HEC MONTRÉAL

Unveiling the Cannibalisation Effects in Renewable Energy: Empirical Insights and Implications for Battery Integration

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Mémoire présenté en vue de l'obtention
du grade de maîtrise ès sciences en gestion
(M. Sc.)

April 2024

Résumé

L'étude actuelle examine la durabilité financière des sources d'énergie renouvelable au milieu de la transition vers un paysage énergétique plus vert, en se concentrant sur les défis posés par l'effet de l'effet de cannibalisation. En exploitant des données de l'opérateur indépendant du système de Californie (CAISO) couvrant la période du 1er juin 2018 au 31 décembre 2022, nous fournissons des preuves empiriques de l'effet de cannibalisation dans la production d'énergie renouvelable, révélant une corrélation négative significative entre les sorties renouvelables et leur valeur marchande, à la fois sur des niveaux horaires et quotidiens en utilisant un modèle de régression linéaire. De plus, nous explorons le rôle potentiel du stockage d'énergie par batterie à grande échelle comme solution pour atténuer cet effet. Contrairement à la sagesse conventionnelle, notre analyse de régression indique que les batteries agissent en tant que substituts plutôt que comme compléments à l'énergie renouvelable, exacerbant potentiellement les défis financiers auxquels sont confrontées les énergies renouvelables. Nous attribuons cette relation compétitive aux caractéristiques opérationnelles des batteries, conçues pour capitaliser sur les écarts de prix tout au long de la journée afin de soutenir leur propre viabilité financière. Pour évaluer le potentiel de stockage par batterie en tant que produit complémentaire, nous construisons un scénario hypothétique où la production de batterie est retardée de quatre heures, et découvrons une corrélation positive entre les sorties renouvelables et de batterie, le revenu et le profit dans ce scénario. Dans l'ensemble, notre étude contribue à la compréhension des dynamiques entre l'énergie renouvelable, le stockage par batterie et les forces du marché, fournissant des idées aux décideurs politiques concernant le potentiel de synergie entre la batterie et les énergies renouvelables.

Mots clés : Batterie à grande échelle; cannibalisation; valeur marchande des énergies renouvelables

Abstract

The current study investigates the financial sustainability of renewable energy sources amidst the transition to a greener energy landscape, focusing on the challenges posed by the cannibalization effect. Leveraging data from the California Independent System Operator (CAISO) spanning June 1, 2018, to December 31, 2022, we provide empirical evidence of the cannibalization effect in renewable production, revealing a significant negative correlation between renewable outputs and their market value, both on hourly and daily levels using linear regression model. Additionally, we explore the potential role of utility-scale battery storage as a solution to mitigate this effect. Contrary to conventional wisdom, our regression analysis indicates that batteries act as substitutes rather than complements to renewable energy, potentially exacerbating the financial challenges faced by renewables. We attribute this competitive relationship to batteries' operational characteristics, designed to capitalize on price differentials throughout the day to sustain their own financial viability. To assess battery storage's potential as a complementary product, we construct a hypothetical scenario where battery output is delayed by four hours, and discovered a positive correlation between renewable and battery outputs, revenue, and profit in this scenario. Overall, our study contributes to understanding the dynamics between renewable energy, battery storage, and market forces, providing insights for policymakers regarding the synergy potential between battery and renewables.

Keywords : Utility-scale battery; cannibalisation; renewable market value

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List of Abbreviations

W	Wind
S	Solar
R	Revenue
MV	Market Value
RE	Renewable Energy
DAM	Day-ahead Market
RTM	Real-time Market

Acknowledgements

I would like to extend my sincere appreciation to Dr. Mario Samano for his invaluable guidance and mentorship throughout this exploration of energy research. It has been quite a delightful journey venturing into the complex energy supply systems.

To my wonderful parents, I am profoundly grateful for your unwavering support and encouragement. Your belief in my pursuits, no matter how unconventional, has been a constant source of strength.

I would also like to express my gratitude to my dear friends, both in Montreal and beyond, for their steadfast companionship and encouragement.

Introduction

The increasing global population and technological advancements have spurred an escalating demand for energy, yet the environmental drawbacks of fossil fuel consumption have underscored the urgency for increased investment in alternative energy sources. International efforts in energy transition dates back to initiatives like the 1987 Montreal Protocol, aiming to reduce ozone-depleting substances, and culminating in milestones such as the 2015 Paris Agreement, which urges nations to set emission reduction targets and mobilize support for sustainable energy transitions (Qadir et al., 2021a). Over recent decades, countries and regions have set ambitious goals for energy transition, including the European Commission's proposal for a 40% reduction in greenhouse gas emissions by 2030 through turning to renewable energy supply (Meletiou et al., 2019). The United States aims for a 50-52% reduction in net greenhouse gas emissions below 2005 levels by 2030 through increased electrification and adoption of renewable technologies (U.S. Energy Information Administration, 2023). Other regions such as India, China, South America, and UAE also pledged with increase in renewable targets of various degree (Gielen et al., 2019a).

Throughout these transitions, governments in all regions have consistently grappled with the challenge of subsidizing the renewable energy industry to render it financially viable, considering renewables' inherent features of extended return periods and substantial initial investments. A myriad of subsidies has historically been utilized to incentivize investment in renewable energy (Del Río & Kiefer, 2022). In the United States, renewable subsidies have increased, with combined conservation and end-use subsidies rising from \$9.0 billion in FY 2016 to \$10.1 billion in FY 2022 (U.S. Energy Information Administration, 2023). Similarly, in the European Union, total energy subsidies escalated from EUR 177 billion in 2015 to EUR 216 billion in 2021, reaching an estimated EUR 390 billion in 2022 (2023 Report on Energy Subsidies in the EU, 2023). However, previous literature has outlined certain drawbacks, notably the cannibalization effect, which suggests that increased production diminishes the market value of renewables. Consequently, it becomes imperative to explore solutions to mitigate and manage these obstacles to ensure the financial sustainability of renewable energy initiatives. Otherwise, as renewable production continues to scale up, the more subsidies will be required for sustaining the high level of production.

In this context, the present study aims to investigate two key aspects pertaining to renewable energy production: the precise impact of increased renewable output on market prices, and the potential role of large-scale batteries as a solution to this issue. The subsequent discussion is structured into three chapters. Chapter 1 will provide an overview of governmental subsidy efforts, past literature on the merit-order effect and cannibalization effect of renewable energy, and an examination of the operational characteristics of batteries. In Chapter 2, we delve into real-world manifestations of the cannibalization effect, leveraging data from the California Independent System Operator (CAISO) to demonstrate renewable outputs' impact on day-ahead market prices and the market value of renewables of different technologies. Chapter 3 explores the concept of using large-scale batteries to mitigate the cannibalization effect, drawing on the framework proposed by Andres-Cerezo & Fabra (2023), which posits that the cannibalization effect of renewables serves as the foundation for a complementary relationship between renewables and batteries. We apply this framework to the CAISO dataset to assess whether batteries can indeed complement renewables, offering synergies that make the combination of renewables and batteries a profitable and attractive investment, thereby potentially reducing reliance on subsidies for renewable energy.

Literature review

Renewable Subsidies

The ambitious global commitment to decarbonization, spanning diverse geographic regions and involving numerous countries, has positioned the increase in renewable capacity as a pivotal solution. However, despite considerable attention given to this endeavor, significant barriers persist in the transition to clean energy. Foremost among these challenges is the perception of renewable energy sources as costly and unpredictable, leading to doubts regarding their reliability and affordability (Diesendorf & Elliston, 2018a). Factors such as extended return periods, substantial initial investments, and operational challenges have contributed to the perception of renewable energy as a risky venture from an investor's standpoint (Egli, 2020).

A plethora of subsidies has historically been employed to stimulate investment in renewable energy (Del Río & Kiefer, 2022). In Europe, feed-in tariffs have emerged as a prominent tool to foster the expansion of grid-connected renewable energy sources. These tariffs stipulate the price per kilowatt-hour (kWh) that local distribution companies are mandated to compensate for renewable power integrated into the grid, thereby compelling utilities to facilitate such connections and remunerate accordingly (Sijm, 2022). Similarly, the implementation of net metering, mandated in 23 US states, enables small-scale generators to offset their energy consumption or sell surplus power back to the grid, thereby incentivizing the adoption of solar technology and transforming consumers into active participants, or "prosumers" (Lamp & Samano, 2023; Schelly et al., 2017).

While critical in catalyzing the adoption of renewable energy, instruments such as tax reductions, investment subsidies, feed-in tariffs, and net metering are perceived as interim measures. These mechanisms are essential for initiating renewable technologies but fall short of ensuring long-term cost efficiency. The overarching aspiration is for renewable energy to attain financial self-sufficiency and become a viable investment avenue. Nonetheless, despite financial backing, doubts persist regarding the market competitiveness of renewable energy after years of expansion, primarily due to the merit-order effect and cannibalisation effect. The merit-order effect delineates how an expanded renewable energy capacity can drive down the average wholesale electricity price (Antweiler & Muesgens, 2021; Bahn et al., 2021), exacerbating the disparity between the actual market value of renewables and the escalating subsidies required to sustain feed-in tariffs. Consequently, this dynamic undermines the attractiveness of investing in renewable energy, confronting policy makers with the pressing question of the sustainability of support policies in the face of escalating costs triggered by the widening disparity between guaranteed feed-in tariff prices and the market value of renewable energy (López Prol & Steininger, 2018). Given these disadvantages, there has been an ongoing debate regarding whether renewable energy can attain profitability without necessitating financial subsidies (Held et al., 2019).

Intermittency and Cannibalisation Effect

Diving into the obstacles to renewables' profitability, which is also the primary focus of the current study, we seek to understand and provide evidence to on the impact of cannibalisation effect on market value and cost-effectiveness of solar and wind power, the two most promising forms of renewable energy. Despite their potentials, both technologies encounter similar challenges, merit-order effect and its more specific form – cannibalisation effect. The merit-order effect posits that due to the inelasticity of electricity demand in the short term, the introduction of renewable energy can displace electricity that would otherwise be generated by conventional power plants. Consequently, this displacement diminishes the variable profits for all technologies in the market, including solar and wind power, by reducing the demand for conventional technologies, resulting in a downward pressure on wholesale electricity prices (Palmer & Burtraw, 2005). This phenomenon, often cited as a drawback of renewable energies, suggests that the wholesale price of electricity decreases as installed renewable technology increases its production (Sensfuß et al., 2008).

Originating from the merit-order effect, the cannibalization effect signifies the adverse consequence of high penetration levels of renewable energy on their own market values. Previous literature, particularly in markets with significant penetration of variable renewables such as Texas (Woo et al., 2023), Germany (Dillig et al., 2016), Spain

(Ballester & Furió, 2015), and Italy (Clò et al., 2015), has consistently highlighted this phenomenon. The past research generally agree that the value of renewables tends to decline as renewable penetration increases, which in turn translates into reduced revenues for renewable energy generators. While the merit-order effect broadly explains how increasing renewable penetration leads to downward pressure on prices, the cannibalization effect specifically emphasizes the negative impact that high penetration levels have on the market values of renewables themselves.

Apart from the merit-order effect, solar and wind production also encounters the challenge of curtailment at times, which refers to the reduction in the output of a generator from its potential capacity, often involuntarily due to various factors. It is widely recognized as a loss of clean energy, detrimental not only to generators and investors but also to system operators and regulators (Yasuda et al., 2022). Both curtailment and the cannibalization/merit-order effect may be exacerbated by the intermittent nature of wind and solar technologies, which are influenced by weather conditions and mismatch between supply and demand. Peak solar generation typically occur during mid-day and wind generation increase in the evening. This volatility underscores the necessity of comprehending the evolution of wholesale electricity prices throughout a 24-hour cycle, as such understanding would be critical in matching supply and demand and thereby mitigate the cannibalisation effect and maximize the profitability and market value of solar and wind power plants (Liebensteiner & Naumann, 2022a).

Batteries: Development and Operational Patterns

The inherent unpredictability and non-dispatchable nature of variable renewable energy necessitate precise balancing of supply and demand in real-time to avert system failures and reduce renewable losses. Consequently, a significant outcome of this challenge has been the increasing deployment of large-scale, non-hydro storage technologies like lithium-ion batteries (Lamp & Samano, 2022a). Utility-scale battery energy storage systems have long been acknowledged for their potential to bolster the grid, stabilize renewable energy output, and provide an integrated solution to environmental challenges. The expansion of solar and wind energy has thus induced an advocacy for the development of energy storage technologies. In support of electricity storage deployment, California enacted legislation in 2010 mandating the state's three largest investor-owned utilities to procure 1,325 MW of electricity storage (excluding large-scale pumped hydro storage) by 2020 (Balakrishnan et al., 2019).

In the existing body of literature, battery operation is typically characterized as that of a price-taking arbitrager. Throughout the day, the patterns of charging and discharging align with fluctuations in wholesale electricity prices (Lamp & Samano, 2022a). Research findings indicate that the output of batteries tends to adjust in response to changes in prices, emphasizing the importance of capitalizing on arbitrage opportunities within the electricity market for the profitability and financial sustainability of battery facilities. This strategy essentially involves seeking economic advantages by purchasing electricity when prices are low and selling when they are high, or by charging batteries during periods of low wholesale prices and discharging them during high-price periods (Brivio et al., 2016). While individual batteries are generally considered as price-takers, there is also evidence suggesting that when aggregated, batteries can help mitigate peak prices, thereby influencing market dynamics and the economic feasibility of battery investments (Lamp & Samano, 2022a). For the purposes of this study, the assumption is made that batteries operate as price-takers.

