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Environmental Assessment and Sustainable Development in the United States

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Abstract: This study aims to overview the U.S. sustainable development by measuring the environmental performance of 50 states over the period of 2009–2018. To attain the objective, we employ data envelopment analysis for environmental assessment where we prioritize the minimization of CO_2 emissions first and the maximization of gross state product later under the concept of managerial disposability (i.e., an environment-based performance measure). Then, we examine how the state-level environmental performance measures are associated with their political and spatial contexts. For the purpose, we conduct the Kruskal-Wallis rank sum test across groups of states characterized by their political transitions in the presidential and gubernatorial elections and defined by the regions of the U.S. Economic Development Administration and Environmental Protection Agency. Based on our empirical results, we find that (a) overall environmental performance has gradually enhanced over time, (b) there are statistically significant differences in the environmental performance measures along with the political transitions, and (c) states on both coasts have outperformed those of the middle in the measurement.

Keywords: data envelopment analysis; environmental assessment; sustainable development

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1. Introduction

The United Nations Conference on Environment and Development (or the Rio de Janeiro Earth Summit) in 1992 and ensuing pacts, such as the Kyoto Protocol in 1997 and the Paris Agreement in 2016, have impacted the public's awareness of and attitude toward sustainable development around the world. It was true for the United States but it has had different impacts on different groups depending on the contexts in which they were situated. A spatial context is one of them. More environmentally friendly states, such as California and Massachusetts, have aggressively formulated and implemented environmental policies (particularly, climate policy programs that seek to mitigate and adapt themselves to climate change and its adverse consequences) while their counterparts, such as Montana and North Dakota, have played a passive role (for instance, they are still relying on the production or use of fossil fuels or are reluctant to address environmental or climate issues). A political context also matters. There have been historically many debates over environmental or climate issues (e.g., the establishment of the U.S. Environmental Protection Agency in 1970 and the more recent withdrawal from the Paris Accord) drawing on partisan identification and political ideology. Democrats or liberals tend to place more value on the environment (e.g., environmental protection or spending) than Republicans or conservatives do [1].

Such divergence in environmental awareness and attitude, however, did not date back to a long time ago. As Baldassarri and Gelman [2] argued, the degree of issue partisanship over environmental concern was low and environmental protection or spending was not a contentious issue among different voters prior to the late 1970s. Since then (particularly, after the Rio Summit in 1992), however, it has not been the case anymore [3]. As environmental issues emerge as a politically important agenda, public opinion and politicians' preferences over the environment have diverged across geographic regions and political beliefs [4]. For instance, Democrats tend to be more aware of environmental issues and more supportive of environmental spending than Republicans do [5]. From the establishment of the U.S. Environmental Protection Agency (EPA) to a series of environment/climate-related pacts, environmental awareness and attitude became one of the litmus tests that identify people's geographic location and political partisanship.

Polarization on environmental/climate concern culminates in the Trump Administration's withdrawal from the Paris Agreement and the to-be-soon Biden Administration's resolve to return to the Agreement. Since each administration relies on voters who have different preferences over the environment/climate, their decisions show stark contrast against each other. The U.S. withdrawal from the Agreement threatened its (or federal) leadership on the environmental issues on one hand, but it offered sub-national entities (e.g., states or cities) an opportunity to exert their environmental leadership [6]. While the EPA (a federal environmental agency) is staffed by climate deniers rather than environmental activists, some states (alone or consortium) have taken pivotal environmental measures. States on both coasts, for instance, have made decarbonization efforts such as the "West Coast Electric Highway" initiative and the establishment of the "Northeast States for Coordinated Air Use Management." In the electricity sector, particularly, some states have transitioned from fossil fuels to renewables [7,8]. In the transportation sector, additionally, they have deployed low- or zero-emission vehicles [9].

In this vein, this study aims to measure the environmental performance of 50 states in the United States (U.S.) over the past decade (from 2009 to 2018) and explore how political and spatial contexts influence states' environmental performance. To that end, we employ data envelopment analysis for environmental assessment (DEA-EA) to evaluate state-level environmental performance and then conduct a series of the Kruskal-Wallis tests to examine whether there are statistical differences in the environmental performance across states with different partisan identification and political ideology and with different regional environment.

The remaining sections are organized as follows: Section 2 conducts a literature survey on the DEA applications to the state-level performance evaluation. Sections 3 and 4 describe the underlying concepts of DEA-EA and elucidate our proposed DEA-EA as an approach to evaluate the performance of U.S. states. Section 5 summarizes our empirical results obtained from the analysis. Section 6 concludes this study along with future extensions.

All abbreviations used in this study are summarized as follows: BTU: British thermal unit, D: Democratic, DEA: Data Envelopment Analysis, DMU: Decision Making Unit, DTS: Damages to Scale, EA: Environmental Assessment, EDA: Economic Development Administration, EPA: Environmental Protection Agency, GSP: Gross State Product, NESCAUM: Northeast States for Coordinated Air Use Management, MMT: Million Metric Tons, R: Republican, R&D: Research and Development, URS: Unrestricted and U.S.: United States.

2. Previous Studies

2.1. State-Level Performance Measurement

Table 1 lists previous studies of measuring various types of performance assessment in the U.S. The. institutions are based on federalism where the federal and state governments split power. Except for interstate concerns (e.g., national security), state governments have the authority to collect taxes, and formulate and implement policy programs that reflect on the needs and desires of their own constituents. Since state governments' policy programs affect all entities in their jurisdictions, states can be regarded as a decision making unit (DMU) in this study and the assessment of their performance can attract the public's attention. It is particularly true from the perspective of constituents who want to maximize their utilities in various ways (e.g., voting for their economic interests and/or political preferences).

Table 1. Previous Assessments on Performance of U.S. States.

Author(s)	Method	Summary	Input	Output
Yilmaz & Dinc [10]	Conventional DEA	This study explored 48 states' telecommunications infrastructure use performance over the period of 1984–1997.	Private, public, and telecommunications capital stocks and labor	Total value added of states' private industries
Lee & Joo [11]	Conventional DEA	This study examined 50 states' operational performance of correctional facilities in 2005.	Capacity and expenditure	Number of inmates and recidivism
Khan & Murova [12]	Conventional DEA	This study looked into 50 states' operational performance over the period of 1992–2012.	State expenditure, employment, and population	Gross state product
Thomas et al. [13]	Efficiency ratio	This study shed light on changes of 50 states' R&D efficiency ratios between 2004 and 2008.	R&D expenditure	Patents granted and scientific publications
Drivas et al. [14]	SFA	This study measured 50 states' output and knowledge production efficiencies over the period of 1993–2006.	Gross capital stock, the number of workers, business R&D stock, and the number of scientists and engineers	Gross state product and patents
Gearhart [15]	Hyperbolic order-α estimator	This study analyzed 50 states' health care efficiency over the period of 2002–2008.	Vaccine, citizens/hospital, inpatient days, hospital beds, cost, etc.	Infant/teen survival rate and life expectancy
Gearhart & Michieka [16]	Conditional order-m estimator	This study analyzed 50 states' health care efficiency over the period of 2014–2017.	Healthcare costs and the fraction of individuals with some college	Years of life gained and the fraction of infants born normal birthweight
Park et al. [17]	Non-radial SBM-DEA	This study evaluated 50 states' environmental performance in the transportation sector over the period of 2004–2012.	Capital expense, energy consumption and labor in the transportation sector	Transportation value added and CO_2 emissions
Halkos & Polemis [18]	Window DEA	This study assessed 50 states' environmental efficiency in the power generation sector over the period of 2000–2012.	Total energy transmission and total operating cost	Use of net capacity, CO_2, SO_2 and NOx emissions

Despite its eligibility for the DMU, surprisingly, there is a paucity of studies on assessing the state-level performance. A majority of studies use macroscopic (e.g., nations) or microscopic (e.g., companies, hospitals, and schools) entities as DMUs. As a mesoscopic entity, states have some advantages over or differences from other government units (e.g., counties or cities) when used as a DMU. Some of them are as follows: First, states have some degree of latitude to decide how to expend their budgets, which leads to heterogeneous policy sets and make some states stand out from others. While each state's budget items are almost homogeneous (e.g., education, public health, corrections, etc.), the mix of budget items are somewhat different across states. Second, the various policy sets stem from political elites or leaders that need to listen to their constituents' voices. Presidential or gubernatorial candidates should reflect their policy agenda on the interests of voters to win the elections. Third, states are nested in their regions (agglomerates of multiple states) that often characterize states' sociocultural, industrial, economic, environmental, and political contexts. Thus, states in the same regions tend to share similar identities and sometimes facilitate them to cooperate or form an alliance to attain the same goals. Lastly, state-level data tend to be more accessible than county or city-level data. Public or private sources in the U.S. offer at least state-level data so that data availability issues can be addressed.

As summarized in Table 1, many previous studies are mainly concerned with the state level. For instance, Lee and Joo [11], Thomas et al. [13], and Gearhart [15] assessed states' performance in the fields of corrections, research and development, and health care, respectively. Of the studies in Table 1, Park et al. [17] and Halkos and Polemis [18] evaluated environmental performance in the transportation and electricity sectors, respectively. While both studies focused on the environmental performance of 50 states, they were sector-specific and their data were relatively outdated (up to 2012) so that the studies could not capture more recent focusing events, such as the political transition from Obama Administration to Trump Administration, which lead to significant policy changes.

2.2. Political and Spatial Contexts on Climate/Environmental Policy

A political context can influence the formulation and implementation of climate/environmental policy. A clear example is partisan sorting where elite cues impact mass opinion on climate/environmental issues and the public opinion becomes more divergent so that Democrats move left (i.e., to the pro-environment) and Republicans do right (i.e., to the anti-environment) [19]. Such polarization of both politicians and the public has been substantial, particularly since the 1990s [3]. While there were pivotal global events such as the Rio Earth Summit and the Kyoto Protocol at that time, the Republican took over Congress from the Democratic in the U.S. so that policy hegemony was shifted to the conservatives [1]. The disharmony between the external pro-environmental movement and internal anti-environmental movement rendered Democrats and Republicans move in the opposite direction, which created the polarization over environmental protection and spending.

