Causal Impact of Wind Energy on the UK Day-ahead Market

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***Abstract*—We provide the first causal evidence of the impact of wind power penetration on UK electricity prices, leveraging an advanced causal inference framework. Using data from 2018 to 2024, we uncover the non-linear conditional average treatment effect (CATE) of predicted wind power generation on prices across different penetration ranges. A 1 GW increase in predicted wind generation reduces day-ahead electricity prices by up to 6 GBP/MWh at low penetration levels, with the price-reduction effect weakening at moderate penetration before intensifying again at higher levels. In contrast to previous studies relying on regression analysis only, this work employs an extension of the double machine learning (DML) framework to disentangle the causal relationship between wind power and electricity prices, accounting for confounding factors such as demand, fuel prices, and seasonality. Numerical simulations confirm the robustness of the DML approach, while findings on real-world data underscore the importance of advanced causal tools in understanding price formation mechanisms and guiding market policies for renewable energy integration.**

***Index Terms*—Electricity markets, wind forecast, spot price, causal inference, machine learning.**

I. Introduction

Over the past two decades, the rapid integration of renewable energy sources has transformed the global energy landscape, driven by the urgency to combat climate change. This shift has fundamentally altered electricity generation and market operations worldwide. Wind power, with its zero emissions and low marginal costs, has become a cornerstone of the energy transition. In the UK, wind power became the largest source of electricity generation for the first time in 2024, contributing 30% to the energy mix [1]. However, the intrinsic characteristics of renewable generation, such as near-zero marginal costs and limited predictability, pose both significant challenges and opportunities for electricity markets.

One of the most significant market impacts of renewable energy is the merit-order effect, where low-cost renewable generation displaces more expensive conventional sources, driving down wholesale electricity prices. Initially documented in the Danish market [2], [3], this phenomenon has since been observed across numerous energy markets worldwide [4]–[23]. However, studies specific to the UK market remain limited [24], [25]. The merit-order effect of wind power integration has notable consequences, including price reductions, increased price volatility, and the cannibalisation effect [26], where higher penetration of renewables reduces their own market value. As more renewables enter the market, peak generation periods (e.g., during sunny or windy conditions) see wholesale prices decline, eroding the revenue per unit of electricity generated by these sources. Besides market effects, increased wind power penetration presents challenges such as the need for greater balancing reserves [27]–[29], economic pressure on conventional power plants, and the risk of stranded assets due to prolonged low electricity prices.

Most studies to date rely on traditional regression analyses that fall short in capturing the non-linear interactions and high-dimensional dependencies of modern electricity markets, leaving a critical gap in understanding the causal impact of wind power penetration. In contrast, this study is the first to provide robust causal evidence of these effects using a novel adaptation of the double machine learning (DML) framework [30]. Our approach disentangles the true causal effects of predicted wind power penetration from confounding factors such as demand, gas prices, and seasonal variations. By quantifying non-linear effects and heterogeneity across penetration levels, we not only challenge conventional wisdom but also deliver actionable insights for policymakers and market participants. Applied to the UK electricity market, this advanced causal inference methodology reveals the precise mechanisms by which wind power reshapes electricity prices, underscoring the need for sophisticated analytical tools to navigate the challenges introduced by high renewable penetration. This study sets a new standard for evidence-based energy policy, demonstrating the central role of causal inference in understanding and managing the economic implications of renewable energy integration.

The remainder of this paper is structured as follows. Section II describes the methodologies employed, including the proposed DML framework. In Section III, we showcase the effectiveness of DML using simulated data, while Section IV presents empirical results based on UK market data. Finally, Section V provides some conclusions.

II. Methodology

Deriving causal conclusions about the impact of wind power penetration requires adopting more sophisticated techniques than simple regression models. While regression analyses can reveal associations between variables, they often fail to identify causal effects, particularly in the presence of confounding variables. For a more comprehensive treatment of causal inference techniques for electricity markets, please refer to Cacciarelli and Pinson [31].

Confounders are variables that influence both the *treatment* (renewable penetration) and the *response* (electricity prices), creating a spurious relationship between the two if not properly controlled. For example, factors such as fuel prices, demand fluctuations, seasonal components, and broader economic conditions can simultaneously affect wind power penetration and electricity prices. These overlapping influences can bias estimates, making it challenging to isolate the true causal effect of renewable penetration.

