Forecast of CO_2 Emissions From the U.S. Transportation Sector: Estimation From a Double Exponential Smoothing Model

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Forecast of CO_2 Emissions From the U.S. Transportation Sector: Estimation From a Double Exponential Smoothing Model

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This study examines whether the decreasing trend in U.S. CO_2 emissions from the transportation sector since the end of the 2000s will be shown across all states in the nation for 2012–2021. A double exponential smoothing model is used to forecast CO_2 emissions for the transportation sector in the 50 states and the U.S., and its findings are supported by the validity test of pseudo out-of-sample forecasts. We conclude that the decreasing trend in transportation CO_2 emissions in the U.S. will continue in most states in the future.

INTRODUCTION

The movement of people and goods is brought about through methods of transportation that use fossil fuel combustion, which proportionally emits carbon dioxide (CO_2) into the Earth's atmosphere. The impacts of this greenhouse gas (GHG) are fundamentally connected to transport modes, their energy supply structures, and the basic facilities over which they operate (Rodrigue 2013). As Lakshmanan and Han (1997) and Schipper et al. (2011) pointed out, CO_2 emissions from U.S. transportation energy use increased up until 2008 due to the growth of three factors: travel demand, population, and gross domestic product (GDP); however, both the consumption of fossil fuels by and CO_2 emissions from the transportation sector in the U.S. have shown significantly decreasing trends since 2008 because of multiple short-term and long-term factors, including slow growth after the economic recession, a hike in fuel prices, increasing fuel efficiency, and a decrease in vehicle mileage of passenger cars (U.S. Energy Information Administration 2014).

The decrease in U.S. CO_2 emissions in transportation over time is considerably related to the significant decrease in fuel consumption by light-duty vehicles,[1] which outweighs increases in fuel consumption by other modes. Fuel consumption by light-duty vehicles is projected to decrease from 4,539 million barrels of oil in 2012 to 4,335 million by 2040, which is the opposite of the increasing fuel consumption trend over the past three decades (The U.S. Energy Information Administration 2014). However, heavy-duty vehicles, airplanes, marine vessels, lubricants, and military use are expected to continue to increase fuel consumption for the next two decades (U.S. Energy Information Administration 2014).

Since the Kyoto Protocol in 1997, the international treaty has established binding obligations for both developed and developing countries to reduce emissions of greenhouse gases in the atmosphere. It is noteworthy that the U.S. was emitting the second highest CO_2 emissions in the world, but the long-term and significant decrease of CO_2 emissions from the transportation sector is now in progress (U.S. Department of Energy 2010).