Based on the small-government doctrine oriented toward laissez-faire or marketized and privatized economy, which restricts government interventions such as environmental regulations, the Republican elites have placed more value on economic development rather than environmental protection. Such positions have been maintained particularly under the Republican presidents and in the Republican-ruling states. With the inauguration of the Obama Administration in 2009, however, the Democratic leaders recognized science-based climate risks and embraced climate actions such as mitigation and adaptation measures. For instance, clean energy innovation and transportation decarbonization became an important political agenda and they were placed in the front burner, which previously was in the back burner. While the Trump Administration has filled environment-related positions with climate deniers, it would be dramatically changed with the start of the Biden Administration in 2021.

To take such political transition into account, we explore each state's partisans that have won presidential and gubernatorial elections over the past decade and categorize states into four groups: D to D (the Democratic to the Democratic), R to D (the Republican to the Democratic), D to R (the Democratic to the Republican), and R to R (the Republican to the Republican). Table 2 summarizes the election results and political transition in 50 states. Considering the role of the political context in the climate/environmental policy, we construct the first hypothesis as follows:

Hypothesis 1. *Political context influences the states' environmental performance.*

Hypothesis 1a (H1a). *States' environmental performance varies significantly by political transition by presidential elections.*

Hypothesis 1b (H1b). *States' environmental performance varies significantly by political transition by gubernatorial elections.*

A spatial context also matters in the climate/environmental policy. In the U.S. that boasts its vast territory, particularly, geographic conditions vary by region and residents are impacted by their different regional situations. With the emerging role of state governments in managing climate risks, they have played a key role in the formulation and implementation of climate policy [20]. In the clean energy policy area, for instance, state governments have created many policy innovations [21]. However, climate actions were not limited to each state's independent measures. States have interacted with their neighboring states/regions [22] and state initiatives have gradually evolved into regional collaborations [23]. The Northeast States for Coordinated Air Use Management (NESCAUM) and the Regional Electric Vehicle Plan for the West are examples of state/regional efforts to deploy electric vehicles as a means to address climate issues.

Table 2. States by Results of Presidential and Gubernatorial Elections.

State	Presidential Elections		Gubernatorial Elections		State	Presidential Elections		Gubernatorial Elections	
	Winners	Transition	Winners	Transition		Winners	Transition	Winners	Transition
Alabama	RRR	R to R	RRRR	R to R	Montana	RRR	R to R	DDD	D to D
Alaska	RRR	R to R	RRIR	R to R	Nebraska	RRR	R to R	RRRR	R to R
Arizona	RRR	R to R	DRRR	D to R	Nevada	DDD	D to D	RRRD	R to D
Arkansas	RRR	R to R	DDRR	D to R	New Hampshire	DDD	D to D	DDRR	D to R
California	DDD	D to D	RDDD	R to D	New Jersey	DDD	D to D	DRRD	D to D
Colorado	DDD	D to D	DDDD	D to D	New Mexico	DDD	D to D	DRRD	D to D
Connecticut	DDD	D to D	RDD	R to D	New York	DDD	D to D	DDDD	D to D
Delaware	DDD	D to D	DDD	D to D	N. Carolina	DRR	D to R	DRD	D to D
Florida	DDR	D to R	RRRR	R to R	N. Dakota	RRR	R to R	RRR	R to R
Georgia	RRR	R to R	RRRR	R to R	Ohio	DDR	D to R	DRRR	D to R
Hawaii	DDD	D to D	RDDD	R to D	Oklahoma	RRR	R to R	DRRR	D to R
Idaho	RRR	R to R	RRRR	R to R	Oregon	DDD	D to D	DDDD	D to D
Illinois	DDD	D to D	DDRD	D to D	Pennsylvania	DDR	D to R	DRDD	D to D
Indiana	DRR	D to R	RRR	R to R	Rhode Island	DDD	D to D	RIDD	R to D
Iowa	DDR	D to R	DRRR	D to R	S. Carolina	RRR	R to R	RRRR	R to R
Kansas	RRR	R to R	DRRD	D to D	S. Dakota	RRR	R to R	RRRR	R to R
Kentucky	RRR	R to R	DDR	D to R	Tennessee	RRR	R to R	DRRR	D to R
Louisiana	RRR	R to R	RRD	R to D	Texas	RRR	R to R	RRRR	R to R
Maine	DDD	D to D	DRRD	D to D	Utah	RRR	R to R	RRR	R to R
Maryland	DDD	D to D	DDRR	D to R	Vermont	DDD	D to D	RDDDRR	R to R
Massachusetts	DDD	D to D	DDRR	D to R	Virginia	DDD	D to D	DRDD	D to D
Michigan	DDR	D to R	DRRD	D to D	Washington	DDD	D to D	DDD	D to D
Minnesota	DDD	D to D	RDDD	R to D	W. Virginia	RRR	R to R	DDD	D to D
Mississippi	RRR	R to R	RRR	R to R	Wisconsin	DDR	D to R	DRRD	D to D
Missouri	RRR	R to R	DDR	D to R	Wyoming	RRR	R to R	DRRR	D to R

Note: D = Democratic, R = Republican, and I = Independent. For instance, DDD or DDDD means Democratic candidates have won three or four elections in a row over the past decade (e.g., Colorado and New York). RRR or RRRR means Republican candidates have won three or four elections in a row (e.g., Alabama and South Dakota). DDR or DRRR represents the political transition from the Democratic to Republican Party (e.g., Florida in the Presidential elections and Wyoming in the Gubernatorial elections). RDDD or RRRD presents the political transition from the Republican to Democratic Party (e.g., California and Nevada in the Gubernatorial elections).

In this regard, there is a great body of studies that focused on regional variations in climate/environmental policy. For instance, regional assessments have been conducted in the fields of watershed management [24], environmental inequality (particularly, industrial air toxics exposure) [25], perceptions about climate change [26], and public opinion on climate change [27]. However, few studies shed light on regional variations in environmental performance. To address this issue, we use the regional schemes proposed by EDA and EPA in that two federal agencies deal with two important outputs (economic development and environmental protection) in evaluating state-level performance. Table 3 shows the EDA and EPA regions and their member states. Drawing on the regional schemes, we construct the second hypothesis as follows:

Hypotheses 2. *Spatial context influences states' environmental performance.*

Hypotheses 2a (H2a). *States' environmental performance varies significantly by EDA regions.*

Hypotheses 2b (H2b). *States' environmental performance varies significantly by EPA regions.*

Table 3. States by EDA and EPA Regions.

EDA Region	EPA Region	State
Philadelphia Regional Office	Region 1	Connecticut Maine Massachusetts New Hampshire Rhode Island Vermont
	Region 2	New Jersey New York
	Region 3	Delaware Maryland Pennsylvania Virginia West Virginia
Atlanta Regional Office	Region 4	Alabama Florida Georgia Kentucky
		Mississippi North Carolina South Carolina Tennessee
Chicago Regional Office	Region 5	Illinois Indiana Michigan Minnesota Ohio Wisconsin
Austin Regional Office	Region 6	Arkansas
	Region 7	Louisiana New Mexico Oklahoma Texas Iowa Kansas Missouri Nebraska
Denver Regional Office	Region 8	Colorado
	Region 9	Montana North Dakota South Dakota Utah Wyoming Arizona California Hawaii Nevada
Seattle Regional Office	Region 10	Alaska
		Idaho Oregon Washington

Note: EDA = Economic Development Administration and EPA = Environmental Protection Agency.

3. Underlying Concepts

We apply DEA-EA to the prepared data set, which contains not only a column vector (X) of m inputs and that of G of s desirable outputs but also a column vector (B) of h undesirable outputs. Please note that a conventional use of DEA excludes the existence of B in the computational process although the environmental assessment needs a unification process between G and B. The unification process is classified under two (natural and managerial) disposability concepts. We focus upon the concept of "managerial disposability" because we are interested in environmental assessment. See the study [28] that provides a use of DEA for natural disposability. This research is an extension of the work by shifting natural to managerial disposability.

Natural Disposability: This research starts the concept of sustainability from a description of "natural disposability" in which the first priority is economic prosperity and the second one is pollution prevention. This type of disposability implies the elimination of inefficiency within the framework of performance assessment. In the concept, an inefficient DMU decreases some components of X or maintains them at their current level. The X decrease occurs with increasing some components of G. The decrease of X naturally reduces B. The previous DEA studies did not consider an existence of B.

Managerial disposability: The concept discussed in this study is the opposite of natural disposability. For example, a coal-fired power plant increases the amount of coal combustion to increase the amount of electricity generation. Here, even if the power plant increases the amount of coal combustion, the increase can reduce the amount of CO_2 emission by a managerial effort such as a use of high-quality coal with less CO_2 emission and/or an engineering effort to use new generation technology (e.g., clean coal technology) that can reduce the amount of CO_2 emission. Management of the power company considers such a change as a business opportunity to adjust them to a change of environmental regulation. Under the managerial disposability, the investment in green technology may provide firms with an opportunity to enhance not only environmental protection but also economic success. Thus, both economic prosperity and green technology are not mutually exclusive in modern business. Rather, we need to consider that both are necessary conditions toward sustainable development. This type of disposability was never considered in the previous DEA studies.

Null-Joint Hypothesis: An important concept to be thought of is the null-joint relationship between G and B. The hypothesis implies that components of B are "by-products" of G. In other words, B cannot exist without G. The concept is straight forward in discussing the relationship between G and B if we do not consider technology advancement and governmental regulation on B. Thus, it is necessary for us to consider the assumption between G and B when examining a unified efficiency measure under managerial disposability.

4. Method

This subsection describes mathematical formulations to measure the degree of unified efficiency (operational and environmental) using a forecasted data set. The nomenclatures are specified in the following manner:

X: A column vector of m inputs,
x_{ijt}: The i th input of the j th DMU at the t th period,
G: A column vector of s desirable outputs,
g_{rjt}: The r th desirable output of the j th DMU at the t th period,
B: A column vector of h undesirable outputs,
b_{fjt}: The f th undesirable output of the j th DMU at the t th period,
ξ_{kt}: An inefficiency score of the k th DMU at the t th period,
d_i^x: A slack variable of the i th input,
d_r^g: A slack variable of the r th desirable output,
d_f^b: A slack variable of the f th undesirable output,
λ_{jt}: A vector of intensity variables on the j th DMU at the z th period,

ε_s: A prescribed very small number,
R_i^x: A data range related to the i th input
R_f^b: A data range related to the f th undesirable output,
t: The observed t th period (t = 1,.., T).

