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**To cite this article:** Umit Bulut (03 Jan 2025): State-level energy intensity convergence in the US: fresh empirical evidence, Applied Economics Letters, DOI: [10.1080/13504851.2024.2449547](https://doi.org/10.1080/13504851.2024.2449547)

**To link to this article:** <https://doi.org/10.1080/13504851.2024.2449547>



Published online: 03 Jan 2025.



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## State-level energy intensity convergence in the US: fresh empirical evidence

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### ABSTRACT

Energy intensity refers to energy consumption per unit of GDP. Therefore, a decline in energy intensity implies that either more output is produced with the same amount of energy use or less energy is used to produce the same output level. Considering that fossil energy dominates the energy mix in the US and that fossil energy use causes many environmental problems, it is crucial to determine the levels of energy intensities of the states in the US and whether they tend to converge over time.

This study aims to analyze the possible convergence patterns in energy intensity for the states in the US over the period 2000–2021. Accordingly, the paper first examines  $\beta$ -convergence and then investigates stochastic convergence. This study diverges from prior research in two respects. First, the study gives state-specific findings. Second, one of the unit root tests employed in this work considers structural breaks, whilst the other is based on machine learning methodologies. The findings indicate that the convergence hypothesis is validated solely for Alaska, Oklahoma, Texas, and Vermont, suggesting there is minimal evidence supporting energy intensity convergence among the states. This study contends that to decrease energy intensity in the US, it is crucial to provide greater support for environmental innovations, particularly in states with high energy intensities.

### KEYWORDS

Convergence analysis; energy intensity convergence;  $\beta$ -convergence; stochastic convergence

