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Abstract

This study applies a nonparametric time dependent conditional frontier model to estimate and evaluate the convergence in eco-efficiency of a group of 51 US states over the period 1990-2017. Specifically, we utilize a mixture of global and local pollutants (carbon dioxide CO_2, sulphur dioxide SO_2 and nitrogen oxides NO_x) to capture the environmental damage caused by the anthropogenic activities. The empirical findings indicate divergence for the whole sample, while specific groups of convergence club regions are formulated dividing the US states into worst and best performers. Moreover, Our findings reveal significant convergence patterns between the US regions over the sample period.

Keywords: Eco-efficiency; Convergence clubs; Order-m estimators; Non parametric frontier analysis; US regions

JEL classification: C15, Q57, Q40, Q53

1. Introduction

Despite the primary contribution of the French physicist and philosopher Jean-Baptiste Joseph Fourier, *The analytical Theory of Heat*, who was the first to describe back in 1822 the greenhouse effect and the underlying theoretical mechanisms of climate change, the scientific community has recently acknowledged that environmental damage triggered by anthropogenic activities is a global challenge that incurs a global response.[1]

As a result, Kyoto Protocol was adopted in December 1997, setting legally binding targets to mitigate greenhouse gas emissions for the period 2008-2012. To achieve these objectives, three flexible instruments were created (i.e., emissions trading, joint implementation and clean development mechanism) giving the opportunity to ratified countries to use the market mechanism. This global awareness covers also the post Kyoto period and a new international agreement is in force from December 2015 (Paris Agreement).[2]

One of the main aspects in achieving these goals is sustainable development and eco-efficiency. Kuosmanen and Kortelainen (2005) were the first who coined the term "*eco-efficiency*" to describe the ability of an economy to produce the maximum level of economic output (desirable output) while causing the minimum environmental distortion (undesirable output).

In an influential study, Kuosmanen and Kortelainen, (2005) employ a Data Envelopment Analysis (DEA) framework in order to measure eco-efficiency, accounting for various substitution possibilities between different natural resources and

[1] Actually he was the first to argue that the Earth's atmosphere acts to raise the planet's temperature latter known as the "*greenhouse*" effect (Fourier, 1878)
[2] Paris Agreement, aims to strengthen the ability of countries to deal with the impacts of climate change by keeping a global temperature rise well below 2 degrees Celsius above pre-industrial levels.

emissions. However, this analysis is developed in a static setting since it does not account for technical change or explain changes in environmental performance over time (Kortelainen, 2008). In order to deal with this limitation, Kortelainen (2008), builds a general framework to account for dynamic environmental performance analysis. Specifically, this study, constructs an environmental performance index (EPI) by applying frontier efficiency techniques combined with a Malmquist index approach. The sample used in this work includes 20 European Union (EU) member states over the period 1990–2003. The empirical findings indicate that improvement in overall environmental performance can mostly be attributed to environmental technical change, while relative eco-efficiency change has minor contribution for most of the sample countries.

In another study, Halkos et al, (2013) apply an additive two-stage DEA model along the lines of Chen et al., (2009) to create a sustainability composite index consisting of production efficiency and eco-efficiency. Specifically, they employ a window-based approach on a sample of 20 countries over the time period 1990–2011. The empirical findings justify inequalities among the sample countries over the two distinct stages. Specifically, they argue that eco-efficiency stage is characterized by large inequalities among the sample countries and significantly lower efficiency scores than the overall sustainability efficiency and the production efficiency. Moreover, the authors suggest that a country's high production efficiency level is not related to a high eco-efficiency performance.

During the last years, several researchers have attempted to investigate convergence patterns in eco-efficiency in greenhouse gas emissions. The study of Camarero et al, (2013a) employ DEA techniques and directional distance functions to assess the existence of convergence-divergence hypothesis among a sample of EU countries following Phillips and Sul (2007) methodology. The empirical results indicate the existence of four convergence groups among the EU-periphery. In a similar vein, Camarero et al, (2013b) examine convergence patterns in eco-efficiency scores drawn from a sample of 22 OECD countries over the period 1980–2008 taking also into account three "*undesirable*" outputs (CO_2, NO_X and SO_X emissions). The authors argue that in general terms, eco-efficiency indicator has been increased over the sample period, indicating environmental performance. Moreover, some convergence groups are formed consisting of various sample countries based on their eco-efficiency performance. Specifically, Switzerland can be characterized as the most eco-efficient country, followed by some Scandinavian countries (i.e, Sweden, Iceland, Norway and Denmark). On the other hand, some Southern EU member states (e.g., Portugal, Spain and Greece) followed by Canada and the United States, are among the worst performers.

This study contributes the literature in many fronts. First and foremost, we apply one of the most innovative Data Envelopment Analysis (DEA) methods (i.e., time dependent conditional frontier model) to estimate the eco-efficiency indicator drawn from a separable production function of the electricity sector. Specifically, we use a flexible nonparametric partial frontier analysis to estimate in the first stage the eco-efficiency scores per US region (states). Second, in the applying methodological framework we take into account time effects and the effects generated by environmental degradation without imposing any restrictive assumptions on the statistical models describing the data generating process (Simar and Wilson, 2011; Daraio et al., 2018). The third novelty of this study lies on its application of the proposed model. To our knowledge there are few studies for EU member states or OECD countries estimating eco-efficiency at a regional level. Our application is the first that investigates such a relationship for the 51 US states. Fourth, we deliver for the first time in the literature a convex Order-m eco-efficiency measure, which is analogous to the original DEA based eco-efficiency indicator developed by Kuosmanen and Kortelainen (2005) but more robust to extreme values and potential outliers. We then use this indicator to test for the robustness of our findings. Lastly, we move beyond the well-known convergence methodology of Phillips and Sul (2007; 2009) by employing distributional dynamics organized along a Markov chain. In this way, we use stochastic kernels to describe both the change in the external shape and the intra-distribution dynamics of the cross-sectional distribution in order to trace possible convergence clubs (Kounetas and Zervopoulos, 2019).

The remainder of the paper is structured as follows. Section 2 presents the data and the methodology applied. Section 3 discusses the empirical findings concerning the estimation of eco-efficiency scores on each US region over the sample period (1990-2017), and the formulation of convergence clubs. In Section 4 the necessary robustness checks are presented by comparing our main results with two alternative eco-efficiency measures (e.g., conventional DEA based indicator and convexified order-m estimator). Lastly, Section 5 encapsulates the main findings of the paper.

