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Efficiency and productivity of renewable energy technologies: Evidence from U.S. investor-owned utilities across regional markets

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ABSTRACT

This study employs a Data Envelopment Analysis (DEA) modeling technique to investigate the efficiency and productivity of renewable energy (RE) adoption across technologically diverse electricity-generating utilities. By employing metrics capturing policy effects, the study evaluates the RE adoption efficiency and productivity using a dynamic DEA model and the Malmquist DEA technique. First, the findings reveal that RE adoption is not significantly different across regional electricity markets. Second, the study revealed that RE adoption increased over the last three years. The total mean productivity change over the entire study period showed a mean improvement of 4.8%.

1. Introduction

The U.S. recently increased its commitment to leading the clean energy revolution through its Climate Change Action Plan, targeting a 100% carbon-free power sector by 2035 (Fact Sheet, 2021). The need to decarbonize the electricity sector to address climate change is urgent. According to the Energy Information Administration (EIA), only about 20% of the total electricity generated comes from renewable energy sources, while over 60% is from fossil fuels (EIA, 2021a). This situation poses a problem because the electricity sector is responsible for about a third of the total energy-related carbon emissions in the U.S., thus, making substantial contributions to global warming. A decarbonized grid would consist mainly of renewable and low-carbon energy technologies (such as solar-PV and wind energy systems) alongside energy storage systems with optimal cost and flexibility (Pourahmadi et al., 2020). Therefore, decarbonizing the electricity sector represents one of the most viable strategies for achieving the nation's ambitious climate change targets (Fact Sheet, 2021).

In the U.S., it is expected that electric utilities will continue to be critical in the efforts aimed at addressing climate change by increasing investments in low-carbon and renewable energy technologies with increases in technological learning (Shittu, 2013; Shittu et al., 2019). Over the past years, several policies and incentives have been introduced to encourage private sector investment in renewable energy at the state and federal government levels (Ogunrinde and Shittu, 2021). These

include renewable portfolio standards, carbon pricing, tax benefits, and clean energy grants and loan programs (Elie et al., 2021; Fowler and Breen, 2013). These have led to increased capacity additions for renewable energy technologies like solar-PV and wind energy (Baker et al., 2020; Jiang et al., 2016). For instance, in 2020, solar-PV and wind energy capacities grew by 22% and 14%, respectively, from 2019 values leading to a renewable energy consumption record of 12% of the total U. S. energy consumption within a year (EIA, 2021b).

Benchmarking power systems and electricity generation is necessary to evaluate the potential for GHG emission reductions (Alizadeh et al., 2020). As a result, the increased expansion in renewable energy technologies within the mix of conventional energy technology portfolios makes it imperative to perform performance evaluation and benchmarking in the electricity sector. Benchmarking involves comparing the performance of production units to a reference or frontier performance. Benchmarking is critical because it not only allows utilities to compare themselves to the best possible set but also allows for the identification of areas of potential improvements and the development of strategic pathways to enhance their performance (Khetrapal and Thakur, 2014; Pahwa et al., 2003; Thakur et al., 2006). Performance benchmarking in the electricity sector is also needed because it aids policymakers in designing incentive-based policy instruments that encourage the production of electricity from cleaner energy sources (Baker and Shittu, 2008; DeLuque and Shittu, 2019).

This study aims to evaluate the dynamic performance and

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productivity of technologically diverse electricity generation utilities in the U.S., focusing on renewable energy (RE) adoptions. Renewable energy adoption refers to the ability of production units to maximize the share of renewable energy capacity additions within their generation mix in the presence of various incentives and policies designed to drive the growth of renewable energy (Ogunrinde and Shittu, 2020, 2021). This study considers only emerging renewable energy technologies, specifically solar PV, and wind energy. Previous studies have focused on the performance evaluation of overall efficiencies for a single technology, electricity generation, electricity distribution, and vertically integrated utilities. To our knowledge, no previous study has evaluated renewable energy efficiency and productivity related to technologically diverse electric utilities. This study makes these evaluations under the lens of whether the utility belongs to a Regional Transmission Organization (RTO), and highlights the differences across these metrics for both groups.

Central to the analysis in this paper is the recognition that electricity generators and policy effects designed to drive the growth of renewable energy are located within geographical state lines under the umbrella of an electric grid that spans multiple states. To that effect, RTOs, equally known as Independent System Operators (ISOs), are saddled with the responsibility of managing and coordinating the multi-state electric grid system. A total of seven RTOs/ISOs exist in the United States and are responsible for managing about two-thirds of the country's annual electricity demand (FERC, 2021). Utilities operating in the RTO regions are expected to provide an easy entry into private investment in emerging renewable energy technologies and improve renewable energy adoption within the regions (Hogan, 2010). Therefore, this study focuses on evaluating the efficiency and productivity of utilities across RTO and non-RTO regions.

This study contributes to the performance benchmarking literature on electricity utilities by employing a framework that evaluates RE adoption efficiency and productivity within the electricity sector. In addition, the findings from this study also provide relevant policy insights to policymakers and technology managers on the crucial drivers for RE adoption among large, technologically diverse generation utilities. The value drawn from this exercise extends our knowledge in understanding disparities in energy technology investments considering the ambivalence faced by decision-makers and investors in adopting emerging RE technologies in the place of existing conventional technologies.

In sum, to evaluate the renewable energy adoption efficiencies, this study employs a dynamic non-linear parametric programming approach in the form of Data Envelopment Analysis (DEA). DEA estimates an efficient frontier for the best-performing utilities in terms of RE adoptions. The DEA model maximizes the share of RE within the generation mix of utilities' portfolios. As a result, a utility on the frontier is termed efficient if it makes the best use of available input resources to maximize its RE capacity share. Inefficient units on the other hand, operate below the frontier, implying that they produce lower RE capacities outputs with relatively higher, or equal, inputs than those that operate on the frontier. The study further employs non-parametric statistical analysis to assess the performance of the utilities across electricity market regions. Finally, the study applies a DEA-Malmquist index technique to evaluate the utilities' RE productivity change across adjacent periods over the study horizon.