To address this, it is essential to disentangle the effect of the treatment variable from the influence of confounders. By leveraging advanced causal inference methods, we can attempt to estimate the causal impact of wind power penetration on electricity prices while controlling for the wide range of confounding factors. In this study, we employed the DML framework introduced by Chernozhukov et al. [30]. This approach integrates machine learning with econometric techniques to provide unbiased causal estimates even when the data is characterised by non-linear relationships among numerous confounders. Within the DML framework, we assume that the response $\mathbf{y}$ is a function of the treatment $\mathbf{t}$ and other confounding variables $\mathbf{X}$, i.e.,

$$\mathbf{y} = f(\mathbf{t}, \mathbf{X}) + \varepsilon, \tag{1}$$

where f is a potentially non-linear function of the treatment $\mathbf{t}$ and confounders $\mathbf{X}$, and ε is an error term. Similarly, we assume that the treatment variable itself can be modelled as a function of the confounders, or a subset of them. This yields

$$\mathbf{t} = g(\mathbf{X}) + \boldsymbol{\eta}, \tag{2}$$

where g represents the relationship between $\mathbf{t}$ and $\mathbf{X}$, and $\boldsymbol{\eta}$ is an error term. The DML framework is designed to isolate the causal effect of the treatment variable by adjusting for confounding influences in two stages:

1) Nuisance parameter estimation: we train two machine learning models to estimate the functions f and g.
2) Orthogonalisation and estimation: the trained models are used to "remove" the influence of confounders from both the treatment and the response variables. Then, we regress the residualised response on the residualised treatment to estimate the average treatment effect (ATE).

The ATE represents the expected change in the response variable (electricity prices) resulting from a one-unit change in the treatment variable (wind power penetration), averaged across the entire population. The core idea behind DML is that after adjusting for confounders, the residual variation in the response variable is attributable only to the treatment variable. This method presumes we have knowledge of the causal structure and that there are no omitted variables that could bias the estimates.

In the context of DML, one of the most commonly encountered setup is the partially linear one [32]. In a partially linear DML framework, we assume the outcome $\mathbf{y}$ and the treatment $\mathbf{t}$ are linearly related, while allowing for potentially complex non-linear effects between the confounders $\mathbf{X}$ and both $\mathbf{t}$ and $\mathbf{y}$. The partially linear model can be specified as

$$\mathbf{y} = \mathbf{t}\,\beta + h(\mathbf{X}) + \boldsymbol{\varepsilon}\,, \tag{3a}$$

$$\mathbf{t} = g(\mathbf{X}) + \boldsymbol{\eta}\,, \tag{3b}$$

where β represents the true ATE we aim to estimate, and the functions $h(\mathbf{X})$ and $g(\mathbf{X})$ capture the effects of the confounders on the outcome and the treatment, respectively. Under the partially linear assumption, the effect β can be estimated using an ordinary least squares (OLS) model. The The main steps of the partially linear DML framework are reported in Algorithm 1.

Compared to more traditional approaches such as instrumental variables and propensity score matching, the DML framework offers greater flexibility by leveraging machine learning to handle high-dimensional confounders and non-linear relationships, making it particularly well-suited for the complex dynamics of electricity prices. Indeed, the DML is a model-agnostic framework and the models trained in steps 5 and 6 can be any machine learning model, allowing for flexibility in capturing complex relationships between variables. In our implementation, we employed a LightGBM regression model [33] due to its efficiency and ability to handle high-dimensional data.

Algorithm 1 Partially linear DML

1: **Input:** dataset $D = \{(\mathbf{x}_i, t_i, y_i)\}_{i=1}^{n}$, number of folds K
2: **Output:** effect estimate $\hat{\beta}$
3: Randomly partition the dataset into K folds. ▷ Split the data
4: **for** each fold $k = 1, \ldots, K$ **do** ▷ Train predictive models
5: Train a model $\hat{g}_{-k}(\mathbf{X})$ using $K-1$ folds to predict $\mathbf{t}$ from $\mathbf{X}$.
6: Train a model $\hat{h}_{-k}(\mathbf{X})$ using $K-1$ folds to predict $\mathbf{y}$ from $\mathbf{X}$.
7: Use $\hat{g}_{-k}$ and $\hat{h}_{-k}$ to predict $\mathbf{t}$ and $\mathbf{y}$ in the held-out fold k.
8: Compute residuals ▷ Orthogonalisation

$$\tilde{\mathbf{t}} = \mathbf{t} - \hat{g}_{-k}(\mathbf{X})$$
$$\tilde{\mathbf{y}} = \mathbf{y} - \hat{h}_{-k}(\mathbf{X})$$