Given the intricate interplay between batteries and renewable energy sources, our investigation extends to theoretical frameworks that seeks to understand how batteries operate to capture surplus renewable energy while bridging gaps when renewables alone cannot meet demand. Despite conventional wisdom often implying a complementary rapport between batteries and renewables, the theoretical hypothesis indicates that for such synergy to exist, specific underlying conditions must be fulfilled concerning the correlation between renewable energy outputs and pricing dynamics (Andres-Cerezo & Fabra, 2023). Specifically, there must be a sufficiently high capacity of renewable energy generation, leading to volatility in output substantial enough to influence and depress the wholesale prices, thereby rendering arbitrage opportunities feasible for batteries. Additionally, there must exist a negative correlation between prices and renewable energy outputs, allowing batteries to absorb excess energy at favorable prices conducive to capitalizing on arbitrage opportunities. Interestingly, within this theoretical framework, the cannibalization effect of renewable energy, often perceived as a drawback to the market value of renewable energy, emerges as a pivotal factor facilitating synergy between batteries and renewable energy sources.

Chapter 1
Data Sources and Definition of Variables

1.1 Data Sources

The present research leverages data sourced from the California Independent System Operator (CAISO) website. The sampling period spans from June 7th, 2018, to December 31st, 2022, and encompasses hourly and daily records of electricity production categorized by different generation types, encompassing predominant renewable sources like wind and solar, as well as smaller contributors such as biogas, biomass, small hydro, and geothermal. Additionally, the dataset considered output from non-renewable sources such as coal and nuclear as control variables. Furthermore, we augment our analysis with supplementary data pertaining to the import dynamics within the California electricity production landscape. The dataset also provides information on prices in both the day-ahead and real-time markets, along with load day-ahead forecasts, facilitating a thorough examination of the demand side of the electricity market.

The dataset used in the current study utilizes actual output of various energy sources, as opposed to forecasted amounts. It is important to note that there is a nearly perfect correlation (higher than 0.9) between day-ahead forecasting and the actual realized amount based on demand data. Given this high correlation, we posit that using actual versus forecast amount is unlikely to exert a substantive influence on the validity of the study result.

Table 1 presents an overview of descriptive statistics of our sample, complemented by Figure 1 and Figure 2 on subsequent pages, which visually depict market development concerning renewable energy production. It is noteworthy that the output levels in the present dataset significantly surpass those observed in the European region dataset utilized in previous study related to the cannibalization effect(Liebensteiner & Naumann, 2022a). Based on Figure 1, we see a consistent upward trajectory in renewable energy output over the years. Our sample data, spanning from 2018 to 2022, also suggest that solar and wind jointly contribute, on average, over 80% to the renewable energy output.

In contrast, the cumulative contribution of the four smaller sources averages less than 20% during the same timeframe (Table 1).

1.2 Insights into the California Energy Landscape: Four Key Observations

I. The upward trend in renewable energy production is driven primarily by an increase in solar and wind output. From Figure 1 below we see a consistent upward trajectory in renewable energy output over the years, however, in Figure 2, we notice the upward trends are solely visible in the outputs of wind and solar energy, contrasting with other renewable energy sources that consistently demonstrate a discernible downward trend over the timeframe. This trend is particularly evident in biogas, biomass, and small hydro, with a slight decline also noticeable in geothermal energy. This collective evidence indicates that the surge in renewable energy output is primarily attributed to the robust increase in wind and solar output.

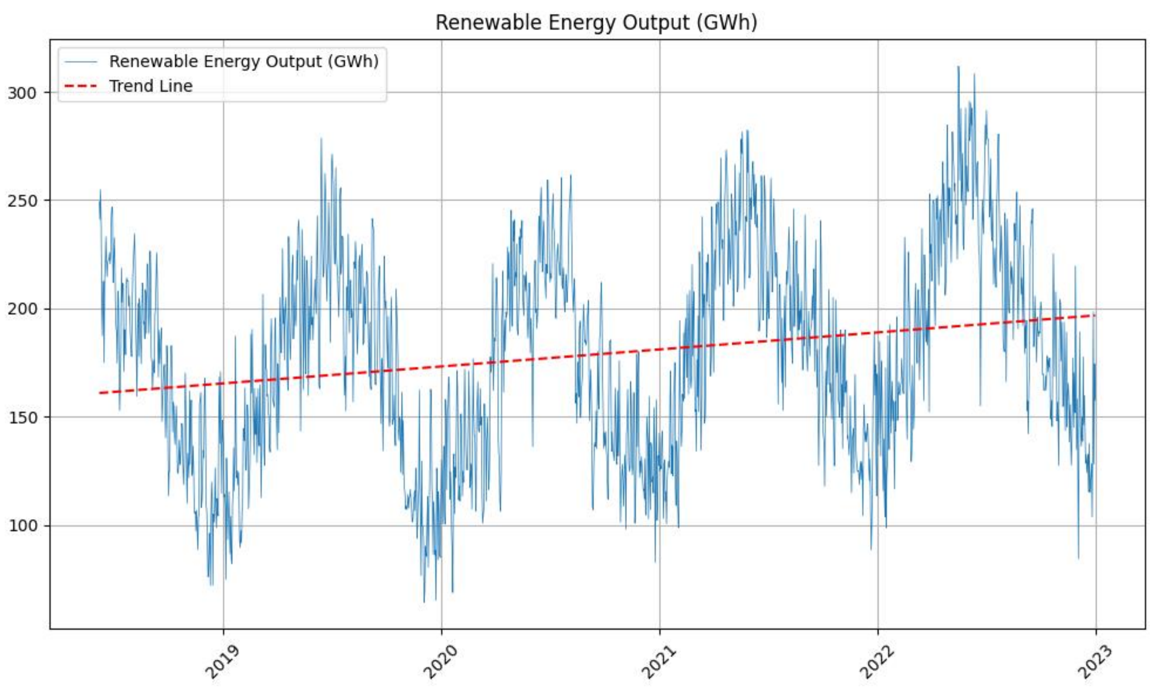

Figure 1. Market developments of total renewable energy.
This figure depicts the developments of renewable energy output in California during the sample period 2018/06/07–2022/12/31.

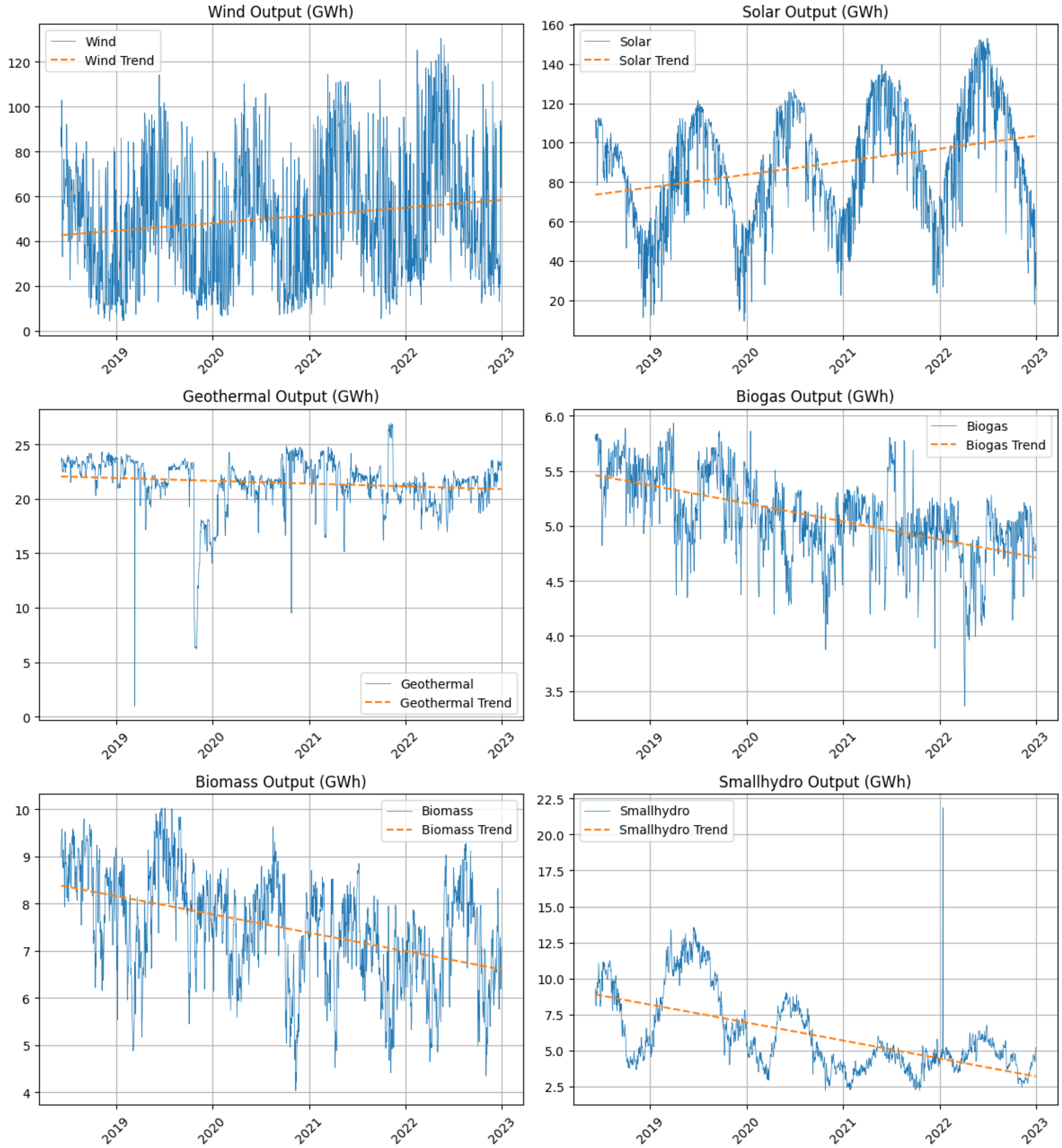

Figure 2. Market developments breakdown by renewable technologies during the sample period 2018/06/07–2022/12/31.

II. Strong seasonality effect of wind and solar output. The impact of seasonality is notable in both solar and wind output, characterized by substantial energy generation during the summer, resulting in a peak in the middle of each year. Conversely, a significant dip is observed at the end of each year, forming a distinctive mountainous pattern of ascent and descent. Despite these periodic fluctuations, an overarching upward trend persists. While a similar effect is identified in wind output, the pattern is less distinctly observable due to heightened variability and greater erraticism in the data. These findings reaffirm the original study's observations regarding the heightened volatility of solar and wind production, along with the observed increase over the year.

III. The energy landscape of California is exhibiting a rising trend towards self-sufficiency. From the trend graphs depicting import amounts and demand over the observed period (

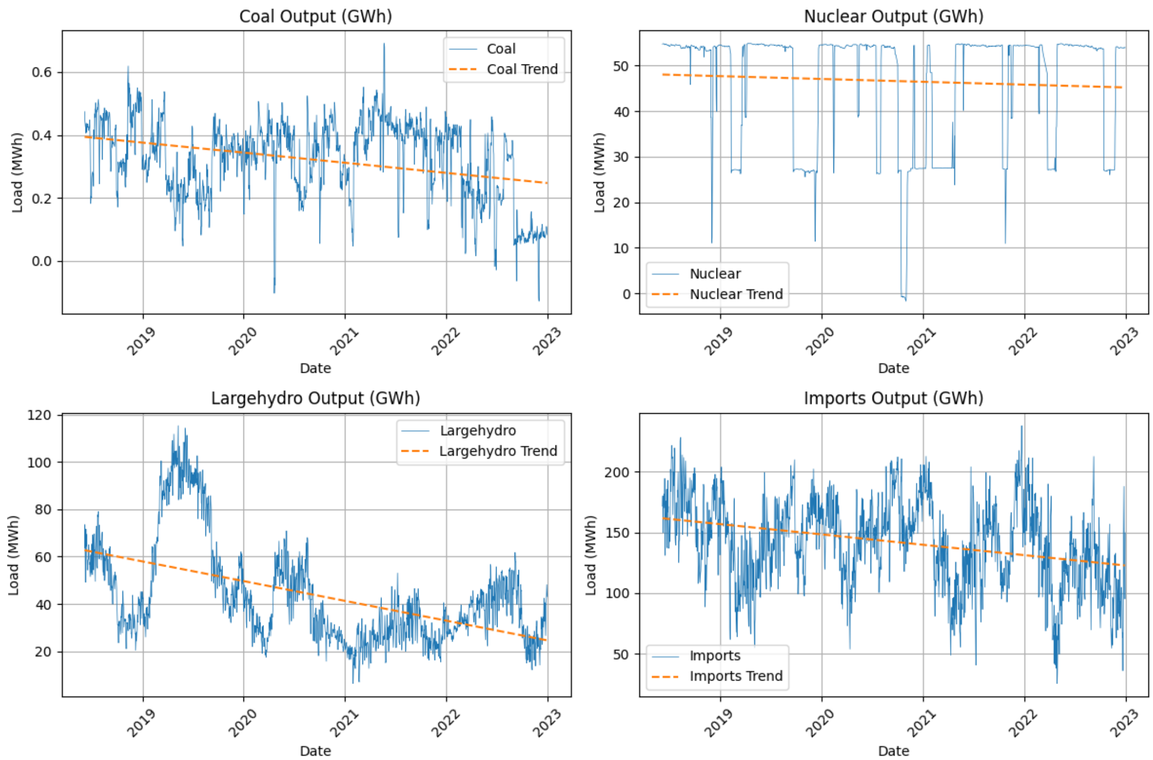

Figure **4**), it is evident that, despite the steady demand, there is a noticeable decline in the import quantity. This observation highlights California's capacity to satisfy its energy needs internally, signaling a growing autonomy from external supply sources. Even with the reduction in imports, California demonstrates proficiency in meeting its energy demands, indicating a substantial transition towards self-reliance in the state's energy supply.