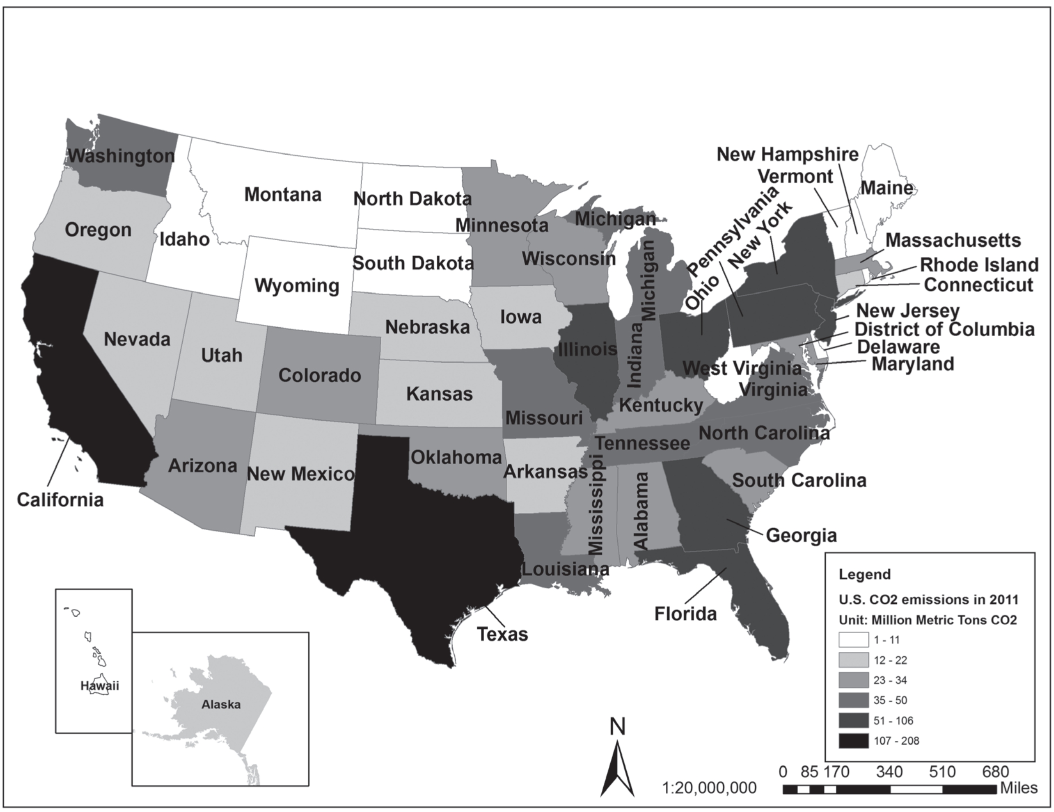
Historically, U.S. CO_2 emissions from the transportation sector have shown a trend over time, and thus they can be forecasted by using a statistical forecasting technique considering such a trend. Since Brown (1956) and Brown and Meyer (1960) developed the double exponential smoothing (DES) procedure to forecast a mean, a trend, and the variation of a noise, this method has been advanced by Goodman (1973), Gardner (1985), and Gijbels et al. (1999). For example, Goodman (1973) developed residual analysis to improve the forecast accuracy of DES models, while Gardner (1985) introduced general exponential smoothing to consider seasonality. In addition, Gijbels et al.

(1999) provided some insights into existing exponential smoothing theory by using a DES model within a nonparametric regression framework.

Numerous studies have used DES models to forecast in a variety of fields, including environmental pollution. Collins (1976) and Chu and Lin (1994) used a DES model to forecast levels of consolidated sales and earnings as well as the relationship between expected yearly recruitment levels and the necessary target requirements in high schools in Hong Kong, respectively. In 1999, Oh et al. (1999) applied a DES model to predict ozone formation in air pollution in South Korea; and Taylor (2003) forecasted electricity demand in England and Wales by using double seasonal exponential smoothing in order to minimize the seasonal effects of electricity consumption. Elliott and Timmermann (2008) empirically applied a DES model to predict U.S. inflation and stock returns, while Taylor (2012) used it to capture the density of the number of calls arriving at call centers. On the other hand, Xie and Su (2010) applied an exponential smoothing model to develop a river water pollution predictor in China, and Gupta (2011) developed an adaptive sampling strategy by using a DES model to evaluate carbon monoxide pollution by urban road traffic.

CO_2 emissions in transportation are different in each state in the U.S. as a result of their geographic characteristics, levels of economic development and population growth, and transportation and environmental regulations[2]. Figure 1 shows CO_2 emissions from the transportation sector by state in the U.S. for 2011. California and Texas emit the largest CO_2 emissions, while Florida, New York, Illinois, New Jersey, Ohio, Georgia, and Pennsylvania make the second largest CO_2 emissions, which are usually in areas of high development of urbanization and industrialization (U.S Energy Information Administration 2013).