### JEL CLASSIFICATION

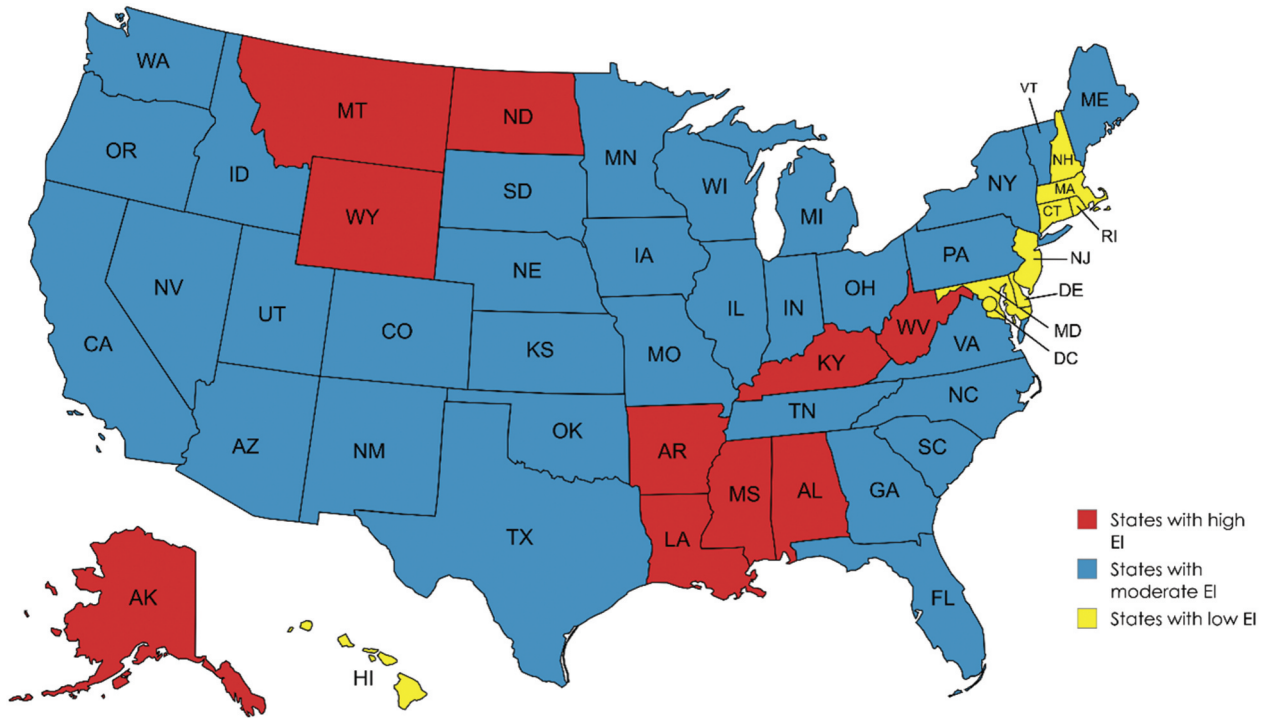
C22; O13

## I. Introduction

Despite the implementation of many renewable energy policies, fossil energy remains the dominant energy source in the United States (US), resulting in global warming and climate change. According to the US Energy Information Administration (2024) data, the proportions of fossil and renewable energy consumption in primary energy consumption in the US were about 83% and 8.5%, respectively, in 2022. Given that energy intensity (EI) is defined as the quantity of energy consumed per unit of GDP (Balado-Naves, Baños-Pino, and Mayor 2023; Miketa and Mulder 2005; Yu, Zhang, and Song 2015), a decrease in EI could simultaneously ensure that growth is not sacrificed and aid in the struggle against climate change.

Figure 1 categorizes the states in the US into three groups based on their EIs, expressed as thousand Btu per chained 2017 dollar of GDP, utilizing the average figures over the 2000–2021 period. States with an EI below 5 are classified as states with low EI, those with an EI ranging from 5 to 10

are classified as states with moderate EI, and those with an EI above 10 are classified as states with high EI. This figure demonstrates that geographical location appears to be significant for EI. Consequently, states with low EI predominantly reside in the Northeast region, whilst states with high EI are primarily located in the West and South regions. The figure illustrates that certain states use energy more efficiently compared to others. This is the moment when a research question becomes quite significant: do the disparities in EIs of the states tend to shrink over time? Alternatively stated, do the EIs of states converge to an average as time progresses? The convergence analysis can provide an appropriate response to this inquiry. Hence, the present study investigates the convergence patterns of EI among the states in the US over the period 2000–2021 through the convergence methodology of Carlino and Mills (1993). This study makes several contributions to the existing literature. First, the sole study specifically investigating the convergence of EI for the US



**Figure 1.** Classification of states by EI (2000–2021). Source: US Energy Information Administration (2024)

belongs to Burnett and Madariaga (2017), who presented evidence supporting convergence. Thus, a significant deficiency exists in the existing body of knowledge regarding this subject. Second, Burnett and Madariaga (2017) investigated the impact of lagged EI on its current value within a panel data framework and did not provide state-specific outcomes. However, this paper presents state-by-state results. Third, this paper considers recent developments in unit root testing, such as machine learning methodology and structural breaks.

The rest of the paper is as follows: methodology and data are given in Section II. Results are reported in Section III, while Section IV concludes the paper.

## II. Methodology and data

Carlino and Mills (1993) introduced a two-stage approach for the conditional convergence analysis by emphasizing the growth rate of the related variable and its dispersion from the average. This paper adopts this methodology to examine the convergence of EI in the US. Accordingly,  $\beta$ -convergence is analysed in the first stage, meaning the following model is estimated:

$$x_{it} = \mu_i + \beta_i t + u_{it} \quad (1)$$

In Equation (1),  $x_{it} = \ln(EI_{i,t}/\bar{EI}_t)$  where  $EI_{i,t}$  represents the EI of a state at period  $t$ ,  $\bar{EI}_t$  denotes the average EI of states at period  $t$ , and  $\ln$  represents the natural logarithm. Besides,  $\mu$  stands for the initial level of  $x_{it}$  and  $u_{it}$  is the error term. In the presence of significant coefficients, if  $\mu > 0$  and  $\beta < 0$  or if  $\mu < 0$  and  $\beta > 0$ , one can conclude there exists  $\beta$ -convergence. In the second stage, unit root testing is conducted on  $x_t$  to examine stochastic convergence. For unit root analysis, the paper first considers the unit root test of Enders and Lee (2012), who take both sharp and smooth breaks into account in series. Then, it employs the unit root test that is derived from the autoregressive neural network (ARNN) model and was propounded by Yaya et al. (2021). As Yaya et al. (2021) and Caglar, Daştan, and Avci (2024) stress, the ARNN model can produce more accurate outcomes than the conventional unit root tests. The model considers all potential functions by employing a non-linear framework for any function during the learning process. The neural network method is based on data and doesn't make any hard assumptions. Hence, the neural network method releases all the possible assumptions and processes it based on how the information is structured. Due to its

