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The Driving Forces of Energy-Related CO_2 Emissions in the United States: A Decomposition Analysis

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Abstract

This paper uses the logarithmic mean Divisia index (LMDI) approach to decomposition analysis to identify the factors that influence changes in carbon dioxide (CO_2) emissions in the United States. The LMDI approach decomposes CO_2 emissions into specific determinants. The data set includes the 50 states plus the District of Columbia from 1998 – 2018. The five factors that influence the change in CO_2 emissions include the emissions per unit of fossil fuel consumption, share of fossil fuels in total energy consumption, energy intensity, GDP per capita, and population. The results indicate that, during the 20-year period, CO_2 emissions declined in 36 states plus the District of Columbia. The reduction in energy intensity served as the most important factor in the change of CO_2 emissions, offsetting 63 percent of the effects of per capita GDP and population. From the perspective of climate change, the importance of a change in energy intensity demonstrates the effectiveness of a decrease in primary energy consumption per unit of GDP.

Keywords: decomposition analysis, carbon dioxide emissions, fossil fuels, carbon intensity, energy intensity

1. Introduction

Fossil fuel consumption serves as the major contributor to CO_2 emissions in the atmosphere (IPCC, 2021). According to the IPCC (2021), a higher atmospheric concentration of CO_2 leads to a rise in global surface temperature, an increase in average global precipitation, the retreat of glaciers, warming of the upper ocean, sea level rise, and poleward shifting of climate zones. The report emphasizes that the increase in CO_2 emissions since 1750 is unequivocally caused by human activities (IPCC, 2021). An increase in the average global temperature of 1.5C is expected to raise the length and intensity of heat waves, floods, and storms, apply pressure to public health systems, and reduce agricultural yields (Hoegh-Guldberg et al., 2019).

The contribution of the paper is to apply the LMDI decomposition approach to identify the factors that alter CO_2 emissions at the state level in the United States from 1998 – 2018. We update Vinuya et al. (2010), who apply the decomposition approach to U.S. states during the period 1990 – 2004. The current paper finds that, between 1998 – 2018, 36 states plus the District of Columbia experienced a decline in CO_2 emissions. The results differ from Vinuya et al. (2010), who found that, during 1990 – 2004, 48 states experienced an increase in emissions. In our paper, the decline in energy intensity served as the most important factor, offsetting 63 percent of the effects of per capita GDP and population.

The five factors that influence the change in CO_2 emissions include (1) carbon intensity, (2) the share of fossil fuel consumption in total energy consumption, (3) total energy consumption per unit of GDP, (4) GDP per capita, and (5) population. The variability of CO_2 emissions can be explained by the states' different economic, energy, and policy effects. States have implemented different policies to curb CO_2 emissions, including renewable portfolio standards, greenhouse gas emission targets, climate action plans, and carbon pricing.

The decomposition approach decomposes emission aggregates into explanatory factors (Chen et al., 2018; Ang, 2015; Ang & Liu, 2001; Ang et al. 1998). As Karmellos et al. (2016) explain, "Although synergies and other interactions between factors are not possible to be detected, decomposition results identify the relative contributions of major driving forces behind changes of various indicators over time, offering valuable information for the design and/or adaption of future policies and measures." Robaina & Neves (2021), Moutinho et al. (2015), Gonzalez et al. (2014), and Diakoulaki & Mandaraka (2007) use the decomposition approach to analyze the driving factors of CO_2 emissions in the European Union. Wang et al. (2020), Jiang et al. (2019), and Vinuya et al. (2010) apply the decomposition approach to CO_2 emissions in the United States. Cheng et al. (2022), Wang et al. (2019), Ma et al. (2018), Zhang et al. (2013), and Donglan et al. (2010) analyze China. Wang et al. (2018) and Andreoni & Galmarini (2016) apply decomposition analysis in comparative country perspectives. To identify the driving forces behind CO_2 emissions in the United States, the paper is organized as follows. Section 2 explains the method. Section 3 provides the results and a discussion. Section 4 concludes.