2. Literature review

Various approaches have been considered in evaluating the performance efficiency of electric utilities. The choice of approach largely depends on data availability and the specific application in question (Pereira de Souza et al., 2010). Jamasb and Pollitt (2000) surveyed electric utilities across several countries and identified the three most widely employed performance evaluation techniques. These techniques are (i) Data envelopment Analysis (DEA), (ii) Corrected Ordinary Least

Square (COLS), and (iii) Stochastic Frontier Analysis (SFA). These approaches involve identifying a frontier of the best performance from a list of qualified utilities. SFA and COLS are econometric approaches that estimate efficiency scores and require specifying a production or cost function. However, as a programming approach, DEA computes the efficiency scores from actual data and does not require the specification of production or cost functions. In addition, DEA can be combined with Malmquist Indices to investigate productivity changes from one period to the other (Sánchez-Ortiz et al., 2020).

Jamasb and Pollitt (2000) and Khetrapal and Thakur (2014) reviewed the merits and demerits of these approaches within the context of performance benchmarking in electric utilities. In addition, prior research has compared these three techniques. For instance, Jamasb and Pollitt (2003) conducted an international benchmarking exercise of 63 electric utilities across six European countries using DEA, COLS, and SFA models. Their findings revealed that the choice of benchmarking techniques significantly influenced both the computed efficiency scores and the performance rankings of the utilities. In a similar study evaluating the cost efficiencies of 52 electric distribution utilities in Switzerland, Farsi and Filippini (2005) also found that both efficiency scores and performance ranks differed across the three techniques: the DEA efficiency scores and ranks are significantly different in comparison with that of COLS and SFA. Nonetheless, DEA remains the most widely employed performance benchmarking technique for electric utilities due to its ability to accommodate multiple input and output variables without predefined functional forms for the decision-making units (Mullarkey et al., 2015).

Studies have focused on evaluating the performance of electric power generation plants with DEA (Park and Lesourd, 2000; Lam and Shiu, 2001; Nemoto and Goto, 2003; Vaninsky, 2006; Barros and Peypoch, 2008; Liu et al., 2010; Ogunrinde and Shittu, 2023). For example, Park and Lesourd (2000) employed DEA to investigate the efficiency of 64 conventional fuel power plants in South Korea and used the DEA efficiencies in an econometric production function to improve the model's correctness. Nemoto and Goto (2003) employed a dynamic DEA framework to model the investment behavior of nine Japanese thermal plants over 15 years. Vaninsky (2006) evaluated the efficiency of U.S. electric power plants using DEA and employed a forecasting technique to compute input and output values required to achieve future efficiency scores of 100%. Barros and Peypoch (2008) evaluated the performance of Portuguese thermoelectric power plants using a combined DEA model and bootstrapping technique to estimate the drivers of the technical efficiencies. In a recent study, Khodadadipour et al. (2021) considered undesirable outputs and evaluated the efficiencies of 32 thermal-powered plants using a stochastic DEA approach for ranking and enhancing discrimination among decision-making units. In summary, these studies were ultimately concerned with the overall technical efficiencies for electricity generation across power plants and also did not consider the generation technologies within the portfolios.

Another group of studies focused on performance benchmarking across electricity distribution utilities (Miliotis, 1992; Yu et al., 2009; Çelen and Yalçın, 2012; Bongo et al., 2018; Medeiros et al., 2022). An early study by Miliotis (1992) employed DEA to evaluate the efficiencies of 45 electricity distribution districts in Greece and concluded that the scores obtained appeared to be more reliable in comparison to other techniques. Yu et al. (2009) reported a significant correlation between weather variables and economic efficiency scores in investigating the effects of weather on the performance of 12 UK distribution network operators using factor analysis and a 2-stage DEA method. In incorporating quality of service in the performance measurement of electricity utilities, Çelen and Yalçın (2012) used a combined FAHP/TOPSIS/DEA approach to assess the performance of 21 Turkish electricity distribution utilities. To improve the discriminating power of traditional DEA in electricity utility benchmarking, Bongo et al. (2018) employed a super-efficiency DEA to evaluate the performance of 12 distribution power lines of a public utility company. A recent study by Medeiros et al.

(2022) focused on evaluating the influence of weight restrictions on the performance efficiency scores of Brazilian electricity utility companies using DEA, cost-efficiency, and ratio-based analysis techniques. These studies focused on performance benchmarking of electricity distribution networks and utilities, and, as such, the studies were concerned with performance measurement variables such as the total customers served and the total electricity sales.

A few more studies considered vertically integrated electricity utilities. Techniques such as assurance region DEA (Goto and Tsutsui, 1998), slack-based DEA (Tsutsui and Goto, 2009), and network DEA models have been employed (Petridis et al., 2019; Alizadeh et al., 2020). Goto and Tsutsui (1998) compared the cost efficiencies and overall technical efficiencies of Japanese and U.S. electric utilities using DEA; the authors reported higher cost efficiency values with Japanese utilities and found the Japanese utilities to be more efficient in terms of technical and scale efficiencies. Petridis et al. (2019) employed a network DEA approach combined with a directional distance function to evaluate the profit efficiencies of Turkish electrical utility companies. Similarly, Alizadeh et al. (2020) presented a dynamic network DEA model to assess the periodic performance of Iranian electricity companies and reported that the distribution sections have increasing efficiencies while the generation and transmission sections have decreasing efficiencies. These studies typically focused on the overall technical efficiencies of vertically integrated electricity generation utilities and evaluated the inter-relationships between the sub-systems in the electricity generation systems.

The focus of this study is to evaluate the overall renewable energy adoption efficiency and productivity across electricity utilities in the U. S. Specifically, this study takes a holistic approach and considers the largest technologically diverse electricity utilities. Technologically diverse, in this case, refers to utilities with varied energy technologies, such as fossil-fuel-powered plants and renewable energy plants within the utilities' generation portfolios. Previous studies in the extant literature have evaluated the overall technical efficiencies in utility power plants, distribution networks, and vertically integrated utilities (DeLuque et al., 2018). However, this study is concerned with performance benchmarking of electricity generation utilities at the firm level and specifically considers renewable energy adoption across mixed-generation portfolios. This research study fills some empirical gaps in the extant literature. First, this study considers how electric utilities have efficiently maximized renewable energy capacity additions over the years, given specific energy policies and incentives available within the utilities' operating regions. Second, this study investigates how these renewable energy adoption efficiencies differ across the RTO and non-RTO regions. Third, this study evaluates how productive utilities have been in maximizing renewable energy capacity additions over adjacent periods. It is also important to note that this study focuses on the strength of RE policies in the presence of renewable energy resource endowment as drivers for RE growth and development. A summary of the input and output variables employed in past studies is shown in Tables 1 and 2, respectively.