foundation on the augmented Dickey-Fuller (ADF) unit root test, this novel test is named the ARNN-ADF unit root test. The regression model for this test is described as follows (Yaya et al. 2021):

$$\Delta x_t = \alpha + \beta t + k_1 \rho x_{t-1} + k_{11} x_{t-1}^2 + k_{111} x_{t-1}^3 + \sum_{j=1}^q z_j \Delta x_{t-j} + \varepsilon_t \quad (2)$$

where  $\alpha$ ,  $t$ ,  $z$ , and  $q$  stand for the constant, the trend, the augmentation coefficient, and the optimal lag length detected via an information

criterion. Besides,  $k_1$ ,  $k_{11}$ , and  $k_{111}$  denote the coefficients for the linear part, the nonlinear part, and the cubic part, respectively. If the test statistic is greater than the critical values, the null hypothesis of a unit root is rejected, implying the series under consideration is stationary.

If there is  $\beta$ -convergence and the series is stationary, then one can conclude that there is convergence. Annual EI (thousand Btu per chained 2017 dollar of GDP) data covering the period 2000–2021 are utilized in this paper. Data are

**Table 1.** Results of the convergence analysis.

State	$\mu$	t-stat.	$\beta$	t-stat.	E&L test	ARNN-ADF test	Result
Alabama	0.881*	37.660	-0.001	-0.002	-3.075	0.688	D
Alaska	0.397*	13.526	-0.010**	-2.585	-2.327	-3.407**	C
Arizona	1.044*	21.321	0.001	1.460	-2.262	-4.317	D
Arkansas	0.908*	29.226	0.001	0.097	-2.247	0.655	D
California	0.854*	35.855	-0.013*	-11.775	0.825	-0.294	D
Colorado	0.681*	12.589	-0.002	-1.456	-4.497*	-0.772	D
Connecticut	0.985*	40.264	-0.001	-0.721	3.369	0.103	D
Delaware	1.066*	24.959	0.006*	4.300	-2.959	0.802	D
District of Columbia	0.972*	95.925	-0.015*	-15.181	-0.518	2.885	D
Florida	0.989*	18.520	-0.001	-1.119	-1.324	-0.028	D
Georgia	0.584*	4.011	-0.003***	-2.078	-1.669	-0.687	D
Hawaii	0.876*	24.723	-0.002	-1.573	-3.955**	-0.272	D
Idaho	0.844*	15.101	-0.003*	-2.864	-2.357	1.972	D
Illinois	0.948*	34.149	0.003*	4.851	-3.248	1.258	D
Indiana	1.192*	21.587	-0.001	-0.823	-2.647	-0.565	D
Iowa	0.893*	5.355	0.012*	8.864	-1.943	-0.222	D
Kansas	1.216*	13.296	-0.003*	-5.074	-1.964	0.101	D
Kentucky	1.411*	19.507	-0.005*	-3.109	-3.504	-0.816	D
Louisiana	0.817*	27.363	0.014*	7.351	-0.496	1.173	D
Maine	0.723**	2.587	-0.002	-1.264	-2.577	1.655	D
Maryland	0.872*	33.603	-0.011*	-14.088	-0.594	1.238	D
Massachusetts	0.943*	55.312	-0.009*	-9.672	-0.021	0.766	D
Michigan	0.777*	10.334	0.003*	3.402	-3.823	-1.166	D
Minnesota	0.771*	14.440	0.001	0.801	-5.343*	-0.101	D
Mississippi	0.934*	53.967	0.001**	2.024	-4.146**	0.316	D
Missouri	0.584*	7.442	0.002**	2.765	-4.211**	0.808	D
Montana	0.891*	17.191	-0.002	-1.368	-2.929***	-0.056	D
Nebraska	0.231	0.073	0.008*	6.149	-1.333	1.923	D
Nevada	1.062*	27.152	0.007*	6.557	-5.184*	-0.229	D
New Hampshire	0.976*	33.328	-0.001	-0.910	-2.950**	-1.100	D
New Jersey	0.845*	25.360	-0.005*	-4.275	-1.928	0.869	D
New Mexico	0.156	0.503	0.006*	5.458	-1.411	-1.705	D
New York	0.940*	54.121	-0.008*	-7.437	-0.942	0.103	D
North Carolina	0.891*	19.091	-0.004*	-6.246	-1.248	0.587	D
North Dakota	0.995*	18.353	-0.001	-0.304	-2.502	0.841	D
Ohio	0.698*	2.993	-0.002*	-3.057	-3.127	0.116	D
Oklahoma	0.985*	29.179	-0.003*	-4.272	-4.105**	0.447	C
Oregon	1.443*	8.488	-0.011*	-14.130	-2.491	-0.091	D
Pennsylvania	0.886*	[18.405]	-0.002*	-3.658	-2.338	-1.342	D
Rhode Island	1.008*	44.540	0.001	1.657	-4.624*	0.050	D
South Carolina	1.192*	16.507	-0.002**	-2.234	-2.496	-0.416	D
South Dakota	0.647	0.791	0.013*	11.532	-1.788	1.117	D
Tennessee	1.944*	10.818	-0.005*	[-6.328]	-1.893	-0.133	D
Texas	0.908*	14.928	-0.007*	-4.692	-1.861	-2.758***	C
Utah	0.931*	5.645	-0.009*	-8.117	-0.523	-0.696	D
Vermont	0.886*	15.457	-0.005*	-4.133	-3.856**	1.278	C
Virginia	0.941*	22.326	-0.002**	-2.738	-3.170	-0.082	D
Washington	0.920*	6.917	-0.016*	-8.387	-1.306	-0.067	D
West Virginia	0.925*	16.831	0.012*	9.371	-0.614	0.222	D
Wisconsin	0.891*	10.905	-0.001	-0.775	-4.606*	-0.017	D
Wyoming	0.867*	22.287	0.011*	6.947	-1.703	2.172	D