2. Method

Since the publications by Ang et al. (1998), Ang & Liu (2001), and Ang (2005) that explain decomposition analysis, academics have used this technique in energy and environmental research. Because the technical description of the approach is found in these articles, this section provides a brief overview. The strengths of the approach are twofold: decomposing an aggregate indicator such as CO_2 emissions provides quantitative measures of the contributions of explanatory factors. In addition, as Ang & Liu (2001) explain, the LMDI model is consistent in aggregation, allowing aggregation of the results in a consistent manner without residuals. The weakness of the technique is that it uses a base year and end year in a time series framework, which may mask trends that occur during the period. The paper acknowledges these pros and cons.

2.1 Theory

The model includes five factors: (1) carbon intensity (CO_2 emissions per unit of fossil fuel consumed), (2) energy mix (fossil fuel consumed per unit of total energy consumed), (3) energy intensity (energy consumed per unit of GDP), (4) GDP per capita, and (5) population (Ang, 2005). In the model, CO_2 emissions are decomposed into the five factors:

CO_2 emissions from energy =

$$\text{(carbon intensity)(energy mix)(energy intensity)(GDP per capita)(population)} \quad (1)$$

Each factor contributes to CO_2 emissions. Carbon intensity provides the emission rate of CO_2, given the intensity of fossil fuel consumption. The energy mix establishes how dependent the economy is on fossil fuels. Energy intensity refers to the extent to which the economy relies on energy consumption for the production of output. Gross Domestic Production per capita establishes the degree of economic development of a state. Population normally correlates directly with economic activity. Following Vinuya et al. (2010), equation (1) includes the following terms:

E = CO_2 emissions from fossil fuel consumption

FEC = total fossil fuel consumption

TEC = total primary energy consumption

GDP = gross domestic product

POP = population

Using these terms, equation (1) may be rewritten for each state i as:

$$E_i = (E_i/FEC_i) \text{ x } (FEC_i/TEC_i) \text{ x } (TEC_i/GDP_i) \text{ x } (GDP_i/POP_i) \text{ x } (POP_i) \quad (2)$$

$$= C_iS_iI_iG_iP_i \quad (3)$$

The change in a state's CO_2 emissions (ΔE_i) between a base year 0 and end year T decomposes into a (1) ΔC_i (carbon intensity, called the coefficient effect C_{eff}), (2) ΔS_i (energy mix, called the substitution effect, S_{eff}), (3) ΔI_i (energy intensity effect, I_{eff}), (4) ΔG_i (GDP per capita, G_{eff}), and (5) ΔP_i (population effect, P_{eff}). As Karmellos et al. (2016) explain, each individual effect may be decomposed using the additive LMDI approach into five driving factors:

$$\Delta E_i = E_i(T) - E_i(0) = C_{eff} + S_{eff} + I_{eff} + G_{eff} + P_{eff} \quad (4)$$

The additive approach to decomposition establishes a method to evaluate the relative contribution of each of the five factors. As the Results section below makes clear, the approach provides a framework that establishes which of the factors are more important than others for the change in CO_2 emissions. This is therefore a useful method for both policymaking and academic research.

Ang & Liu (2001) demonstrate that these effects may be calculated in the LMDI approach with the following equations:

$$C_{eff} = [E_i(T) - E_i(0)] \text{ x} \left[\frac{\ln[C_i(T)/C_i(0)]}{\ln[E_i(T)/E_i(0)]} \right] \tag{5}$$

$$S_{eff} = [E_i(T) - E_i(0)] \text{ x} \left[\frac{\ln[S_i(T)/S_i(0)]}{\ln[E_i(T)/E_i(0)]} \right] \tag{6}$$

$$I_{eff} = [E_i(T) - E_i(0)] \text{ x} \left[\frac{\ln[I_i(T)/I_i(0)]}{\ln[E_i(T)/E_i(0)]} \right] \tag{7}$$

$$G_{eff} = [E_i(T) - E_i(0)] \text{ x} \left[\frac{\ln[I_i(T)/I_i(0)]}{\ln[E_i(T)/E_i(0)]} \right] \tag{8}$$

$$P_{eff} = [E_i(T) - E_i(0)] \text{ x} \left[\frac{\ln[I_i(T)/I_i(0)]}{\ln[E_i(T)/E_i(0)]} \right] \tag{9}$$

2.2 Calculation

With data for the variables for the base year (1998) and the end year (2018), decomposition of ΔE_i was calculated for each state according to equations (5) – (9). For each state, ΔE_i reflects changes in the five factors. The reason is the nature of the link between variables. Economic, policy, and demographic circumstances alter the factors that impact CO_2. A shift to fossil fuels that emit lower levels of CO_2 (more natural gas and less coal) reduces the amount of CO_2 emissions per unit of fossil fuel consumption. A shift to renewables reduces the percentage of fossil fuel consumption out of total primary energy consumption. When the share of total energy consumption per unit of GDP declines, a state's energy intensity decreases. The reasons for the latter outcome include state economies shifting toward sectors that are less energy intensive and an increase in energy efficiency in one or more sectors (Vinuya et al., 2010).