9: Regress $\tilde{\mathbf{y}}$ on $\tilde{\mathbf{t}}$ using OLS ▷ Effect estimation

$$\hat{\beta}_k = \text{OLS}(\tilde{\mathbf{y}}, \tilde{\mathbf{t}}) = (\tilde{\mathbf{t}}^\top \tilde{\mathbf{t}})^{-1}\, \tilde{\mathbf{t}}^\top \tilde{\mathbf{y}}$$

10: **end for**
11: Compute the final estimate as the mean:

$$\hat{\beta} = \frac{1}{K} \sum_{k=1}^{K} \hat{\beta}_k$$

To provide a more detailed analysis of wind power's impact on wholesale electricity prices, we employed the partially linear DML framework to estimate the causal effect at varying levels of predicted wind power penetration. Instead of calcu-

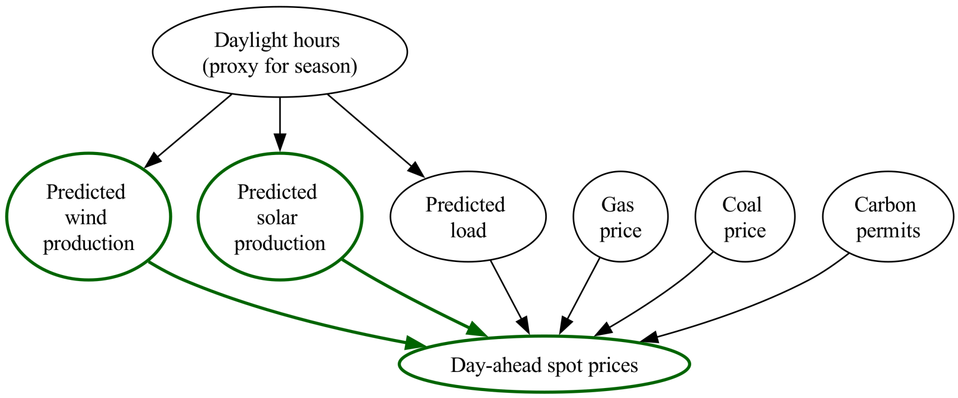

Fig. 1. DAG illustrating the causal structure of the data-generating process of the numerical simulations.

lating a single ATE, this approach enables us to assess how the merit-order effect evolves as wind penetration increases in the energy mix. This allows for the estimation of the conditional average treatment effect (CATE), which quantifies the treatment effect specific to different wind penetration levels. Our causal estimates rely on the unconfoundedness assumption, meaning all relevant confounders are observed and included. While we control for key factors such as demand, fuel prices, and seasonality, this assumption cannot be fully verified. Potential violations could bias results, and future work should consider sensitivity analyses to address unobserved confounding.

III. Numerical Simulations

This section demonstrates the effectiveness of the DML framework in estimating causal effects in the presence of confounders. To achieve this, we conducted numerical simulations designed to replicate real-world electricity market dynamics, capturing the seasonal, daily, and stochastic variations commonly observed in such markets. A synthetic dataset was generated to model these dynamics, providing a controlled environment for evaluating the performance of DML.

A. Setup and Methods

The synthetic dataset comprises one year of hourly observations, encompassing key market variables such as wind power production, solar power production, load forecasts, and fuel prices (e.g., gas and coal). The causal structure of the data-generating process is depicted in the directed acyclic graph (DAG) in Figure 1, which illustrates the causal relationships among the variables included in the experiment. The functional forms of these relationships are:

- Daylight hours: modelled as a sinusoidal function to capture seasonal variations.
- Predicted wind and solar production: simulated with a base value influenced by daylight hours and adjusted with random fluctuations to mimic forecast errors.
- Predicted load: influenced by seasonal daylight patterns.
- Other fuel prices (gas, coal, carbon): modelled using random walks to simulate price volatility.
- Day-ahead spot prices: formulated as a linear combination of the above variables. The ATE of wind and solar power on spot prices is fixed at -0.3, meaning a one-unit increase in the generation of these renewables leads to a 0.3 GBP/MWh reduction in spot prices.