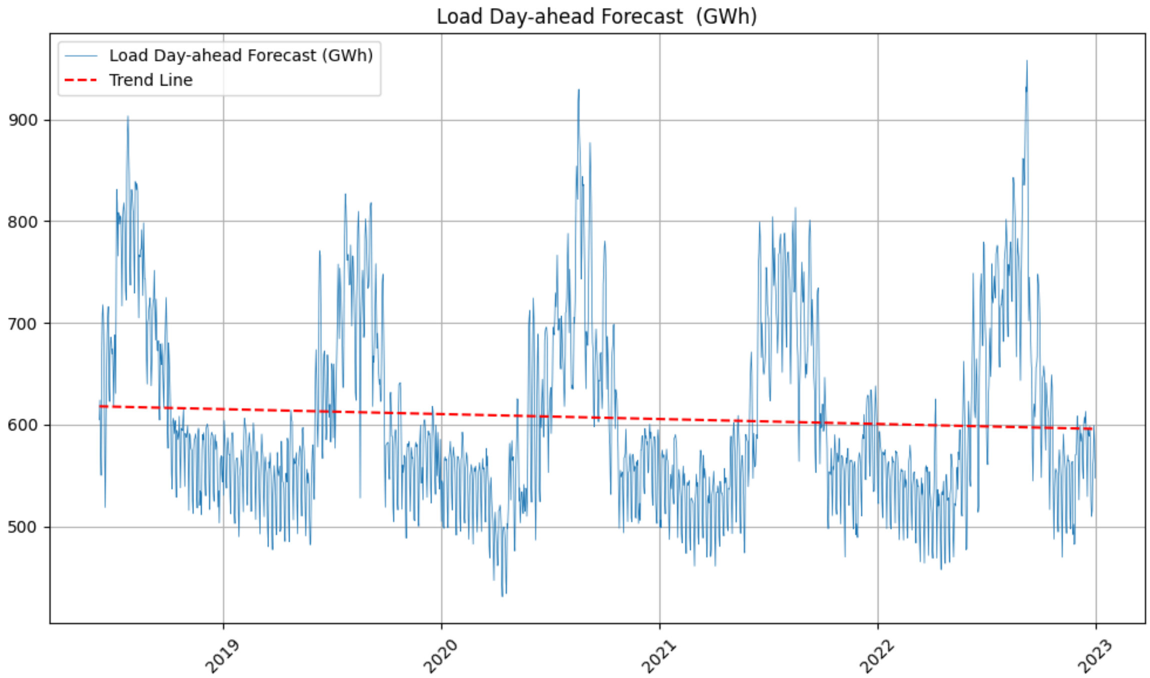

Figure 3. Time trend of daily load day-ahead forecast (demand) during the sample period 2018/06/07–2022/12/31.

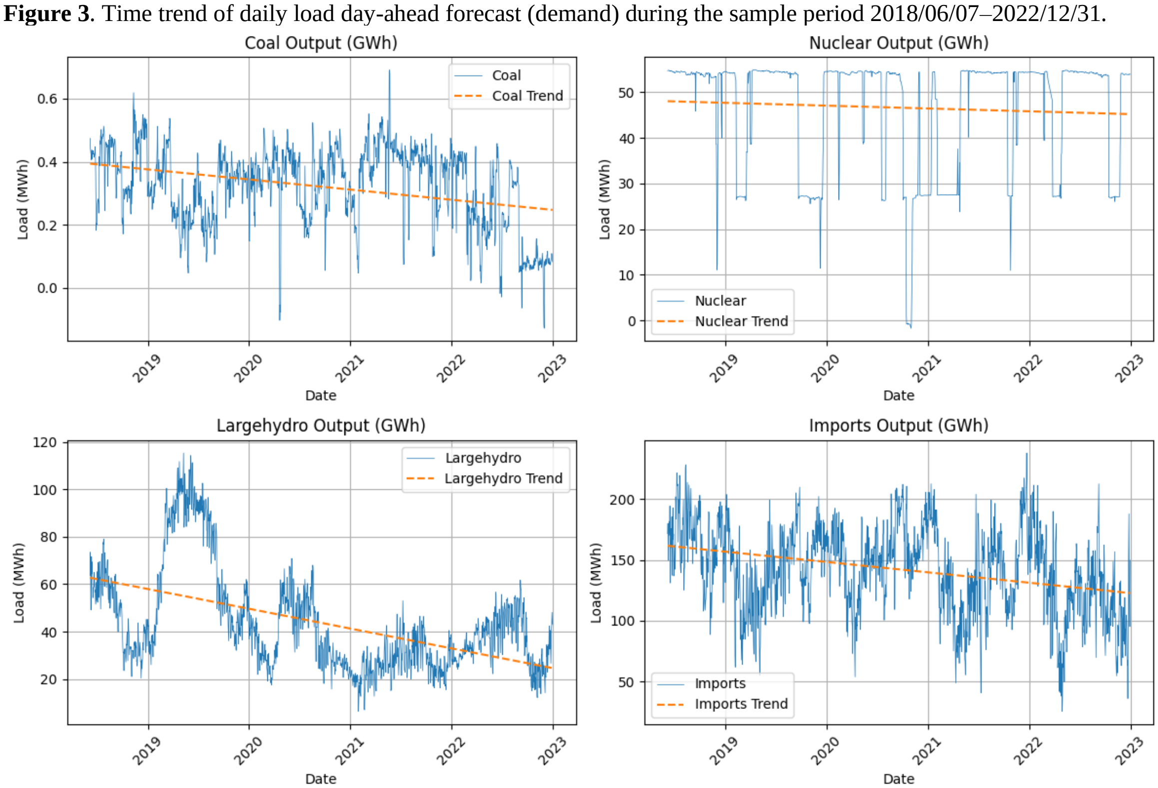

Figure 4. Market developments of various control variables during the sample period 2018/06/07–2022/12/31.

IV. Demand is increasingly met by renewable energy. Based on

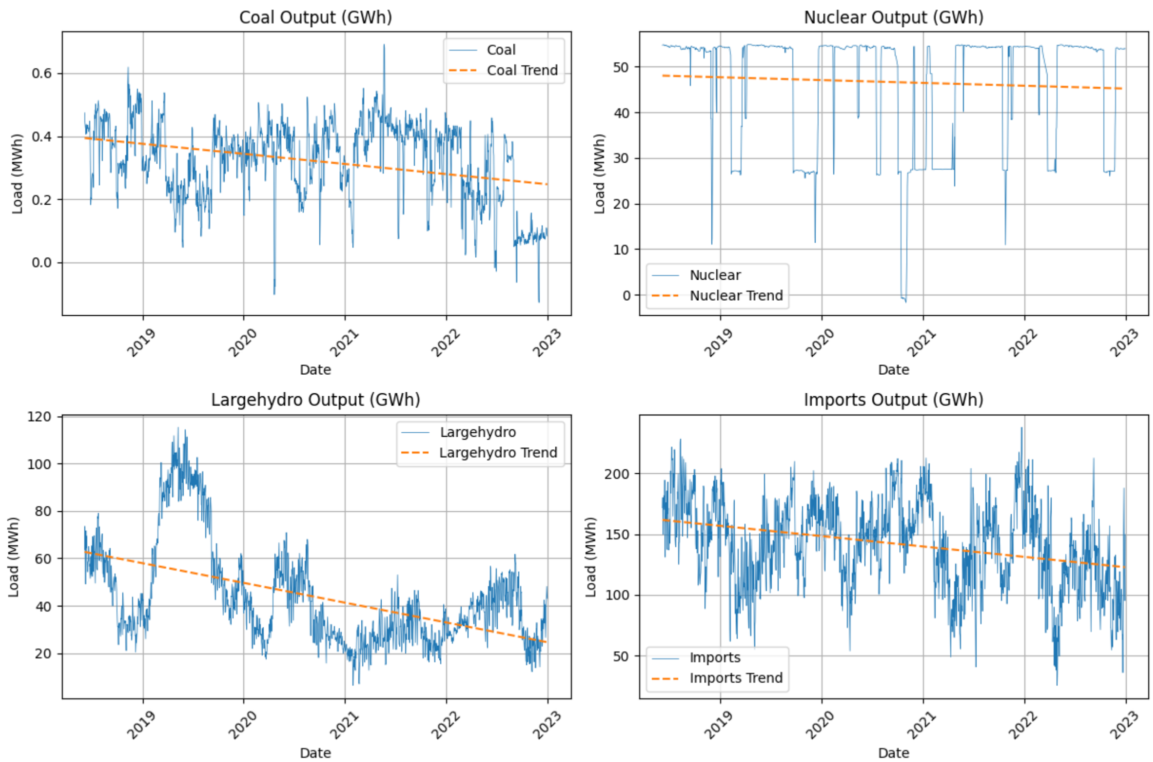

Figure **4**, other forms of non-renewable energy, such as coal and nuclear output, show general trend of decrease over time. Similarly, the import amount also demonstrates a decline over time. Meanwhile, in Figure 3 the trend of load day-ahead forecast indicates that the demand has remain stable and shows no significant changes over the years. In essence, despite the diminishing output of non-renewable energy, the demand, as indicated by the load day-ahead forecast, continues to be met due to the increasing production of renewable energy, particularly in wind and solar. This underscores the ongoing transition of California towards renewable energy sources, demonstrating the state's increasing ability to fulfill its energy demands through renewable technologies.

Chapter 2
Cannibalisation Effect of Renewable Energy

2.1 Study Design

2.1.1 Definition of Market Value

Following the established literature (Liebensteiner & Naumann, 2022a), we compute the market value of wind and solar power as the weighted hourly revenue over each day (24 hours). The calculation involves two steps as depicted by formula (1) and (2). The initial step determines the daily revenue of the specific energy type by summing the product of the day-ahead market price (denoted as p_h in the formula) with the quantity produced (represented by $q_{n,h}$). The formula is expressed as follows:

$$R_{n,t} = \sum_{h=1}^{24} p_h \cdot q_{n,h} \tag{1}$$

We then divide the daily revenue $R_{n,t}$ by the daily output (sum of the hourly output denoted by $q_{n,h}$) in the following formula:

$$MV_{n,t} = \frac{R_{n,t}}{\sum_{h=1}^{24} q_{n,h}} \tag{2}$$

Given that the original high-frequency data was extracted at a 5-minute interval, the hourly data already represents an aggregated form. We thus posit that the hourly data should inherently capture the revenue and market value of renewable energy to some extent. Consequently, we opted to perform regression analysis at both the hourly and daily levels and expect to see the cannibalization effect on both levels.

To provide a general picture, Figure 5 below delineates the temporal evolution of the market value of wind and solar energy throughout the sampling period, revealing a noticeable upward trend over time. Detailed statistics regarding the market values of wind and solar energy could be found in Table 1.

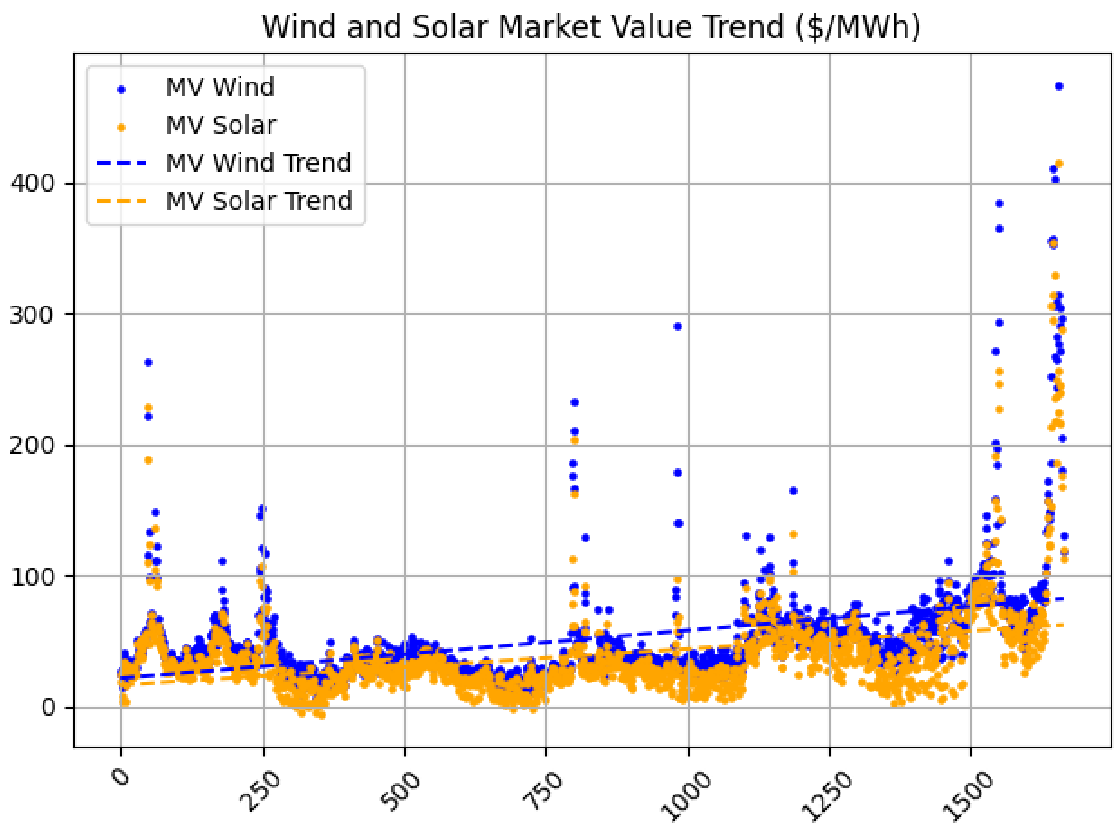

Figure 5. Market values of solar and wind output ($/MWh) and their linear trend during the sample period.

Having just observed Figure 2 an upward trend in wind and solar output, it might be tempting to draw conclusions about a correlation between the rising market value and increasing output. Before making such conclusions, we would like to emphasize that this upward trajectory of the market value of renewable energy may be attributed to various contributing factors, as detailed in our subsequent regression analysis. In essence, the upward trend in output may not necessarily be a positive contributor to the market value of renewables by type or in general, despite the simultaneous increase in both output and market value over time.