The RTO/ISO model created wholesale power markets to incentivize efficient operations and technology investment (Anadon and Holdren, 2009). Ideally, this should create better opportunities for decentralized energy investment decisions in electricity generation plants, end-use-efficiency (Helman et al., 2010; Hogan, 2010; Shittu et al., 2015), and enhance system resilience (Shittu et al., 2021; Shittu and Santos, 2021). In addition, the choice available to consumers on whom to purchase electricity from in fully regulated electricity regions is expected to encourage the growth and development of green energy technologies in these regions (Carley, 2009; Ogunrinde et al., 2020). On the other hand, energy investment decisions for vertically integrated utilities in non-RTO/ISO are at the purview of the electricity utilities and subject to state economic regulation. These utilities may be less likely to adopt new and emerging technologies within their generation portfolios.

Table 1

Summary of input variables employed in DEA electric utility studies.

Inputs	Study references
1 Fuel	(Yaisawarn and Klein, 1994), (Park and Lesourd, 2000), (Nemoto and Goto, 2003), (Liu et al., 2010), (Sarica and Or, 2007)
2 Labor	(Yaisawarn and Klein, 1994), (Park and Lesourd, 2000), (Nemoto and Goto, 2003), (Barros and Peypoch, 2008), (Lam and Shiu, 2001), (Sueyoshi and Goto, 2012), (Thakur et al., 2006)
4 Installed capacity	(Park and Lesourd, 2000), (Liu et al., 2010), (Yang and Pollitt, 2009)
5 Operations and maintenance costs	(Pahwa et al., 2003), (Sueyoshi and Goto, 2012), (Vaninsky, 2006)
6 Capital costs	(Yaisawarn and Klein, 1994), (Barros and Peypoch, 2008), (Lam and Shiu, 2001), (Yang and Pollitt, 2009)
7 SO ₂	(Yaisawarn and Klein, 1994), (Yang and Pollitt, 2009), (Yang and Pollitt, 2010), (Sueyoshi and Goto, 2012), (Zhou et al., 2013), (Lee, 2014)
8 NO _x	(Yang and Pollitt, 2010), (Sueyoshi and Goto, 2012), (Zhou et al., 2013), (Lee, 2014)
9 CO ₂	(Yang and Pollitt, 2010), (Sueyoshi and Goto, 2012), (Zhou et al., 2013), (Zhang et al., 2013), (Shakouri G. et al., 2014), (Yadav et al., 2014), (Lee, 2014)

Table 2

Summary of output variables employed in DEA electric utility studies.

Outputs	Study references
1 Installed capacity (MW)	(Jha and Shrestha, 2006), (Sueyoshi and Goto, 2014), (Sueyoshi and Wang, 2017), (Sueyoshi and Goto, 2017), (You et al., 2018)
2 Electric power generated (MWh)	(Yaisawarn and Klein, 1994), (Barros and Peypoch, 2008), (Sueyoshi and Goto, 2014), (Sueyoshi and Goto, 2017), (You et al. (2018); (Sueyoshi and Wang, 2017)

3. DEA model

This section presents the basic DEA model with recent extensions and the Malmquist DEA approach. The variables and underlying data are also presented.

3.1. Basic DEA model

A decision-making unit (DMU) represents the entity responsible for transforming sets of inputs into outputs. DEA originates from the traditional concept of output-to-input ratio, often used to describe efficiency in science and engineering (Cooper et al., 2006). The concept was pioneered with the CCR (Charnes, Cooper, and Rhodes) model developed by Charnes et al. (1978). The model involves solving an optimization problem that maximizes the ratio of the weighted sum of selected outputs to the weighted sum of their inputs. Consider the CCR output-oriented model described in Model (1).

$$\min \frac{\sum_{i=1}^m v_i x_{ij}}{\sum_{r=1}^s u_r y_{rj}} \quad (1a)$$

$$s.t. \sum_{i=1}^m v_i x_{ij} \geq \sum_{r=1}^s u_r y_{rj}; \quad j = 1, \dots, n \quad (1b)$$

$$u_r, v_i \geq \varepsilon > 0; \quad r = 1, \dots, s; \quad i = 1, \dots, m \quad (1c)$$

If there are n DMUs such that each DMU _{j} ($j = 1, \dots, n$) uses m inputs represented by x_{ij} ($i = 1, \dots, m$) to produce s outputs represented by y_{rj} ($r = 1, \dots, s$), then the efficiency of the DMU _{o} under evaluation is represented by θ_o . Due to difficulties associated with fractional programming, the model is linearized by setting the denominator in (1a) equal to 1. We then obtain the CCR multiplier model described in Model

(2).

$$\min \sum_{i=1}^m v_i x_{io} \quad (2a)$$

$$\sum_{r=1}^s u_r y_{ro} = 1 \quad (2b)$$

$$s.t. \sum_{i=1}^m v_i x_{ij} \geq \sum_{r=1}^s u_r y_{rj}; \quad j = 1, \dots, n \quad (2c)$$

$$u_r, v_i \geq \varepsilon > 0; \quad r = 1, \dots, s; \quad i = 1, \dots, m \quad (2d)$$

The CCR model determines for each DMU optimal values of the output and input multipliers u_r and v_i , respectively, such that Equation (2a) is maximized subject to all the constraints. These multipliers represent the marginal effects of the input and output values x_{io} and y_{ro} on the computed efficiency scores. Equation (2c) implies that the sum of the sum-products of inputs and their respective multipliers always exceeds or equals the sum-products of the outputs and their respective multipliers. This restriction ensures that all DMUs lie on or below the efficient frontier (Ribeiro et al., 2020). The parameter ε represents an arbitrary small (non-Archimedean) positive number introduced to avoid ignoring any factor and ensure strongly efficient conditions (Charnes and Cooper, 1984). These constraints ensure the efficiency score's optimal value (θ^*) always has an upper bound of 1 and a lower bound of 0.