This study specifies the following two types of data ranges (R) according to the upper and lower bounds of production factors:

$$R_i^x = (m+s+h)^{-1}\left(\max_j\{x_{ijt}|j=1,\ldots,n \,\&\, t = 1,..,T\} - \min_j\{x_{ijt}|j=1,\ldots,n \,\&\, t = 1,..,T\}\right)^{-1} \,\&$$
$$R_f^b = (m+s+h)^{-1}\left(\max_j\left\{b_{fjt}\middle|j=1,\ldots,n \,\&\, t = 1,..,T\right\} - \min_j\left\{b_{fjt}\middle|j=1,\ldots,n \,\&\, z = 1,..,T\right\}\right)^{-1}.$$

The purpose of these ranges is that DEA results can avoid an occurrence of zero in multipliers. Such an occurrence implies that corresponding production factors (X, G and B) are not fully used in the evaluation.

Unified Efficiency: This research assumes that there are n DMUs at the t th period to be examined and all of their production factors are strictly positive even if they are imprecise. All DMUs are specified by j = 1, . . . , n in the proposed formulations. This study uses the following formulation to compute the unified efficiency of the specific k th DMU under managerial disposability at the specific t th period:

$$\begin{aligned}
&\text{Maximize } \xi_{kt} + \varepsilon_s\left(\sum_{i=1}^{m} R_i^x d_{ikt}^{x+} + \sum_{f=1}^{h} R_f^b d_{fkt}^b\right) \\
&\text{s.t.} \quad \sum_{t=1}^{T}\sum_{j=1}^{n} x_{ijt}\lambda_{jt} - d_i^{x+} = x_{ikt} \quad (i = 1,..,m \,\&\, \text{specific } t), \\
&\qquad \sum_{t=1}^{T}\sum_{j=1}^{n} g_{rjt}\lambda_{jt} - \xi_{kt} g_{rkt} = g_{rkt} \quad (r = 1,..,s \,\&\, \text{specific } t), \\
&\qquad \sum_{t=1}^{T}\sum_{j=1}^{n} b_{fjt}\lambda_{jt} + d_f^b + \xi_{kt} b_{fkt} = b_{fkt} \quad (f = 1,..,h \,\&\, \text{specific } t), \\
&\qquad \lambda_{jt} \geq 0 \ (j = 1,..,n \,\&\, t = 1,..,T),\ \xi_{kt}: \text{URS } (k\text{: specific } \& \ t\text{: specific}), \\
&\qquad d_{ikt}^{x+} \geq 0 \ (i = 1,..,m) \ \& \ d_{fkt}^b \geq 0 \ (f = 1,..,h).
\end{aligned} \tag{1}$$

Model (1) has eight unique features to be noted. First, the period (t = 1, . . . , T) is used for observed periods. All the periods (t) are together and used in the form of a cross-sectional structure. Second, the unknown vector $\lambda_{jt} = (\lambda_{1t}, \ldots, \lambda_{nt})^{Tr}$ is referred to as "structural" or "intensity" variables in the DEA terminology. They connect all the production factors (X, G and B). Third, the production and pollution possibility set of Model (1) assumes constant Damages to Scale (DTS) because $\sum_{j=1}^{n} \lambda_{jt} = 1$ does not exist from (1). See [29] for a detailed description on DTS. Fourth, Model (1) considers only single-sided input deviations ($d_i^{x+} = \sum_{t=1}^{T}\sum_{j=1}^{n} x_{ijt}\lambda_{jt} - x_{ikt} \geq 0$) on all input factors to attain the status of managerial disposability. Fifth, a scalar value (ξ_{kt}) stands for a unified inefficiency score that measures a distance between two efficiency frontiers and an observed vector of G and B of the k th DMU at the t th period. Sixth, a small scalar value (e.g., ε_s = 0.001) indicates the relative importance between the inefficiency measure and the total sum of slacks. The value (ε_s) is not a non-Archimedean small number that has been used for mathematical convenience in standard DEA. The small number should be prescribed by a use(s) in the range that the efficiency measure of all DMUs locates between zero (standing for full efficiency) and unity (standing for full inefficiency). Seventh, this type of measurement belongs to the "Debreu-Farrell" criterion. The reference [29] provides a detailed description on the criterion. Finally, the equations, $\sum_{t=1}^{T}\sum_{j=1}^{n} g_{rjt}\lambda_{jt} - \xi_{kt} g_{rkt} = g_{rkt}$ on desirable outputs, drop slacks related to G to incorporate a possible occurrence of green technology.

A unified efficiency measure (*UEM*) of the k th DMU at the t th period is measured by

$$UEM_{kt}^{*} = 1 - [\xi_{kt}^{*} + \varepsilon_s(\sum_{i=1}^{m} R_i^x d_{ikt}^{x+*} + \sum_{f=1}^{h} R_f^b d_{fkt}^{b*})]. \quad (2)$$

Here, the inefficiency measure and all slack variables are determined on the optimality of Model (1). The degree of unified efficiency is obtained by subtracting the level of inefficiency from unity as specified in Equation (2).

An important feature of Model (1) is that it specifies the upper bound of inputs by increasing X and reducing B as specified by $\sum_{t=1}^{T}\sum_{j=1}^{n} x_{ijt}\lambda_{jt}^{*} = x_{ikt} + d_{ikt}^{x+*}$ (i = 1, . . . , m) and $\sum_{t=1}^{T}\sum_{j=1}^{n} b_{fjt}\lambda_{jt}^{*} = b_{fkt} - d_f^{b*} - \xi_{kt}^{*} b_{fkt}$ (f = 1, . . . , h) on optimality. The model also considers that the components of G do not have any slack in the formulation.

Unified Index: To extend the efficiency measure to its corresponding index measure, we modify Model (1) as follows:

$$\begin{aligned}
&\textit{Maximize}\ \ \xi_{kt} + \varepsilon_s(\sum_{i=1}^{m} R_i^x d_{ikt}^{x+} + \sum_{f=1}^{h} R_f^b d_{fkt}^{b})\\
&s.t.\ \ \sum_{j=1}^{n} x_{ijt-1}\lambda_{jt-1} - d_{ikt}^{x+} = x_{ikt}\ \ (i = 1,..,m\ \&\ \text{specific } t = 2,..,T),\\
&\sum_{j=1}^{n} g_{rjt-1}\lambda_{jt\text{-}1} - \xi_{kt} g_{rkt} = g_{rkt}\ \ (r = 1,..,s\ \&\ \text{specific } t = 2.,..,T),\\
&\sum_{j=1}^{n} b_{fjt-1}\lambda_{jt} - 1 + d_{fkt}^{b} + \xi_{kt} b_{fkt} = b_{fkt}\ \ (f = 1,..,h\ \&\ \text{secific } t = 2,..,T),\\
&\lambda_{jt\text{-}1} \geq 0\ (j = 1,..,n\ \&\ t = 2,..,T),\ \xi_{kt}: URS\ (k\text{: specific } \&\ \text{all } t = 2,..,T),\\
&d_{ikt}^{x+} \geq 0\ (i = 1,..,m)\ \&\ d_{fkt}^{b} \geq 0\ (f = 1,..,h).
\end{aligned} \quad (3)$$

The index measures the performance of the k th DMU at the t th period by comparing itself with the efficiency frontier of the $t-1$ period. Therefore, Model (3) considers only observations in $t-1$ th period (for making an efficiency frontier) and those of t th periods whose efficiencies are examined by Model (3).

A unified index measure (*UIM*) of the k th DMU at the t th period is measured by

$$UIM_{kt}^{*} = 1 - [\xi_{kt}^{*} + \varepsilon_s(\sum_{i=1}^{m} R_i^x d_{ikt}^{x+*} + \sum_{f=1}^{h} R_f^b d_{fkt}^{b*})]. \quad (4)$$

Here, the inefficiency measure and all slack variables are determined on the optimality of Model (3). The degree of unified index is obtained by subtracting the level of inefficiency from unity as specified in Equation (4). In contrast to the efficiency measure (2), the index measure (4) produces the unfired index that may be larger than unity, so showing a technological progress on pollution prevention.

At the end of this section, this study needs to note the three computational concerns on the proposed two approaches. First, we assume constant DTS to avoid computational infeasibility. Second, we understand that the proposed approaches suffer from an occurrence of multiple solutions (e.g., multiple reference sets and multiple supporting hyperplanes). Finally, there is a possibility that an observed data set (e.g., including an outlier) does not fit with the assumption of the null-joint hypothesis incorporated into the two models. In the case, a computer code may produce an infeasible solution. This indicates that the data set does not satisfy the hypothesis, not the ordinary infeasibility on computing linear programming.

5. An Illustrative Example

5.1. Data

For the analytic framework of inputs, desirable outputs, and undesirable outputs, we collected state-level data during the period of 2009 to 2018 from four different sources: (1) population data from the U.S. Census, (2) government expenditure data from the National Association of State Budget Officers, (3) energy consumption data from the U.S. Energy Information Administration, (4) patent data from the U.S. Patent and Trademark Office, (5) gross domestic product data from the U.S. Bureau of Economic Analysis, and (6) carbon dioxide data from the U.S. Environmental Protection Agency.

There were four inputs: (1) population, (2) government expenditure, (3) energy consumption, and (4) patent grants. The first two inputs represent labor and capital while the last two account for material (or resource) and technological feedstock to the production. The population was measured by thousands of people. Government expenditure was measured by U.S. million dollars. The amount of energy consumption was measured by billion BTU. The number of patents was measured at grants. There were one desirable and one undesirable outputs: gross state product (GSP) and carbon emissions. The former represents economic vitality while the latter takes environmental sustainability into account as a byproduct of production. GSP was measured by U.S. $ million. The amount of carbon emissions was measured in million metric tons of CO_2.

Table 4 exhibits data sets: part (a) lists 25 blue states where Biden won and part (b) does 25 red states where Trump won in the 2020 presidential election. Coincidentally, the election result is half and half by states. The data includes input and output production factors by states. Instead of enumerating all data from 2009 to 2018, we present 2018 data and descriptive statistics over the past 10 years. States are listed in the alphabetical order of their names. There are 25 blue states in part (a) and 25 red states in part (b). As of 2018, blue states have more populations, government expenditures, patent grants, and economic production than red states do. In contrast, red states use more energy and emit more carbon dioxide. On average, blue states have approximately 7.5 million people, spend $51 billion of the budget, use 1.9 quadrillion BTU of energy, receive 5 thousand patents, generate $511 billion of GSP, and emit 93 million tons of CO_2. Meanwhile, red states have approximately 5.6 million people, spend $28 billion of the budget, use 2.2 quadrillion BTU of energy, receive 1.6 thousand patents, generate $303 billion of GSP, and emit 128 million tons of CO_2.