2. Data and Methodology

This section describes the data used in the empirical analysis, while providing the summary statistics for all the sample variables. Moreover, we discuss and analyze the probabilistic frontier analysis along with the convergence methodology applied (see Phillips and Sul, 2007; 2009) that we used to empirically estimate and test for the eco-efficiency scores convergence among the US states (regions).

2.1 Data description

Our empirical analysis is based on a panel dataset of 1,428 annual observations, spanning the period 1990-2017 (N = 51 and T = 28). The selected sample includes all the 51 US states. The starting date for the study was strictly dictated by data availability, while the final date observation, represents the last year for which data mostly regarding the US Energy Information Administration (EIA) were available at the time the research was conducted.

The level of economic growth is proxied by per capita real GDP across US states, measured in millions of 2009 USD. [3] The latter is drawn from the Regional Economic Accounts of the Bureau of Economic Analysis (BEA) and provides the market value of goods and services produced by the labor and property located in a US state.[4] This variable can be regarded as an inflation-adjusted measure that is based on national prices for the goods and services produced within each region (US state).

The environmental variables used in the estimation of the eco-efficiency indicator, refer mainly to global and local pollutants such as CO_2, SO_2 and NO_x emissions. The latter are measured in metric tons for the 51 US states generated by power plants from all energy sources (i.e., coal, petroleum, geothermal, natural gas, wood and wood derived fuels, other biomass, other gases, and other emissions such as CO_2 emissions from municipal solid waste) over the period 1990-2017. The reason for using the CO_2 emissions as the only global pollutant stems from the fact that it constitutes the main contributor to global warming and therefore environmental

[3] Similarly, to Camarero et al, (2013a), we moved the base year to the beginning of the period to avoid bias in favour of convergence around the GDP base year. The results did not exhibit significant differences and are available upon request.
[4] https://www.bea.gov/regional/index.htm

regulations aimed at reducing CO_2 emissions have been in force the longest and in most cases are the most restrictive (Camarero et al, 2013b).

To get a clear picture of the environmental degradation in the US, we include in our analysis all the different types of power plants consisting of commercial (non) co-generators, industrial (non) co-generators, electric utilities, etc. The relevant variables were drawn from the EIA.[5] The following table, portrays the descriptive statistics for all the variables used in the empirical analysis.

<Insert Table 1 about here>

2.2 Probabilistic frontier analysis

According to Kuosmanen (2005) eco-efficiency is referred to the production of economic output with minimal environmental degradation. Based on the work by Koopmans (1951), Kuosmanen and Kortelainen (2005) provide an eco-efficiency measure using data envelopment analysis (DEA) estimators. They have characterized the pollution-generating technology set as:

$$\Phi = \{(v, d) \in \mathbb{R}_{+}^{1+p} \,|\, \text{value added } v \text{ can be generated with damage } d\}. \quad (1)$$

Equation (1) implies all technical feasible combinations of states' value added levels v and environmental damage $d = (d_1, \dots, d_p)$. Then using the Farrell (1957) measure, we can present state's eco-efficiency level as:

$$\varepsilon(d, v) = \inf\{\varepsilon \,|\, (\varepsilon d, v) \in \Phi\}. \quad (2)$$

Following the framework by Daraio and Simar (2007b) an observed state (d_i, v_i) defines an individual possibilities set as:

[5] https://www.eia.gov/tools/a-z/index.php?id=e

$$\varphi(d_i, v_i) = \{(d, v) \in \mathbb{R}_+^{p+1} | d \geq d_i, v \leq v_i\}. \tag{3}$$

The union of these sets (equation 3) provides us a Free Disposal Hull-FDH (Deprins et al. 1984) type of eco-efficiency estimator as:

$$\widehat{\Phi}_{FDH} = \cup_{i=1}^{n} \varphi(d_i, v_i) = \{(d, v) \in \mathbb{R}_+^{p+1} | d \geq d_i, v \leq v_i, i = 1, \dots, n\}. \tag{4}$$

Then the DEA-type of eco-efficiency measure is obtained by the convex hull (CH) of $\widehat{\Phi}_{FDH}$ as:

$$\widehat{\Phi}_{DEA} = CH(\cup_{i=1}^{n} \varphi(d_i, v_i)) = \{(d, v) \in \mathbb{R}_+^{p+1} | v \leq \sum_{i=1}^{n} \omega_i v_i; d \geq \sum_{i=1}^{n} \omega_i d_i,$$

$$\text{for } (\omega_1, \dots, \omega_n) s.t. \sum_{i=1}^{n} \omega_i = 1; \omega_i \geq 0, i = 1, \dots, n\}. \tag{5}$$

Based on the probabilistic framework by Cazals et al. (2002) and Daraio and Simar (2005) the pollution generated technology can be also characterized by the joint probability measure (D, V) as :

$$\mathrm{B}_{DV}(d, v) = \mathrm{Prob}(D \leq d | V \geq v)\mathrm{Prob}(V \geq v) = F_{D|V}(d|v) S_V(v). \tag{6}$$

Then the probabilistic version of the eco-efficiency measure can be defined as:

$$\varepsilon(d, v) = \inf\left\{\varepsilon | \left(F_{D|V}(\varepsilon d|v)\right) > 0\right\} = \inf\{\varepsilon | \mathrm{B}_{DV}(\varepsilon d, v) > 0\}, \tag{7}$$

where $\hat{B}_{D|V,n}(d|v) = \frac{\sum_{i-1}^{n} I(D_i \leq d, V_i \geq v)}{\sum_{i-1}^{n} I(, V_i \geq v)}$.