The dual of the multiplier model is referred to as the envelopment model and is often preferred due to its computational efficiency compared to the multiplier model (Liu et al., 2010). The output-oriented CCR model is shown in Model (3).

$$\max Z = \theta + \varepsilon \left(\sum_{i=1}^m s_i^- + \sum_{r=1}^s s_r^+ \right) \quad (3a)$$

$$s.t. \sum_{j=1}^n \lambda_j x_{ij} + s_i^- = x_{io}; \quad i = 1, \dots, m \quad (3b)$$

$$\sum_{j=1}^n \lambda_j y_{rj} - s_r^+ = \theta y_{ro}; \quad r = 1, \dots, s \quad (3c)$$

$$\lambda_j, s_i^-, s_r^+ \geq 0; \quad j = 1, \dots, n; \quad r = 1, \dots, s; \quad i = 1, \dots, m \quad (3d)$$

Where s_i^- and s_r^+ represent the slacks of the input and output constraints in Equations (3b) and (3c), respectively. λ_j represents the dual weights assigned to each DMU and provides a lower bound for x_{io} and an upper bound for y_{ro} thus enveloping all observations. A DMU is considered efficient if the optimal value of $\theta^* = 1$ and all slacks are equal to zero.

The BCC model (Banker et al., 1984) under variable returns to scale conditions is achieved by including the additional constraint in Equation (3e).

$$\sum_{j=1}^n \lambda_j = 1 \quad (3e)$$

When faced with time-series data, various approaches can be employed in evaluating the performance of DMUs over time. Static approaches consider aggregate values (Kao and Hwang, 2008) and average values (Portela et al., 2012) of input and output variables. Dynamic DEA models evaluate the interdependency between successive periods by considering the transition process between periods and evaluating a single efficiency of each DMU over the period. Consider the multi-period DEA model developed by Park and Park (2009), where a DMU operates over q periods such that $p = 1, \dots, q$. The output-oriented CCR model, Model 4, is shown in Equations (4a) to (4d).

$$\max Z = \theta + \varepsilon \left(\sum_{p=1}^q \sum_{i=1}^m s_i^{-(p)} + \sum_{p=1}^q \sum_{r=1}^s s_r^{+(p)} \right) \quad (4a)$$

$$s.t. \sum_{j=1}^n \lambda_j^{(p)} x_{ij}^{(p)} + s_i^{-(p)} = x_{io}^{(p)}; \quad i = 1, \dots, m; \quad p = 1, \dots, q \quad (4b)$$

$$\sum_{j=1}^n \lambda_j^{(p)} y_{rj}^{(p)} - s_r^{+(p)} = \theta y_{ro}^{(p)}; \quad r = 1, \dots, s; \quad p = 1, \dots, q \quad (4c)$$

$$\lambda_j^{(p)}, s_i^{-(p)}, s_r^{+(p)} \geq 0; \quad j = 1, \dots, n; \quad r = 1, \dots, s; \quad i = 1, \dots, m; \quad p = 1, \dots, q \quad (4d)$$

3.2. Malmquist DEA model

The DEA method can be used to evaluate the productivity change of DMUs over time using the Malmquist Index of productivity change. The Malmquist Index is a distance function combining efficiency and technical change (Kannan et al., 2021). Färe et al. (1994) allowed for the decomposition of total productivity change into an efficiency change relating to the operating DMU and an industry-level productivity change beyond the DMU's control. The Malmquist productivity index (MPI) is computed as shown in Equation (5).

$$MPI = \left[\frac{\theta_{b,b}}{\theta_{a,a}} \right] * \left[\left(\frac{\theta_{a,b}}{\theta_{b,b}} \right) \left(\frac{\theta_{a,a}}{\theta_{b,a}} \right) \right]^{1/2} \quad (5)$$

where,

$\theta_{a,a}$ is the efficiency of a DMU observed in period "a" relative to the frontier in "a".

$\theta_{b,b}$ is the efficiency of a DMU observed in period "b" relative to the frontier in "b".

$\theta_{a,b}$ is the efficiency of a DMU observed in period "a" relative to the frontier in "b".

$\theta_{b,a}$ is the efficiency of a DMU observed in period "b" relative to the frontier in "a".

$\frac{\theta_{a,b}}{\theta_{b,b}}$ is the distance between the two frontiers at the input mix of the DMU in period "b".

$\frac{\theta_{a,a}}{\theta_{b,a}}$ is the distance between the two frontiers at the input mix of the DMU in period "a".

The first component on the LHS in Equation (5) represents the efficiency change or the catching-up component and measures how much closer to the frontier a DMU is in period "b" compared to period "a". The second component on the RHS is computed by taking the geometric mean of two ratios and is referred to as the technical change or boundary-shift component. It represents a measure of the technology or industry changes occurring over adjacent periods (Thanassoulis, 2001). The results from Equation (5) can be interpreted as follows:

$MPI > 1$ implies an increase in productivity between period "a" and "b".

$MPI = 1$ implies that the productivity is unchanged between periods "a" and "b".

$MPI < 1$ implies a decline in productivity between periods "a" and "b".

3.3. Data and variable selection

This study employs data from investor-owned electric utilities operating in the U.S. The qualified utilities are utility companies with a minimum total generation capacity of 5000 MW to limit any unfair comparisons and improve the validity of the analysis. The final dataset comprises 24 electric utilities operating in different regions in the U.S. over six years from 2014 to 2019, for a total of 144 observations. The list of eligible and included electricity utilities is shown in Table A1 in the Appendix.

The DEA methodology is sensitive to the selected input and output variables, thus making the efficiency scores computed and the interpretation of results significantly influenced by the choice of input and output variables (Donthu et al., 2005). In addition, there is no rigid consensus on the choice of input and output variables to be employed in the performance evaluation of electric utility when using DEA (Gianakakis et al., 2005). As such, DEA analysis can be carried out with a subset

of selected inputs and outputs depending on the particular concepts being measured (Pahwa et al., 2003). The selection of inputs and output variables for this study is informed by the extant literature, the goals of this study, and data availability.

All the data employed in this study are from publicly available sources and aggregated together, providing a means of adequately capturing the essential evaluation metrics focal to this study. The study employed five input variables and one output variable, as shown in Fig. 1. The input variables are as follows: policy effects (RPS policy strength and RE financial incentive strength), a financial variable (operations and maintenance (O&M) costs), and environmental variables (solar insolation and wind speed). The output variable employed is the percentage share of renewable energy capacity within each firm's energy generation portfolio.