Table 1. Sample Statistics

Variable	Mean	Std. Dev.	Pctl 10	Pctl25	Pctl50	Pctl75	Pctl90
Dependent variable daily average							
MV Renewbles ($/MWh)	45.49	38.91	19.71	26.55	35.24	52.76	74.73
MV Wind ($/MWh)	52.01	42.84	24.50	31.40	40.54	59.04	82.89
MV Solar ($/MWh)	39.37	36.17	12.87	21.55	30.82	46.71	68.33
Variable of interest daily aggregate							
Renewables Output (GWh)	179.08	46.92	116.45	141.22	180.11	213.81	241.22
Wind Output (GWh)	50.48	26.92	16.18	29.09	48.04	69.73	89.31
Solar Output (GWh)	88.52	28.67	50.08	67.18	89.80	110.55	124.36
Control variables daily aggregate							
Load Day-ahead Forecast (GWh)	606.82	91.98	508.72	542.74	579.15	666.39	749.14
Coal Output (GWh)	0.32	0.13	0.11	0.24	0.35	0.42	0.46
Nuclear Output (GWh)	46.62	12.75	27.11	36.79	54.18	54.43	54.60
Large Hydro Output (GWh)	43.66	21.52	22.68	28.09	37.71	53.03	81.67
Imports Output (GWh)	142.20	35.45	94.21	117.40	145.83	168.17	186.88
Geothermal Output (GWh)	21.46	2.45	18.72	20.82	21.75	23.02	23.69
Biomass Output (GWh)	7.49	1.14	5.94	6.68	7.59	8.31	8.90
Biogas Output (GWh)	5.09	0.38	4.63	4.87	5.08	5.34	5.60
Small Hydro Output (GWh)	6.04	2.70	3.44	4.12	5.05	7.67	10.72
Underlying variables hourly average							
Price_DAM ($/MWh)	50.43	41.39	23.08	30.56	39.71	58.51	80.81
Price_RTM ($/MWh)	31.40	24.48	-	17.23	28.75	41.68	59.51

Note: 1670 daily observations; sample period: 2018/06/017–2021/04/30.

2.1.2 Modelling Approach

The subsequent section details the econometrics approach employed to discern the influence of window solar and feed on the market value of wind and solar. The objective is to ascertain the correlation between the market value of renewable energy, specifically wind and solar energy, and the corresponding output of the two sources, and to discern whether there is evidence of a cannibalizing effect within this relationship. This approach employed the definition of market value expounded upon in the preceding chapter and incorporates a set of control variables that were also previously discussed.

While regressing supply against price may typically introduce endogeneity issues to market value, we align with the perspective proposed in Liebensteiner and Naumann's study (Liebensteiner & Naumann, 2022a) that such issues may not arise in the solar and wind energy market. In the context of solar output, which is often influenced by geographic and natural characteristics such as daily weather patterns, wind speed, and radiation, these variables can be considered exogenous inputs to the model, contrary to typical cases. The validity of this assumption could be supported by practices in the European market, particularly in Germany, where solar energy is given priority in feed-in and is accompanied by a guaranteed tariff, and curtailment is often considered as a last resort after export. Similarly, based on curtailment data relevant to our sample data, daily average of curtailment amounts to around 2.68% of total renewable output and 0.79% of total demand (California ISO - Managing Oversupply, 2024), which would be quite small compare to total demand or supply to impact prices. These arrangements indicate that renewable feed-in or production tends to occur at its natural level and is relatively less affected by daily price fluctuations. Thus, the regression models in the following section will not be impacted by typical endogeneity issues when regressing price on supply or demand.

2.1.3 Simple Linear Model

We initiated our analysis with a simple linear model, wherein the market values of wind and solar served as the dependent variables. The independent variables included wind and solar outputs, as well as a set of control variables covering different types of renewable energy (biogas, biomass, geothermal, and small hydro outputs). Furthermore, nonrenewable energy sources like coal and nuclear, alongside factors like imports and large hydro, were incorporated as controls to address potential confounding effects.

It's worth noting that the control variables in the current model differ slightly from the previous research on the same topic (Liebensteiner & Naumann, 2022a), primarily due to variations in the energy landscape and the composition of the energy market in the European and California contexts. Fixed effects, encompassing days of the week, months, and years, have also been incorporated to facilitate control over seasonality and other temporal influences.

The study was conducted at both the daily and hourly levels, and the two regressions can be represented by the following equation:

1) On the daily level, separate regressions were conducted for wind and solar market values, denoted by the superscript n = {wind, solar}. The subscript *d* indicates that all variables were averaged on a daily basis.

$$\begin{aligned} MV_d^n = \ & \beta_w W_d + \beta_s S_d + \beta_g Geothermal_d + \beta_{bmass} Biomass_d + \beta_{bgas} Biogas_d \\ & + \beta_{sh} Smallhydro_d + \beta_l Load_d + \beta_c Coal_d + \beta_n Nuclear_d \\ & + \beta_{lh} Largehydro_d + \beta_i Imports_d + D_{dow} + D_m + D_y + \varepsilon_d \end{aligned}$$

2) On the hourly level, the regression includes the day-ahead market price with respect to wind and solar, along with control variables. The subscript *t* stands for the hour at which the output was captured.

$$\begin{aligned} Price_{DAM} = \ & \beta_w W_t + \beta_s S_t + \beta_g Geothermal_t + \beta_{bmass} Biomass_t + \beta_{bgas} Biogas_t \\ & + \beta_{sh} Smallhydro_t + \beta_l Load_t + \beta_c Coal_t + \beta_n Nuclear_t \\ & + \beta_{lh} Largehydro_t + \beta_i Imports_t + D_{dow} + D_m + D_y + \varepsilon_t \end{aligned}$$

The interpretation of the model results is rather straightforward. In the daily-level regression, the coefficients reveal the change in market value for wind and solar energy when independent variables change by one GWh. For the hourly-level regression, the coefficients indicate the change in market value for wind and solar energy when dependent variables change by one MWh. The key independent variables W_t and S_t were provided at 5-minute intervals in the original CAISO dataset. These 5-minute data points were subsequently aggregated to hourly and daily levels before being incorporated into the above function. They correspond to the quantity symbolized by $q_{n,h}$ defined in the daily market value. Other independent variables, such as geothermal, biomass, and bio-gas production, were similarly aggregated at hourly and daily levels based on the original downloaded dataset to ensure their applicability in the above regressions.

Two types of prices were provided in the original dataset: day-ahead market (price DAM) and real-time market (price RTM). In the day-ahead market, prices are determined through an auction process that matches supply and demand for electricity for each hour of the next day. Market participants submit bids to buy or sell electricity, and the CAISO uses these bids to determine the market-clearing price. Conversely, the real-time market operates continuously throughout the day, typically updating prices every 5 minutes. This allows for adjustments to account for real-time changes in supply and demand. For the above regression analysis, we chose to use price DAM due to its more complete dataset, which comprises 28,057 observations compared to 22,410 observations for price RTM. Despite this discrepancy in the number of observations, the two fields were found to be highly correlated. Additionally, fixed effect variables - D_{dow}, D_m, D_y – were also included in the regressions to account for weekly, monthly and annual cyclicality.

2.1.4 Flexible Model

Given the drawback in the simple model where it only estimates constant linear relationships, thus neglecting potential non-linearities or interdependencies among some of the predictor variables, we proceed by estimating a richer, more flexible model. We enhanced the model by incorporating interaction terms among the predictor variables. This included interactions between the output of wind and other control variables, as well as interactions between the output of solar and other control variables. This improvement is intended to alleviate the rigidity associated with the simplicity of the linear model. To mitigate multicollinearity, we focused on interactions between wind and solar with the control variables, rather than among the control variables themselves.

$$MV_d^n = \beta_w W_d + \beta_s S_d + \beta_{w\cdot w} W_d \cdot W_d + \beta_{w\cdot s} W_d \cdot S_d + \beta_{s\cdot s} S_d \cdot S_d + \beta_{others} X + D_{dow} + D_m + D_y + \varepsilon_d$$

, where X = control variables and their pairwise combinations (see Appendix I for more details). Once again, separate regressions were performed for wind and solar market values, denoted by the superscript n = {wind, solar}, at both daily and hourly levels. The hourly-level regression utilized the same variables and interaction terms, but with the market value variable on the left-hand side replaced by the day-ahead market price.

The flexible model allows us to calculate non-linear prediction of the market value of renewables for ceteris-paribus changes in variables of interest. To assess the influence of wind and solar output on the market value of solar and wind energy within this adaptable model, we utilized the margin function in STATA. This facilitated the derivation of the analytical derivatives of the market value with respect to the selected type of energy (wind or solar output), which encapsulate the entirety of the impact of wind or solar output (aggregating impacts from all terms including the simple form, squared form and interaction terms) on the market value of wind or solar:

Equation 1. Effect of wind production on wind market value

$$\frac{d\widehat{MV^w}}{dW} = \beta_w + 2\beta_{w\cdot w}\widehat{W_d} + \beta_{w\cdot s}\widehat{S_d} + \beta_{w\cdot G}\widehat{Geothermal}_d + \beta_{w\cdot Bm}\widehat{Biomass}_d + \beta_{w\cdot Bg}\widehat{Biogas}_d + \beta_{w\cdot Sh}\widehat{Smallhydro}_d + \beta_{w\cdot L}\widehat{Load}_d + \beta_{w\cdot C}\widehat{Coal}_d + \beta_{w\cdot N}\widehat{Nuclear}_d + \beta_{w\cdot Lh}\widehat{Largehydro}_d + \beta_{w\cdot I}\widehat{Imports}_d$$

Equation 2. Effect of solar production on wind market value

$$\frac{d\widehat{MV^w}}{dS} = \beta_s + 2\beta_{s\cdot s}\widehat{S_d} + \beta_{w\cdot s}\widehat{W_d} + \beta_{s\cdot G}\widehat{Geothermal}_d + \beta_{s\cdot Bm}\widehat{Biomass}_d + \beta_{s\cdot Bg}\widehat{Biogas}_d + \beta_{s\cdot Sh}\widehat{Smallhydro}_d + \beta_{s\cdot L}\widehat{Load}_d + \beta_{s\cdot C}\widehat{Coal}_d + \beta_{s\cdot N}\widehat{Nuclear}_d + \beta_{s\cdot Lh}\widehat{Largehydro}_d + \beta_{s\cdot I}\widehat{Imports}_d$$

The subscript and hat denote that the variables included in the above equations represent their daily averages. Similarly, the impact of wind and solar output on price can be represented as the following, except that the effect now considers the hourly outputs of various variables:

Equation 3. Effect of wind on price DAM

$$\frac{d\widehat{Price}_{DAM}}{dW} = \beta_{wt} + 2\beta_{wt\cdot wt}\widehat{W_t} + \beta_{wt\cdot st}\widehat{S}_t + \beta_{wt\cdot Gt}\widehat{Geothermal}_t + \beta_{wt\cdot Bmt}\widehat{Biomass}_t + \beta_{wt\cdot Bgt}\widehat{Biogas}_t + \beta_{wt\cdot Sht}\widehat{Smallhydro}_t + \beta_{wt\cdot Lt}\widehat{Load}_t + \beta_{wt\cdot Ct}\widehat{Coal}_t + \beta_{wt\cdot Nt}\widehat{Nuclear}_t + \beta_{wt\cdot Lht}\widehat{Largehydro}_t + \beta_{wt\cdot It}\widehat{Imports}_t$$

The results in graphical form (Figure 9 & Figure 10) are presented and discussed in the following sections.

2.2 Result

2.2.1 Linear Model Result

Table 2 displays the regression estimates related to the market value of wind and solar electricity on the daily level. The initial two columns offer estimates derived from the simple linear model, while columns (3) and (4) present the coefficient estimates resulting from our nonlinear models. The table excludes the coefficient results of the interaction variables in the nonlinear models, which could be found in Appendix I.

Table 2 Main regression results: market values of wind and solar.

	(1)	(2)	(3)	(4)
	Simple linear model		Flexible model	
	MV_Wind	MV_Solar	MV_Wind	MV_Solar
Wind	-0.1940***	-0.1723***	-1.0977**	-1.3165***
	(0.0391)	(0.0330)	(0.4348)	(0.3436)
Solar	-0.3777***	-0.4323***	-1.3413*	-1.7832***
	(0.0575)	(0.0487)	(0.6973)	(0.5482)
Geothermal	1.2180***	1.0742***	5.1480***	4.2199***
	(0.2656)	(0.2180)	(1.1374)	(0.9781)
Biomass	1.3408	0.7060	4.6956	1.9993
	(0.8287)	(0.6475)	(2.8567)	(2.3822)
Biogas	0.9862	2.6637	6.8948	3.9093
	(2.2727)	(1.9083)	(8.4946)	(7.2395)

Smallhydro	0.5659	0.4103	0.3092	0.4333
	(0.6448)	(0.5021)	(1.9663)	(1.6378)
Load Day-ahead Forecast	0.3105***	0.2705***	0.3127***	0.2205***
	(0.0306)	(0.0208)	(0.0795)	(0.0648)
Coal	-11.2197*	-6.0771	-189.4912***	-179.3635***
	(6.1847)	(4.9591)	(35.0257)	(30.0259)
Nuclear	-0.0430	0.0321	0.2176	0.2965*
	(0.0572)	(0.0433)	(0.2021)	(0.1689)
Largehydro	0.1189	0.0339	-0.0761	-0.1524
	(0.0793)	(0.0612)	(0.2964)	(0.2542)
Imports	-0.4458***	-0.3617***	-1.3363***	-1.0691***
	(0.0475)	(0.0396)	(0.1797)	-0.1562
Observations	1,667	1,666	1,667	1,666
R-squared	0.565	0.607	0.626	0.674
Fixed Effect (day of week, month, year)	√	√	√	√

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1
**Interaction terms include pairing of wind/solar with other control variables. For a complete list of interaction terms, see Appendix I*

Based on the findings from the simple linear regression, there is evidence supporting the cannibalization effect on both the market value of wind and solar electricity. In Model (1), a marginal increase in wind output by 1 GWh results in a decrease in the market value of wind electricity by 0.1940 $/MWh. Similarly, the marginal increase in solar electricity is associated with a decrease in the market value of wind electricity by 0.1723 $/MWh.