According to Daraio and Simar (2007b) the eco-efficiency, which are based on the FDH and the DEA estimators, are very sensitive to extreme values and outliers. In order to avoid such shortcomings according to Cazals et al. (2002) it is more appropriate to apply the Order-m estimators in order to construct the eco-efficiency measures. Previously $F_{D|V}(\cdot|v)$ defines state's environmental pollutants (damage) D at the value added level. The Order-m robust estimators instead of looking the lower boundary of this support in order to define state's eco-efficiency levels, it uses the average of the minimal value of environmental pollutants (damage) for m states which are randomly drawn according to $F_{D|V}(\cdot|v)$. As a result in order to evaluate state's eco-efficiency levels it uses as a benchmark only the states producing at least the value added level v. According to Daraio and Simar (2007b) for a given value added level, we consider m i.i.d. random variables $D_1, \dots, D_m$ generated by the conditional p-variate distribution function $F_{D|V}(\cdot|v)$ obtain a random production set as:

$$\widetilde{\Phi}_m(v) = \left\{(d, \acute{v}) \in \mathbb{R}_+^{p+1} \middle| d \geq D_i, \acute{v} \geq v, i = 1, \dots, m\right\}. \tag{8}$$

Therefore, the Order-m eco-efficiency measure can be defined as:

$$\varepsilon_m(d, v) = E_{D|V}(\tilde{\varepsilon}_m(d, v)|V \geq v), \tag{9}$$

where $\tilde{\varepsilon}_m(d, v) = \inf\left\{\varepsilon \middle| (\varepsilon d, v) \in \widetilde{\Phi}_m(v)\right\}$ and $E_{D|V}$ is the expectation in relation to $F_{D|V}(\cdot|v)$. As a result the Order-m eco-efficiency measure is the expectation of the environmental damage efficiency score of the state (d, v) when is compared with the m states randomly drawn with replacement from the population of states producing at least the value added level v. Moreover, the estimated Order-m frontier is the set of$\left(d_m^{\partial}(v), v\right) \in \Phi$, where $d_m^{\partial}(v)$ is the radial projection of $(d, v) \in \Phi$ on the Order-m frontier in the environmental damage direction.

We can calculate the Order-m eco-efficiency measure as:

$$\hat{\varepsilon}_m(d, v) = \hat{E}_{D|V}(\tilde{\varepsilon}_m(d, v)|V \geq v) = \int_0^{\infty} \left(1 - \hat{F}_{D|V}(ud|v)\right)^m du. \tag{10}$$

Finally, we can obtain a convex Order-m eco-efficiency estimator as:

$$\hat{\varepsilon}_m^C(d, v) = \inf\left\{\varepsilon \middle| v \leq \sum_{i=1}^n \omega_i v_i; \varepsilon d \geq \sum_{i=1}^n \omega_i \hat{d}_{m,i}^{\partial}, \text{ for } (\omega_1, \dots, \omega_n) s.t. \sum_{i=1}^n \omega_i = 1; \omega_i \geq 0, i = 1, \dots, n\right\}. \tag{11}$$

According to Daraio and Simar (2007b) it holds:

$$\varepsilon(d, v) \leq \varepsilon_m^C(d, v) \leq \varepsilon_m(d, v), \tag{12}$$

where $\varepsilon(d, v)$ is the Kuosmanen, and Kortelainen's (2005) eco-efficiency measure; $\varepsilon_m^C(d, v)$ is the global convex Order-m based eco-efficiency measure. The eco-efficiency and the convex Order-m measure can take values from zero to one (eco-efficient region). Finally $\varepsilon_m(d, v)$ is an Order-m based eco-efficiency measure. It is worth mentioning that the efficiency scores can take values greater than one (indicating a super eco-efficient region). Lastly, as suggested by Cazals et al. (2002) partial frontiers such as Order-m estimators are less sensitive to outliers.

2.3 Convergence methodology

Phillips and Sul (2007), propose an econometric approach for testing the convergence hypothesis and the identification of convergence clubs. Their method uses a nonlinear time-varying factor model and provides the framework for modelling transitional dynamics as well as long-run behavior (Apergis et al, 2013). The methodology applied can be outlined as follows:

If X_{it} is the solely factor of a panel data set (X denotes the rating for a given journal, i denotes the journal list and t the time), then

$$X_{it} = \delta_{it}\mu_t, \tag{13}$$

where δ_{it} measures the deviation of journal list's i ranking from the common trend μ_t and can be represented as:

$$\delta_{it} = \delta_i + \sigma_i \xi_{it} L(t)^{-1} t^{-a}, \tag{14}$$

where δ_i is fixed, ξ_{it} is weakly dependent over t with $\xi_{it} \sim iid(0,1)$ and $L(t)$ is a slowly varying function with $L(t) \to \infty$ when $t \to \infty$. The null hypothesis of convergence for all i (H_0) versus the alternative of non-convergence for some i (H_A) can be expressed as:

$$H_0 : \delta_i = \delta \text{ and } a \geq 0;\; H_A : \delta_i \neq \delta \text{ or } a < 0. \tag{15}$$

The null hypothesis in (15) can be tested through the following regression:

$$\log\left(\frac{H_1}{H_t}\right) - 2\log L(t) = \hat{c} + \hat{b}\log t + \hat{u}_t, \tag{16}$$

for $t = [rT], [rT]+1, ..., T$ with some $r > 0$.[6] In (4), $H_t = (1/N)\sum_{i=1}^{N}(h_{it} - 1)^2$ $h_{it} = \frac{X_{it}}{N^{-1}\sum_{i=1}^{N} X_{it}} = \frac{\delta_{it}}{N^{-1}\sum_{i=1}^{N}\delta_{it}}$, $L(t) = \log(t+1)$ and $\hat{b} = 2\hat{a}$ where $\hat{a}$ is the least-squares estimate of a in H_0 (null hypothesis).

Based on the above analysis, Phillips and Sul (2007) argue that the hypothesis of convergence can be tested through a one-sided *t*-test. Specifically, the alternative hypothesis of non-convergence cannot be rejected at the 5% level if $t_{\hat{b}} < -1.65$. Finally, we apply Phillips and Sul (2009) procedure to determine the existence of further convergence clubs.

3. Results and discussion

This section presents the empirical findings of the study. In the first stage, we present the results of the eco-efficiency scores of 51 US regions constructed by applying the probabilistic frontier analysis (order-m estimator) and compare these estimates with

[6] Following Phillips and Sul (2007, 2009), *r* is set equal to 0.3.

the results of similar studies reported by the existing literature. Then in the second stage, we test for club formulation convergence between the sample regions utilizing the Phillips and Sul (2007; 2009) methodology. [7]

3.1 Eco-efficiency scores

Table 2 presents the results of the regional eco-efficiency scores for selected years derived from the applied probabilistic frontier analysis (i.e., order-m estimators).[8] We must bear in mind that in contrast to other eco-efficiency indicators appeared in similar studies (see for example Kuosmanen and Kortelainen, 2005; Picazo-Tadeo et al. 2011; Camarero et al, 2013b) the proposed one can take values greater than one, implying higher levels of eco-efficiency. It is worth mentioning that the empirical findings have been obtained setting m = 20.[9] It must be stressed that contrary to the full frontiers the order-m efficiency scores denote the expectation of the minimal input eco-efficiency score of a region, when compared to twenty other regions randomly drawn with replacement from the population of regions having the same or higher GDP per capita (Halkos and Tzeremes, 2013).