2.3 Data

We found the state-level data for CO_2 emissions from fossil fuel consumption in the U.S. Department of Energy's Energy Information Administration website (https://www.eia.gov). The U.S. Energy Information Administration's State Energy Data System includes the state-level energy consumption for fossil fuels, renewable energy sources, and total energy consumption in billions of British thermal units (https://catalog.data.gov/dataset/state-energy-data-system-seds). Fossil fuel consumption includes the following categories: coal, natural gas, asphalt and road oil, aviation gasoline, distillate fuel, jet fuel, kerosene, LPG, lubricants, motor gasoline, residual fuel and other petroleum products. Emissions intensity of fossil fuels is the ratio of CO_2 emissions from fossil fuels to the consumption of fossil fuels. The ratio of consumption of fossil fuels to the total consumption of energy provides the value for the share of fossil fuels in total energy. Data for GDP come from the Bureau of Economic Analysis' website for Regional Economic Accounts (https://bea.gov/data/economic-accunts/regional). The ratio of total energy consumption to state GDP provides the measure for state-level energy intensity. Population data come from the St. Louis Federal Reserve's FRED database (https://fred.stlouisfed.org).

3. Results and Discussion

3.1 Level of emissions

Table 1 provides a state ranking for absolute CO_2 emission levels. The top 10 states for CO_2 emissions in 2018 account for 50 percent of the country's total emissions. The state in the top position, Texas, emits 326 million metric tons (mmt) more than the state in the second position, California. The states in positions two through 10 cluster between 163 million metric tons of CO_2 (Michigan) and 355 million metric tons of CO_2 (California). In contrast, Vermont, the state at the bottom, emits less than 6 mmt of CO_2. The District of Columbia emits less than 3 mmt.

Table 1. CO_2 emissions, 2018 (mmt) and change since 1998

State	Rank	Emissions in 2018	Change since 1998	% Change since 1998	State	Rank	Emissions in 2018	Change since 1998	% Change since 1998
TX	1	681.91	4.02	0.59	SC	27	73.20	-1.31	-1.76
CA	2	355.50	-3.30	-0.92	AR	28	70.90	9.60	15.66
FL	3	242.48	9.01	3.86	MA	29	64.36	-19.92	-23.64
PA	4	219.84	-46.27	-17.39	WY	30	63.44	-0.68	-1.06
IL	5	211.53	-5.02	-2.32	MS	31	63.15	6.23	10.95
OH	6	208.51	-51.47	-19.80	KS	32	62.08	-8.73	-12.33
LA	7	198.69	-9.08	-4.37	MD	33	61.49	-14.02	-18.57
IN	8	188.30	-30.70	-14.02	UT	34	60.93	-2.81	-4.41
NY	9	175.40	-28.91	-14.15	ND	35	58.89	9.89	20.19
MI	10	163.62	-28.67	-14.91	NE	36	52.31	8.98	20.72
GA	11	142.40	-16.61	-10.44	NM	37	45.21	-10.51	-18.86
NC	12	124.36	-19.15	-13.34	NV	38	40.91	-0.08	-0.21
MO	13	124.33	-6.10	-4.68	OR	39	39.75	-1.56	-3.77
KY	14	120.80	-18.87	-13.51	CT	40	37.50	-3.10	-7.64
AL	15	112.90	-22.00	-16.31	AK	41	35.00	-8.40	-19.35
VA	16	107.44	-5.21	-4.62	MT	42	30.72	-0.06	-0.21
NJ	17	105.08	-14.13	-11.86	HI	43	20.46	1.53	8.07
WI	18	101.65	-0.36	-0.35	ID	44	18.91	4.76	33.62
OK	19	97.40	-0.23	-0.23	SD	45	15.55	2.64	20.41
MN	20	94.88	2.81	3.05	ME	46	14.71	-4.82	-24.69
TN	21	94.38	-27.08	-22.30	NH	47	14.22	-2.55	-15.18
AZ	22	93.60	16.50	21.40	DE	48	13.30	-1.70	-11.33
CO	23	90.30	11.90	15.18	RI	49	11.07	-2.88	-20.63
WV	24	89.75	-25.44	-22.09	VT	50	5.83	-0.45	-7.14
IA	25	82.56	4.94	6.37	DC	51	2.90	-1.20	-29.27
WA	26	76.73	0.31	0.40					