In Model (2), the market value of solar electricity experiences the same cannibalization effect from wind and solar output. A marginal increase in wind electricity by 1 GWh results in a decrease in the market value of solar electricity by 0.1723 $/MWh, and an increase in solar electricity by 1 GWh leads to a decrease in the market value of solar electricity by 0.4323 $/MWh. In other words, both wind and solar power exhibit cannibalization of their own market value as well as each other's market value. The effects of wind output seem to have a stronger impact on the market value of both wind and solar market value compared to solar output. Additionally, the output of each technology has stronger negative effect on their own market value compared to the market value of other technology - solar output has stronger negative impact on solar market value and wind output has stronger negative impact on wind market value.

In addition, our results in both model (1) and (2) illustrate a positive correlation between the increase in demand (load day-ahead forecast) and the market value of renewable energy, which closely align with previous studies supposition (Ruhnau, 2022) that increase in flexible load may significantly counteract RE's cannibalization problem, as well as a negative impact of imports on the market values of wind and solar power, which aligns with our expectation regarding the competitive effect of substitute goods. Figure 6 and Figure 7 present graphical forms based on the results of model (1) and (2) in **Table *2***, depicting the influence of solar and wind production on their respective market values independently and in conjunction with each other, through changing only the renewable outputs while keeping other variables constant at their respective sample means. The regression results for Figure 6 could be found in Appendix II.

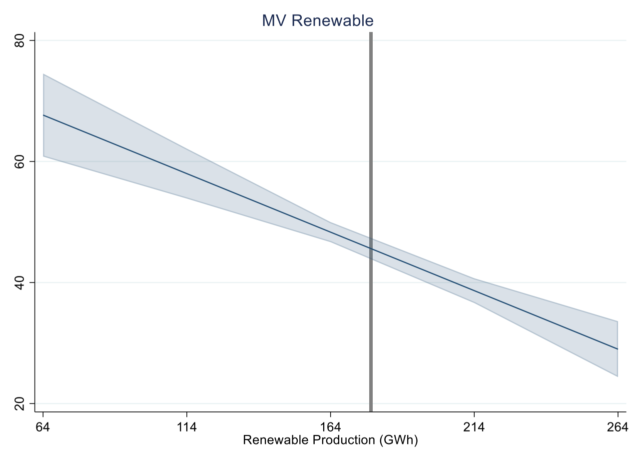

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Figure 6. Predicted market values of renewable energy in total ($/MWh) dependent on total renewable output (GWh).

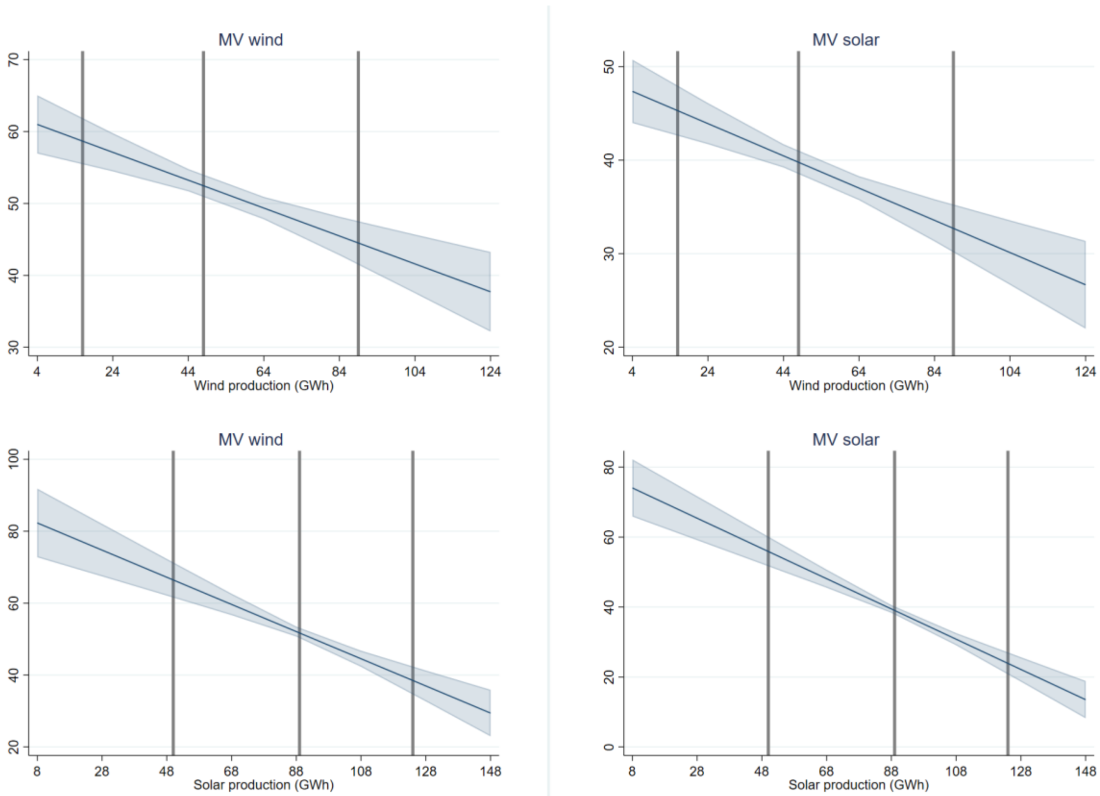

Figure 7. Predicted market values of renewable energies by type ($/MWh) dependent on solar and wind output (GWh). The vertical gray lines represent the sample mean of each independent variable. The grey vertical lines represent 10th, 50th and 90th percentile of the output level.

The observed negative downward trend serves as empirical evidence suggesting that heightened solar and wind production leads to diminished market values not only for their own technologies but also for each other and for renewables in general, encompassing various other technologies. This outcome aligns with expectations and offers tangible data support for the merit order effect theory (Sensfuß et al., 2008)

Despite the adverse impact of increased renewable output on its individual market value, our analysis reveals a nuanced perspective. While heightened output exerts downward pressure on renewable market values, our findings suggest that this reduction typically does not drive market values close to, or below, zero, especially at daily level. However, the correlatoin at the hourly level paints a different picture. Consistent with findings from Libenstriner and Nauman's study (Liebensteiner & Naumann, 2022a), we observe that solar market values may indeed turn negative at peak hourly output levels (Figure 8). On the other hand, wind energy, while similarly affected on an hourly basis, maintains a positive market value even at maximum output levels. This discrepancy with the findings of Libensteiner and Nauman (2022a) becomes even more apparent in our results from the hourly level flexible model, where neither solar nor wind market values were pushed below zero, even at maximum output (see discussion in the section 2.2.2).

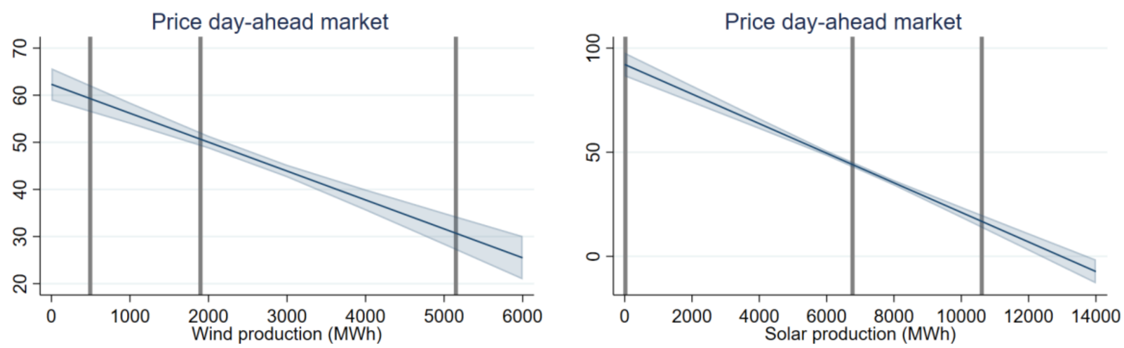

Figure 8. Predicted market values ($/MWh) dependent on hourly solar and wind output (MWh) based on simple linear model.

2.2.2 Flexible Model Result

In models (3) and (4) outlined in Table 2, we adopt more flexible functional forms to estimate the variation in the market values of wind and solar. These models incorporate squared terms of the independent variables and interaction terms between the independent variables and the control variables. Although Table 2 presents the coefficients and regression results, isolating the effect of wind and solar output proves challenging due to their involvement in the interaction terms. The involvement of the interaction term also makes the coefficients in model (3) and (4) different significantly from that of model (1) and (2). To determine the impact of solar and wind production in these flexible models, we utilize marginal graphs (Figure 9), to isolate the effect of wind and solar output on their own and cross-technology market values. Equation 1 and Equation 2 in section 2.1.4. describe the mechanism of the margin function in detail.

Figure 9 illustrates the model predictions of wind and solar market values, accounting for the effect of wind and solar output combining the impact from their simple form, squared form, and their contribution through the interaction terms, while holding all other variables constant at their sample means. The grey vertical lines denote the 10th, 50th, and 90th percentiles of production. Despite a noticeably intensified curvature, indicating a tapering off of the decrease in market value at the highest production levels compared to the simple linear model, our findings consistently demonstrate that, across the majority of production levels ranging from the 10th to the 90th percentile, increased renewable production continues to depress not only the market value of its own technology but also that of the other renewable technologies.

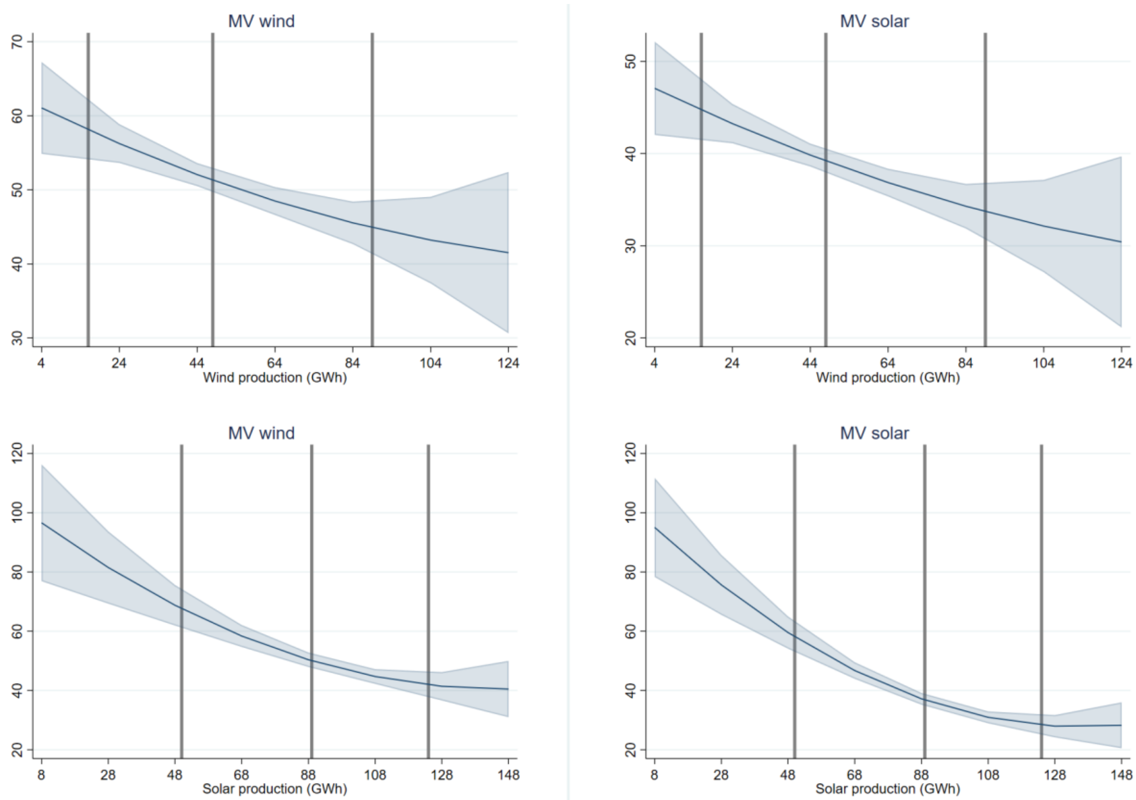

Figure 9. Predicted market values of renewable energies by type (\$/MWh) dependent on solar and wind output (GWh) based on the flexible mode (3) and (4). The vertical gray lines represent the sample mean of each independent variable. The grey vertical lines represent 10th, 50th and 90th percentile of the output level.

We also applied the flexible model using hourly-level data Table 3. In contrast to the simple linear model, which suggests that both solar and wind production exert a significant negative impact on market price, our findings with the flexible model suggests that only increase in solar production significantly affects market price. The simple linear model at an hourly level indicates that a 1 MWh increase in wind production leads to a decrease in market price by \$0.0053/MWh, and a 1 MWh increase in solar production leads to a decrease in market price by \$0.0066/MWh. In contrast, the flexible model suggests that only solar production significantly impacts market price, with each additional MWh of solar production leading to a \$0.0097/MWh decrease in market price, while the wind production, although negatively correlated with the market values, exert no significant contributions. These negative correlations align with the existing theory of the cannibalisation effect documented in the literature (Liebensteiner & Naumann, 2022a; López Prol et al., 2020a).