The eco-efficiency score results reveal that 3 out of 51 states (e.g., Vermont, Rhode Island and District of Columbia) constitute the most eco-efficient regions since their scores exceed unity for all the selected years (see Panel A). In other words, these three states are the only regions across the US territory that remain above the efficient boundary of the order-m frontier ("*best*" performing regions). As a result, they can be characterised as eco-efficient since they use fewer pollutants levels (CO_2, SO_2 and

[7] For our empirical estimations, we used the STATA codes appeared in Du (2017).
[8] To conserve space, we only report the eco-efficiency scores for the selected four years (1990, 2000, 2010 and 2017). The detailed results for each sample year are available from the authors on request.
[9] To check for robustness, we have experimented with other values for m (m = 10, 15, 25, 30) but the results which are not reported here converge quickly to the FDH scores. These results are available from the authors upon request.

NOx) compared only to states having the same or higher level of economic growth (GDP per capita). On the other hand, the regions of West Virginia and Wyoming report the lowest eco-efficiency scores ranging from 0.736 to 0.806 ("*worst*" performing regions).

As it is evident, Wyoming is the region with the lowest eco-efficiency factor equal to 0,8 for the latest available year (2017). This means that the specific region uses 20% more inputs in the production process than the expected value of the minimum input level of m other regions (in our case 20) drawn from the population of regions producing a level of output equal or greater than the efficient one (see Daraio and Simar, 2007b; Halkos and Tzeremes, 2013). On the other hand, the state of Vermont exhibits the highest score compared to the rest US regions remaining well above the efficient boundary of the order-m frontier taking the value of 1,609 in 2017.

In addition, the eco-efficiency score in four regions (California, District of Columbia, Illinois and Indiana) equals to unity, implying that the specific entities are on the efficient boundary of the order-m frontier. As a consequence, we argue that the relevant regions appear to have the same levels of pollutants than the expected value of the minimum level of pollutants of the twenty other regions (i.e., m = 20) drawn from the total population of regions having at least the same level of economic growth.

Overall, the summary statistics reveal low disparities of regional eco-efficiency scores among the US states since the standard deviation and the coefficient of variation appear to be relatively low exhibiting a downward trend throughout the selected years (see Panel B). Lastly, the average eco-efficiency indicator shows an upward trend over the sample period (i.e., reaching 1,008 in 2017 compared to 0,923 in 1990).

<Insert Table 2 about here>

3.2 Convergence clubs formulation

Having estimated the efficiency scores by applying the probabilistic frontier analysis, we limit our attention to the existence of eco-efficiency convergence clubs using the Phillips and Sul (2007) methodology.

The results drawn from the convergence algorithm are illustrated in Table 3. As it is evident, the null hypothesis of convergence cannot be accepted for the US as a whole (full sample) since the t-statistic is smaller than the critical value (-1.65) at 5% level of statistical significance. This means that we must test for the existence of separate convergence clubs drawn from the whole sample (i.e., 51 regions).

It can be easily shown that there are six convergence clubs (see Column 1) consisting of different number of regions. In particular Club 1 consists of 35 states (Alaska, Arkansas, California, Colorado, Connecticut, Delaware, District of Columbia, Florida, Georgia, Idaho, Illinois, Indiana, Kansas, Louisiana, Maryland, Massachusetts, Michigan, Missouri, Nevada, New Hampshire, New Jersey, New York, North Carolina, Oklahoma, Oregon, Rhode Island, South Carolina, South Dakota, Tennessee, Texas, Vermont, Virginia, Washington and Wisconsin). Club 2 has 2 members (Minnesota, Pennsylvania and Utah), while Club 3 consists of 6 regions (Alabama, Arizona, Kentucky, Mississippi, Nebraska and New Mexico). Moreover, Club 4 and 5 have also 2 members (Hawaii and Iowa; Montana and North Dakota respectively). Finally, the rest of the regions (i.e., West Virginia and Wyoming) do convergence formulating Club 6.

<Insert Table 3 about here>

In these clubs, the estimated t-statistics are larger than -1.65, indicating convergence (i.e., acceptance of null hypothesis). However, the state of Maine (20) formulates a non-converging group by itself. It is worth emphasizing that the "*best*" performing regions fall within the first Club (i.e., Vermont, Rhode Island and District of Columbia). On the contrary, the "*worst*" performers (i.e., West Virginia and Wyoming) do convergence formulating Club 6.

Having delineated the convergence clubs based on Phillips and Sul (2007) generic algorithm, the analysis continues with the interpretation of the speed of convergence among the formulated clusters. A deeper inspection of Table 3 uncovers some important remarks.

First, the speed of convergence varies significantly across the six formulated clubs.[10] Second, the first club, which includes among others the "*best*" performing regions, records an absolute value of α = 2,8 approximately, indicating a high adjustment speed to convergence among other clubs. This finding runs contrary to the study of Camarero et al, (2013b), in which convergence speed is slower in those clubs consisting of higher eco-efficiency country scores, compared to other clubs with lower efficiency scores. Apart from the different sample, this discrepancy might also be attributed to the different methodology applied, since the study of Camarero et al, (2013b) employs a full frontier analysis in which the variable of interest (i.e., eco-efficiency indicator) is bounded between zero and one, where one (zero) denotes the most (least) eco-efficient country. Third, the "*worst*" performers (Club 6) are characterized by a large value of convergence speed equal to α = 1,37 approximately. This means that the two members of this club (West Virginia and Wyoming) are approaching one another more rapidly in relative terms. This value is almost six times greater than the relevant one (α = 0.235) appeared in Camarero et al, (2013b). Lastly,

[10] According to Phillips and Sul (2007), the speed of convergence α can be calculated as half the estimated convergence coefficient ($\gamma/2$).

slow convergence is found among the regions of Clubs 5, 4 and 2, whereas the members of Clubs 1 and 6 are approaching more rapidly.

As a final step, we use the Phillips and Sul (2009) methodology to investigate the existence of convergence merging clubs. The following table, presents the empirical results drawn from the applied methodology. As it is evident, we accept the null hypothesis of convergence only in one case (Club 3 and Club 4), since the relevant t-stat (2.3307) is larger than its critical value (-1.65). This means that these two primary clubs formulate one larger (merged) club with moderate convergence speed ($\alpha = 0.575$). On the contrary, none of the other existing primary clubs can be merged since the null hypothesis of club-merging for all the combinations of two or three clubs is rejected (t-stat>-1.65). In this case, the initially formed clubs as described above are the appropriate ones. Therefore, after club-merging, there are five convergence clubs (i.e. primary clubs 1,2,5, 6 and one merged Club 3+4).