After generating the data, we employed three different approaches to estimate the ATE of wind and solar power production on spot prices:

- *Linear regression with two features*: as a baseline model, we performed a linear regression using only predicted wind ($\mathbf{w}$) and and solar ($\mathbf{s}$) power production as predictors:
$$\mathbf{p} = \beta_0 + \beta_1 \mathbf{w} + \beta_2 \mathbf{s} + \varepsilon, \tag{4}$$
where $\mathbf{p}$ denotes the vector of spot prices, and ε represents the error term.
- *Linear regression with all features*: to address the limitations of the baseline model, we extended it to include a broader set of predictors, such as gas prices ($\mathbf{g}$), coal prices ($\mathbf{c}$), carbon permits ($\mathbf{e}$), predicted load ($\mathbf{l}$), and daylight hours ($\mathbf{d}$):
$$\mathbf{p} = \beta_0 + \beta_1 \mathbf{w} + \beta_2 \mathbf{s} + \beta_3 \mathbf{g} + \beta_4 \mathbf{c} + \beta_5 \mathbf{e} + \beta_6 \mathbf{l} + \beta_7 \mathbf{d} + \varepsilon \tag{5}$$
By incorporating these additional features, this model aims to account for potential confounders omitted in the simpler model (4). However, challenges such as multicollinearity among predictors and noise from irrelevant variables can undermine the precision of the estimated coefficients for β_1 and β_2, which measure the effects of wind and solar production, respectively.
- *Partially linear DML*: to isolate the causal effects of wind and solar power on spot prices, we applied the partially linear DML approach. This method uses the two-stage procedure described in Algorithm 1 to remove the influence of confounders from both the treatment variables and the outcome variable. Specifically, we adjusted for the effects of seasonality ($\mathbf{d}$) on wind ($\mathbf{w}$) and solar ($\mathbf{s}$), as well as for the effects of demand ($\mathbf{l}$), gas prices ($\mathbf{g}$), coal prices ($\mathbf{c}$), carbon permit prices ($\mathbf{e}$), and seasonality ($\mathbf{d}$) on spot prices ($\mathbf{p}$).

B. Results

The estimation results, based on 1000 replications of the data generation and estimation process, are presented in Figure 2.

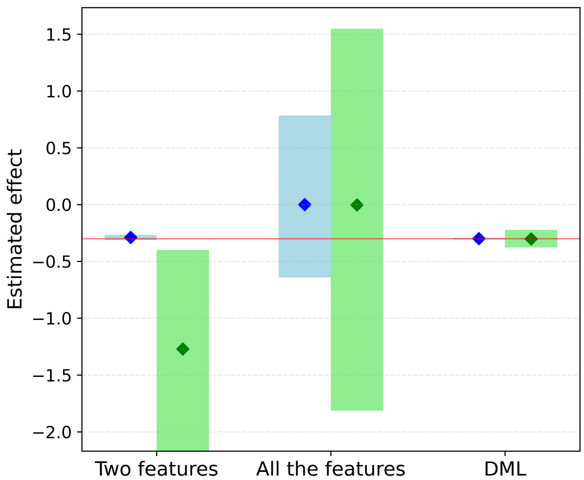

Fig. 2. Comparison of estimated effects across the three methods. The diamond-shaped markers represent the median estimates, with blue indicating wind power and green indicating solar power. The shaded bars denote the 80% confidence intervals (CIs), and the red solid line represents the true causal effects.

The partially linear implementation of the DML framework demonstrates a high degree of accuracy, closely approximating the true ATE of wind and solar power production on spot prices, which is set at -0.3. In contrast, the simple linear regression model, which uses only wind and solar power production as predictors, substantially overestimates the causal effect of solar power. This overestimation stems from omitted variable bias, as the model fails to account for key factors influencing spot prices, such as fuel prices, demand, and seasonal variations. By ignoring these confounders, the simple model improperly attributes their effects to renewable energy variables, resulting in a biased and exaggerated estimate of their impact. The multivariate regression approach, which includes a broader set of covariates, offers some improvement by controlling for additional factors. However, it underestimates the merit-order effects of renewables, likely due to multicollinearity among the predictors and its inability to adequately capture non-linear relationships and high-dimensional dependencies in the data. This highlights the limitations of traditional regression models when dealing with the complexities of modern electricity markets and underscores the robustness of the DML framework for causal estimation in the presence of confounders.