Table 4. Production Factors Data of (a) 25 Blue States and (b) 25 Red States in 2018.

State	Input				Desirable Output	Undesirable Output
	Population (Thousands)	Expenditure ($ Million)	Energy Consump. (Billion BTU)	Patent (Grants)	GSP ($ Million)	CO_2 (MMT)
(a)						
Arizona	7158	35,147	1,487,797	2812	350,718	91
California	39,462	269,668	7,966,578	43,960	2,975,083	376
Colorado	5691	39,814	1,513,286	3259	372,453	90
Connecticut	3572	33,149	753,010	2977	279,782	38
Delaware	957	10,847	290,283	285	74,187	14
Georgia	10,511	49,509	2,876,097	3064	602,024	135
Hawaii	1421	15,199	292,895	136	93,101	20
Illinois	12,723	72,783	4,011,952	5655	863,040	215
Maine	1335	8412	395,251	228	64,557	15
Maryland	6036	43,796	1,361,165	2042	411,619	60
Massachusetts	6883	57,124	1,458,647	7687	570,464	65
Michigan	9984	56,613	2,894,187	7293	521,803	164
Minnesota	5606	39,819	1,913,919	4513	371,930	94
Nevada	3027	14,843	727,227	745	169,180	39
New Hampshire	1349	6131	324,693	998	84,584	15
New Jersey	8886	60,775	2,240,709	4682	612,979	111
New Mexico	2093	20,402	702,827	535	100,080	47
New York	19,530	163,744	3,854,184	9780	1,705,010	172
Oregon	4182	40,619	1,012,242	3522	241,978	40
Pennsylvania	12,801	84,908	3,961,566	4456	778,375	227
Rhode Island	1058	9262	197,377	415	59,925	12
Vermont	624	5675	139,153	388	32,981	6
Virginia	8501	52,078	2,401,238	2542	533,510	105
Washington	7524	46,021	2,078,665	7445	575,417	82
Wisconsin	5807	48,199	1,885,868	2702	337,553	103

Table 4. *Cont.*

State	Input				Desirable Output	Undesirable Output
	Population (Thousands)	Expenditure ($ Million)	Energy Consump. (Billion BTU)	Patent (Grants)	GSP ($ Million)	CO_2 (MMT)
			(b)			
Alabama	4888	27,475	1,954,823	510	221,031	114
Alaska	735	10,291	609,786	57	54,293	36
Arkansas	3010	25,506	1,119,701	403	127,761	72
Florida	21,244	78,523	4,281,336	4893	1,050,298	233
Idaho	1751	7963	553,287	843	79,091	19
Indiana	6695	33,621	2,837,602	2265	368,425	192
Iowa	3149	23,382	1,616,101	1056	190,147	85
Kansas	2911	15,911	1,134,492	894	171,719	63
Kentucky	4461	34,053	1,743,944	745	207,849	123
Louisiana	4660	31,253	4,403,154	490	253,236	258
Mississippi	2989	19,118	1,192,670	208	113,579	71
Missouri	6122	26,038	1,847,810	1406	317,949	124
Montana	1061	6952	435,230	172	50,692	32
Nebraska	1916	12,141	914,565	314	124,705	53
N. Carolina	10,382	47,795	2,616,133	3781	567,452	122
N. Dakota	758	5889	660,959	123	56,287	55
Ohio	11,676	69,682	3,755,870	4608	675,030	211
Oklahoma	3940	22,669	1,706,535	614	198,596	100
S. Carolina	5084	25,257	1,671,781	1142	235,287	75
S. Dakota	879	4457	396,837	157	53,239	16
Tennessee	6772	33,562	2,255,868	1289	362,737	97
Texas	28,629	114,592	14,258,824	11,359	1,795,635	823
Utah	3154	14,789	835,121	1795	181,623	61
W. Virginia	1804	16,857	832,914	152	77,633	89
Wyoming	578	4425	558,594	118	39,703	64
Average	5570	28,488	2,167,757	1576	302,960	128

Table 5 shows the data statistics of two outputs: GSP and CO_2. States' mean values over 10 years are presented along with standard deviation values in the parenthesis. The descriptive statistics of blue states are presented first and that of red states later. Although some blue and red states have similar sizes of their economies, they emit different levels of CO_2. For instance, New York (a blue state) and Texas (a red state) produce $1406 billion and $1480 billion of GSP whereas they emit 170 MMT and 766 MMT of CO_2.

Table 5. Descriptive Statistics of 50 States' Production Factors Data from 2009–2018.

State	Output		State	Output		State	Output	
	GSP ($ Million)	CO_2 (MMT)		GSP ($ Million)	CO_2 (MMT)		GSP ($ Million)	CO_2 (MMT)
Arizona	287,023	93	New York	1,405,735	170	Louisiana	230,649	253
	(35,701)	(3)		(181,537)	(5)		(11,677)	(8)
California	2,378,366	371	Oregon	192,397	40	Mississippi	102,472	66
	(369,901)	(6)		(28,022)	(1)		(6464)	(4)
Colorado	300,269	92	Pennsylvania	675,190	241	Missouri	281,455	129
	(41,370)	(3)		(66,497)	(13)		(22,228)	(6)
Connecticut	253,028	36	Rhode Island	53,838	11	Montana	43,513	33
	(15,974)	(1)		(4087)	(1)		(4480)	(1)
Delaware	65,142	14	Vermont	29,578	6	Nebraska	107,755	51
	(6038)	(1)		(2236)	(0)		(12,431)	(2)
Georgia	486,445	145	Virginia	465,731	105	N. Carolina	475,184	127
	(67,949)	(14)		(40,253)	(3)		(55,673)	(7)
Hawaii	78,317	19	Washington	443,099	78	N. Dakota	48,816	53
	(9248)	(0)		(73,307)	(4)		(9093)	(3)
Illinois	750,271	225	Wisconsin	289,261	100	Ohio	574,078	226
	(72,389)	(11)		(30,245)	(3)		(64,807)	(15)
Maine	56,007	17	Alabama	193,687	121	Oklahoma	175,884	104
	(4738)	(1)		(16,091)	(7)		(16,887)	(4)

Table 5. *Cont.*

State	Output		State	Output		State	Output	
	GSP ($ Million)	CO_2 (MMT)		GSP ($ Million)	CO_2 (MMT)		GSP ($ Million)	CO_2 (MMT)
Maryland	354,469 (36,743)	63 (5)	Alaska	53,554 (3003)	38 (2)	S. Carolina	192,027 (26,110)	76 (5)
Massachusetts	473,342 (58,661)	67 (3)	Arkansas	112,736 (9882)	66 (4)	S. Dakota	45,056 (5378)	15 (0)
Michigan	444,015 (51,995)	161 (5)	Florida	850,014 (114,589)	230 (6)	Tennessee	302,121 (38,863)	103 (4)
Minnesota	314,641 (36,274)	93 (2)	Idaho	63,577 (8347)	18 (1)	Texas	1,480,361 (195,335)	766 (41)
Nevada	138,583 (16,208)	37 (2)	Indiana	314,810 (33,301)	199 (13)	Utah	141,672 (22,173)	63 (3)
New Hampshire	72,073 (7637)	15 (1)	Iowa	165,018 (18,500)	84 (5)	W. Virginia	70,020 (4009)	93 (4)
New Jersey	543,682 (43,957)	113 (4)	Kansas	146,999 (15,432)	68 (5)	Wyoming	38,029 (1407)	65 (2)
New Mexico	89,857 (5267)	53 (4)	Kentucky	183,293 (16,538)	137 (12)			

Note: Standard deviation in the parenthesis.

5.2. *Efficiency/Index Measures*

Figure 1 maps states' mean *UEM* scores over the past decade. Greener states indicate higher environmental performance while redder ones point out lower performance. States on both coasts tend to outperform those in the middle. Figures 2 and 3 depict mean *UEM* and *UIM* scores of blue and red states over time. The mean *UEM* and *UIM* scores gaps between blue and red states are obvious but they become slightly wider in the mean *UEM* (the environmental performance of blue states has improved more than that of red states has) while becoming narrower in the mean *UIM* (the environmental performance of blue states has stagnated whereas that of red states has enhanced). One notable thing is that mean *UEM* and *UIM* scores both tend to increase since 2009 but they started to decrease or level off from 2017. Although it requires more data (in 2019 and 2020) to confirm, the possible reason may be the political change from the Obama Administration to the Trump Administration.

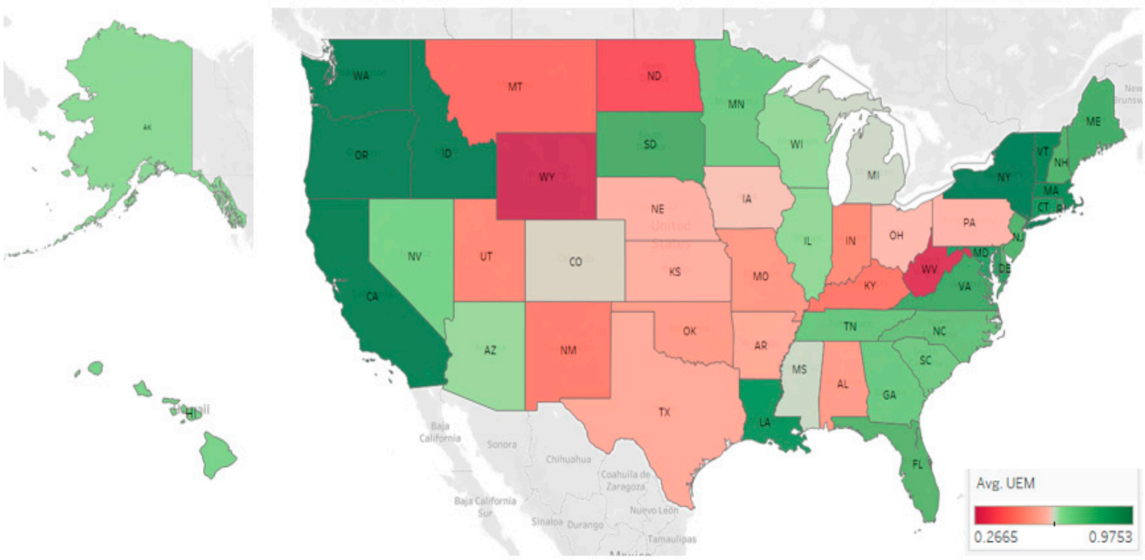

Figure 1. Average Unified Efficiency Scores of Fifty States over Period of 2009–2018.