Table 3. Main regression results on hourly level

	(1) Simple linear model Price DAM	(2) Flexible model Price DAM
Wind	-0.0053***	-0.0097
	(0.0006)	(0.0061)
Solar	-0.0066***	-0.0097***
	(0.0004)	(0.0013)
Geothermal	0.0331***	0.0472***
	(0.0063)	(0.0093)
Biomass	0.0343*	0.0951**
	(0.0193)	(0.0391)
Biogas	0.0138	-0.0624
	(0.0441)	(0.0779)
Small Hydro	0.0218*	-0.0056
	(0.0121)	(0.0170)
Load day-ahead forecast	0.0055***	0.0065***
	(0.0003)	(0.0007)
Coal	-0.3621***	-0.9671***
	(0.1302)	(0.3305)
Nuclear	-0.0002	0.0014
	(0.0014)	(0.0026)
Large Hydro	0.0000	0.0050***
	(0.0010)	(0.0019)
Imports	-0.0082***	-0.0155***
	(0.0007)	(0.0018)
Observations	39,927	39,927
R-Squared	0.479	0.498
Fixed Effect (day of week, month, year)	√	√

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Additionally, similar to the findings of the simple linear model, our research reveals a nuanced discrepancy when contrasted with Liebensteiner and Nauman's exposition (2022a) regarding the lower end of market value. Despite the downward trend as production increases, the market values of solar and wind do not approach or dip below zero, whether at the daily level (Figure 9) or hourly level (Figure 10). Notably, the decline in market value tapers off at the highest level of production, evident from the concaved shape of the curves, and market values of both technologies remain positive even at the extreme right end.

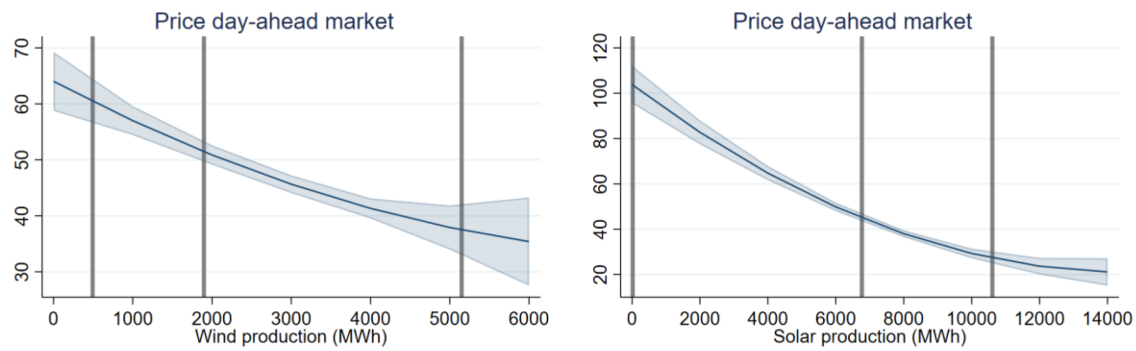

Figure 10. Hourly level flexible model prediction of market values ($/MWh) based on solar and wind output (MWh)

In regard to the discrepancy concerning whether market values dip below zero at peak production, we posit that this variance could arise from disparities in the geographic locations of the datasets utilized in different studies. The previous study (Liebensteiner & Naumann, 2022a) utilizes a dataset originated in Europe, where demand trends may differ compared to North America. Moreover, variations in usage characteristics due to geographic differences are commonly observed, as noted in Lamp, Liebensteiner and Samano's working paper (2024). Additionally, differences in the composition of technologies competing within the market landscape could also contribute to these outcome disparities. The technology composition of the European market differs from that of the North American market. These factors collectively underscore the significance of nuanced contextual considerations and highlight that, while increased production negatively impacts the market value of renewables, whether market value depression would worsen or stabilize as production increases remains contextual and inconclusive.

Chapter 3
Energy Storage and Cannibalisation

The preceding chapter elucidated the cannibalization effect, highlighting the imperative of exploring alternative methods to manage supply-demand disparities inherent in the volatile supply of renewable energy. This endeavor is crucial for maximizing the market value of renewables and ensuring their financial sustainability. Among the solutions commonly cited in scholarly literature, lithium-ion utility-scale batteries have garnered significant attention (López Prol et al., 2020a).

Storage infrastructure facilitates the transfer of electricity production between periods of high and low demand, as well as enables energy transfer between geographic locations—redressing imbalances between regions characterized by surplus supply and those with high demand and low supply (Mills & Wiser, 2015). Numerous research studies advocate for such measures as logical steps toward mitigating the aforementioned cannibalization effect (Andres-Cerezo & Fabra, 2023.; Lamp & Samano, 2022a). Consequently, building upon the insights gleaned from the literature review, the following section will delve into the potential of battery storage as a solution for addressing the cannibalization effect.

This chapter will be structured as follows: Section 3.1 will assess the current operational characteristics and profitability of battery storage systems. Section 3.2 will explore the theoretical foundations necessary for understanding battery storage as a viable solution for mitigating the cannibalization effect. Section 3.3 will investigate the complementary or substitutive relationship between renewables and batteries, drawing upon empirical data and theoretical constructs. Finally, Section 3.4 will analyze discrepancies between empirical observations and theoretical frameworks, proposing explanations and potential remedies.

3.1 Overall Battery Operational Characteristics

The assimilation of battery technology into the energy sector does not align precisely with the initial phases of transitioning to renewable energy sources. Rather, the adoption of renewable energy has been in progress for a substantial duration, whereas the integration of battery technology represents a more recent development. Consequently, the decisions concerning investment in these respective domains are not inherently interlinked.

The subsequent graphical representation illustrates a marked upward trajectory in battery revenue, costs, and profit, indicative of notable shifts in operational scale occurring around mid-2020. Notably, according to (CAISO battery special report), battery storage capacity experienced a tenfold increase between 2020 and 2023 within the balancing area covered by the current dataset, predominantly encompassing regions of California and a smaller portion of Nevada.

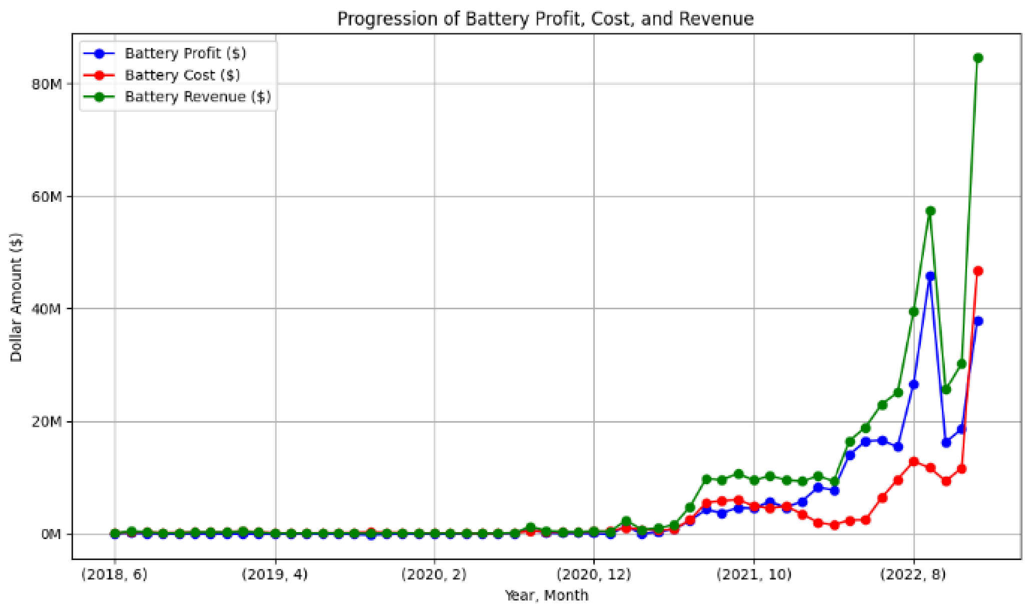

Figure 11. Battery revenue, cost and profit time trend during the sample period (2018/06/01 – 2022/12/01)

As illustrated in the Figure 12, the expansion of battery operational scale exhibits a notable surge, in contrast to the comparatively gradual rise observed in renewable market share. This observation highlights the asynchronous progression of batteries and renewables, indicating development trajectories that may not necessarily mirror each out and potentially independent decision-making processes.

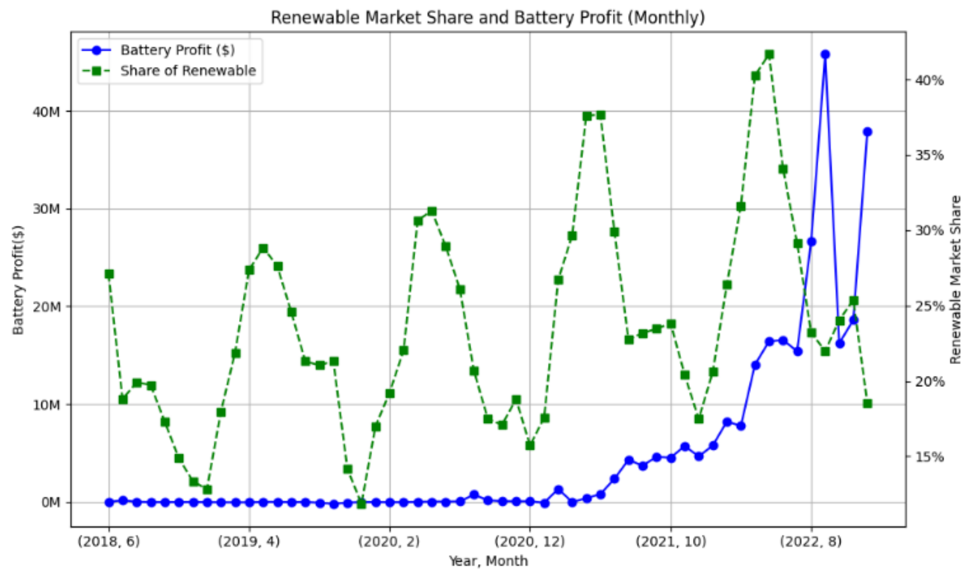

Figure 12. Battery profit trend versus renewable capacity trend during the sample period (2018/06/01 – 2022/12/01); Note: the renewable market share represented in the graph is defined renewable energy output/energy demand.

Our research provides further confirmation of the alignment between battery charging and discharging patterns in previous scholarly discussions, as outlined in (Lamp & Samano, 2022a; Antweiler, 2021), which addresses the charging and discharging behaviors of batteries in relation to wholesale price trends, as illustrated in the Figure 13. Batteries charges during midday and exploit price depression and subsequently discharge during late afternoon and early evening when price peaks, thus capitalizing on price fluctuations through arbitrage and generate profit for batteries. In fact, upon examination of battery profitability, it becomes evident that the profit curve closely follows the hourly price curve, as evidenced in Figure 14.

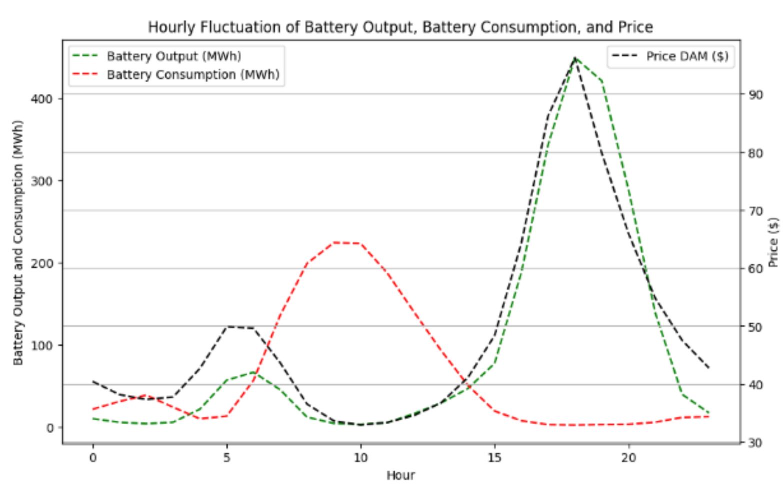

Figure 13. Battery output and consumption pattern over 24-hour period

Furthermore, our analysis also compared of battery charging (consumption) and discharging (output) patterns with both renewable energy output and the hourly load trend. It is a prevailing hypothesis that batteries hold potential to mitigate the cannibalization phenomenon by effectively storing excess energy during periods characterized by abundant supply, such as midday when solar output is at its peak and energy prices are comparatively diminished (Andres-Cerezo & Fabra, 2023). Subsequently, this stored energy can be released during periods of peak demand, typically late afternoon to early evening when prices are higher. This benefits both batteries, through price arbitrage, and renewables, by enhancing their market value through balancing supply and demand.

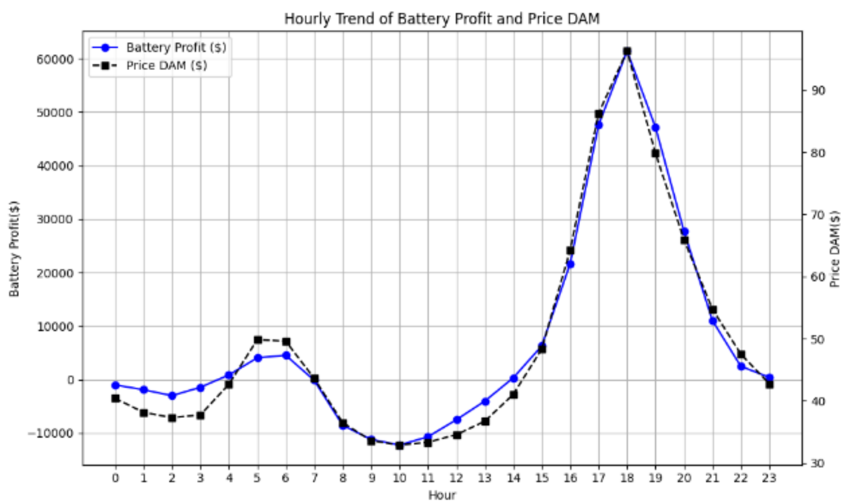

Figure 14. Price day-ahead-market and battery profit pattern over 24-hour period

Figure 15 compares the hourly output of renewables, charging and discharging of battery in comparison with hourly demand (load). The graphical representation seems to align quite well with the conventional wisdom on the potential synergy between battery and renewables. We observed that when battery charges due to midday price decreases, coinciding with peaks in renewable output that creates a surplus relative to demand, batteries absorb the excess outputs from renewables, which excess batteries then discharge during hours when demand increases and renewable output decreases, effectively filling the gap to meet the demand.