The first input variable employed was the total operations and maintenance cost. These data were estimated from the average nominal values in \$/MWh provided by the EIA for each generation technology each year. The second input variable employed is the RPS target strength. RPS requires that a fixed portion of the electricity utilities produce, come from renewable energy sources. According to the U.S. EIA (Energy Information Administration), RPS has been implemented across 30 states and the District of Columbia as of 2021, with 12 states having requirements for 100% clean energy on or before 2050. It is expected that the strength of RPS policies within regions would directly impact the production of renewable energy (Barbose et al., 2016; Upton and Snyder, 2017).

Data on state RPS targets over the study horizon was obtained from the U.S. renewable portfolio standards database of the Lawrence Berkeley National Laboratory (LBNL). The percentage RPS target for each state was obtained by dividing the nominal RPS requirements in megawatt hours (MWh) by the total retail electricity sales in MWh (Ogunrinde et al., 2018). As shown in Equation (6), a variable was developed to capture the strength of RPS for every utility j by employing a weighted sum of the policy strength computed by combining the RPS policy strength $R_{k,p}$ for each state k in each period p and the utility's share of total generation capacity $W_{k,p}$ in each state k within each period p .

$$RPS_j^{(p)} = \sum_{k=1}^K W_{k,j}^{(p)} R_k^{(p)}; \quad (j = 1, \dots, n); \quad (p = 1, \dots, q) \quad (6)$$

The third input variable in this study is the strength of renewable energy financial incentives. Several federal and state financial incentives have been introduced to promote the growth and development of renewable energy technologies within the U.S., such as tax-credit

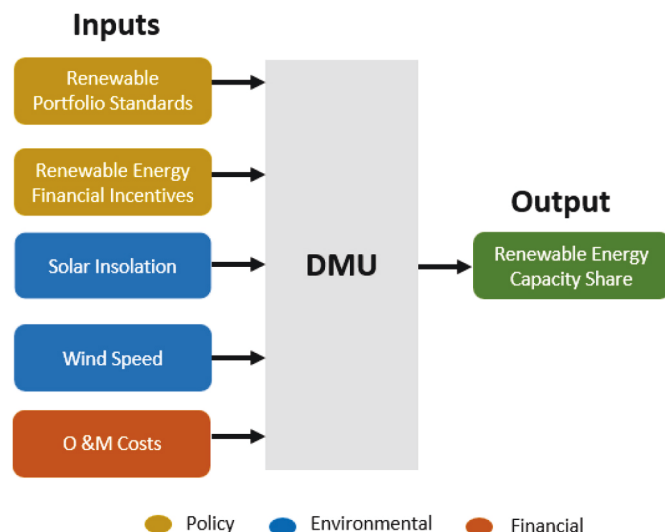


Fig. 1. Input and output variables.

programs, buy-down programs, and loan programs (Gouchoe et al., 2002). Data on federal and state renewable energy financial incentives were obtained from the Database of State Incentives for Renewable Energy (DSIRE, 2021). These incentives provide a crucial foundation that complements renewable energy policies such as RPS. Consistent with related approaches, the count of financial incentives available to utility within each period was used as a proxy for the strength of the financial incentive input variable (Shittu and Weigelt, 2022a, 2022b), as shown in Equation (7).

Similarly, this variable was computed for each j utility by employing a weighted sum of the total financial incentive count, computed from the incentives count $f_{k,p}$ for each state k in each period p and the utility's share of total generation capacity $W_{k,p}$ in each state k within each period p .

$$FIN_j^{(p)} = \sum_{k=1}^K W_{k,j}^{(p)} f_k^{(p)}; \quad (j = 1, \dots, n); \quad (p = 1, \dots, q) \quad (7)$$

Resource endowments are expected to drive the development and adoption of renewable energy growth in the regions (Carley et al., 2018; Olivier and Del Lo, 2022; Weigelt and Shittu, 2016). The fourth input variable employed is solar insolation measured in kWh/m²/day. It represents the total amount of solar radiation per unit area annually. Since sun rays strike the earth's surface at different angles, locations with higher latitudes have a smaller angle of incidence and thus less solar isolation compared to locations closer to the equator. Therefore, a location's solar resource allocation would directly impact the amount of renewable solar energy. The insolation parameter was obtained from each location's average annual solar insolation over each operating year. This data was obtained from NASA's POWER (Prediction of Worldwide Energy Resources) database. The final input variable employed is wind energy resource allocation, measured by the wind speed in m/s. In general, higher wind speeds are associated with greater wind power density. As a result, regions with higher wind power resource allocations are more attractive for the advancement and subsequent adoption of renewable wind energy (Wang et al., 2021). Data on wind resource endowment was also obtained from NASA's POWER database.

4. Results

Table 3 shows the summary statistics and correlation matrix of all variables employed in the study. The time series data were plotted, as shown in Figs. 2 and 3. The vertical axes represent the average values of these input and output variables, while the horizontal axes show the study period. Fig. 2 shows that the average values of RPS percentage targets and percentage share of RE capacity addition increased from 2014 to 2019. However, from Fig. 3, it can be seen that the average value of the estimated operations and maintenance costs dropped slightly in 2015 and then in 2019, which could indicate a reduction in fossil-fuel technology investment during the period. Furthermore, Fig. 3 shows that the average number of available financial incentives for renewable energy adoption considerably increased over the study horizon.