Figure 1: U.S. CO_2 Emissions by State and the District of Columbia in 2011



Although the effect of fossil fuel energy consumption on future CO_2 emissions from private vehicle use in North America was analyzed in 2008 (Poudenx 2008) and the CO_2 emissions from the transportation sector in the U.S. were projected with other statistical models in 2012 (Bastani, Heywood and Hope 2012, Rentziou, Gkritza and Souleyrette 2012), their research was limited to a particular transportation industry and did not suggest future-specific CO_2 emissions per state in the U.S. over time. Most importantly, their findings lacked the provision of a validity test of their forecasts. For these reasons, this study forecasts U.S. CO_2 emissions by state from the overall transportation sector with the reliable validity test of pseudo out-of-sample forecasts.

The objectives of this study are i) to forecast national and state-level CO_2 emissions from 2012 to 2021 and ii) to review whether the decreasing trend in U.S. transportation CO_2 emissions will be shown across all states during this period. From the findings, this study will be able to provide administrators and state policy planners with detailed CO_2 emissions changes in the future in order to help them plan transportation CO_2 emissions regulations. The second section of this study presents discussions of alternative forecasting techniques, and the third section the state and federal air pollution regulations, including GHG. The fourth and fifth sections are the methodology and the data. After the results are presented, the conclusions discuss future CO_2 emissions changes in the United States.

DISCUSSIONS OF ALTERNATIVE FORECASTING TECHNIQUES

There exist many mathematical forecasting models today. These models include the autoregressive integrated moving average (ARIMA) technique and the seasonal autoregressive integrated moving average (S-ARIMA) technique. These methods are statistically sophisticated and mathematically complex methods that have been popular for forecasting the changes of time series in a broad number of applications (Zhai 2005). As a couple of researchers pointed out, these techniques regard past data and error terms of time series as essential information to forecast future changes. With a large amount of time series data, this technique shows quite a good accuracy of forecasting (Shumway and Stoffer 2011, Stock and Watson 2011).

However, as Zhai (2005) mentioned in her research, there are a few disadvantages of ARIMA and S-ARIMA techniques compared with a DES model. First, they have many possible models due to the number of possible combinations coming from the changes of the numbers in (seasonal) autoregressive terms, (seasonal) moving average terms, and/or (seasonal) autoregressive terms. Identifying the correct model among the possible models is likely to be subjective and depends on the experience and professional knowledge of the researcher. Second, "the underlying theoretical model and structural relationships are not as distinct as a DES model." (Zhai 2005, p.10)

STATE AND FEDERAL AIR POLLUTION REGULATIONS INCLUDING GHG

Of the 50 U.S. states, 32 have completed a climate change action plan to reduce their GHG emissions in their states since about 2005, which incorporates many specific policy recommendations (U.S. Environmental Protection Agency 2014C). For instance, the policy recommendations of Arkansas in 2008 included making a renewable portfolio standard, enacting a carbon tax, increasing energy efficiency, etc., and other participating states show similar policy recommendations for addressing GHG emissions (U.S. Environmental Protection Agency, 2014C).

A federal regulation to reduce air pollution initially started in 1955 as the Air Pollution Control Act and was complemented over time with the Clean Air Act (1963), the Air Quality Act (1967), the Clean Air Act (1970), and the Clean Air Act Amendments (1990). Since the middle of the 2000s with the Energy Policy Act (2005), Energy Independence and Security Act (2007), and President Obama's announcements of national policies (2009–2011 and 2014), stricter national air quality standards have been established by the U.S. Environmental Protection Agency (EPA). For more detailed information, Table 1 provides each air pollution act and its key points regarding reducing air pollution and/or GHG emissions (U.S. Environmental Protection Agency, 2014A, 2014B).

Table 1: Federal Acts and Announcements and Their Key Points

Federal Acts and Announcements	Key points
Air Pollution Control Act (1955)	First federal-level act to prevent air pollution and provided a research fund to define scope and sources in air pollution.
Clean Air Act (1963)	Establishment of a national program for preventing air pollution and started researching into techniques to reduce it.
Air Quality Act (1967)	Authorized enforcement to reduce air pollution problems caused by interstate transport of pollutants.
Clean Air Act (1970)	Established national air quality standards.
Clean Air Act Amendments (1990)	Established a program to reduce 189 air pollutants and complemented provisions regarding the attainment of national air quality standards.
Energy Policy Act (2005)	Authorized to develop renewable energy or use innovative energy-efficient technology for reducing air pollution, including GHG emissions.
Energy Independence and Security Act (2007)	Authorized to increase energy efficiency and the production of clean renewable fuel.
Obama announcements of national policies (2009–2011 and 2014)	Presidential announcements to enhance GHG and fuel efficiency standards.