Notes: C and D respectively mean convergence and divergence. Critical values for unit root tests are available upon request. \*, \*\*, and \*\*\* respectively illustrate 1%, 5% and 10% statistical significance.

extracted from the US Energy Information Administration (2024).

### III. Empirical findings

The outputs of the convergence analysis are exhibited in Table 1. It should be reminded that if  $\beta$ -convergence exists and the series is stationary according to at least one unit root test, then convergence can be inferred. Hence, EI convergence is only available for Alaska, Oklahoma, Texas, and Vermont. In other words, the confirmation of EI convergence is limited to these four states. Therefore, the empirical results present compelling evidence in support of divergence in the EIs of the states.

### IV. Conclusion

This study examined the convergence of EIs of the states in the US over the period 2000–2021. The results suggested that EI convergence was present in only four states, namely Alaska, Oklahoma, Texas, and Vermont. The study's results have some significant implications. First, the efforts of the US to address climate change can be jeopardized by the presence of states with high EI and the discovery of EI divergence, which may necessitate the incremental implementation of energy conservation strategies (see e.g. Herrerias 2012; Markandya, Pedrosogalino, and Streimikiene 2006). Second, it is widely acknowledged the manufacturing industry consumes a greater amount of energy than the services sector. The data indicate that there can be an association between the proportion of manufacturing in GDP of states and their EIs. For instance, as per The National Association of Manufacturers (2024) data, in Arkansas, Kentucky, Louisiana, and Mississippi, which have high EI, the share of the manufacturing sector in GDP for 2021 was 14.75%, 17.39%, 16.84%, and 14.67%, respectively. Conversely, in Delaware, Hawaii, Maryland, and New York, which have low EI, this share was 6.80%, 1.63%, 6.31%, and 4.21%, respectively. Besides, it can be contended that geographical proximity can result in comparable production structures, as the states with low EI are situated in the

Northeast region. Recent research has demonstrated that environmental innovations enhance energy efficiency (Paramati, Shahzad, and Doğan 2022; Sun et al. 2021). As a result, to enhance energy efficiency in manufacturing, particularly in states with high EI, environmental innovations must be promoted and supported further. Third, future research may examine club convergence rather than the overall convergence for EI across states, as the share of manufacturing in GDP and geographical location seem to influence EI in the US.

### Disclosure statement

No potential conflict of interest was reported by the author(s).

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### Data availability statement

The data are available upon request.

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