Table 1 also reveals that 14 states experienced an increase in CO_2 emissions between 1998 and 2018 with Arizona and Colorado in the top positions with their emissions increasing by 16.5 mmt and 11.9 mmt, respectively. In terms of increasing emissions, North Dakota (9.89 mmt), Arkansas (9.60 mmt), and Florida (9.01 mmt) complete the top five.

The most important result from Table 1, however, is that, between 1998 – 2018, CO_2 emissions declined in 36 states plus the District of Columbia. This result differs from the analysis of Vinuya et al. (2010), in which only two states (Massachusetts and Delaware) experienced a decrease in CO_2 emissions between 1990 – 2004. At the top of the list of states experiencing a decline in CO_2 emissions is Ohio with a decrease in 51.47 mmt, followed by Pennsylvania (46.27 mmt), Indiana (30.70 mmt), New York (28.91 mmt), and the District of Columbia (29.27 mmt).

Table 2 includes emissions in metric tons per unit of GDP in 2018. With this variable, Wyoming has the highest level (1,670.08), followed by West Virginia (1,227.49) and North Dakota (1,053.79). The District of Columbia (23.42), New York (120.30), and Massachusetts (127.97) have the lowest levels. The District of Columbia, New York, and Massachusetts have the highest levels of GDP per capita.

Table 2. CO_2 emissions per unit of GDP and GDP per capita, 2018

State	Emissions/GDP (metric tons per million US$)	GDP Per Capita	Area	Emissions/GDP (metric tons per million US$)	GDP Per Capita
AL	562.25	41,049.91	MT	659.05	43,900.27
AK	657.28	72,288.71	NE	447.49	60,713.41
AZ	298.45	43,775.64	NV	271.46	49,727.90
AR	611.54	38,489.84	NH	188.23	55,742.46
CA	134.48	67,032.11	NJ	191.03	61,862.48
CO	263.62	60,124.03	NM	496.84	43,462.32
CT	150.00	69,938.13	NY	120.30	74,600.31
DE	215.44	63,842.87	NC	246.73	48,506.61
DC	23.42	175,866.83	ND	1053.79	73,525.58
FL	257.01	44,387.99	OH	348.14	51,273.23
GA	264.04	51,267.26	OK	493.50	50,046.63
HI	256.19	56,113.12	OR	184.69	51,441.82
ID	266.07	40,566.44	PA	312.30	54,956.68
IL	273.27	60,831.76	RI	210.91	49,553.40
IN	558.51	50,332.25	SC	352.32	40,806.14
IA	477.45	54,899.97	SD	334.69	52,825.61
KS	390.66	54,555.46	TN	292.50	47,601.05
KY	642.29	42,130.85	TX	394.33	60,412.68
LA	840.97	50,652.40	UT	373.08	51,765.16
ME	252.83	43,413.03	VT	196.87	47,401.26
MD	166.80	61,012.01	VA	224.86	56,141.97
MA	127.97	73,043.09	WA	148.81	68,505.92
MI	349.73	46,842.60	WV	1227.49	40,485.11
MN	280.27	60,356.37	WI	339.50	51,540.64
MS	624.45	33,903.99	WY	1670.08	65,603.38
MO	434.73	46,685.56			

For the states with increasing levels of CO_2, Figure 1 includes the top 10 in percentage terms. Two western states, Idaho (33.62%) and Arizona (21.40%) top the list, followed by Nebraska (20.72%), South Dakota (20.41%), and North Dakota (20.19%). States in the south (Arkansas and Mississippi), Midwest (Iowa), and west (Colorado and Hawaii) are in the top 10.