Note: Information about federal acts and announcements and their key points is from USEPA (2014A, 2014B).

METHODOLOGY

Let us define:

α = Smoothing weight for the level of the time series.
β_t = Time-varying slope.
ε_t = Disturbances.
u_t = Time-varying mean.
S_t = Smoothed state of the time series estimates u_t in Eq. (1).
S'_t = Smoothed state of the time series estimates u_t in Eq. (2).
S''_t = Smoothed values of the S'_t estimates β_t.
Y_t = Observed value at time t.
$\hat{Y}_t(m)$ = Forecast value ahead to m periods at time t.

We start with a simple exponential smoothing (SES) model to derive the DES model. The model equation for the SES is:

(1) $Y_t = \mu_t + \varepsilon_t, \qquad t = 1, \ldots, T.$

The smoothing equation is:

(2) $S_t = \alpha Y_t + (1 - \alpha) S_{t-1}.$

The m-step prediction equation is:

(3) $\hat{Y}_t(m) = S_t,$

The *m*-step prediction value $\hat{Y}_t(m)$ is estimated through Eq. (1) and Eq. (2) (Elliott and Timmermann 2008, SAS 9.2 User's Book 2013). Eq. (1) is an estimation of the time-varying mean and disturbances, while the smoothed state S_t that is computed after Y_t is observed is updated through Eq. (2). The smoothed state is a result of the combination of its actual observation plus the first lagged smoothed state with the control of smoothed weight. Exponential smoothing does not regard the effect of each past lag equally, and rather gives more weight to recent observations; hence, the smoothing weight between 0 and 1 is adjusted for this purpose. The smoothing process is backdated from time to time 1 to determine the starting value of the smoothed state at time 0 (Chatfield and Yar 1988). The SES model cannot deal with trending data since all predictions at time t from one-step-ahead to m-step-ahead are always the same as the value of in S_t Eq. (3). Thus, a DES model is used to reflect the effect of a trend in the data.

The model equation for this is:

(4) $Y_t = \mu_t + \beta_t t + \varepsilon_t, \qquad t = 1, \dots, T.$

The smoothing equations are:

(5) $S'_t = \alpha Y_t + (1-\alpha)S'_{t-1},$

(6) $S''_t = \alpha S'_t + (1-\alpha)S''_{t-1}.$

The m-step prediction equation is:

(7) $\hat{Y}_t(m) = \left(2 + \frac{\alpha m}{1-\alpha}\right)S'_t - (1 + \frac{\alpha m}{1-\alpha})S''_t.$

The *m*-step prediction value $\hat{Y}_t(m)$ is the forecast value from the DES model, which is estimated by using the same process as in the SES model, but uses another smoothed series in Eq. (5) and Eq. (6). (Elliott and Timmermann 2008, SAS 9.2 User's Book 2013). The DES model is constructed when the SES method is twice run through the two different smoothed series in Eq. (5) and Eq. (6). The DES method can extrapolate nonseasonal patterns and trends such that the time series is smooth and has a slowly time-varying mean.

DATA

The data on CO_2 emissions[3] measured in million metric tons (MMT) from the transportation sector in the 50 states and the District of Columbia through fossil fuel combustion were obtained from the EPA for 1990–2011 (U.S. Environmental Protection Agency 2013). However, according to the central limit theorem, only 22 observations in a state may not be large enough to make the assumption that our sample data are well approximated by a normal distribution. To confirm this statistically, the normality of every state's CO_2 emissions data was tested by using an Anderson–Darling test, and the null hypothesis of no normality was not rejected, even at the 10% significance level.