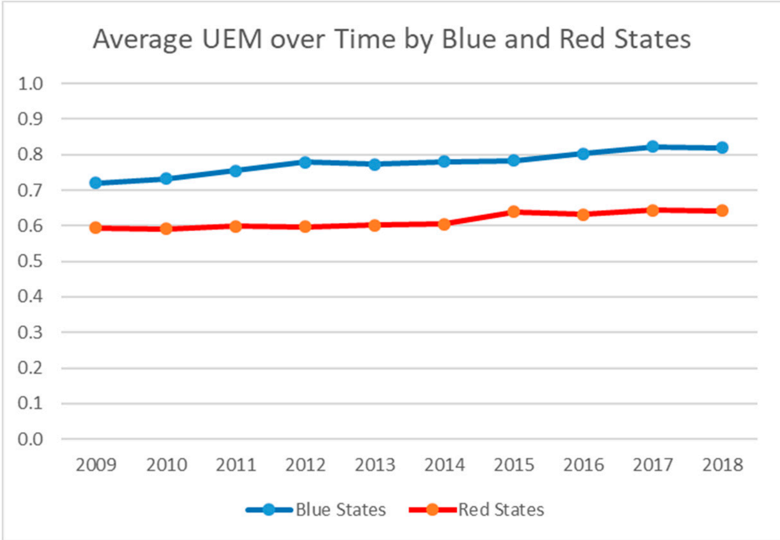

Figure 2. Average Unified Efficiency Scores of Blue and Red States from 2009–2018.

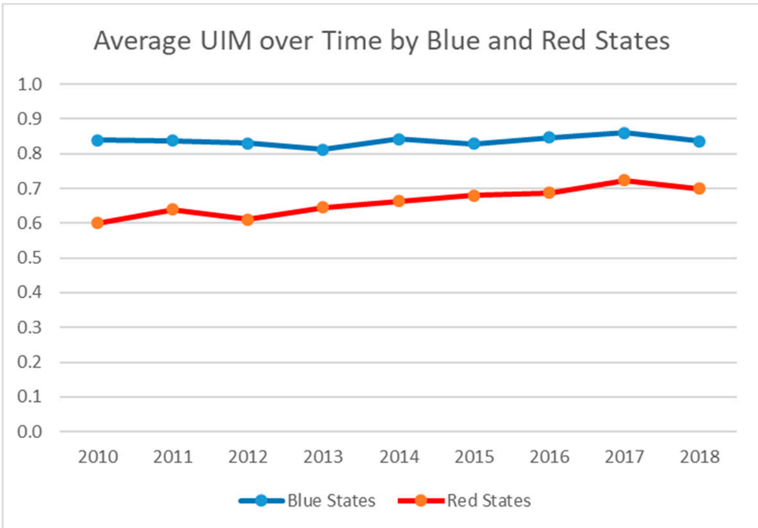

Figure 3. Average Unified Index Scores of Blue and Red States from 2009–2018.

Tables 6 and 7 summarize *UEM* and *UIM* scores and ranks of blue and red states over time. They are results of Models (1) and (3) estimations for efficiency measures. As of 2018, the *UEM* and *UIM* scores of blue states (0.819 and 0.836) are higher than those of red states (0.642 and 0.700). The top five states include California, Massachusetts, New York, Oregon, and Washington, all of which are located on both coasts and are politically liberal. Over the past decade, the *UEM* score of blue states has increased by 13.75% while that of red states has increased by 8.08%. However, the *UIM* score of blue states has slightly decreased (−0.36%) whereas that of red states has increased by 16.47%. It implies that (a) overall blue states outperform red states, (b) blue states' environmental performance has improved more than red states has, and (c) red states' technological progress has been made faster than blue states' has. Both environmental performance and technological progress declined between 2017 and 2018: from 0.822 to 0.819 and from 0.860 to 0.836 in blue states and from 0.644 to 0.642 and from 0.723 to 0.700 in red states, respectively.

Table 6. Unified Efficiency Scores of (a) Blue States and (b) Red States from 2009–2018.

UEM	2009		2010		2011		2012		2013		2014		2015		2016		2017		2018	
(a)																				
Arizona	0.611	(27)	0.602	(29)	0.619	(28)	0.637	(27)	0.617	(29)	0.638	(27)	0.660	(28)	0.698	(27)	0.711	(26)	0.686	(27)
California	0.876	(7)	0.920	(6)	0.958	(6)	0.961	(7)	0.972	(2)	1.000	(1)	0.990	(3)	0.995	(2)	1.000	(1)	0.987	(4)
Colorado	0.572	(31)	0.573	(31)	0.591	(32)	0.595	(30)	0.606	(30)	0.614	(30)	0.630	(31)	0.646	(31)	0.658	(30)	0.670	(29)
Connecticut	0.852	(9)	0.848	(9)	0.863	(7)	0.886	(8)	0.876	(9)	0.880	(8)	0.873	(10)	0.932	(9)	0.959	(8)	0.911	(9)
Delaware	0.830	(10)	0.813	(11)	0.776	(16)	0.740	(18)	0.763	(18)	0.794	(15)	0.800	(16)	0.770	(19)	0.813	(16)	0.850	(14)
Georgia	0.620	(26)	0.621	(26)	0.662	(24)	0.715	(21)	0.732	(21)	0.731	(19)	0.750	(21)	0.754	(21)	0.766	(22)	0.792	(21)
Hawaii	0.637	(23)	0.617	(27)	0.610	(30)	0.633	(28)	0.648	(25)	0.685	(24)	0.695	(26)	0.745	(22)	0.783	(20)	0.786	(22)
Illinois	0.607	(29)	0.611	(28)	0.618	(29)	0.644	(26)	0.627	(27)	0.635	(28)	0.667	(27)	0.700	(26)	0.707	(27)	0.710	(26)
Maine	0.746	(18)	0.770	(16)	0.790	(15)	0.838	(12)	0.823	(12)	0.828	(13)	0.829	(13)	0.813	(15)	0.852	(13)	0.898	(11)
Maryland	0.754	(17)	0.779	(14)	0.813	(13)	0.856	(10)	0.876	(10)	0.854	(10)	0.883	(9)	0.901	(11)	0.984	(5)	0.904	(10)
Massachusetts	0.796	(13)	0.810	(12)	0.858	(9)	0.976	(6)	0.935	(6)	0.977	(4)	0.955	(6)	0.978	(3)	1.000	(1)	1.000	(1)
Michigan	0.567	(32)	0.582	(30)	0.609	(31)	0.622	(29)	0.619	(28)	0.629	(29)	0.622	(33)	0.657	(30)	0.657	(31)	0.650	(32)
Minnesota	0.658	(22)	0.684	(20)	0.692	(22)	0.720	(20)	0.721	(23)	0.710	(23)	0.726	(24)	0.724	(24)	0.747	(24)	0.746	(24)
Nevada	0.609	(28)	0.639	(23)	0.705	(21)	0.700	(23)	0.676	(24)	0.670	(25)	0.711	(25)	0.701	(25)	0.729	(25)	0.732	(25)
New Hampshire	0.678	(21)	0.698	(19)	0.712	(19)	0.789	(17)	0.822	(13)	0.791	(17)	0.790	(17)	0.867	(12)	0.891	(12)	0.872	(12)
New Jersey	0.769	(15)	0.768	(17)	0.765	(18)	0.802	(14)	0.803	(17)	0.781	(18)	0.783	(18)	0.780	(17)	0.813	(17)	0.808	(18)
New Mexico	0.395	(47)	0.428	(45)	0.417	(46)	0.431	(46)	0.438	(45)	0.475	(44)	0.477	(45)	0.496	(45)	0.499	(45)	0.552	(42)
New York	0.939	(3)	0.934	(4)	0.996	(4)	1.000	(1)	1.000	(1)	0.954	(7)	0.958	(5)	0.971	(4)	1.000	(1)	1.000	(1)
Oregon	0.876	(8)	0.898	(7)	1.000	(1)	0.990	(5)	0.934	(7)	0.981	(3)	1.000	(1)	1.000	(1)	1.000	(1)	1.000	(1)
Pennsylvania	0.533	(36)	0.530	(37)	0.546	(37)	0.560	(35)	0.566	(34)	0.583	(33)	0.613	(34)	0.635	(33)	0.642	(32)	0.656	(30)
Rhode Island	0.812	(11)	0.818	(10)	0.824	(11)	0.858	(9)	0.893	(8)	0.861	(9)	0.820	(15)	0.943	(7)	0.905	(11)	0.812	(16)
Vermont	0.930	(4)	1.000	(1)	0.975	(5)	1.000	(1)	0.963	(4)	0.966	(6)	0.891	(8)	0.934	(8)	0.940	(10)	0.945	(6)
Virginia	0.799	(12)	0.796	(13)	0.834	(10)	0.844	(11)	0.817	(14)	0.831	(12)	0.828	(14)	0.816	(14)	0.850	(15)	0.850	(13)
Washington	0.899	(6)	0.924	(5)	0.999	(3)	1.000	(1)	0.971	(3)	1.000	(1)	0.968	(4)	0.953	(5)	0.976	(6)	0.986	(5)
Wisconsin	0.630	(24)	0.631	(25)	0.639	(27)	0.671	(25)	0.635	(26)	0.654	(26)	0.650	(29)	0.673	(28)	0.663	(28)	0.674	(28)
Avg.	0.720	(19)	0.732	(19)	0.755	(19)	0.779	(17)	0.773	(17)	0.781	(17)	0.783	(18)	0.803	(18)	0.822	(17)	0.819	(17)
Max.	0.939	(47)	1.000	(45)	1.000	(46)	1.000	(46)	1.000	(45)	1.000	(44)	1.000	(45)	1.000	(45)	1.000	(45)	1.000	(42)
Min.	0.395	(3)	0.428	(1)	0.417	(1)	0.431	(1)	0.438	(1)	0.475	(1)	0.477	(1)	0.496	(1)	0.499	(1)	0.552	(1)
S.D.	0.141	(11)	0.147	(11)	0.158	(12)	0.159	(12)	0.153	(11)	0.149	(11)	0.138	(11)	0.138	(11)	0.142	(12)	0.131	(11)
(b)																				
Alabama	0.493	(41)	0.479	(42)	0.486	(42)	0.507	(40)	0.528	(40)	0.528	(41)	0.532	(42)	0.556	(39)	0.580	(36)	0.579	(38)
Alaska	0.907	(5)	0.528	(38)	0.808	(14)	0.546	(38)	0.556	(36)	0.555	(38)	1.000	(1)	0.556	(38)	0.549	(41)	0.555	(39)
Arkansas	0.554	(33)	0.557	(33)	0.547	(36)	0.540	(39)	0.538	(39)	0.544	(39)	0.609	(35)	0.573	(36)	0.563	(39)	0.539	(44)
Florida	0.771	(14)	0.717	(18)	0.769	(17)	0.799	(15)	0.810	(15)	0.794	(16)	0.783	(19)	0.802	(16)	0.812	(18)	0.806	(19)
Idaho	1.000	(1)	1.000	(1)	1.000	(1)	0.999	(4)	0.956	(5)	0.976	(5)	0.932	(7)	0.932	(10)	0.949	(9)	0.944	(7)
Indiana	0.433	(43)	0.437	(43)	0.452	(44)	0.474	(43)	0.484	(43)	0.481	(43)	0.513	(43)	0.522	(44)	0.526	(43)	0.514	(45)
Iowa	0.540	(35)	0.535	(35)	0.555	(35)	0.572	(33)	0.594	(32)	0.602	(31)	0.633	(30)	0.667	(29)	0.661	(29)	0.639	(33)
Kansas	0.503	(39)	0.513	(39)	0.530	(39)	0.556	(36)	0.542	(38)	0.557	(37)	0.592	(36)	0.609	(35)	0.640	(33)	0.634	(34)
Kentucky	0.427	(44)	0.425	(46)	0.420	(45)	0.444	(45)	0.437	(46)	0.426	(46)	0.448	(46)	0.457	(46)	0.490	(46)	0.486	(46)