IV. Real-world Data

In this section, we investigate the effect of wind power penetration on electricity prices in the UK, using data from 2018 to 2024.

A. Overview

In Figure 3, we can see the average wholesale electricity prices across three markets (day-ahead APX, day-ahead Nordpool, and within-day) categorised by intervals of predicted wind power penetration. The figure reveals a general trend of decreasing electricity prices as wind power penetration increases, highlighting the influence of the merit-order effect.

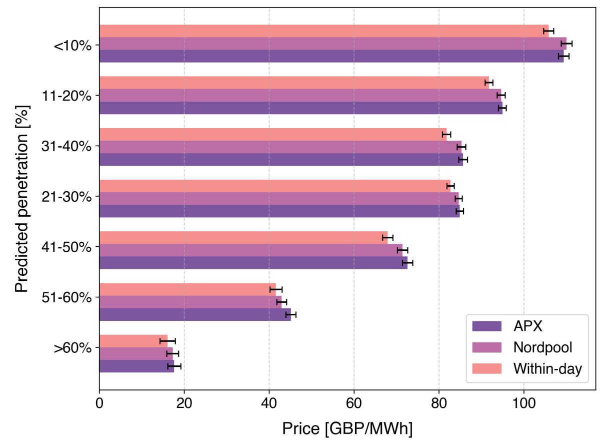

Fig. 3. Average wholesale electricity prices (APX, Nordpool, and within-day) with 95% confidence intervals, computed using the bias-corrected and adjusted bootstrap method, categorised by predicted wind power penetration levels.

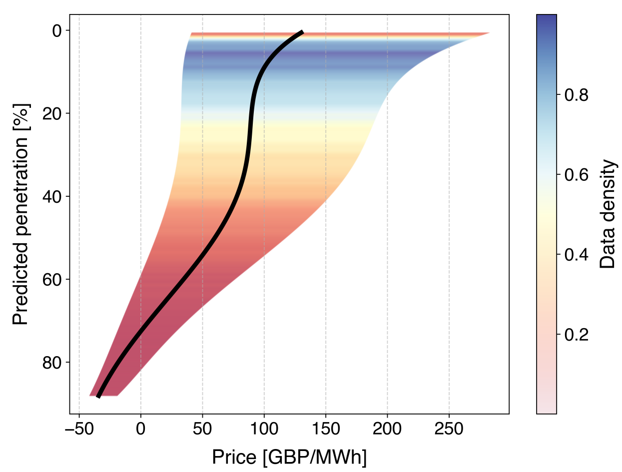

Fig. 4. Day-ahead APX price modelled using a quantile regression approach, with predicted wind power penetration as the input. The y-axis is in reverse order, with 0% wind power penetration at the top and increasing penetration levels towards the origin, providing a complementary view to the barplots.

The average wholesale prices offer valuable insights into market behaviour. However, given the inherent uncertainty associated with wind power, it is crucial to also examine the distribution of data around the mean trend. Quantile regression allows us to explore the conditional distribution of prices, revealing the value below which a certain proportion of observations fall for a specific quantile level. Figure 4 displays the range within which 80% of the data lies, represented by the 10% and 90% quantiles. The shaded areas indicate this range, with the mean prediction denoted by a solid line. The colour intensity reflects data density, which decreases with higher levels of wind power production and penetration. This gradient is important as it highlights areas with fewer observations, suggesting that conclusions drawn from these regions should be interpreted with caution. The mean prediction line shows a clear downward trend, reinforcing the observation that higher wind power penetration correlates with lower electricity prices. Additionally, the narrowing of the quantiles indicates a reduction in price variability as wind penetration increases.