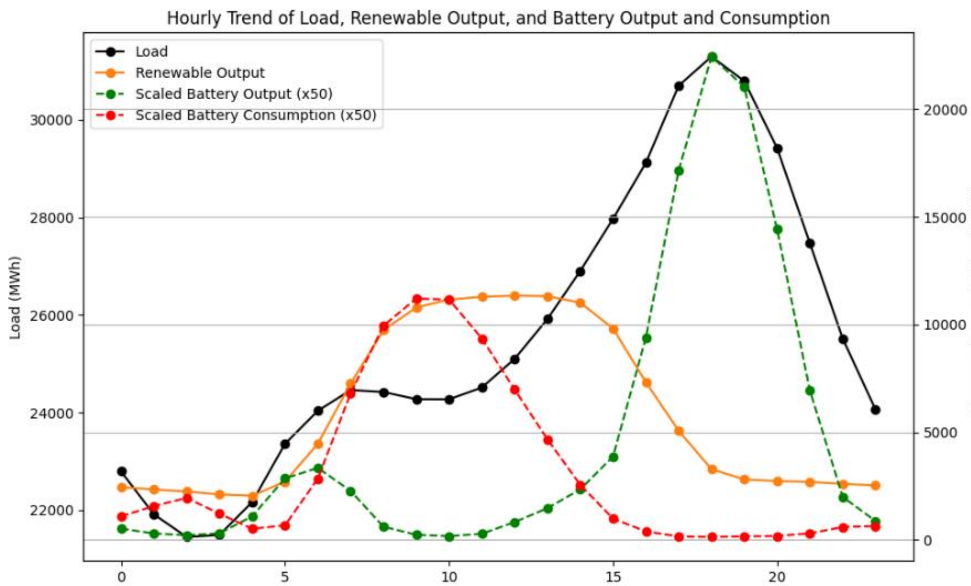

Figure 15. Demand, renewable output, battery output and consumption pattern over 24-hour period; Note: battery consumption and output were scaled up 50 times in the graph to assist with visualization.

The empirical evidence gleaned from actual battery charging patterns appears to substantiate the hypothesis that batteries facilitate the redistribution of surplus energy from periods of low demand to those of high demand. This functionality contributes to bridging the gap between energy demand and supply while concurrently absorbing excess energy to mitigate curtailment. However, additional research is needed to evaluate the financial feasibility of implementing such a process.

3.2 Theoretical Framework

In the context of renewable energy integration and the potential role of battery storage, it is imperative to assess the economic viability of both renewable energy sources and battery technologies. This entails an examination of their respective profitability and how their financial performance interrelates. Determining whether batteries complement renewable energy sources requires a comprehensive analysis of their profitability dynamics and their synergy in addressing supply-demand imbalances.

To reiterative the context, given the phenomenon of cannibalization within the renewable energy sector, wherein renewable sources face challenges due to their inherently fluctuating market values, the financial viability of these sources becomes a concern. It is well-established that renewable energy often relies on governmental subsidies to remain financially viable, and the exacerbation of the cannibalization effect only compounds these challenges. The widening gap between the expected returns from renewable energy investments and their actual market values underscores the urgency to explore complementary solutions.

However, on the other hand, as we examine the operation of battery, it semes like the disadvantage resulted from cannibalization effect benefits battery storage systems by enabling them to access surplus energy at reduced prices during charging, albeit at the expense of renewable energy's market worth. Therefore, restricting the expansion of renewable energy could potentially bolster the market value of renewables by alleviating downward price pressures but, at the same time, create negatively impact storage systems, which rely on excess renewable energy and cheaper prices for charging. Batteries would then have to charge at higher costs, diminishing their own profitability and potentially becoming financially unsustainable. This dilemma underscores the complexity of achieving an optimal equilibrium and synergy between renewable energy sources and battery storage systems.

In its essence, the intricate relationship between renewable energy and battery storage gives rise to a nuanced landscape where actions favorable to one component may inadvertently hinder the other. This underscores the critical necessity of managing the interaction of renewable and battery to optimize the overall efficiency of the system, and to integrate batteries as a effective mediator of the cannibalization effect, bolstering market value of renewables, while sustaining its own economic viability (Andres-Cerezo & Fabra, 2023).

In our investigation of the question whether battery storage could effectively mitigate the cannibalization effect, we utilize the theoretical framework proposed in Andres-Cerezo and Fabra’s study (2023). Our aim is to assess whether the current dataset provides empirical evidence to support this framework. Central to this framework is the hypothesis that the relationship between renewable energy availability and market price is pivotal in elucidating the profitability of both renewable energy and storage systems. Specifically, the synergy between renewable energy and battery storage hinges on the ability of batteries to capitalize on excess renewable energy, which simultaneously drives down prices. In other words, cannibalisation effect serves as the foundation for synergy between battery and renewables.

Electricity prices are contingent upon consumption patterns and renewable availability, which vary across markets and technologies. The theoretical framework in Andres-Cerezo and Fabra's study (2023) posits that wind production exhibits a negative correlation with price due to its output peaking at night when electricity demand is low. On the other hand, solar output may display a positive correlation with price as it is more abundant during mid-day when electricity demand peaks. Based on these assumptions, the framework proposes that wind and battery storage outputs are complementary, while solar and storage outputs are substitutive.

We employed a basic linear regression model to explore the hourly relationship between renewable energy output and prices through out the day (Figure 16), while accounting for fixed effects. The primary objective was to validate the negative correlation posited in the theoretical framework outlined above regarding renewable outputs and prices.

Our investigation confirmed the countercyclical pattern proposed for in wind output and price - across all hours, wind outputs consistently exhibited a significant negative correlation with price, as evidenced in the above graphs. However, contrary to the expectation established in Andres-Cerezo and Fabra's study (2023), our findings demonstrated that solar output also displayed a negative correlation with prices on an hourly basis, rather than the anticipated positive correlation.

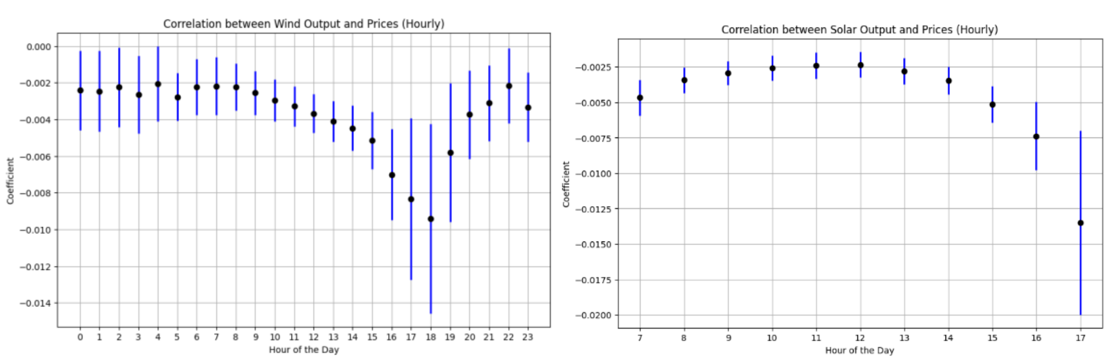

Figure 16. Correlation between wind and solar output at each hour during the day

This deviation from expected results may arise from regional differences, particularly in demand patterns between Europe and North America. The theoretical framework was originally formulated within a European context, where demand typically peaks during midday. In contrast, North American demand tends to reach its peak in the late afternoon or early evening (Lamp et al, 2024). Despite these contextual variations, our analysis emphasizes the enduring absence of a positive correlation between solar output and prices. Overall, both wind and solar technologies consistently exhibit a negative correlation with prices on an hourly basis despite complex market dynamics.

3.3 Battery and Renewables: Complement or Substitute?

With the negative correlation between price and renewable output now substantiated, aligning with our prior findings in Chapter 2 where a negative correlation between renewable output and market value was identified, we take the next step to investigate the interaction between the profitability of battery storage and renewables, an inquiry holding particular significance for investors aiming to capitalize on synergistic opportunities between these two components.

Table 4 Renewable and Battery as Substitute Regression Result

	(1)	(2)	(3)	(4)	(5)	(6)
	Net Battery Output		Battery Output		Battery Consumption	
Wind	-0.0138***	-0.0058***	-0.0133***	-0.0104***	0.0005	-0.0046***
	(0.0021)	(0.0021)	(0.0012)	(0.0012)	(0.0014)	(0.0014)
Solar	-0.0456***	-0.0413***	-0.0273***	-0.0257***	0.0184***	0.0156***
	(0.0016)	(0.0016)	(0.0009)	(0.0009)	(0.0010)	(0.0010)
N	18,053	18,053	18,053	18,053	18,053	18,053
R2	0.25	0.28	0.37	0.38	0.39	0.41
Load		✓		✓		✓
DV Avg (Hourly)	11.02933		94.1146		83.0853	

Standard errors in parentheses ∗ $p < 0.10$, ∗∗ $p < 0.05$, ∗∗∗ $p < 0.01$
All models include hour, day of the week, month, quarter, and year fixed effects. All columns include nuclear, coal, output as controls

We regressed the battery output, battery consumption, and net battery output (dependent variables) over the production of wind and solar energy (independent variables), controlling for fixed effects and other relevant variables. In contrast to our initial expectations, informed by the results from Section 3.2 highlighting a negative correlation between renewable energy output and prices, suggesting the potential for batteries to capitalize on price disparities and foster a complementary relationship with renewables, our findings unveiled a distinct scenario—a substitutive relationship between battery storage and renewable energy sources.

The regression analysis revealed a significant negative correlation between battery output and both wind and solar energy, with solar demonstrating a stronger negative association with battery output and net battery output. Furthermore, there was a notable positive correlation between battery consumption and solar output. The relationship between wind output and battery output appeared somewhat ambiguous.

Specifically, an additional MWh of wind output was associated with an average decrease in battery output of around 0.01 MWh, whereas the same increase in solar output was linked to a decrease in battery output of approximately 0.03 MWh. Conversely, an additional MWh of solar output corresponded to an increase in battery consumption of 0.02 MWh. Moreover, net battery output (computed as battery output minus consumption) exhibited a negative association with solar output, with each additional MWh of solar output contributing to a decrease in net battery output of about 0.04 MWh. Wind output also correlated negatively with net battery output, albeit with varying magnitudes depending on whether demand (load forecast) was considered in the regression. Although the observed effects may appear relatively modest in relation to the scale of the dependent variables, they provide empirical support for the substitutive relationship between renewables and battery storage.

Additionally, we conducted regression analyses involving battery profit, revenue, and cost in relation to renewable outputs. The results indicate a negative correlation between battery profit and revenue with renewable outputs, with solar exerting a more pronounced negative impact on battery profit and revenue compared to wind. These findings are summarized in the table above.

Table 5. Renewable and Battery Profitability Regression Result

	(1)	(2)	(3)	(4)	(5)	(6)
	Battery Profit		Battery Revenue		Battery Cost	
Wind	-2.1731***	-1.0389***	-2.6225***	-1.6530***	-0.4493***	-0.6141***
	(0.3783)	(0.3787)	(0.3300)	(0.3304)	(0.1472)	(0.1488)
Solar	-5.2347***	-4.6230***	-4.0667***	-3.5438***	1.1680***	1.0791***
	(0.2793)	(0.2781)	(0.2436)	(0.2426)	(0.1087)	(0.1092)
N	18,053	18,053	18,053	18,053	18,053	18,053
R-squared	0.1	0.12	0.14	0.16	0.22	0.23
Load		✓		✓		✓
DV Avg (Hourly)	6274.748		10878.87		4604.122	

Standard errors in parentheses $*$ $p < 0.10$, $**$ $p < 0.05$, $***$ $p < 0.01$; all models include hour, day of the week, month, quarter, and year fixed effects. All columns include nuclear, coal, output as controls

Specifically, for every MWh increase in wind output, there is an estimated decrease in battery revenue ranging between $1.6 - $2.6, and a decrease in battery profit ranging between $1 - $2. Conversely, for every MWh increase in solar output, there is a decrease in battery revenue ranging between $3.5 - $4.1, and a decrease in battery profit ranging between $4.6 - $5.2. Again, despite the seemingly modest effects relative to the scale of the dependent variables, these results underscore a substitutive relationship between renewables and battery.

3.4 Simulation

The findings presented in section 3.3 diverge from the theoretical constructs established in section 3.2. The theoretical framework delineated in section 3.2 posits that a negative correlation between price and renewable output would give rise to an optimal scenario where batteries absorbing surplus renewable energy during periods of low prices and subsequently discharging it during peak demand, thus fostering a complementary relationship between renewable energy and battery storage. This framework appeared substantiated by our empirical examination of the provided dataset, where a negative correlation between renewable outputs and prices was indeed confirmed. However, despite confirming the negative correlation between price and renewable output as the foundation for a complementary relationship between renewable output and batteries, our analysis in section 3.3 reveals that batteries continue to act as substitutes rather than complements to renewable energy.

In further analysis, we posit that the observed substitute relationship between renewable and battery output may be attributed to a perceived competitive dynamic between battery and renewable energy output patterns during certain timeframes. Specifically, our observations between noon and late afternoon indicate that while renewable output remains active, albeit decreasing, battery output shows an increasing trend. This suggests that the battery begins discharging before renewable energy depletes its output. If, during these time intervals, battery output was prioritized as infeed, it could potentially erode the profitability of renewable energy sources.