<Insert Table 4 about here>

4. Robustness checks

In this section, we perform the necessary robustness checks by using two alternative eco-efficiency indicators namely the conventional eco-efficiency and the robust eco-efficiency indicator.

Firstly we calculate the original eco-efficiency measure as proposed by Kuosmanen and Kortelainen (2005) and formally presented in Equation (5). This measure constitutes a DEA based indicator under the assumption of Variable Returns to Scale (VRS). However, as any other DEA estimator is sensitive to potential extreme values and outliers (Daraio and Simar, 2007b). Alternatively by following the theoretical framework by Cazals et al. (2002) we provide an Order-m based eco-efficiency measure (see Equation 10). This indicator is more robust compared to the original DEA based eco-efficiency indicator since it does not envelop all the data points and therefore is more resistant to potential effects form outliers and extreme values. However, this indicator is not convex as the DEA estimator, therefore, we convexify the Order-m based eco-efficiency indicator to provide rigorous economic intuition. (see Equation 11). [11]

The results from the initial club clustering are displayed in Table 5. To get a full picture of convergence patterns and club classifications among the sample regions, we conserve the order-m estimator results. From the careful examination of the relevant table some interesting results emerge. First, the null hypothesis of convergence does not seem to hold for the whole sample regions since the t-statistic is smaller than the critical value (-1.65) at least at 5% level of significance. Second, regarding conventional eco-efficiency indicator, the Phillips and Sul (2007) algorithm revealed nine initial convergence clubs and one non-converging group. Third, the robust eco-efficiency scores provided similar convergence patterns (i.e., ten clubs and one non-converging group). Finally, in line with the order-m eco-efficiency indicator, we exemplify that the best (worst) performing regions fall within the first (last) convergence club respectively. This implies that the empirical findings are rather robust.

<Insert Table 5 about here>

Having identified the existence of specific convergence clubs among the sample regions, we turn our attention on whether it is possible to merge some of the initial convergence clubs found above. Therefore, we apply the Phillips and Sul (2009)

[11] This is highlighted in the expression (12).

methodology on the two different eco-efficiency measures (conventional and robust eco-efficiency scores).

The relevant results are illustrated in Table 6. Regarding the conventional eco-efficiency indicator, we fail to reject the null hypothesis of convergence in two cases (Club 7+8 and Club 8+9). On the contrary, none of the other existing primary clubs can be merged. Similar findings can be postulated by examining the robust eco-efficiency indicator. In this case, only the initial convergence club 7 (Alaska and Hawaii) and club 8 (Mississippi, Nebraska, New Mexico and North Dakota) can be merged since the relevant t-statistic (-0.718) falls within the null hypothesis region (i.e., larger than the critical value of -1.65).

<Insert Table 6 about here>

Finally, to draw sharp conclusions about the interpretation and the comparison of the three alterative eco-efficiency indicators, we provide the average efficiency score over time (1990–2017) for each region along with the average annual growth rate (% percent change from 1990 to 2017).

As it is evident from the following table, the average annual growth rates do not appear to have significant differences across the three eco-efficiency indicators providing a stable convergence pattern. Regarding the magnitude, we argue that eco-efficiency as it is measured by three different indicators (i.e., conventional, convexified robust estimator and order-m estimator), portrays significant positive changes in most of the sample regions (see for example Delaware, New Hampshire, South Dakota and Connecticut and Arizona). Regarding order-m eco-efficiency scores, Rhode Island and Delaware are the regions with the highest average annual growth rate (+44.39% and +37.10% respectively), whereas District of Columbia achieves the lowest growth rate (-22.59%). The two above regions have substantially improved their eco-efficiency scores since 1990. This might be attributed to various reasons mainly stemming from the legislative and regulatory framework for environmental protection, which has been greatly improved within the last twenty years, targeting, among others, global warming and sustainable development (Halkos et al., 2015). As a result, the SO_2 emissions in Rhode Island have been significantly reduced reaching an annual growth rate of -95% (from 3,282 in 1990 to 156 in 2017). Similarly, SO_2 and NO_x emissions have been successfully mitigated in Delaware (99% and 94% respectively).

However, the positive average growth rates are much smaller when we measure eco-efficiency by the other two approximations (e.g., conventional and robust eco-efficiency indicators). Regarding robust eco-efficiency indicator, only six efficiency scores change more than 15% in average during the time period (District of Columbia with 25.51%, Colorado with 18.42%, Arizona with 17.77%, Massachusetts with 17.60%, Tennessee with 16.66% and finally Maryland with 16,27%). We must mention thought that the results do not dramatically change when we account for conventional eco-efficiency indicator. In this case, we observe that there are ten regions with an annual growth rate more than 15%.

It is worth emphasizing that most of the sample regions appear to have a similar ranking pattern across the three indicators for the latest available sample year (2017). From the careful inspection of the relevant table (see ranking column), one cannot fail to observe that specific states such as Vermont (1st place in two indicators and 2nd place in the third one), District of Columbia (2nd place in one indicator and 3rd place in the other two) and New Jersey (5th place in all of the three indicators) belong to the highly ranked regions in all of the three different eco-efficiency measures. This means that the relevant regions constitute the "*best*" performers in terms of their eco-efficiency capability.

On the other hand, Wyoming, West Virginia, North Dakota, Montana and New Mexico constitute the "*worst*" performing regions based on their low ranking positions across the three different indicators. The above findings confirm the existence of the previously discussed convergence clubs (clusters) across the US territory. However, for some US states (see for instance Rhode Island, Connecticut and Oregon), the order-m indicator reveals substantial differences compared with the rest two eco-efficiency approximations.

<Insert Table 7 about here>

5. Conclusions

The need of modern economies to produce with fewer impacts on the environment and less consumption of natural resources constitutes a challenging issue for the environmental economists and researchers worldwide. Despite the significant contributions on this field, mostly made from the empirical standpoint, the existing literature on this topic is still in its infancy. We attempt to shed light on this ongoing research by applying a nonparametric time dependent conditional frontier model to estimate and evaluate the convergence in eco-efficiency of a group of 51 US states over the period 1990-2017. For this reason, we utilize a mixture of global and local pollutants (carbon dioxide CO_2, sulphur dioxide SO_2 and nitrogen oxides NO_x) to capture the environmental damage caused by the anthropogenic activities.