Nevertheless, motor gasoline consumption data,[4] which are strongly correlated with CO_2 emissions from the transportation sector, were available for 1960–2011 from the State Energy Data System in the U.S. Energy Information Administration (USEIA) (U.S Energy Information Administration 2013). Thus, following some calculation processes, 29 new observations in each state from 1960 to 1989 were added for the state-level CO_2 emissions. First, we calculated the ratio of CO_2 emissions and motor gasoline consumption from 1990 to 2011 in a state. Second, we summed the 22 calculated ratios and divided it by 22 to find the average annual CO_2 emissions per unit of motor gasoline consumption (the value of 22 was from the difference between 1990 and 2011). Third, motor gasoline consumption from 1960 to 1989 in a state was multiplied by the calculation result from step 2. Finally, the CO_2 emissions for the transportation sector from 1960 to 1989 by state were calculated through the third process. To check that the new dataset from 1960 to 2011 was normally distributed, an Anderson–Darling test in each state was again performed, and the non-normality assumption was statistically rejected at the 5% significance level.

Table 2 shows the CO_2 emissions from the transportation sector in the 50 states, the District of Columbia, and the U.S. for 1960–2011. Total U.S. CO_2 emissions increased until 2007, but decreased thereafter. Most states showed a similar trend, but 14 states have recently increased their CO_2 emissions: Alabama, Alaska, Hawaii, Idaho, Iowa, Louisiana, Nebraska, New Jersey, North Dakota, Ohio, Oklahoma, Tennessee, Texas, and Utah.

EMPIRICAL RESULTS

Before discussing the empirical results, this study's discussion is built around an assumption based on a technical report from the U.S. Energy Information Administration (2014). We assumed that motor gasoline consumption in the transportation sector will decrease in the next 10 years even though the U.S. economic recovery occurs, since a decrease in vehicle mileage from passenger cars, which is a possible cause of the recent decrease in CO_2 emissions in the U.S. transportation sector, is expected to be maintained.

As discussed in the methodology section, an SES model was not appropriate with the trending data of CO_2 emissions in the U.S. transportation sector, since it only gives reliable forecasts when a time series fluctuates about a base level. For this reason, a DES model that yields good forecasts with trending data was performed to forecast CO_2 emissions in the U.S. transportation sector.

Pseudo out-of-sample forecasts[5] were estimated to test the out-of-sample performances of the DES models in each state and the U.S. The models were fitted with the CO_2 emissions data from 1960 to 2005, and then the forecasted CO_2 emissions from 2006 to 2011 were compared with the actual observations during the same period, which were 10% of the sample size to verify forecasting accuracy. Table 3 provides the actual observations and 95% forecast confidence intervals for 2006–2011. The overall forecasting accuracies by the DES models in the 47 states and the U.S. are high; the actual observations of CO_2 emissions in 20 states are within the 95% forecast confidence intervals, which means that in 95% of all samples, they would contain the actual CO_2 emissions; 27 states and the U.S. only have one or two actual observations of CO_2 emissions among six of the 95% forecast confidence interval(s). On the other hand, Alaska, Idaho, North Carolina, and North Dakota show poor forecasting accuracies since three or four actual observations of CO_2 emissions are not within the 95% forecast confidence intervals for 2006–2011.

Next, the DES models in every state, the District of Columbia, and the U.S. were regressed with the transportation CO_2 emissions data from 1960 to 2011 by using the statistical package program SAS 9.3. The regression results in Table 4 show the parameter estimates for smoothed level, smoothed trend, smoothing weight, root mean square error (RMSE), and goodness of fit (R^2). Columns 1, 2, and 3 start with the information on smoothed level, smoothed trend, and smoothing weight, with the three concepts explained as follows: if a smoothed level is 1869 and a smoothed trend is -19.8, then the forecast value in the first forecast year has a value of 1849 (=1869-19.8). In the second forecast year, the forecast value is 1829 (=1849-19.8), and so on. A smoothing weight between 0 and 1 is adjusted to give more weight to recent observations.