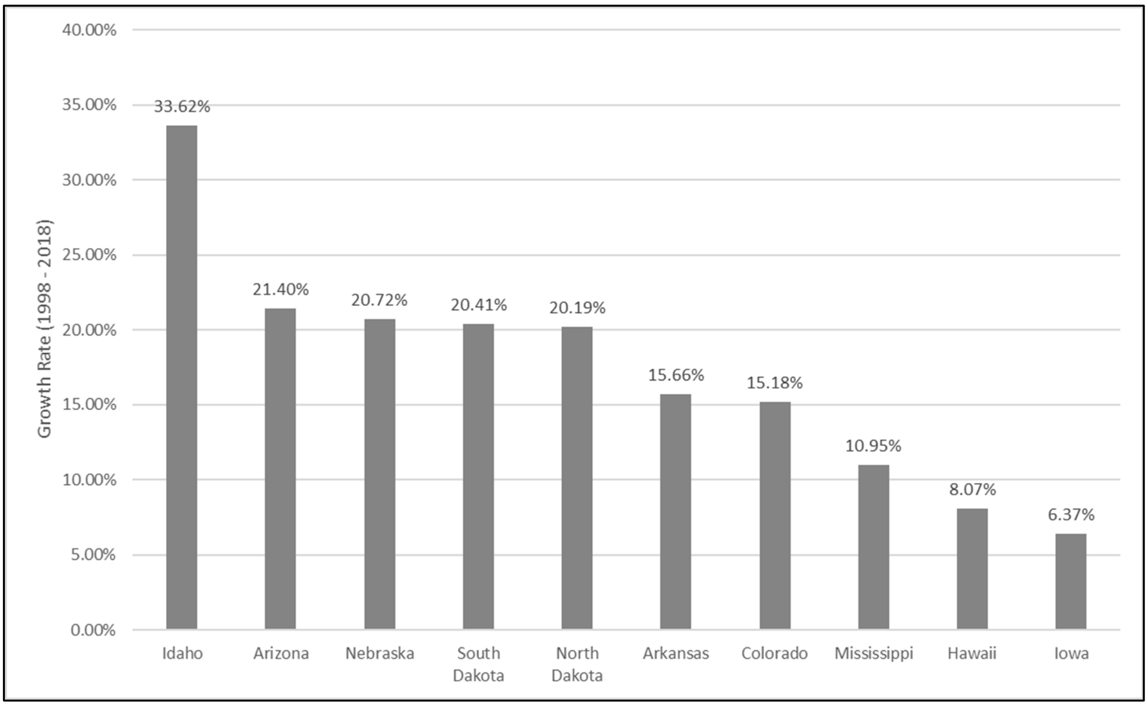
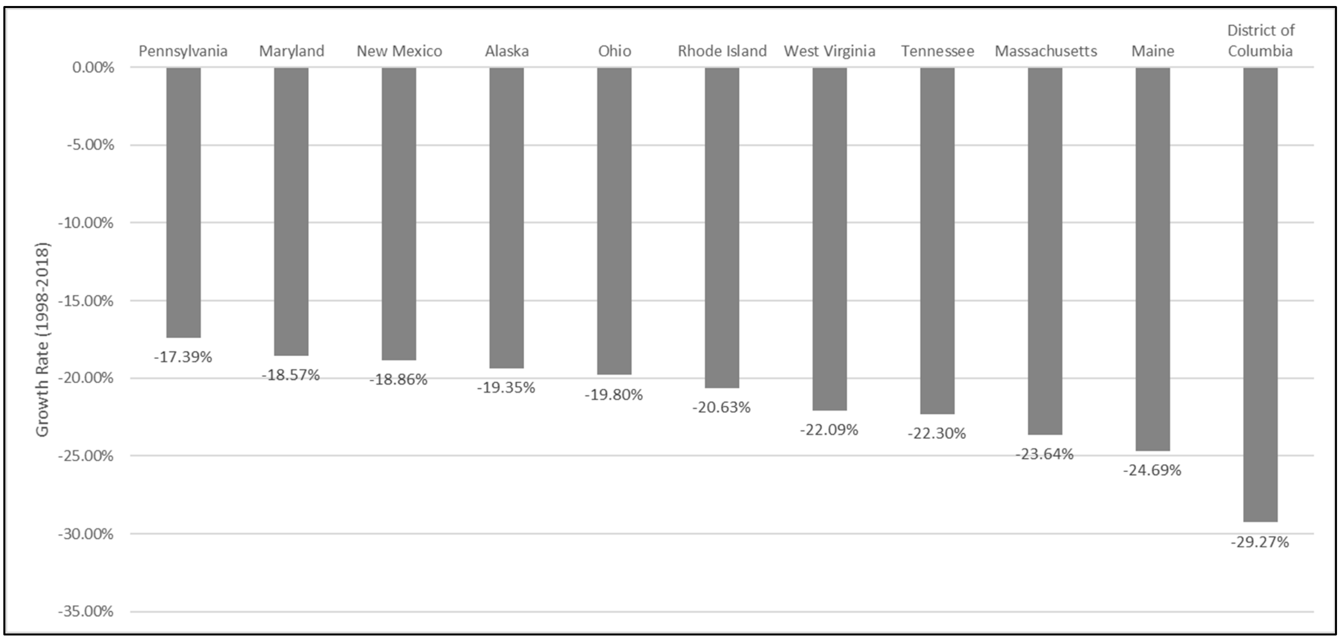