The empirical findings indicate divergence for the whole sample, while specific groups of convergence club regions are formulated dividing the US states into worst and best performers. Our findings reveal significant convergence patterns between the US regions over the sample period. Lastly, our results survive robustness checks under the inclusion of two alternative measures of eco-efficiency (e.g. robust and conventional eco-efficiency indicators).

List of Tables

Table 1: Summary statistics

Variables	**Observations**	**Mean**	**Standard Deviation**	**Min**	**Max**
GDP *(Millions USD)*	1,428	269,644	335,648	16,712	2,576,223
CO_2 emissions *(Metric tonnes)*	1,428	88,034,823	86,413,836	13,166	534,928,184
SO_2 emissions *(Metric tonnes)*	1,428	371,159	543,423	0	4,091,966
NO_X emissions *(Metric tonnes)*	1,428	711.9	410.7	1	1,421

Table 2: Order-m Eco-efficiency scores $\hat{\varepsilon}_m(d, v)$ per selected year

State	1990	2000	2010	2017
Panel A: Eco-efficiency scores				
Alabama [1]	0.883	0.892	0.902	0.938
Alaska [2]	0.907	0.903	0.972	0.979
Arizona [3]	0.882	0.930	0.939	0.988
Arkansas [4]	0.834	0.863	0.878	0.913
California [5]	0.970	0.979	0.989	1.000
Colorado [6]	0.939	0.936	0.950	0.986
Connecticut [7]	0.995	1.000	1.158	1.267
Delaware [8]	0.863	0.899	0.951	1.184
District of Columbia [9]	1.292	1.357	1.426	1.000
Florida [10]	0.908	0.935	0.934	0.950
Georgia [11]	0.906	0.909	0.914	0.961
Hawaii [12]	0.885	0.876	0.894	0.908
Idaho [13]	0.998	1.016	1.007	1.000
Illinois [14]	0.931	0.948	0.946	1.003
Indiana [15]	0.885	0.886	0.889	0.913
Iowa [16]	0.858	0.917	0.923	0.957
Kansas [17]	0.864	0.902	0.939	1.047
Kentucky [18]	0.857	0.888	0.890	0.920
Louisiana [19]	0.927	0.914	0.922	0.925
Maine [20]	0.894	0.883	0.920	0.972
Maryland [21]	0.950	0.950	0.969	1.036
Massachusetts [22]	0.959	0.967	0.998	1.110
Michigan [23]	0.910	0.915	0.917	0.937
Minnesota [24]	0.940	0.943	0.954	0.977
Mississippi [25]	0.856	0.871	0.883	0.922
Missouri [26]	0.920	0.913	0.914	0.921
Montana [27]	0.793	0.827	0.839	0.863
Nebraska [28]	0.853	0.848	0.883	0.922
Nevada [29]	0.844	0.894	1.024	1.150
New Hampshire [30]	0.891	0.908	0.933	1.130
New Jersey [31]	1.000	0.988	1.046	1.190
New Mexico [32]	0.808	0.824	0.881	0.913
New York [33]	0.960	0.964	0.983	1.037
North Carolina [34]	0.922	0.908	0.921	0.962
North Dakota [35]	0.745	0.756	0.804	0.819
Ohio [36]	0.892	0.908	0.918	0.966
Oklahoma [37]	0.857	0.919	0.920	0.957
Oregon [38]	0.976	1.023	1.018	1.050
Pennsylvania [39]	0.899	0.930	0.937	0.980
Rhode Island [40]	1.069	1.034	1.625	1.543
South Carolina [41]	0.893	0.929	0.937	0.993
South Dakota [42]	0.870	0.904	0.918	1.113
Tennessee [43]	0.911	0.908	0.945	0.979
Texas [44]	0.910	0.894	0.893	0.931
Utah [45]	0.825	0.866	0.946	0.997
Vermont [46]	1.758	1.242	1.699	1.609
Virginia [47]	0.957	0.929	0.950	0.986
Washington [48]	1.016	0.992	1.016	1.052
West Virginia [49]	0.769	0.777	0.793	0.806
Wisconsin [50]	0.929	0.919	0.937	0.962
Wyoming [51]	0.736	0.763	0.790	0.803
Panel B: Diagnostics				
Average	*0.923*	*0.926*	*0.971*	*1.008*
Standard deviation	*0.147*	*0.096*	*0.169*	*0.148*
Coefficient of variation (%)	*15.9*	*10.4*	*17.4*	*14.7*
Min	*0.736*	*0.756*	*0.790*	*0.803*
Max	*1.758*	*1.357*	*1.699*	*1.609*

Table 3: Primary club convergence results

Order-m Eco-efficiency $\hat{\varepsilon}_m(d, v)$	***log t***	***t-stat***
Full sample	-5.8971 (1.5561)	-3.7896**
Club 1 {35 states} [2,4,5,6,7,8,9,10,11,13,14,15,17,19,21,22,23,26,29, 30,31,33,34,36,37,38,40,41,42,43,44,46,47,48,50]	-5.745	-1.420
Club 2 {3 states} [24,39,45]	0.514	0.596
Club 3 {6 states} [1,3,18,25,28,32]	1.274	3.935
Club 4 {2 states} [12,16]	0.442	0.350
Club 5 {2 states} [27,35]	0.259	0.771
Club 6 {2 states} [49,51]	2.740	2.628
Non-converging Group 7 {1 state} [20]	-	-

Notes: The numbers in parentheses denote the standard errors. The term *log t* denotes the convergence coefficient, while *t-stat* is the convergence test statistic. The latter is distributed as a simple one-sided t-test with a critical value of −1.65. The first nine periods are discarded before each regression. ** denotes rejection of the null hypothesis (convergence) at 5% level of statistical significance.