All the models in the 50 states, the District of Columbia, and the U.S. in Table 4 have statistically significant smoothing weights at 1%, and the overall model fits run from 0.8 to 0.98, meaning that the DES models used show high model fits for 1960–2021. On the other hand, the RMSE increases when the CO_2 emissions in a state increase, and thus California, Florida, and Texas show high RMSEs relative to the other states.

To make the estimation efficient and proper, a Ljung–Box chi-square test for error autocorrelation and a Dickey–Fuller test for stationarity were performed. In the DES models of each state and the U.S., the Ljung–Box chi-square tests showed that the autocorrelations of lags 1 and 2 in the prediction error are zero at the 1% significance level, while the Dickey–Fuller tests showed that a stationary time series is likely at the 1% significance level. The lagged variables in the DES models were assumed to be exogenous since the error terms were not serially correlated (Gujarati and Porter 2009).

In Table 4, the District of Columbia, Idaho, Iowa, Kansas, Nebraska, North Dakota, Oklahoma, South Dakota, Tennessee, and Utah are projected to increase CO_2 emissions from the transportation sector for 2012–2021 since their smoothed trends are greater than 0; however, owing to the possible poor forecasting accuracy of North Dakota in the pseudo out-of-sample forecast procedure, the findings for this state need to be carefully interpreted. On the other hand, 41 states are projected to show a decrease in CO_2 emissions because of the negative smoothed trends in Table 4. The levels of decreasing emissions will be different in each state, with California showing the largest CO_2emissions decrease due to the largest negative smoothed trend value of -5.31.

Table 5 shows the forecast values of CO_2 emissions from the transportation sector in the 50 states, the District of Columbia, and the U.S. for 2012–2021. The summation of CO_2emissions in all states is well matched to the forecast of U.S. CO_2 emissions. In California, CO_2 emissions from the transportation sector will significantly decrease by as much as one quarter of its 2011 CO_2 emissions by 2021, while Texas and Florida, which emitted the second and third highest CO_2 emissions in 2011, will gradually decrease their CO_2 emissions, too. In contrast, the 10 states in Table 4 projected to increase CO_2 emissions will increase their CO_2 emissions for 2012–2021, but their proportion of total CO_2 emissions will only range from 9% to 11% during this period; hence, the overall decreasing CO_2 emissions trend in the U.S. will remain. The findings for these 10 states might be a result of factors such as sudden population increases, less strict air pollution regulations in the transportation sector, and/or local economic growth through oil booms, agriculture production increases, or industrial development.

Table 2: CO_2 Emissions from the Transportation Sector by State, the District of Columbia, and the U.S. from 1960 to 2011 (Unit: MMT)