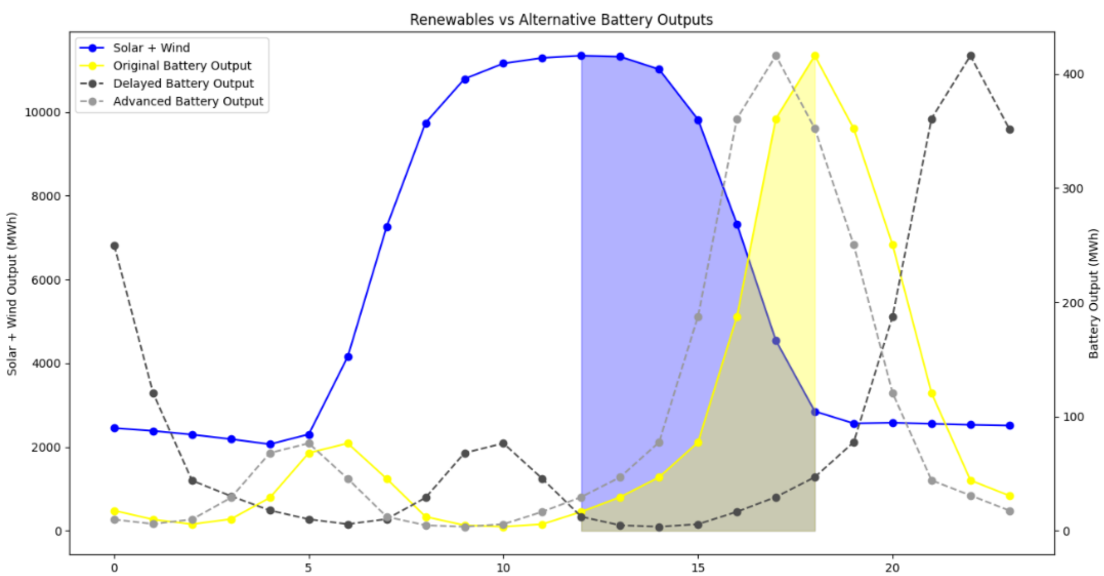

Figure 17. Renewable vs battery output pattern over 24-hour period; the blue shared area represents renewable output; the yellow shared area represents battery output; the gray doted lines represent delayed or advanced battery output. The overlapping region of blue and yellow shades indicate a potential competition between renewable and battery.

Our prior analysis has demonstrated that battery output predominantly correlates with the price trend rather than the renewable output trend. This prompted us to explore whether deliberately delaying battery output, as opposed to allowing it to strictly adhere to the price curve, could alleviate the competitive dynamics between battery storage and renewable energy sources. To investigate this hypothesis, we manually manipulated the timing of battery output by shifting it four hours later, ensuring that the peak acceleration in battery output occurs when renewable output nears zero around 19H (as depicted by the black line in Figure 17). We then re-ran the regression analysis of the alternative battery output over wind and solar output. We also apply the same regression in another hypothetical scenario where we advanced the output by 1 hour (denoted by the grey line in Figure 17). Our results reveal that delaying battery output effectively attenuates the competition between renewable energy and battery output, as we now observe a positive correlation between renewable and battery output, as outlined in the subsequent table.

Table 6 Renewable and Alternative Battery Outputs Regression Result

	(1)	(2)	(3)	(4)	(5)	(6)
	Actual Battery Output		Advanced Battery Output (1H)		Delayed Battery Output (4H)	
Wind	-0.0133***	-0.0105***	-0.0116***	-0.0080***	0.0005	0.0000
	(0.0012)	(0.0012)	(0.0015)	(0.0015)	(0.0014)	(0.0014)
Solar	-0.0272***	-0.0257***	-0.0181***	-0.0161***	0.0096***	0.0094***
	(0.0009)	(0.0009)	(0.0011)	(0.0011)	(0.0010)	(0.0010)
N	18,052	18,052	18,052	18,052	18,052	18,052
R2	0.37	0.38	0.39	0.40	0.26	0.26
Load		✓		✓		✓

Standard errors in parentheses ∗ $p < 0.10$, ∗∗ $p < 0.05$, ∗∗∗ $p < 0.01$
All models include hour, day of the week, month, quarter, and year fixed effects. All columns include nuclear, coal, output as controls

After implementing a four-hour delay in battery output, we observe a notable shift in the relationship between renewable output and battery output, particularly in the solar-battery relationship, which exhibits a significant positive correlation (Table 6). Following the four-hour delay (as indicated in the last two columns of the table), an additional 1 MWh output of solar energy corresponds to an approximate increase of 0.009 MWh of battery output. This finding underscores a complementary relationship between renewable and battery output in this hypothetical scenario when battery output is delayed rather freely following the price trend, contrasting with our previous observation of a negative correlation between battery and solar output (as demonstrated in the first two columns in the Table 6).

Moreover, we recalculated the battery revenues under alternative scenarios involving delaying or advancing battery output, while keeping the price data unchanged. The resulting revenues were compared to the previous figures in Table 7. As anticipated, a reversal in the relationship dynamics was observed. Previously, there was a negative correlation between battery revenue and renewable output, as evidenced in the first two columns in Table 7, where both wind and solar outputs were linked to a decrease in battery revenue. However, with a four-hour delay in battery output, a notably positive correlation emerged between solar output and battery revenue. Specifically, each 1 MWh increase in solar output is now associated with \$0.2 to \$0.3 of increase in battery revenue. This underscores a complementary relationship rather than a substituted one between renewable energy and battery systems, particularly when battery output is delayed.

Table 7. Renewable and Alternative Battery Revenues Regression Result

	(1)	(2)	(3)	(4)	(5)	(6)
	Actual Battery Revenue		Advanced Battery Output Revenue		Delayed Battery Output Revenue	
Wind	-2.6251***	-1.6557***	-2.6256***	-1.4612***	-0.1878	-0.0103
	(0.3300)	(0.3305)	(0.3343)	(0.3334)	(0.1499)	(0.1514)
Solar	-4.0646***	-3.5417***	-3.1830***	-2.5549***	0.2155*	0.3113***
	(0.2436)	(0.2426)	(0.2468)	(0.2448)	(0.1106)	(0.1111)
N	18,052	18,052	18,052	18,052	18,052	18,052
R2	0.1409	0.1584	0.1792	0.2026	0.1299	0.1328
Load		✓		✓		✓

Standard errors in parentheses ∗ $p < 0.10$, ∗∗ $p < 0.05$, ∗∗∗ $p < 0.01$
All models include hour, day of the week, month, quarter, and year fixed effects. All columns include nuclear, coal, output as controls

We also recomputed the profit of battery in both advanced and delayed output scenarios. We observed a notable reversal in correlation patterns when delaying the battery output. Formerly, battery profits displayed a notable negative correlation with both solar and wind outputs, as depicted in the initial two columns of Table 8. However, following the delay in battery output, we identified a substantial positive correlation between battery profit and renewable outputs. Specifically, every 1 MWh increase in wind output corresponded to an approximate \$2.3 increase in battery profit, contrasting with the earlier scenario where an extra 1 MWh of wind output would have decreased battery profit by approximately \$1 to \$2. Similar positive correlations were evident for solar energy. Each 1 MWh increase in solar output was associated with around \$2.3 of battery profit, a marked deviation from the previous situation where every additional 1 MWh of solar output would decrease battery profit by roughly \$5.

Moreover, we observed an intensified competitiveness between renewables and battery output when we advanced battery output by an hour, as depicted by the gray line in **Figure *17***. This advancement led to an increase in the overlapping area and battery output, describing a potential heightened competition between renewable and battery output. The subsequent table revealed a negative correlation in columns (3) and (4), with a larger magnitude compared to column (1) and column (2), which was anticipated given the described potential increase in existing competition.

Table 8. Renewable and Alternative Battery Profit Regression Result

	(1)	(2)	(3)	(4)	(5)	(6)
	Actual Battery Profit		Advanced Battery Output Profit		Delayed Battery Output Profit	
Wind	-2.1783***	-1.0441***	-2.4041***	-1.1935***	2.2711***	2.3230***
	-0.378	-0.3787	-0.3856	-0.3855	-0.2682	-0.2714
Solar	-5.2308***	-4.6190***	-4.0739***	-3.4209***	2.3350***	2.3630***
	-0.2793	-0.2781	-0.2846	-0.2831	-0.1980	-0.1993
N	18,052	18,052	18,052	18,052	18,052	18,052
R2	0.10	0.12	0.13	0.15	0.08	0.08
Load		✓		✓		✓

Standard errors in parentheses $*$ $p < 0.10$, $**$ $p < 0.05$, $***$ $p < 0.01$
All models include hour, day of the week, month, quarter, and year fixed effects. All columns include nuclear, coal, output as controls

Conclusion

During the transition to renewable energy, many countries face challenges regarding the financial sustainability of renewable energy sources. Despite various forms of subsidies, it remains necessary to find ways to ensure the financial viability of renewable production. One obstacle hindering renewable energy's financial viability is the merit-order effect, including cannibalization effect, wherein the expansion of renewable energy lowers market prices and diminishes its own market value, and consequently demanding greater financial support through subsidies as renewable production ramp up.

Our current study provides empirical evidence for the existence of the merit-order effect and cannibalization effect in renewable energy. Leveraging data from the California Independent System Operator (CAISO) over a four-year period (June 1, 2018, to December 31, 2022), we identified a significant negative correlation between renewable outputs and renewable market value on both hourly and daily levels. Our findings, align with previous studies, contribute to the body of evidence that have demonstrated the existence and characteristics of the cannibalization effect based on datasets from various geographic locations.

Additionally, as utility-scale battery storage has been proposed as a solution to mitigate the cannibalization effect, and government mandates increasingly advocate for the construction of battery storage systems alongside renewable infrastructure, we investigated whether battery storage effectively complements renewable energy. Contrary to conventional wisdom, our regression analysis revealed that batteries act as substitutes rather than complements to renewable energy. We hypothesize that this competitive relationship arises due to batteries' operational characteristic where batteries were designed to follow price fluctuations throughout the day in order to sustain their own financial viability by capitalizing on price differentials. We constructed a hypothetical scenario where battery output is delayed by four hours and observed a complementary relationship between batteries and renewables in this hypothetical scenario as evidenced in the positive correlation between renewable output and battery output, revenue, and profit in the delayed output scenario.

While the present investigation has successfully verified the presence of a cannibalization effect within the realm of renewable energy production, the extent of this effect requires nuanced interpretation within the specific geographical context. Moreover, despite the theoretical proposition of deliberately delaying output to engender an artificial complementary relationship between battery storage and renewable energy sources, more sophisticated modeling approaches are required to further explore the operational mechanisms that could help establish such complementary dynamics, creating synergies between battery storage systems and renewable energy technologies.

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Appendix I

Table 9. Flexible complete result including all interaction terms

	(3)	(4)
Variables	Flexible model	
	MV_Wind	MV_Solar
Wind	-1.0977**	-1.3165***
	(0.4348)	(0.3436)
Solar	-1.3413*	-1.7832***
	(0.6973)	(0.5482)
Geothermal	5.1480***	4.2199***
	(1.1374)	(0.9781)
Biomass	4.6956	1.9993
	(2.8567)	(2.3822)
Biogas	6.8948	3.9093
	(8.4946)	(7.2395)
Smallhydro	0.3092	0.4333
	(1.9663)	(1.6378)
Load_Dayaheadfc	0.3127***	0.2205***
	(0.0795)	(0.0648)
Coal	-189.4912***	-179.3635***
	(35.0257)	(30.0259)
Nuclear	0.2176	0.2965*
	(0.2021)	(0.1689)
Largehydro	-0.0761	-0.1524
	(0.2964)	(0.2542)
Imports	-1.3363***	-1.0691***
	(0.1797)	(0.1562)
c.wind#c.wind	0.0008	0.0005
	(0.0012)	(0.0010)
c.wind#c.solar	0.0067***	0.0041**
	(0.0023)	(0.0020)
c.wind#c.geothermal	0.0084	0.0082
	(0.0114)	(0.0094)
c.wind#c.biomass	-0.0071	-0.0140
	(0.0254)	(0.0185)
c.wind#c.biogas	0.0621	0.0680
	(0.0721)	(0.0588)
c.wind#c.smallhydro	0.0108	0.0049
	(0.0236)	(0.0170)

Table 9. Continued

Variables	(3)	(4)
	Flexible model	
	MV_Wind	MV_Solar
c.wind#c.load_dayaheadfc	-0.0014**	-0.0002
	(0.0007)	(0.0005)
c.wind#c.coal	0.0793	-0.0076
	(0.2720)	(0.2219)
c.wind#c.nuclear	0.0004	0.0007
	(0.0023)	(0.0018)
c.wind#c.largehydro	-0.0010	-0.0002
	(0.0027)	(0.0020)
c.wind#c.imports	0.0042***	0.0030**
	(0.0015)	(0.0013)
c.solar#c.solar	0.0029**	0.0041***
	(0.0013)	(0.0012)
c.solar#c.geothermal	-0.0615***	-0.0508***
	(0.0163)	(0.0142)
c.solar#c.biomass	-0.0270	-0.0017
	(0.0283)	(0.0220)
c.solar#c.biogas	-0.1113	-0.0716
	(0.0897)	(0.0778)
c.solar#c.smallhydro	-0.0008	0.0013
	(0.0229)	(0.0190)
c.solar#c.load_dayaheadfc	0.0008	0.0008
	(0.0008)	(0.0006)
c.solar#c.coal	1.9696***	1.9578***
	(0.3741)	(0.3268)
c.solar#c.nuclear	-0.0044	-0.0046**
	(0.0027)	(0.0022)
c.solar#c.largehydro	0.0030	0.0022
	(0.0032)	(0.0027)
c.solar#c.imports	0.0082***	0.0067***
	(0.0017)	(0.0015)
Observations	1,667	1,666
R-squared	0.626	0.674
Fixed Effect (day of week, month, year)	√	√

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Appendix II

Table 10. Regression results of market value of combined renewable energy

Variables	MV Renewable (model (5))
Renewables	-0.1934***
	(0.0286)
Load Day-ahead Forecast	0.2760***
	(0.0235)
Coal	-12.3580**
	(5.6096)
Nuclear	0.0068
	(0.0516)
Largehydro	0.1572***
	(0.0548)
Imports	-0.3952***
	(0.0432)
Observations	1,666
R-squared	0.567
Fixed Effect (day of week, month, year)	√

*** p<0.01, ** p<0.05, * p<0; robust standard errors in parentheses
Note: renewables include wind, solar, geothermal, biomass, biogas and small hydro output