Table 6. *Cont.*

UEM	2009		2010		2011		2012		2013		2014		2015		2016		2017		2018	
(b)																				
Louisiana	1.000	(1)	0.888	(8)	0.862	(8)	0.835	(13)	0.843	(11)	0.835	(11)	0.858	(12)	0.948	(6)	0.970	(7)	0.930	(8)
Mississippi	0.585	(30)	1.000	(1)	0.647	(26)	0.585	(32)	0.604	(31)	0.583	(34)	0.565	(38)	0.545	(42)	0.558	(40)	0.554	(40)
Missouri	0.493	(40)	0.498	(40)	0.487	(41)	0.502	(41)	0.501	(42)	0.516	(42)	0.537	(41)	0.551	(41)	0.525	(44)	0.552	(41)
Montana	0.412	(46)	0.379	(47)	0.412	(47)	0.425	(47)	0.420	(47)	0.416	(47)	0.419	(47)	0.437	(47)	0.452	(47)	0.469	(47)
Nebraska	0.550	(34)	0.571	(32)	0.556	(34)	0.570	(34)	0.555	(37)	0.572	(35)	0.583	(37)	0.615	(34)	0.629	(35)	0.602	(35)
N. Carolina	0.691	(19)	0.664	(22)	0.710	(20)	0.737	(19)	0.728	(22)	0.730	(20)	0.765	(20)	0.771	(18)	0.791	(19)	0.802	(20)
N. Dakota	0.291	(49)	0.314	(48)	0.337	(48)	0.347	(48)	0.360	(48)	0.378	(48)	0.370	(48)	0.373	(48)	0.390	(48)	0.393	(48)
Ohio	0.531	(38)	0.532	(36)	0.558	(33)	0.591	(31)	0.573	(33)	0.588	(32)	0.625	(32)	0.637	(32)	0.639	(34)	0.653	(31)
Oklahoma	0.461	(42)	0.487	(41)	0.488	(40)	0.497	(42)	0.522	(41)	0.539	(40)	0.538	(40)	0.555	(40)	0.579	(37)	0.579	(37)
S. Carolina	0.624	(25)	0.633	(24)	0.656	(25)	0.695	(24)	0.742	(19)	0.723	(21)	0.744	(23)	0.757	(20)	0.781	(21)	0.759	(23)
S. Dakota	0.764	(16)	0.774	(15)	0.817	(12)	0.791	(16)	0.807	(16)	0.815	(14)	0.866	(11)	0.833	(13)	0.851	(14)	0.834	(15)
Tennessee	0.678	(20)	0.677	(21)	0.688	(23)	0.708	(22)	0.734	(20)	0.721	(22)	0.746	(22)	0.738	(23)	0.759	(23)	0.810	(17)
Texas	0.532	(37)	0.538	(34)	0.540	(38)	0.549	(37)	0.556	(35)	0.560	(36)	0.562	(39)	0.569	(37)	0.573	(38)	0.593	(36)
Utah	0.422	(45)	0.436	(44)	0.453	(43)	0.473	(44)	0.460	(44)	0.464	(45)	0.482	(44)	0.527	(43)	0.543	(42)	0.547	(43)
W. Virginia	0.310	(48)	0.275	(49)	0.276	(50)	0.294	(49)	0.295	(49)	0.269	(49)	0.287	(49)	0.278	(49)	0.290	(49)	0.320	(49)
Wyoming	0.262	(50)	0.265	(50)	0.277	(49)	0.264	(50)	0.256	(50)	0.263	(50)	0.257	(50)	0.266	(50)	0.274	(50)	0.281	(50)
Avg.	0.594	(30)	0.591	(31)	0.599	(31)	0.597	(32)	0.602	(32)	0.604	(32)	0.639	(31)	0.632	(32)	0.644	(32)	0.642	(32)
Max.	1.000	(49)	1.000	(48)	1.000	(48)	0.999	(48)	0.956	(48)	0.976	(48)	1.000	(48)	0.948	(48)	0.970	(48)	0.944	(48)
Min.	0.291	(1)	0.314	(1)	0.337	(1)	0.347	(4)	0.360	(5)	0.378	(5)	0.370	(1)	0.373	(6)	0.390	(7)	0.393	(7)
S.D.	0.188	(15)	0.183	(14)	0.166	(14)	0.154	(12)	0.153	(13)	0.150	(13)	0.168	(14)	0.151	(13)	0.154	(12)	0.150	(13)

Note: Rank in the parenthesis.

Table 7. Unified Index Scores of (a) Blue States and (b) Red States from 2009–2018.

UIM	2010		2011		2012		2013		2014		2015		2016		2017		2018	
(a)																		
Arizona	0.628	(31)	0.655	(32)	0.647	(28)	0.618	(33)	0.663	(30)	0.701	(29)	0.743	(27)	0.750	(28)	0.719	(29)
California	1.108	(1)	1.036	(6)	1.102	(2)	1.025	(3)	1.034	(3)	1.008	(4)	1.019	(4)	1.028	(3)	0.991	(8)
Colorado	0.646	(29)	0.662	(31)	0.637	(30)	0.637	(31)	0.654	(32)	0.665	(32)	0.683	(32)	0.693	(34)	0.681	(31)
Connecticut	1.055	(5)	1.023	(7)	1.021	(6)	0.952	(11)	0.964	(10)	0.966	(8)	1.023	(3)	1.018	(5)	0.918	(11)
Delaware	1.005	(7)	0.880	(13)	0.803	(16)	0.825	(19)	0.891	(13)	0.861	(16)	0.814	(20)	0.846	(20)	0.855	(17)
Georgia	0.670	(27)	0.716	(25)	0.732	(22)	0.746	(23)	0.768	(23)	0.775	(24)	0.798	(23)	0.811	(24)	0.815	(22)
Hawaii	0.807	(17)	0.763	(22)	0.740	(20)	0.707	(27)	0.830	(19)	0.795	(22)	0.811	(21)	0.828	(23)	0.787	(24)
Illinois	0.683	(26)	0.688	(28)	0.683	(27)	0.653	(30)	0.673	(29)	0.699	(30)	0.739	(28)	0.747	(29)	0.728	(28)