State/Year	1960	1970	1980	1990	2000	2007	2009	2011
Alabama	13.6	20.7	24.9	28.1	33.6	36.2	32.7	33.6
Arizona	6.7	11.9	17.0	22.8	32.5	38.0	33.1	31.7
Arkansas	8.5	13.3	15.9	16.2	21.0	21.2	20.4	20.1
Alaska	3.6	5.3	7.7	12.1	15.7	18.0	13.7	14.3
California	82.9	131.6	156.2	202.8	215.8	238.1	217.5	207.7
Colorado	8.6	14.2	19.0	19.2	25.7	31.5	29.4	28.9
Connecticut	9.0	13.3	14.1	14.7	16.2	17.7	16.4	15.8
Delaware	2.1	3.2	3.4	4.5	5.1	5.2	4.8	4.2
District of Columbia	2.2	2.6	1.8	1.8	1.8	1.2	1.1	1.2
Florida	23.4	41.3	59.6	81.4	100.6	115.7	99.4	105.6
Georgia	17.6	30.6	37.2	48.7	61.5	67.1	65.4	65.0
Hawaii	3.5	5.9	7.6	11.1	9.0	14.1	9.5	10.2
Idaho	3.5	5.3	6.1	6.4	8.8	9.6	8.7	9.1
Illinois	39.3	55.6	57.8	54.4	67.1	73.8	68.4	66.9
Indiana	25.2	35.0	36.8	40.9	46.6	45.5	40.9	42.9
Iowa	12.9	16.5	17.8	16.3	18.8	22.3	21.1	21.8
Kansas	12.1	16.5	17.9	19.3	18.8	19.6	19.8	19.1
Kentucky	13.3	21.2	25.3	26.4	31.5	35.0	32.7	32.6
Louisiana	23.1	36.3	49.9	48.9	61.0	50.8	47.2	50.2
Maine	4.4	5.8	6.2	8.3	8.6	9.1	8.6	8.4
Maryland	10.7	18.1	21.5	23.6	28.6	31.7	31.8	29.3
Massachusetts	17.1	24.3	25.2	28.9	32.1	33.6	30.8	30.9
Michigan	30.2	45.3	46.2	47.9	57.3	55.4	50.0	48.7
Minnesota	15.8	22.6	25.0	23.8	35.0	36.5	32.3	32.3
Mississippi	10.6	16.6	18.5	20.2	25.2	26.7	25.1	24.6
Missouri	21.2	29.9	32.0	33.8	39.5	42.9	39.7	39.4
Montana	4.0	5.7	6.5	5.9	7.5	9.0	8.0	8.2
Nebraska	6.5	8.6	9.2	10.5	12.2	12.6	12.5	14.2
Nevada	2.2	4.5	7.0	9.4	14.5	18.3	14.8	13.4
New Hampshire	2.2	3.6	4.1	5.2	7.3	7.5	7.2	7.1
New Jersey	33.1	45.2	50.1	57.1	65.0	72.6	62.3	66.0
New Mexico	6.5	9.1	11.8	14.9	15.3	15.6	14.0	14.1
New York	47.1	65.0	64.2	64.1	67.2	74.6	72.4	67.0
North Carolina	17.4	27.7	32.7	38.4	50.0	54.9	49.0	47.8
North Dakota	3.4	4.5	5.4	4.6	5.6	7.1	6.0	8.1
Ohio	41.3	57.8	61.1	56.1	68.9	72.9	64.6	65.2
Oklahoma	14.7	22.1	27.1	23.9	30.3	32.5	31.1	32.0
Oregon	9.7	15.4	19.1	20.0	22.7	24.5	22.9	21.2
Pennsylvania	44.1	56.4	61.6	59.5	70.6	72.2	66.4	64.5

Table 2 (continued)

State/Year	1960	1970	1980	1990	2000	2007	2009	2011
Rhode Island	2.8	3.8	4.0	4.1	4.7	4.4	4.3	4.0
South Carolina	8.8	14.4	18.0	22.0	27.1	32.2	31.3	30.9
South Dakota	3.5	4.6	4.9	4.7	5.8	6.4	6.3	6.6
Tennessee	15.7	24.5	32.4	32.8	41.6	46.3	41.6	43.1
Texas	64.2	102.3	130.2	152.5	182.9	205.1	190.2	195.5
Utah	4.8	7.9	10.2	10.6	15.7	18.5	16.4	17.5
Vermont	1.5	2.4	2.6	3.0	3.7	3.9	3.6	3.4
Virginia	16.9	26.9	32.9	41.5	48.6	57.2	50.9	48.3
Washington	15.8	25.3	30.1	41.0	44.8	47.9	42.2	41.2
West Virginia	6.9	9.5	11.7	10.4	12.7	12.5	11.4	11.2
Wisconsin	15.3	21.9	24.4	24.3	29.8	31.1	29.5	29.2
Wyoming	4.0	5.3	8.0	5.8	7.6	8.9	8.3	7.8
U.S. Total	814	1217	1420	1585	1880	2045	1868	1862

Note: The CO_2 emissions for the transportation sector from 1960 to 1989 by state and the District of Columbia were calculated using motor gasoline consumption data from 1960 to 1989 in USEIA (2013); the CO_2 emissions from 1990 to 2011 were obtained from USEPA (2013).