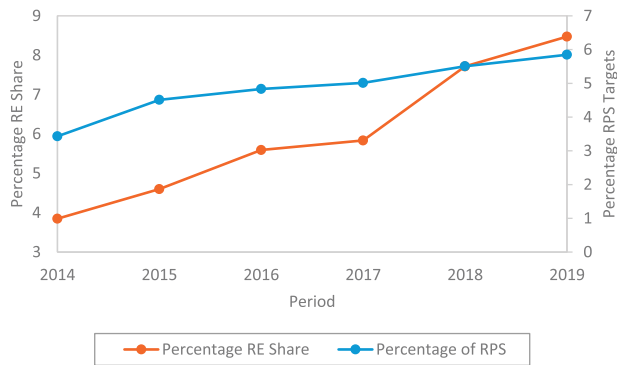
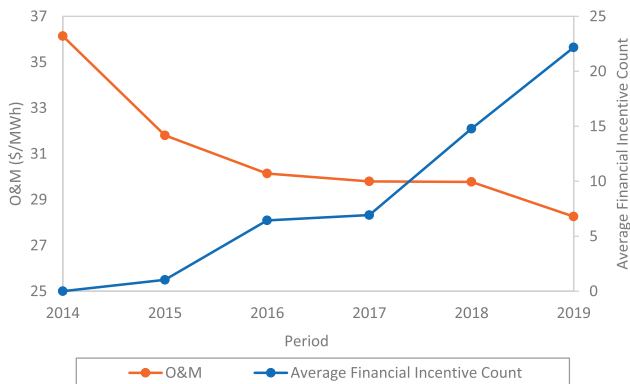
The CCR out-oriented dynamic DEA model described in Model 4 was employed to evaluate the dynamic performance of the 24 electric utilities during the study period. The output-oriented model maximizes the outputs while keeping the inputs concerned. This approach is best suitable for this study because the utilities seek to maximize their outputs for a given level of inputs (Mohd Chachuli et al., 2021; You et al., 2018).

The efficiency scores were then computed for each utility described in the dynamic CCR-output-oriented model. The non-RTO group comprises ten utilities represented using the notations F1 to F10. The RTO group consists of 14 utilities designated by notations E1 to E14; see Table A1 in the Appendix for a complete listing of the utilities. The results from the dynamic DEA model are shown in Fig. 4. The top section

Table 3

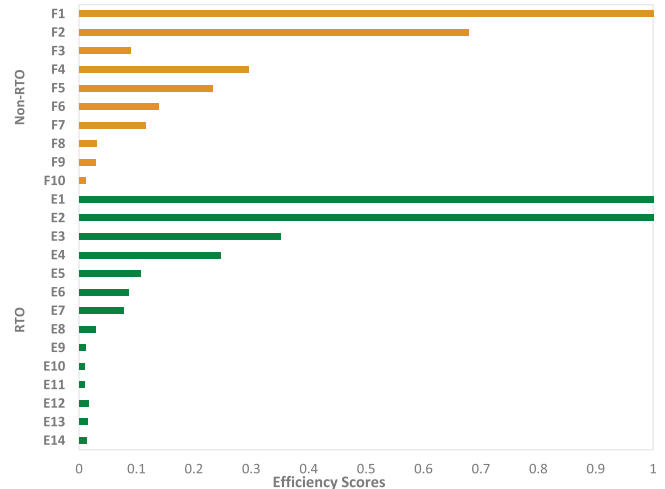
Summary statistics and correlation matrix of all variables.

	Mean	Standard Deviation	RPS (%)	Financial Incentives	O&M (\$/MWh)	Renewable Energy (%)	Solar Insolation (kWh/m ² /day)	Wind Speed (m/s)
RPS (%)	0.0486	0.0670	1.0000					
Financial Incentives	8.5584	9.3977	0.3577	1.0000				
O&M (\$/MWh)	30.9837	4.5835	-0.4014	-0.4216	1.0000			
Renewable Energy (%)	0.0601	0.1611	0.0344	0.1157	-0.5909	1.0000		
Solar Insolation (kWh/m ² /day)	5.7780	0.2827	-0.2530	-0.1331	0.1573	-0.2749	1.0000	
Wind Speed (m/s)	3.1889	1.0770	0.3082	0.0827	-0.1354	0.3711	-0.5879	1.0000

**Fig. 2.** Graph of average percentage RPS target and RE capacity share across the study horizon.**Fig. 3.** Graph of average financial incentive count and O&M expenses across the study horizon.

shows the efficiency scores for utilities (F1 to F10) operating in the non-RTO regions, while the lower section shows utilities operating in the RTO regions (E1 to E14). The results show that three utilities (F1, E1, and E2) have efficiency scores equal to unity and lie on the efficient frontier. This finding implies that relative to other utilities in the dataset, these utilities have been able to optimally maximize the share of renewable energy within their generation portfolios for a given level of inputs. Utilities with relative efficiency scores of less than one lie below the efficient frontier and have been inefficient in maximizing their renewable energy capacities for the given level of inputs.

Table 4 shows a breakdown of the efficiency scores for both groups of utilities. On average, the efficiency scores for utilities in the non-RTO are higher than those in the RTO regions. A Mann-Whitney *U* test was conducted on the two groups of efficiency scores to investigate whether the differences were statistically significant. Generally, a Mann-Whitney *U* test provides statistical power advantages over the paired-*t* tests when conditions of normality are not satisfied for independent samples and, as

**Fig. 4.** Efficiency scores of dynamic DEA model. F1 – F10: Utilities in Non-RTO Group; E1 - E14: Utilities in RTO Group (see the Appendix for exact names).**Table 4**

Summary of efficiency scores.

Region	Obs.	Mean	Std. Dev.	Min.	Max.
RTO	14	0.2123	0.3486	0.0100	1.0000
Non-RTO	10	0.2620	0.3263	0.0110	1.0000

such, is employed to distinguish between two distributions drawn from independent samples (Sawilowsky, 2005). The test statistic, *p*-value, and non-parametric confidence interval were computed as 48.5, 0.2182, and $[-0.2171+0.0580]$, respectively. Since $48.5 > 36$ (the critical value at $\alpha = 5\%$) and $p > 0.05$, we do not reject the null hypothesis that the difference between the two pairs has a probability distribution centered at zero.