Table 7. *Cont.*

UIM	2010		2011		2012		2013		2014		2015		2016		2017		2018	
(a)																		
Maine	0.833	(15)	0.842	(17)	0.854	(14)	0.851	(15)	0.900	(12)	0.863	(15)	0.871	(14)	0.908	(16)	0.935	(10)
Maryland	0.880	(12)	0.910	(11)	0.909	(10)	0.920	(12)	0.909	(11)	0.940	(10)	0.957	(11)	1.017	(7)	0.917	(12)
Massachusetts	1.082	(2)	1.078	(2)	1.156	(1)	1.122	(1)	1.133	(2)	1.015	(3)	1.034	(2)	1.106	(1)	1.030	(1)
Michigan	0.636	(30)	0.663	(30)	0.642	(29)	0.629	(32)	0.661	(31)	0.643	(35)	0.694	(31)	0.700	(32)	0.675	(32)
Minnesota	0.752	(19)	0.753	(23)	0.738	(21)	0.731	(26)	0.743	(26)	0.750	(27)	0.763	(25)	0.794	(26)	0.774	(25)
Nevada	0.720	(23)	0.768	(21)	0.727	(23)	0.702	(28)	0.705	(28)	0.744	(28)	0.748	(26)	0.768	(27)	0.748	(27)
New Hampshire	0.822	(16)	0.792	(19)	0.828	(15)	0.847	(16)	0.834	(18)	0.828	(19)	0.919	(12)	0.932	(11)	0.894	(13)
New Jersey	0.863	(14)	0.850	(14)	0.857	(13)	0.843	(17)	0.827	(20)	0.827	(20)	0.824	(18)	0.853	(19)	0.820	(20)
New Mexico	0.480	(44)	0.458	(45)	0.449	(45)	0.459	(46)	0.519	(43)	0.503	(45)	0.526	(45)	0.524	(46)	0.565	(43)
New York	1.062	(3)	1.087	(1)	1.051	(4)	1.019	(4)	1.001	(8)	1.037	(2)	1.053	(1)	1.067	(2)	1.001	(5)
Oregon	0.999	(8)	1.061	(4)	1.015	(8)	0.954	(10)	1.017	(5)	1.042	(1)	0.974	(8)	0.925	(13)	1.001	(4)
Pennsylvania	0.596	(34)	0.610	(33)	0.595	(32)	0.589	(35)	0.617	(36)	0.639	(36)	0.671	(35)	0.680	(36)	0.674	(33)
Rhode Island	0.998	(9)	0.922	(10)	0.881	(11)	0.909	(13)	0.990	(9)	0.886	(14)	0.991	(6)	0.927	(12)	0.817	(21)
Vermont	1.039	(6)	1.038	(5)	1.044	(5)	0.983	(7)	1.002	(6)	0.991	(5)	0.959	(10)	0.948	(10)	0.969	(9)
Virginia	0.867	(13)	0.907	(12)	0.870	(12)	0.835	(18)	0.874	(14)	0.857	(17)	0.860	(15)	0.898	(17)	0.874	(15)
Washington	1.058	(4)	1.069	(3)	1.052	(3)	1.056	(2)	1.138	(1)	0.987	(6)	0.988	(7)	1.026	(4)	1.011	(2)
Wisconsin	0.698	(25)	0.702	(27)	0.701	(25)	0.667	(29)	0.713	(27)	0.688	(31)	0.717	(29)	0.702	(31)	0.695	(30)
Avg.	0.839	(17)	0.837	(18)	0.829	(17)	0.811	(20)	0.842	(18)	0.828	(19)	0.847	(18)	0.860	(19)	0.836	(19)
Max.	1.108	(44)	1.087	(45)	1.156	(45)	1.122	(46)	1.138	(43)	1.042	(45)	1.053	(45)	1.106	(46)	1.030	(43)
Min.	0.480	(1)	0.458	(1)	0.449	(1)	0.459	(1)	0.519	(1)	0.503	(1)	0.526	(1)	0.524	(1)	0.565	(1)
S.D.	0.183	(12)	0.173	(12)	0.181	(11)	0.170	(12)	0.168	(12)	0.147	(12)	0.140	(12)	0.144	(12)	0.129	(11)
(b)																		
Alabama	0.496	(42)	0.511	(42)	0.509	(41)	0.530	(41)	0.554	(41)	0.547	(42)	0.597	(40)	0.624	(39)	0.609	(39)
Alaska	0.543	(40)	0.849	(15)	0.552	(38)	1.000	(5)	0.872	(15)	0.924	(11)	0.854	(17)	0.922	(14)	1.007	(3)
Arkansas	0.602	(32)	0.578	(37)	0.549	(39)	0.560	(37)	0.632	(34)	0.777	(23)	0.612	(38)	0.696	(33)	0.566	(42)
Florida	0.746	(20)	0.821	(18)	0.803	(16)	0.810	(21)	0.839	(17)	0.833	(18)	0.857	(16)	0.859	(18)	0.871	(16)
Idaho	0.910	(10)	1.016	(8)	1.016	(7)	0.959	(9)	1.031	(4)	0.956	(9)	1.000	(5)	1.018	(6)	0.993	(7)
Indiana	0.460	(45)	0.480	(44)	0.477	(44)	0.486	(44)	0.505	(44)	0.528	(43)	0.557	(44)	0.563	(43)	0.537	(45)
Iowa	0.555	(37)	0.583	(36)	0.575	(34)	0.597	(34)	0.632	(33)	0.651	(33)	0.714	(30)	0.710	(30)	0.672	(35)
Kansas	0.549	(38)	0.571	(39)	0.562	(36)	0.547	(40)	0.585	(39)	0.610	(37)	0.647	(37)	0.683	(35)	0.659	(36)
Kentucky	0.437	(47)	0.440	(46)	0.446	(46)	0.439	(47)	0.449	(46)	0.467	(46)	0.492	(46)	0.525	(45)	0.510	(46)
Louisiana	0.888	(11)	0.968	(9)	0.975	(9)	0.985	(6)	1.002	(7)	0.977	(7)	0.965	(9)	1.011	(8)	0.998	(6)

Table 7. *Cont.*

UIM	2010		2011		2012		2013		2014		2015		2016		2017		2018	
(b)																		
Mississippi	0.740	(21)	0.715	(26)	0.591	(33)	0.882	(14)	0.783	(21)	0.897	(12)	0.674	(33)	0.997	(9)	0.759	(26)
Missouri	0.547	(39)	0.535	(40)	0.523	(40)	0.514	(43)	0.544	(42)	0.557	(40)	0.582	(42)	0.557	(44)	0.570	(41)
Montana	0.399	(48)	0.439	(47)	0.428	(47)	0.422	(48)	0.438	(47)	0.431	(47)	0.467	(47)	0.485	(47)	0.491	(47)
Nebraska	0.599	(33)	0.593	(35)	0.573	(35)	0.559	(39)	0.600	(37)	0.600	(38)	0.655	(36)	0.673	(38)	0.628	(37)
N. Carolina	0.728	(22)	0.776	(20)	0.767	(19)	0.754	(22)	0.772	(22)	0.803	(21)	0.822	(19)	0.838	(21)	0.824	(19)
N. Dakota	0.321	(49)	0.350	(48)	0.349	(48)	0.362	(49)	0.398	(48)	0.381	(48)	0.402	(48)	0.422	(48)	0.417	(48)
Ohio	0.578	(35)	0.608	(34)	0.606	(31)	0.584	(36)	0.618	(35)	0.644	(34)	0.673	(34)	0.679	(37)	0.674	(34)
Oklahoma	0.509	(41)	0.518	(41)	0.500	(43)	0.526	(42)	0.566	(40)	0.553	(41)	0.595	(41)	0.622	(40)	0.609	(40)
S. Carolina	0.653	(28)	0.686	(29)	0.698	(26)	0.746	(24)	0.758	(24)	0.765	(26)	0.809	(22)	0.836	(22)	0.795	(23)
S. Dakota	0.787	(18)	0.846	(16)	0.795	(18)	0.810	(20)	0.854	(16)	0.889	(13)	0.892	(13)	0.913	(15)	0.876	(14)
Tennessee	0.708	(24)	0.729	(24)	0.711	(24)	0.738	(25)	0.756	(25)	0.768	(25)	0.784	(24)	0.809	(25)	0.845	(18)
Texas	0.566	(36)	0.575	(38)	0.552	(37)	0.559	(38)	0.588	(38)	0.579	(39)	0.608	(39)	0.614	(41)	0.621	(38)
Utah	0.495	(43)	0.508	(43)	0.501	(42)	0.479	(45)	0.494	(45)	0.509	(44)	0.559	(43)	0.574	(42)	0.557	(44)
W. Virginia	0.451	(46)	0.305	(49)	0.295	(49)	0.980	(8)	0.294	(49)	0.300	(49)	0.298	(50)	0.308	(50)	0.338	(50)
Wyoming	0.270	(50)	0.286	(50)	0.265	(50)	0.291	(50)	0.279	(50)	0.264	(50)	0.298	(49)	0.337	(49)	0.343	(49)
Avg.	0.601	(33)	0.639	(32)	0.611	(33)	0.646	(32)	0.664	(31)	0.680	(30)	0.688	(31)	0.723	(30)	0.700	(31)
Max.	0.910	(49)	1.016	(48)	1.016	(48)	1.000	(49)	1.031	(48)	0.977	(48)	1.000	(48)	1.018	(48)	1.007	(48)
Min.	0.321	(10)	0.350	(8)	0.349	(7)	0.362	(5)	0.398	(4)	0.381	(7)	0.402	(5)	0.422	(6)	0.417	(3)
S.D.	0.150	(12)	0.175	(12)	0.167	(12)	0.189	(14)	0.176	(13)	0.178	(14)	0.160	(13)	0.175	(14)	0.172	(14)

Note: Rank in the parenthesis.

5.3. Statistical Test

To examine our hypotheses, we graphically describe differences in *UEM* scores and conducted the Kruskal-Wallis tests of *UEM*/*UIM* scores among different groups of states. Specifically, panels (a) and (b) of Figure 4 demonstrate mean *UEM* scores across states with different political transitions in presidential and gubernatorial elections. In the former, states with D to D transition outperformed their counterparts (i.e., states with D to R or R to R transition). It is noted that there was no state with R to D transition in the presidential election. In the latter, states with R to D or D to D outperformed their counterparts. Interestingly, states with R to D transition performed the best even if they are compared to states with D to D. On one hand, it implies that some Republican governors (particularly, those in blue states) committed to environmental protection or climate actions. They include California, Connecticut, Hawaii, Minnesota, and so forth. On the other hand, states with D to R transition improved faster than those with R to R transition. Even though political hegemony was shifted to the Republican from the Democratic in those states, it seems that the learning curve from the Democratic gubernatorial administration may influence the following Republican administration. States with R to R transitions performed the worst and their mean *UEM* scores stagnated.