Table 4: Final club convergence results

Order-m Eco-efficiency $\hat{\varepsilon}_m(d,v)$	***Merged clubs***	***log t***	***t-stat***	***Final club classification***	***log t***	***t-stat***
Initial classification						
Club 1 {35 states} [2,4,5,6,7,8,9,10,11,13,14,15,17,19,21,22,23,26,29, 30,31,33,34,36,37,38,40,41,42,43,44,46,47,48,50]	Club 1+ Club 2	-7.5553 (2.8529)	-2.6483**	Club 1	-5.745	-1.420
Club 2 {3 states} [24,39,45]	Club 2+ Club 3	-1.3376 (0.2137)	-6.2593**	Club 2	0.514	0.596
Club 3 {6 states} [1,3,18,25,28,32]	Club 3+ Club 4	1.1503 (0.4935)	2.3307	**Club 3 + Club 4**	1.1503	2.3307
Club 4 {2 states} [12,16]	Club 4 + Club 5	-0.2818 (0.1146)	-2.4579**			
Club 5 {2 states} [27,35]	Club 5+ Club 6	-0.6641 (0.2361)	-2.8129**	Club 5	0.259	0.771
Club 6 {2 states} [49,51]	Club 6+ Group 7	-2.0125 (0.1506)	-13.3662**	Club 6	2.740	2.628
Non-converging Group 7 {1 state} [20]						

Notes: The numbers in parentheses denote the standard errors. The term *log t* denotes the convergence coefficient, while *t-stat* is the convergence test statistic. The latter is distributed as a simple one-sided t-test with a critical value of −1.65. The first nine periods are discarded before each regression. ** denotes rejection of the null hypothesis (convergence) at 5% level of statistical significance. Final converging merged clubs in bold.

Table 5: Initial club classifications for the three indicators

***Order-m* *Eco-efficiency* $\hat{\varepsilon}_m(d,v)$**			***Conventional* *Eco-efficiency* $\hat{\varepsilon}(d,v)$**			***Robust* *Eco-efficiency(convexified Order-m)* $\hat{\varepsilon}_m^C(d,v)$**		
	log t	***t-stat***		***log t***	***t-stat***		***log t***	***t-stat***
Full sample	-5.8971 (1.5561)	-3.7896**	Full sample	-1.2497 (0.0447)	-27.9561**	Full sample	-1.2304 (0.0443)	-27.7789**
Club 1 {35 states} [2,4,5,6,7,8,9,10,11,13,14,15,17,19,21,22,23,26,29,30,31,33,34,36,37,38,40,41,42,43,44,46,47,48,50]	-5.745	-1.420	**Club 1 {3 states}** [5,8,33]	-3.156	-6.795**	**Club 1 {3 states}** [5,8,33]	-3.320	-6.425**
Club 2 {3 states} [24,39,45]	0.514	0.596	**Club 2 {4 states}** [22,31,44,48]	0.592	1.414	**Club 2 {4 states}** [22,31,44,48]	0.580	1.424
Club 3 {6 states} [1,3,18,25,28,32]	1.274	3.935	**Club 3 {6 states}** [10,15,21,34,39,47]	0.005	0.034	**Club 3 {6 states}** [10,15,21,34,39,47]	-0.010	-0.074
Club 4 {2 states} [12,16]	0.442	0.350	**Club 4 {3 states}** [7,11,36]	0.688	0.493	**Club 4 {2 states}** [11,36]	2.831	3.640
Club 5 {2 states} [27,35]	0.259	0.771	**Club 5 {9 states}** [4,6,23,24,38,40,42,43,50]	-0.040	-0.127	**Club 5 {7 states}** [6,7,23,24,38,43,50]	0.394	1.643
Club 6 {2 states} [49,51]	2.740	2.628	**Club 6 {17 states}** [1,2, 9,12,13,14,16,17, 18, 19,20,26,29,30,37,41,45]	-0.055	-0.328	**Club 6 {18 states}** [1,4,9,13,14,16,17, 18,19,20,26,29,30, 37,40,41,42,45]	-0.164	-0.973
Non-converging Group 7 {1 state} [20]	-	-	**Club 7 {4 states}** [25,27,28,32]	0.036	0.131	**Club 7 {2 states}** [2,12]	-1.394	-0.801
			Club 8 {2 states} [3,35]	0.187	0.608	**Club 8 {4 states}** [25,28,32,35]	0.625	3.069
			Club 9 {2 states} [49,51]	-0.005	-0.011	**Club 9 {2 states}** [3,27]	0.256	1.029
			Non-converging Group 10 {1 state} [46]			**Club 10 {2 states}** [49,51]	-0.188	-0.381
						Non-converging Group 11 {1 state} [46]	-	-

Notes: The numbers in parentheses denote the standard errors. The term *log t* denotes the convergence coefficient, while *t-stat* is the convergence test statistic. The latter is distributed as a simple one-sided t-test with a critical value of −1.65. The first nine periods are discarded before each regression. ** denotes rejection of the null hypothesis (convergence) at 5% level of statistical significance.

Table 6: Merging convergence club results for the three indicators

Order-m ***Eco-efficiency*** $\hat{\varepsilon}_m(d,v)$			***Conventional*** ***Eco-efficiency*** $\hat{\varepsilon}(d,v)$			***Robust (convexified Order-m)*** ***Eco-efficiency*** $\hat{\varepsilon}_m^C(d,v)$		
	log t	***t-stat***		***log t***	***t-stat***		***log t***	***t-stat***
Club 1 + Club 2	-7.5553 (2.8529)	-2.6483**	Club 1 + Club 2	-2.219 (0.2317)	-9.577**	Club 1 + Club 2	-2.318 (0.2275)	-10.190**
Club 2 + Club 3	-1.3376 (0.2137)	-6.2593**	Club 2 + Club 3	-1.201 (0.1079)	-11.136**	Club 2 + Club 3	-0.980 (0.0533)	-18.380**
Club 3+ Club 4	1.1503 (0.4935)	2.3307	Club 3+ Club 4	-0.459 (0.0932)	-4.923**	Club 3+ Club 4	-0.332 (0.0963)	-3.447**
Club 4 + Club 5	-0.2818 (0.1146)	-2.4579**	Club 4 + Club 5	-0.386 (0.2268)	-1.701**	Club 4 + Club 5	-0.143 (0.0802)	-1.783**
Club 5 + Club 6	-0.6641 (0.2361)	-2.8129**	Club 5 + Club 6	-0.645 (0.0661)	-9.757**	Club 5 + Club 6	-0.580 (0.0879)	-6.596**
Club 6 + Group 7	-2.0125 (0.1506)	-13.3662**	Club 6 + Club 7	-0.723 (0.0858)	-8.425**	Club 6 + Club 7	-0.256 (0.1466)	-1.745**
			Club 7 + Club 8	-0.008 (0.1802)	-0.046	**Club 7 + Club 8**	-0.090 (0.1259)	-0.718
			Club 8 + Club 9	-0.291 (0.1820)	-1.600	Club 8 + Club 9	0.486 (0.1714)	2.835**
			Club 9 + Group 10	-1.198 (0.2532)	-4.731**	Club 9 + Club 10	-0.402 (0.0786)	-5.119**
						Club 10 + Group 11	-1.434 (0.3005)	-4.773**

Notes: The numbers in parentheses denote the standard errors. The term *log t* denotes the convergence coefficient, while *t-stat* is the convergence test statistic. The latter is distributed as a simple one-sided t-test with a critical value of −1.65. The first nine periods are discarded before each regression. ** denotes rejection of the null hypothesis (convergence) at 5% level of statistical significance. Final converging merged clubs in bold.

