandiford, M., Dunn, R., Wright, M., Bateman, L., 2013. Retrospective modeling of the merit-order effect on wholesale electricity prices from distributed photovoltaic generation in the Australian National Electricity Market. Energy Policy 58, 17–27. URL: https://linkinghub.elsevier.com/retrieve/pii/S0301421513000797, doi:10.1016/j.enpol.2013.01.052.

Meus, J., Vits, S.D., S'heeren, N., Delarue, E., Proost, S., 2021. Renewable electricity support in perfect markets: Economic incentives under diverse subsidy instruments. Energy Economics 94, 105066. URL: https://www.sciencedirect.com/science/article/pii/S0140988320304060, doi:https://doi.org/10.1016/j.eneco.2020.105066.

Mosquera-López, S., Nursimulu, A., 2019. Drivers of electricity price dynamics: Comparative analysis of spot and futures markets. Energy Policy 126, 76–87. URL: https://doi.org/10.1016/j.enpol.2018.11.020, doi:10.1016/j.enpol.2018.11.020. publisher: Elsevier Ltd.

Nastac, D.I., Ulmeanu, A.P., 2013. An advanced model for electric load forecasting. 2013 IEEE Integration of Stochastic Energy in Power Systems Workshop, ISEPS 2013 - Proceedings , 14–19doi:10.1109/ISEPS.2013.6707942. iSBN: 9781479915118.

of National Statistics, O., Department for Business, E..I.S., 2020. Digest of United Kingdom Energy Statistics 2020. Technical Report. URL: https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/924591/DUKES_2020_MASTER.pdf.

Nieta, A.A.S.d.l., Contreras, J., 2020. Quantifying the effect of renewable generation on day–ahead electricity market prices: The Spanish case. Energy Economics 90, 104841. URL: https://www.sciencedirect.com/science/article/pii/S014098832030181X, doi:https://doi.org/10.1016/j.eneco.2020.104841.

Panos, E., Densing, M., 2019. The future developments of the electricity prices in view of the implementation of the Paris Agreements: Will the current trends prevail, or a reversal is ahead? Energy Economics 84, 104476. URL: https://www.sciencedirect.com/science/article/pii/S0140988319302579, doi:https://doi.org/10.1016/j.eneco.2019.104476.

Paraschiv, F., Erni, D., Pietsch, R., 2014. The impact of renewable energies on EEX day-ahead electricity prices. Energy Policy 73, 196–210. URL: http://dx.doi.org/10.1016/j.enpol.2014.05.004, doi:10.1016/j.enpol.2014.05.004. publisher: Elsevier.

Prol, J.L., Steininger, K.W., Zilberman, D., 2020. The cannibalization effect of wind and solar in the California wholesale electricity market. Energy Economics 85, 104552. URL: https://www.sciencedirect.com/science/article/pii/S0140988319303470, doi:https://doi.org/10.1016/j.eneco.2019.104552.

Sensfuß, F., Ragwitz, M., Genoese, M., 2008. The merit-order effect: A detailed analysis of the price effect of renewable electricity generation on spot market prices in Germany. Energy Policy 36, 3086–3094. doi:10.1016/j.enpol.2008.03.035.

for Solar Energy Systems, F.I., . Energy Charts. URL: https://energy-charts.info/.

Staffell, I., . Electric Insights. URL: https://electricinsights.co.uk/.

Traber, T., Kemfert, C., 2009. Impacts of the German support for renewable energy on electricity prices, emissions, and firms. The Energy Journal 30. doi:10.5547/ISSN0195-6574-EJ-Vol30-No3-8.

Volker-Quaschning, 2015. Specific Carbon Dioxide Emissions of Various Fuels. URL: https://www.volker-quaschning.de/datserv/CO2-spez/index_e.php.

Weigt, H., 2009. Germany's wind energy: The potential for fossil capacity replacement and cost saving. Applied Energy 86, 1857–1863. URL: https://linkinghub.elsevier.com/retrieve/pii/S0306261908003139, doi:10.1016/j.apenergy.2008.11.031.

Weron, R., 2014. Electricity price forecasting: A review of the state-of-the-art with a look into the future. doi:10.1016/j.ijforecast.2014.08.008. iSSN: 01692070 Publication Title: International Journal of Forecasting.

Wilson, A.G., Adams, R.P., 2013. Gaussian process kernels for pattern discovery and extrapolation. 30th International Conference on Machine Learning, ICML 2013 28, 2104–2112. _eprint: 1302.4245.

Wilson, I.A.G., Staffell, I., 2018. Rapid fuel switching from coal to natural gas through effective carbon pricing. Nature Energy 3, 365–372. URL: https://doi.org/10.1038/s41560-018-0109-0, doi:10.1038/s41560-018-0109-0.

Würzburg, K., Labandeira, X., Linares, P., 2013. Renewable generation and electricity prices: Taking stock and new evidence for Germany and Austria. Energy Economics 40, S159–S171. URL: https://linkinghub.elsevier.com/retrieve/pii/S0140988313002065, doi:10.1016/j.eneco.2013.09.011.

Yang, Y., Li, S., Li, W., Qu, M., 2018. Power load probability density forecasting using Gaussian process quantile regression. Applied Energy 213, 499–509. URL: https://doi.org/10.1016/j.apenergy.2017.11.035, doi:10.1016/j.apenergy.2017.11.035. publisher: Elsevier.

Zipp, A., 2017. The marketability of variable renewable energy in liberalized electricity markets An empirical analysis. Renewable Energy 113, 1111–1121. doi:10.1016/j.renene.2017.06.072. publisher: Elsevier B.V.