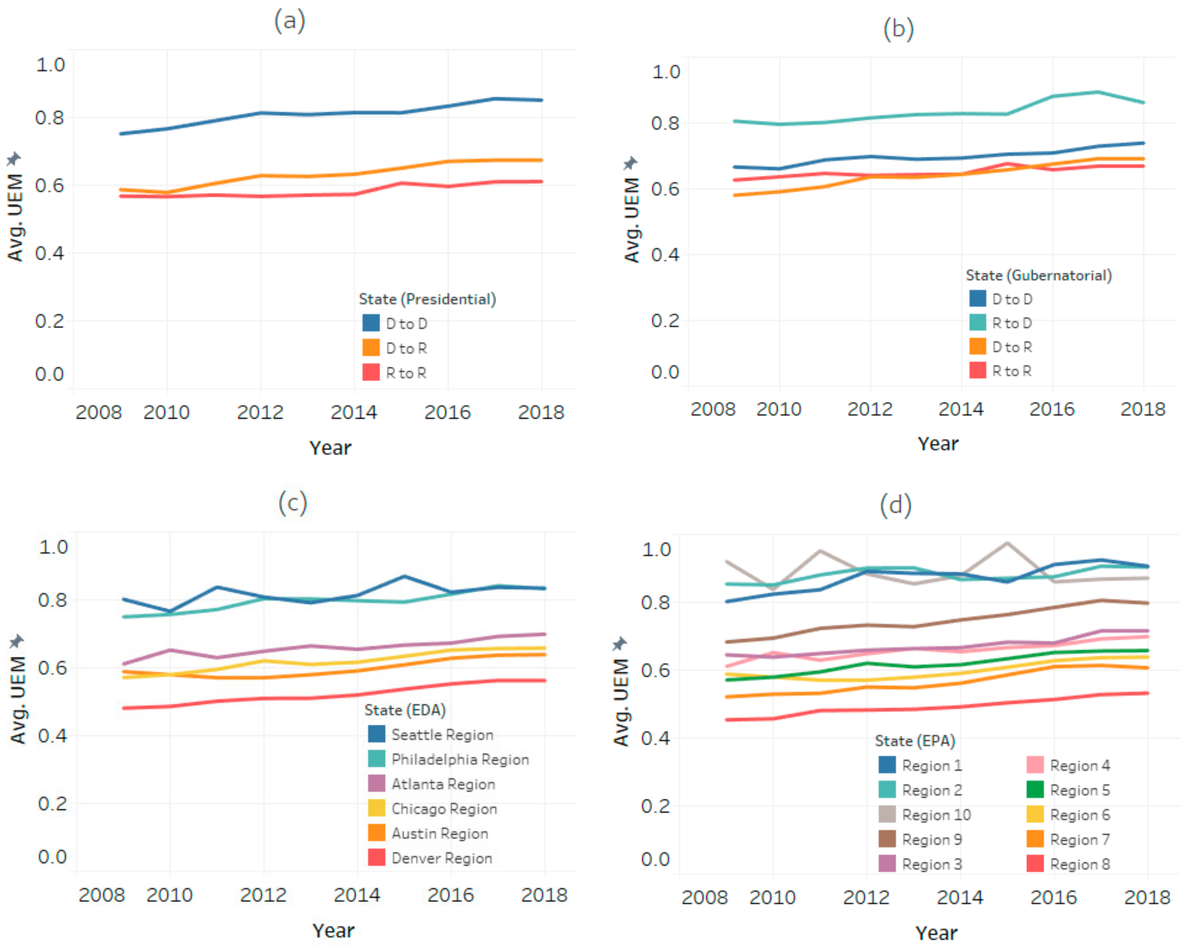

Figure 4. *UEM* Scores over Time by States (**a**) with History of Presidential Elections Transitioning from the Democratic to the Democratic (D to D, Blue-Colored), from the Democratic to the Republican (D to R, Orange-Colored), and from the Republican to the Republican (R to R, Red-Colored), (**b**) with History of Gubernatorial Elections Transitioning D to D (Blue-Colored), R to D (Cyan-Colored), D to R (Orange-Colored), and R to R (Red-Colored), (**c**) of EDA's Six Different Regions, and (**d**) of EPA's Ten Different Regions.

Panels (c) and (d) of Figure 4 demonstrate regional variations in mean *UEM* scores. It is clear that Seattle and Philadelphia regions (defined by EDA) and Regions 1, 2, and 10 (defined by EPA) outperformed their counterparts. They include Pacific Northwest (e.g., Oregon and Washington) and New England states (e.g., Massachusetts and New York). EDA's Denver region, which is composed of EPA's Regions 8 and 9, underperformed other regions. While EPA's Region 9 (e.g., California and Hawaii) performed well, Region 8 (e.g., North and South Dakotas) performed poorly.

Tables 8 and 9 summarize the results of the Kruskal-Wallis tests vis-à-vis a political context (hypothesis 1). Chi-squares (χ^2) statistics indicate that we can reject null hypotheses of identical mean *UEM*/*UIM* scores among three or four groups of states with different presidential or gubernatorial election results. The *UEM*/*UIM* scores of D to D or R to D groups are statistically significantly higher than those of D to R or R to R groups. Tables 10 and 11 summarize the results of the Kruskal-Wallis tests regarding a spatial context (hypothesis 2). The χ^2-statistics indicate that we can reject null hypotheses of identical mean *UEM*/*UIM* scores among six or ten groups of states situated in different EDA or EPA regions. The *UEM*/*UIM* scores of Seattle and Philadelphia regions or Regions 1, 2, and 10 are statistically significantly higher than those of other regions.

Table 8. Kruskal-Wallis Tests of States with Different Presidential Election Results.

Efficiency/Index	Mean (Rank Sum)			χ^2-Statistic
	D to D	D to R	R to R	
UEM	0.816 (70,082)	0.638 (16,747)	0.586 (38,421)	162.777 ***
UIM	0.874 (56,885)	0.672 (12,803)	0.634 (31,787)	146.295 ***

Note: *** = significant at 1%.

Table 9. Kruskal-Wallis Tests of States with Different Gubernatorial Election Results.

Efficiency/Index	Mean (Rank Sum)				χ^2-Statistic
	D to D	D to R	R to D	R to R	
UEM	0.695 (44,269)	0.628 (24,458)	0.817 (24,888)	0.660 (31,635)	54.365 ***
UIM	0.742 (35,251)	0.671 (19,723)	0.887 (20,447)	0.710 (26,055)	51.119 ***

Note: *** = significant at 1%.

Table 10. Kruskal-Wallis Tests of States of EDA's Six Different Regions.

Efficiency/Index	Mean (Rank Sum)						χ^2-Statistic
	Atlanta	Austin	Chicago	Denver	Philadelphia	Seattle	
UEM	0.664 (18,442)	0.587 (14,492)	0.625 (11,997)	0.600 (19,154)	0.802 (45,129)	0.887 (16,036)	161.557 ***
UIM	0.711 (14,939)	0.625 (11,437)	0.659 (9112)	0.639 (15,285)	0.869 (37,221)	0.966 (13,482)	168.804 ***

Note: *** = significant at 1%.

Table 11. Kruskal-Wallis Tests of States of EPA's Ten Different Regions.

Efficiency/Index	Mean (Rank Sum)										χ^2-Statistic
	Region 1	Region 2	Region 3	Region 4	Region 5	Region 6	Region 7	Region 8	Region 9	Region 10	
UEM	0.880 (24,095)	0.884 (8041)	0.674 (12,993)	0.664 (18,442)	0.625 (11,997)	0.600 (8629)	0.571 (5863)	0.497 (7107)	0.753 (12,047)	0.887 (16,036)	230.318 ***
UIM	0.955 (19,904)	0.941 (6516)	0.738 (10,801)	0.711 (14,939)	0.659 (9112)	0.646 (7045)	0.598 (4392)	0.525 (5474)	0.810 (9811)	0.966 (13,482)	234.047 ***

Note: *** = significant at 1%.

5.4. Results and Discussion

This study demonstrated the variations of the environmental performance of 50 states of the U.S. by temporal, political, and spatial contexts. The summarized results are as follows. Temporally, the environmental performance of states tends to have improved regardless of their political transitions and locations. Politically, the *UEM/UIM* scores of blue states have been significantly higher than those of red states, suggesting that the overall environmental performance is better in blue states than in red states. Meanwhile, it is worth noting that red states' technological progress is substantial. It was dramatic particularly in the states with the political transition from D to R, implying that even though there was a political hegemony change in those states, climate/environmental learning from the previous Democratic administration may have some impacts on their residents/public opinions and the following Republican administration. Geographically, the Pacific Northwest and New England regions (Seattle and Philadelphia regions defined by EDA and Regions 1, 2, and 10 defined by EPA) demonstrated better environmental performance than their counterparts.

To some degree, states with the political transition from D to D or from R to D overlap those on both coasts. However, it does not explain everything. Over the past decade, on one hand, political partisanship has transitioned from D to R, particularly in the presidential elections where there were eight states with the political transition from D to R but no state with the political transition from R to D. On the other hand, more and more states (or governors) have committed to climate/environmental policy regardless of their dominant political partisanship. For instance, Montana had the political transition from R to R in the presidential elections but signed up for the U.S. Climate Alliance to meet the goals proposed by the Paris Agreement. In some states, in addition, there is discordance in political transition between presidential and gubernatorial elections. For example, Vermont had the political transition from D to D in the presidential elections but from R to R in the gubernatorial elections.

While many studies (mostly focused on cross-country analyses) examined the relationships between environmental performance and socioeconomic factors (suggested by the environmental Kuznets Curve), this study centered on the examination of temporal, political, and spatial factors in the U.S. When compared to some studies in this vein, our results showed some consistent results. For instance, Leal et al. [30] demonstrated the association between environmental performance and political globalization that represents the dissemination and sharing of government environmental policies. Also, Esty and Porter [31] showed the relationship between environmental performance and the quality of the environmental regulations (particularly, the rigor and structure of enforcement). They further argued that environmental performance is related to a country's broader institutions (not only environmental regulatory regime but also economic and legal context). As shown in the previous literature, the political dimension interplays with the establishment and elimination of national institutions (particularly, environmental regulatory regime), which can lead to improvement or degradation of environmental performance. Our study reinforces the previous results and offers new policy insights in that we studied the dynamic political transition, not static political section at a specific time point.

Regional variations in environmental performance in this study are also bolstered by the existing literature whose studies were conducted in different countries. For instance, Zuo et al. [32] showed province-level variations in environmental performance in China by creating a composite index. In a similar vein, Yang and Yang [33] demonstrated province-level differences in eco-innovations in China, which are critical for environmental performance, by employing a non-radial directional distance function.

6. Conclusions

Drawing on the combination of the nonparametric DEA-EA with Kruskal-Wallis tests, we attempted to assess the dynamic environmental performance of 50 states of the U.S. and shed light on their associations with political/spatial contexts. As a result, we found that (a) overall environmental performance has gradually enhanced over time, (b) there were statistically significant differences in the environmental performance by political transitions, and (c) states on both coasts outperformed those in the middle.

Meanwhile, we need to acknowledge that those contexts are a subset of all explanatory factors for state-level environmental performance. As some studies discussed, there may be other dimensions, such as public and local government leader opinions [34], religion [35], and the structure of the energy market [36,37], in explicating environmentalism.

There are some other limitations in this study. First, we considered only two outputs (i.e., GSP and CO_2 emissions) to assess the performance of states in terms of sustainable development. While CO_2 attracts the most attention in climate change, other greenhouse gases (e.g., methane) and pollutants (e.g., SOx and NOx) were omitted. Second, our study period was not sufficient to fully capture the change from the Obama Administration to the Trump Administration. While we included data from a part of the Trump Administration (2017–2018) and observed some decline in the environmental performance in the time window, we would be able to argue better if we could extend our dataset up to 2020. However, it was not possible due to the data availability issue. Finally, it is possible for us to use other type of DEA methods such as the "intermediate approach" [38]. The methodological comparison may avoid a methodological bias. It is hoped that our future studies will address those limitations. See [39–42] for a general direction on DEA applied to energy and environment.

As it is anticipated that the Biden Administration steps in, the public and political leaders in the U.S. will face different national mood and focusing events from the Trump Administration in the near future. The Biden Plan for a Clean Energy Revolution and Environmental Justice includes many pro-environmental ideas such as the Green New Deal and recommitment to the Paris Agreement [43]. In particular, the incoming administration proposes to "achieve a 100% clean energy economy and reach net-zero emissions no later than 2050." With the promise, we expect the states' environmental performance to keep improving.

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