Figure 1. Ten largest percentage increases in CO_2 emissions (1998 – 2018)

This study demonstrates that most of the states during 1998 – 2018 experienced a decrease in CO_2 emissions. Figure 2 includes the top 10 states with decreasing CO_2 emissions in percentage terms. The District of Columbia (-29.27%) and Maine (-24.69%) experienced the largest percentage declines. Because they start with a small base, however, these two do not have much of an impact on the country's total. The remaining states with the largest percentage decreases include Massachusetts, Rhode Island, and Maryland in the east, Tennessee in the south, New Mexico and Alaska in the west, and a cluster of midwestern and mid-Atlantic states: Pennsylvania,



Ohio, and West Virginia.

Figure 2. Ten largest percentage decreases in CO_2 emissions (1998 – 2018)

With respect to total emissions, Figure 3 includes the 10 states with the largest decline in CO_2 emissions in millions of metric tons. These states contribute the most to the country's total decrease in emissions. The top five states include Ohio (-51.47 mmt), Pennsylvania (-46.27 mmt), Indiana (-30.70), New York (-28.91 mmt), and Michigan (-28.67 mmt).

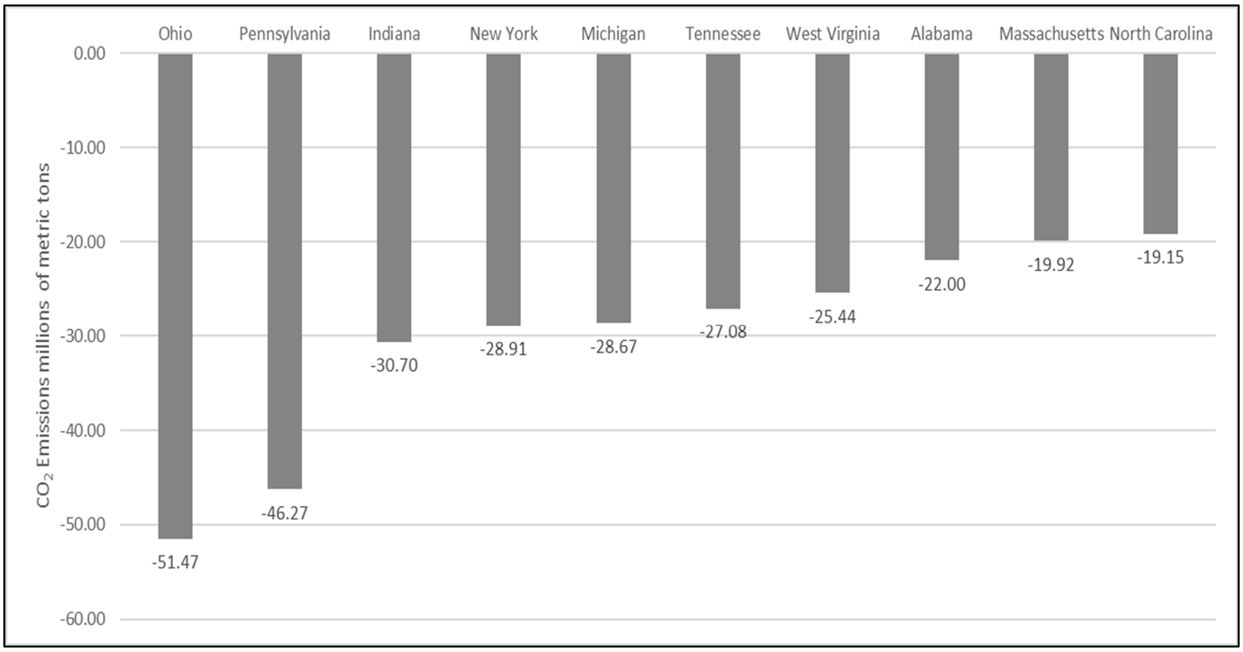


Figure 3. Ten largest decreases in CO_2 emissions in mmt (1998 – 2018)