The Malmquist Productivity Index (MPI) was computed as described in Equation (5) to investigate the periodic productivity changes for renewable energy adoption across the utilities. For each year, the efficiency change (catching-up effect), technology change (boundary-shift effect), and total productivity change (MPI) were computed. The indices less than one indicate a decline in productivity, while those greater than unity indicate productivity growth. Fig. 5 shows the mean efficiency change (Effch), technology change (Techch), and total factor productivity change (Tpch) over time for all the utilities. A detailed summary of the differences in productivity change across the utilities is shown in Table A2 in the Appendix. Table A2 is interpreted by the bubble plots for utilities in non-RTO (Fig. 6) and RTO (Fig. 7) regions. In both Figures, the size of the bubbles represents the MPI. Notably in Fig. 6, non-RTO utilities seem to have their technological change explained by their efficiency change given the moderate but significant R-squared value, represented by the broken straight line in both Figures. On the other hand, the RTO utilities do not demonstrate the same relationship as

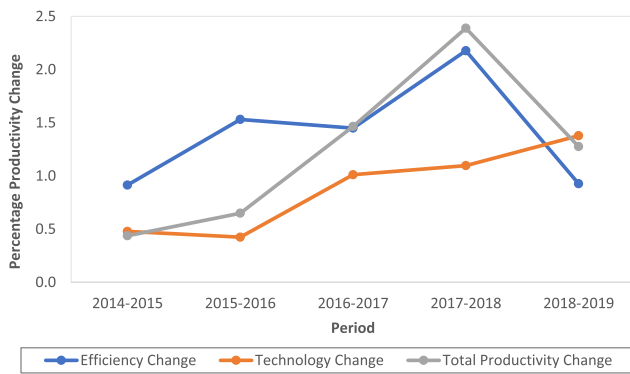


Fig. 5. Efficiency scores from the dynamic DEA model.

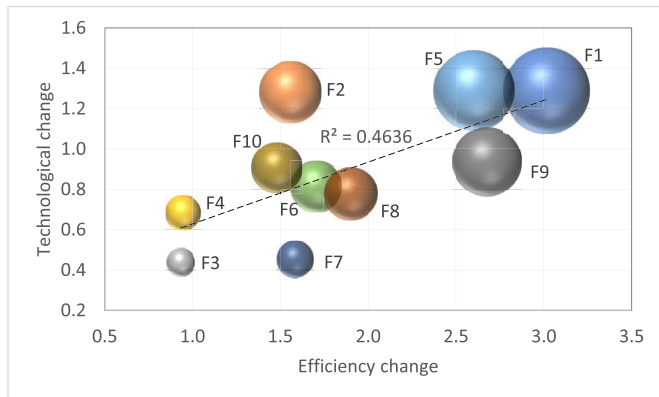


Fig. 6. The relationship between technological change and efficiency change for non-RTO utilities.

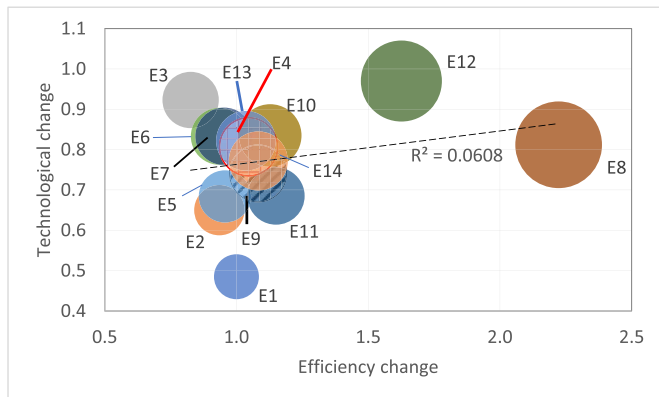


Fig. 7. The relationship between technological change and efficiency change for RTO utilities.

shown in Fig. 7.

These different effects, i.e., these differences in RE adoption patterns across the utilities, differentiated by their belonging to a balancing authority or not, and within periods can also be seen in the overall periodic mean productivities shown in Fig. 4. In addition to these, Table A3 in the Appendix also provides a summary of the periodic mean productivities.

5. Discussion

An analysis of the bar graphs shown in Fig. 4 and the summary in Table A2 reveal that the variation in RE productivity is significant across the utilities in both groups. While some utilities show considerable

improvements in RE productivity over the period, others appear less productive in RE adoption. The results from the Mann-Whitney U test imply that the differences in renewable energy adoption efficiencies across utilities in the two groups are not statistically significant. This finding is unexpected, counter-intuitive, and contrary to assumptions that utilities operating in RTO markets provide an easy entry for private investment into emerging energy technologies and improve the integration of renewable energy sources into the existing generation portfolios (GAO, 2008; Hogan, 2010).

The findings counter those reported by Sueyoshi and Goto (2012), who focus on the overall technical efficiencies for coal-fired utility plants in the U.S. and report a higher performance for those utilities in the non-RTO as compared to those in the RTO regions. The implication of the findings from our study policy-wise, is that for technologically diverse utilities operating in regions where the transmission coordination and control have been unbundled, the renewable energy adoption efficiencies may not be significantly different from those of utilities operating in regions where the utilities can exercise more control over their transmission networks and are mostly vertically integrated. Our results provide empirical evidence that over the observed period, the investment rate in emerging renewable energy technologies targeted at displacing existing fossil technologies may be independent of the electricity market structure in which the utilities operate.

Therefore, it may be the case that new investments in emerging renewable energy technologies would be concentrated mainly in separate and independent utilities that have specialized in specific energy technology deployments. Therefore, investors may find it more challenging to develop hybrid systems that accommodate investments driven by regulatory incentives and market conditions. Our findings reinforce those of Ogunrinde et al. (2018), who observed that some utilities specialize in specific energy technologies within specific market regions.

From Fig. 5, for all the periods except 2014–2015 and 2018–2019, there is a growth in efficiency change for renewable energy adoption. The highest growth of 118% occurred in 2017–2018, while the least growth was 45% from 2016 to 2017. The periods 2014–2015 and 2018–2019 experienced a slight decline in efficiency change of 9% and 7%, respectively. The efficiency change component measures the proximity of the DMUs to the efficient frontier, and it reflects improvement in the utilization of input resources available to the qualified utilities. This study captures how well the firms have utilized the available renewable energy incentives, renewable energy resource endowments, and policy mandate impacts in maximizing the share of renewable energy within their generation portfolios.

By considering technology change, Fig. 5 shows that despite a decline in technology change over the first two observed periods (2014–2015 and 2015–2016), the last three periods experienced an improvement of 1%, 9%, and 39% over adjacent years. Technology change refers to frontier shifts and compares the observation of DMUs in one period to the technology of an adjacent period. As a result, it refers to changes in the industry which may be due to process or product innovations. With respect to this research study, technology change represents technological improvements that have driven the adoption of renewable energy in the electricity sector over the years. These changes could range from improvements in operational efficiencies to optimized grid integration technologies and processes for renewable energy generators.