Table 7: Average eco-efficiency scores and rankings (1990-2017)

State	***Order-m Eco-efficiency*** $\hat{\varepsilon}_m(d,v)$			***Conventional Eco-efficiency*** $\hat{\varepsilon}(d,v)$			**Robust** ***(convexified Order-m) Eco-efficiency*** $\hat{\varepsilon}_m^C(d,v)$		
	Average efficiency	*Average growth rate (%)*	*Ranking*	*Average efficiency*	*Average growth rate (%)*	*Ranking*	*Average efficiency*	*Average growth rate (%)*	*Ranking*
Alabama [1]	0.901	+6.23	39	0.631	+10.12	37	0.640	+9.70	32
Alaska [2]	0.935	+7.93	22	0.636	+2.44	35	0.638	+2.63	33
Arizona [3]	0.938	+11.94	20	0.680	+18.31	27	0.685	+17.77	26
Arkansas [4]	0.872	+9.57	45	0.609	+4.76	46	0.614	+4.25	46
California [5]	0.983	+3.10	10	0.939	+11.72	2	0.941	+11.43	1
Colorado [6]	0.946	+5.04	17	0.694	+19.35	22	0.699	+18.42	23
Connecticut [7]	1.077	+27.32	4	0.747	+11.11	14	0.740	+7.73	17
Delaware [8]	0.941	+37.10	18	0.639	+17.52	33	0.636	+12.31	35
District of Columbia [9]	1.427	-22.59	2	0.914	+21.47	3	0.906	+25.51	3
Florida [10]	0.932	+4.68	24	0.787	+11.11	9	0.793	+10.49	8
Georgia [11]	0.918	+6.07	31	0.737	+15.97	16	0.744	+14.99	15
Hawaii [12]	0.889	+2.66	42	0.631	+4.34	38	0.635	+4.39	37
Idaho [13]	1.011	+0.19	8	0.712	-4.28	19	0.701	+1.31	21
Illinois [14]	0.953	+7.82	14	0.794	+8.77	7	0.798	+7.88	7
Indiana [15]	0.889	+3.11	43	0.675	+12.49	29	0.685	+11.82	27
Iowa [16]	0.911	+11.54	35	0.629	+10.50	39	0.635	+10.27	38
Kansas [17]	0.919	+21.21	30	0.624	+9.25	41	0.629	+7.68	41
Kentucky [18]	0.890	+7.33	41	0.622	+9.96	42	0.632	+9.73	40
Louisiana [19]	0.920	-0.24	29	0.676	+4.21	28	0.684	+4.17	28
Maine [20]	0.907	+8.80	36	0.634	+9.27	36	0.635	+9.76	39
Maryland [21]	0.963	+9.02	12	0.735	+17.46	18	0.738	+16.27	18
Massachusetts [22]	0.991	+15.75	9	0.783	+19.90	10	0.784	+17.60	10
Michigan [23]	0.917	+2.90	32	0.744	+7.50	15	0.752	+7.06	14
Minnesota [24]	0.949	+3.89	15	0.711	+14.18	20	0.716	+13.52	19
Mississippi [25]	0.878	+7.74	44	0.616	+2.30	43	0.621	+1.71	43
Missouri [26]	0.914	+0.21	34	0.683	+6.62	26	0.691	+6.47	25
Montana [27]	0.832	+8.79	48	0.576	+7.54	48	0.570	+7.12	48
Nebraska [28]	0.872	+8.18	46	0.614	4.83	44	0.619	+4.12	44
Nevada [29]	0.955	+36.30	13	0.637	+13.82	34	0.638	+10.26	34
New Hampshire [30]	0.938	+26.90	21	0.646	+15.59	31	0.646	+14.62	31
New Jersey [31]	1.034	+19.05	5	0.828	+9.62	5	0.825	+7.11	5
New Mexico [32]	0.851	+13.01	47	0.594	+10.82	47	0.599	+9.66	47
New York [33]	0.977	+8.10	11	0.891	+15.15	4	0.893	+14.30	4
North Carolina [34]	0.923	+4.34	27	0.736	+13.55	17	0.743	+12.84	16
North Dakota [35]	0.779	+9.91	50	0.554	+4.37	49	0.546	+11.06	50
Ohio [36]	0.921	+8.37	28	0.752	+9.45	13	0.759	+8.40	13
Oklahoma [37]	0.907	+11.68	37	0.629	+12.88	40	0.636	+12.65	36
Oregon [38]	1.017	+7.62	7	0.705	+7.01	21	0.704	+6.08	20
Pennsylvania [39]	0.929	+9.05	25	0.766	+10.91	11	0.772	+9.85	11
Rhode Island [40]	1.213	+44.39	3	0.694	-5.05	23	0.666	-5.14	29
South Carolina [41]	0.939	+11.26	19	0.652	+11.73	30	0.657	+11.23	30
South Dakota [42]	0.917	+27.99	33	0.642	+12.49	32	0.627	+13.42	42
Tennessee [43]	0.929	+7.37	26	0.692	+17.84	25	0.698	+16.66	24
Texas [44]	0.904	+2.34	38	0.811	+14.03	6	0.819	+13.61	6
Utah [45]	0.896	+20.78	40	0.611	+14.16	45	0.615	+12.77	45
Vermont [46]	1.602	-8.45	1	0.940	+0.63	1	0.926	+1.56	2
Virginia [47]	0.949	+3.04	16	0.756	+11.03	12	0.761	+10.59	12
Washington [48]	1.018	+3.47	6	0.794	+13.45	8	0.792	+13.09	9
West Virginia [49]	0.783	+4.87	49	0.554	+5.05	50	0.563	+4.37	49
Wisconsin [50]	0.933	+3.56	23	0.694	+11.02	24	0.700	+10.41	22
Wyoming [51]	0.772	+9.15	51	0.539	+6.11	51	0.538	+5.98	51

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