3.2 Decomposition of Emissions

Table 3 includes the decomposition results for the change in CO_2 emissions between 1998 and 2018. In the aggregate, during the 20-year period of time, the United States experienced a decrease in 350 million metric tons of CO_2. At the state level, 36 states plus the District of Columbia experienced a decrease in CO_2 emissions. Fourteen states experienced an increase in CO_2 emissions. With the additive LMDI decomposition method, we calculate the increment of energy-related CO_2 emissions.

Table 3. Decomposition of the change in CO_2 emissions (1998 – 2018)

State	Change in emissions	Carbon intensity	Share of fossil fuels	Energy intensity	GDP per capita	Population
AL	-8.40	-0.40	-0.91	-17.21	3.08	7.03
AK	-22.00	-18.10	-1.15	-39.15	21.93	14.47
AR	16.50	-5.77	4.06	-27.59	9.35	36.46
AZ	9.60	-0.90	8.49	-18.80	9.52	11.30
CA	-3.30	5.15	-11.81	-206.55	142.81	67.10
CO	11.90	-3.85	-5.84	-23.44	14.59	30.44
CT	-3.10	-4.59	3.22	-11.15	5.97	3.45
DE	-1.70	-1.75	-1.21	-1.60	-0.85	3.70
DC	-1.20	-0.41	-0.55	-1.70	0.42	1.04
FL	9.01	-31.47	6.81	-78.86	28.13	84.39
GA	-16.61	-16.72	-11.71	-52.20	15.81	48.22
HA	1.53	-0.19	-0.49	-5.35	4.04	3.51
ID	4.76	0.69	2.63	-8.50	4.14	5.80
IL	-5.02	-4.75	-9.50	-46.86	44.78	11.31

IN	-30.70	-14.87	-25.63	-54.54	38.80	25.54
IA	4.94	-8.11	-14.71	-5.53	25.60	7.70
KS	-8.73	-0.37	-11.01	-22.86	18.95	6.56
KY	-18.87	-8.75	-11.94	-26.92	12.32	16.43
LA	-9.08	-7.66	-10.95	-16.73	12.68	13.59
ME	-4.82	-1.66	-1.86	-6.00	3.48	1.22
MD	-14.02	-5.05	-9.20	-31.43	20.50	11.17
MA	-19.92	-7.50	-14.73	-32.25	26.14	8.41
MI	-28.67	-10.37	-9.71	-33.73	22.15	3.00
MN	2.81	-3.11	-10.72	-22.11	22.74	16.00
MS	-6.10	0.20	-7.04	-26.08	11.63	15.18
MO	6.23	-5.95	14.25	-12.36	5.44	4.85
MT	-0.06	-0.78	-2.65	-9.83	7.41	5.79
NE	8.98	0.12	-5.03	-9.17	16.00	7.05
NV	-0.08	-6.21	-5.29	-7.63	-3.60	22.64
NH	-2.55	-1.75	-3.00	-3.69	3.85	2.06
NJ	-14.13	-2.57	1.10	-39.32	16.15	10.51
NM	-10.51	-4.54	-10.82	-10.59	5.94	9.49
NY	-28.91	-12.91	-17.24	-70.73	58.04	13.93
NC	-19.15	-18.03	-11.81	-47.25	15.16	42.78
ND	9.89	-3.24	-21.33	-11.74	36.77	9.43
OH	-51.47	-19.69	-12.90	-66.89	38.98	9.02
OK	-0.23	-8.09	-8.13	-34.50	34.28	16.21
OR	-1.56	0.66	1.67	-26.23	12.51	9.83
PA	-46.27	-35.99	-23.40	-65.17	62.53	15.76
RI	-2.88	-0.30	-0.74	-4.64	1.93	0.87
SC	-1.31	-6.73	0.53	-24.52	8.56	20.85
SD	2.64	-0.94	-3.55	-0.87	5.37	2.63
TN	-27.08	-9.23	-23.74	-33.43	15.56	23.75
TX	4.02	-35.65	-56.90	-328.41	171.37	253.61
UT	-2.81	-3.99	-9.86	-29.14	14.82	25.36
VT	-0.45	-0.38	-0.12	-2.12	1.83	0.34
VA	-5.21	-14.14	-1.18	-35.70	20.94	24.87
WA	0.31	4.05	2.64	-50.93	23.09	21.45
WV	-25.44	-5.18	-32.81	-7.86	20.73	-0.32
WI	-0.36	-5.14	-3.27	-24.74	21.95	10.85
WY	-0.68	-3.18	-15.45	-7.39	13.39	11.96