On a general note, efficiency change (catching-up effects) was seen to improve at different rates over each adjacent study period with only some slight declines. However, in analyzing the technology change (frontier-shift effects), we see declines in the initial periods, followed by considerable improvements from period to period in the later years.

Furthermore, Fig. 5 also shows the total productivity change (MPI) that combines the efficiency change with the technology change. The MPI measures the overall effects and reflects how well electricity utilities have been able to adopt renewable energy within their generation

portfolios over the periods. The first two periods, 2014–2015 and 2015–2016, were observed to have the greatest decline in total productivity change, with a mean productivity growth of 56% and 35%, respectively, driven by the decline in technology change across these periods. However, the subsequent three periods experienced improvements in mean productivity growth, 47% in 2016–2017, 139% in 2017–2018, and 28% in 2018–2019. These improvements in total productivity change were observed to be driven by improvements in both efficiency and technology change. The overall mean productivity change was computed as a geometric mean of the change across every period (Førsund and Kittelsen, 1998). The mean efficiency change showed a growth of 1.325 (32.5% increase) for all utilities, while the mean technology change showed a decline of 0.791 (20.91% decrease) across utilities. In addition, the mean total factor productivity change across all periods was computed as 1.048, indicating a mean improvement of 4.8% in renewable energy adoption across all utilities over this period.

6. Conclusion

This study examines renewable energy adoption efficiencies across the largest investor-owned electric utilities in the U.S. The investigation focuses on utilities with diverse energy technologies within their generation portfolio, specifically fossil-fuel-based generators and emerging renewable energy generators, such as solar-PV and wind energy. The study employs a dynamic DEA technique to evaluate the overall technical efficiencies of these utilities. The results show significant differences in renewable energy adoption across the qualified utilities. Only three utilities have efficiency values of one and, as a result, operate on the efficient frontier. In addition, the mean overall efficiency for the included utilities was 23%.

A Mann-Whitney test was employed to investigate how the renewable energy adoption efficiencies for utilities operating in the RTO regions compare with those in the non-RTO regions. The results showed that despite the non-RTO group having a higher mean efficiency, the differences in performance between the two groups are not statistically significant.

This study employs the DEA Malmquist Index technique to analyze utility productivity on the adoption of renewable energy across adjacent periods. The result shows that the total productivity change for renewable energy adoption increased in the last three years within the study period by 47%, 139%, and 28%, respectively. The results observed are typically driven by differences across the utilities in RE energy adoption

over the different periods. While some utilities have consistently improved RE adoption over the entire study period, others displayed slow growth with individual spikes across different periods. As a result, the mean overall technical change for renewable energy adoption was observed to be 1.048, indicating a mean growth rate of 4.8% through the period, driven by both technology and efficiency change. This finding implies that the utilities in this study have recorded an effective growth in the average renewable energy adoption over this period. It is expected that as gaps in process and product innovation within the industry close and the utilities continue to improve their efficiency changes by efficiently utilizing firm resources, available state incentives, and natural resource availability, coupled with effective regulation policies, the overall total productivity changes for renewable energy adoption would continue to improve steadily in subsequent years.

The scope of this study was limited to the largest electricity generation utilities in the U.S., with a mix of fossil and renewable energy technologies in their generation portfolios. Due to data availability limitations, the study did not incorporate undesirable outputs such as SO_x, NO_x, and CO₂ into the model. This study can be extended by incorporating undesirable outputs into the model. More robust comparative analysis and productivity indices for renewable energy adoption can be evaluated by considering undesirable outputs. Further extensions can be included by performing comparison benchmarking studies for various regions outside of the U.S. to observe how renewable energy adoption could also compare across geographical lines.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Appendix A

Table A1
Participating Electricity Utilities

Group	Utility	Notation
RTO	MidAmerican Energy Co	E1
	Oklahoma Gas & Electric Co	E2
	Pacific Gas & Electric Co.	E3
	Northern States Power Co	E4
	Wisconsin Electric Power Co	E5
	DTE Electric Company	E6
	Consumers Energy Co	E7
	Virginia Electric & Power Co	E8
	Appalachian Power Co	E9
	Union Electric Co - (MO)	E10
	Southwestern Electric Power Co	E11
	Duke Energy Indiana, LLC	E12
	Entergy Arkansas LLC	E13
	Entergy Louisiana LLC	E14
Non-RTO	Tampa Electric Co	F1
	Florida Power & Light Co	F2
	Arizona Public Service Co	F3

(continued on next page)

Table A1 (continued)

Group	Utility	Notation
	PacifiCorp	F4
	Duke Energy Florida, LLC	F5
	Georgia Power Co	F6
	Public Service Co of Colorado	F7
	Alabama Power Co	F8
	Duke Energy Progress - (NC)	F9
	Duke Energy Carolinas, LLC	F10

Table A2

Mean efficiency change, productivity change, and total productivity change across utilities.

Utility Code	Efficiency Change	Technology Change	MPI
F1	3.018	1.288	3.887
F2	1.558	1.280	1.994
F3	0.931	0.439	0.408
F4	0.948	0.682	0.646
F5	2.603	1.288	3.353
F6	1.705	0.813	1.386
F7	1.585	0.452	0.715
F8	1.902	0.777	1.478
F9	2.677	0.935	2.503
F10	1.481	0.906	1.341
mean (non-RTO)	1.715	0.829	1.421
E1	1.000	0.485	0.485
E2	0.935	0.650	0.608
E3	0.826	0.923	0.762
E4	1.082	0.741	0.801
E5	0.956	0.684	0.654
E6	0.935	0.833	0.779
E7	0.953	0.833	0.793
E8	2.223	0.812	1.804
E9	1.046	0.807	0.844
E10	1.128	0.835	0.942
E11	1.150	0.685	0.788
E12	1.626	0.970	1.577
E13	1.036	0.822	0.852
E14	1.083	0.772	0.836
mean (RTO)	1.102	0.765	0.844
Overall	1.325	0.791	1.048

Table A3

Mean efficiency change, technology change, and total productivity change across periods

Period	Efficiency Change	Technology Change	MPI
2014–2015	0.914	0.478	0.437
2015–2016	1.531	0.424	0.649
2016–2017	1.449	1.011	1.465
2017–2018	2.177	1.097	2.389
2018–2019	0.926	1.378	1.276
Mean	1.325	0.791	1.048

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