B. Causal Effects

The estimated CATEs of predicted wind power production on wholesale electricity prices at various levels of wind power penetration are shown in Figure 5. This plot reveals the complex relationship between wind power integration and electricity prices, highlighting the non-linear effects at different penetration levels. The CATEs represent the average price effect (GBP/MWh) associated with increases in wind power (predicted GWs), accounting for confounding variables such as demand, fuel prices, and seasonal fluctuations.

At low levels of wind penetration, the results show a strong price reduction effect of approximately 6 GBP/MWh. However, as wind power penetration increases, this price-reduction effect begins to diminish for intermediate levels (approximately between 11% and 30%). The weakening of the price-reduction effect at moderate penetration levels may reflect the structure of the UK supply stack. As penetration increases to moderate levels, wind begins to displace units with more similar marginal costs, potentially leading to a flatter portion of the supply curve where the incremental price effect becomes smaller. At very high penetration levels, wind may start to displace more inflexible or baseload generators, leading to steeper price drops. This non-monotonic pattern reflects changes in the slope of the supply curve at different penetration levels, illustrating how the influence of wind power on electricity prices is dynamic and context-dependent.

The violin plots in Figure 5 provide a detailed distribution of the CATE estimates across varying levels of wind power penetration. The central line in the plot represents the median CATE estimate, providing a measure of central tendency for the price effects at each penetration level. The plot also highlights the variability in the CATE estimates, which is more pronounced at both low and high penetration levels. At these extremes, the causal effect of wind power on electricity prices is more variable, suggesting that other factors may have a more substantial role in price formation.

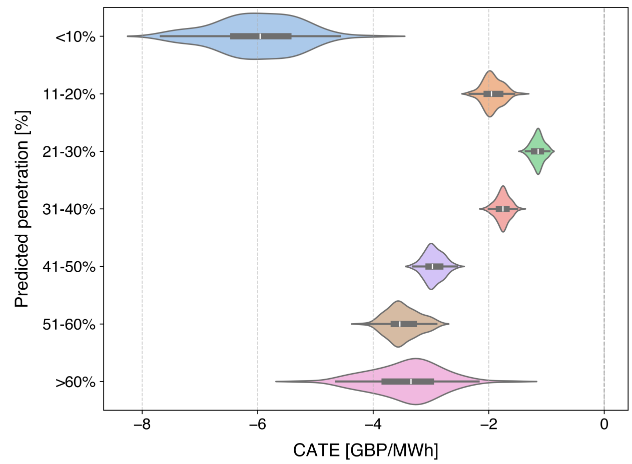

Fig. 5. Causal effect of predicted wind power production on wholesale electricity prices.

V. Conclusions

A. Overview of contributions

Our work provides a comprehensive analysis of the impact of (predicted) wind power penetration on wholesale electricity prices in the UK, leveraging advanced causal inference techniques, particularly the DML framework. Our findings reveal that wind power has a significant effect on reducing electricity prices, particularly at lower penetration levels. However, the relationship between wind power penetration and price reduction is not linear, as the effect diminishes with increasing wind power penetration and then intensifies at higher levels. These results provide valuable insights into the merit-order effect and highlight the importance of considering non-linear (causal) interactions in energy markets, which can be missed by traditional regression approaches. We have also demonstrated the effectiveness of the DML framework in disentangling the effects of wind power from other influencing variables such as fuel prices, demand, and seasonal factors. Our results highlight the potential for policy-makers and market participants to better understand and navigate the complexities of integrating renewable energy into electricity markets.

B. Future Research Directions

There are several avenues for future research. Currently, the DAG is assumed based on prior knowledge, but integrating machine learning or other data-driven methods to construct the DAG dynamically could offer more flexibility and precision in capturing complex market relationships. Moreover, the relationship between wind power penetration and electricity prices may not be stationary over time. Testing the stability of the DAG over time could provide deeper insights into the dynamics of the energy market and how renewable integration influences price formation in different market phases.

Looking ahead, combining the effects of day-ahead electricity market prices with balancing costs would provide a more comprehensive understanding of the economic impacts of renewable energy integration. Balancing costs, particularly in systems with high renewable penetration, are critical for maintaining grid stability and ensuring that price fluctuations do not undermine the economic viability of conventional generation. This combined approach would enable policymakers and market participants to account for both market and operational challenges, guiding the integration of renewables while ensuring reliable and cost-effective energy systems.

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