With respect to the five factors, growth in both GDP per capita and population put upward pressure on CO_2 emissions, with the exception of Delaware and Nevada (declining GDP per capita) and West Virginia (declining population). But for most states the reduction of energy intensity, share of fossil fuels, and carbon intensity more than offset the combined effect of per capita GDP and population growth. The decline in energy intensity serves as the most important factor, offsetting 63 percent of the effects of per capita GDP and population. The reasons that energy intensity declined varied by state, but a decrease in the amount of total primary energy consumption per unit of GDP resulted from overall efficiency gains, shutting down power plants with low efficiency, and promoting power plants with higher levels of capacity and efficiency. The other two factors leading to a decline in CO_2 emissions include the share of fossil fuels (23 percent of the offset), and declining carbon intensity (14 percent of the offset). With the share of fossil fuels in the energy mix, a decline in total fossil fuel consumption per unit of total energy consumption reflects the increase in renewables with lower levels of CO_2 emissions. With declining carbon intensity, a decrease in the level of CO_2 emissions per unit of fossil fuels consumed reflects the ability of states to substitute natural gas for coal in the power plants.

Overall, increases in GDP per capita and population contributed positively to CO_2 emissions. Forty-nine states plus the District of Columbia demonstrated positive population effects. The population of West Virginia declined. Only Delaware and Nevada had a negative GDP per capita. An increase in GDP per capita contributes to CO_2 because higher levels of economic production lead to higher levels of emissions. Some states experienced higher population effects than others, demonstrating different population trends throughout the United States.

In most states, decreases in carbon intensity, share of fossil fuels, and energy intensity offset the rise in both GDP per capita and population. The reasons included decreases in (a) total primary energy consumption per unit of GDP, (b) share of fossil fuels in total energy, and (c) emissions per unit of fossil fuels. With this methodology, we acknowledge the potential for fault-resilience issues such as valuation in different scales as discussed by Shang (2018).

4. Conclusions

This paper uses the decomposition approach to identify the factors that alter CO_2 emissions at the state level in the United States. The model decomposes the change in emissions according to five factors: include carbon intensity, share of fossil fuel consumption in total energy consumption, total energy consumption per unit of GDP, GDP per capita, and population. The paper finds that, between 1998 – 2018, 36 states plus the District of Columbia experienced a decrease in CO_2 emissions. The results of this paper differ from the results of Vinuya et al. (2010), who found that, between 1990 – 2004, 48 states experienced an increase in emissions. In our paper, the decline in energy intensity serves as the most important factor, offsetting 63 percent of the effects of per capita GDP and population. The other two factors leading to a decline in CO_2 emissions include the share of fossil fuels (23 percent of the offset), and declining carbon intensity (14 percent of the offset). The results demonstrate that declining energy intensity, share of fossil fuels in total energy consumption, and carbon intensity are important in reducing CO_2 emissions. Future research will consider three areas:

- The top states experiencing a decline in CO_2 emissions between 1998 – 2018, Ohio, Pennsylvania, Indiana, and New York, are clustered geographically. A future area of research will analyze the clustering effect.
- The District of Columbia, New York, and Massachusetts have the lowest levels of emissions per unit of GDP; however, they also have the highest levels of GDP per capita. A future area of research will determine the extent to which emissions/GDP and GDP per capita are correlated.
- The coronavirus pandemic impacted economic and environmental conditions. Future research will consider whether the pandemic altered the trajectory of CO_2 emissions at the state level.

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