Table 3: Pseudo Out-of-Sample Forecasts of CO_2 Emissions (MMT) from the Transportation Sector to Evaluate the DES Models' Performances by State, the District of Columbia, and the U.S. from 2006 to 2011

State/Year	2006	2007	2008	2009	2010	2011
Alabama	35.5 (33.7, 37.6)	36.1 (34.2, 38.1)	33.5† (34.7, 38.7)	32.6 (31.8, 35.7)	33.7 (30.1, 34.0)	33.5 (31.1, 35.1)
Arizona	38.2 (36.7, 39.0)	37.9† (38.0, 40.4)	35.0† (37.3, 39.7)	33.1 (33.2, 35.6)	32.0 (30.4, 32.8)	31.7 (29.3, 31.7)
Arkansas	20.6 (19.1, 22.4)	21.1 (19.1, 22.4)	20.5 (19.6, 22.8)	20.3 (19.0, 22.3)	20.4 (18.7, 21.9)	20.1 (18.7, 21.9)
Alaska	19.1 (17.9, 21.6)	18.0† (18.2, 22.0)	15.4† (17.3, 21.1)	13.6† (14.7, 18.5)	15.0 (12.1, 15.9)	14.2 (12.2, 16.0)
California	234 (221, 245)	238 (226, 250)	222† (230, 254)	217 (212, 237)	215 (202, 226)	207 (198, 223)
Colorado	30.7 (29.2, 32.3)	31.5 (30.1, 33.2)	30.1† (30.8, 34.0)	29.3 (29.3, 32.5)	29.8 (27.9, 31.1)	28.8 (28.1, 31.2)
Connecticut	17.6† (18.1, 20.0)	17.6 (17.0, 18.9)	16.7 (16.6, 18.6)	16.4 (15.7, 17.6)	16.1 (15.1, 17.0)	15.8 (14.7, 15.7)
Delaware	5.1 (4.7, 5.6)	5.2 (4.8, 5.6)	5.0 (4.9, 5.7)	4.8 (4.6, 5.4)	4.4 (4.4, 5.2)	4.2 (4.0, 4.8)
District of Columbia	1.23 (1.15, 1.56)	1.22 (0.94, 1.35)	1.07 (0.90, 1.32)	1.12 (0.77, 1.18)	1.10 (0.82, 1.24)	1.22 (0.83, 1.25)
Florida	116 (111, 124)	115 (113, 127)	105† (111, 125)	99 (99, 113)	105† (89, 103)	105 (95, 109)
Georgia	68.3 (68.2, 74.4)	67.0 (66.8, 73.0)	61.2† (64.4, 70.7)	65.4† (56.7, 62.9)	66.7 (61.2, 67.4)	65.0 (63.9, 70.1)
Hawaii	13.0 (12.5, 14.6)	14.0 (12.5, 14.6)	9.71† (13.6, 15.7)	9.44 (7.93, 10.0)	9.65† (7.14, 9.28)	10.23† (7.81, 9.95)
Idaho	9.30 (8.17, 9.31)	9.63 (8.92, 10.06)	8.78† (9.36, 10.51)	8.68 (8.22, 9.36)	9.47† (7.94, 9.08)	9.13 (8.97, 10.12)
Illinois	73.3† (75.3, 87.9)	73.7 (68.9, 81.5)	69.8 (67.9, 80.5)	68.3 (62.1, 74.7)	67.6 (60.2, 72.8)	66.8 (60.0, 72.6)
Indiana	46.4 (42.2, 49.0)	45.5 (43.0, 49.9)	42.3† (42.4, 24.2)	40.8 (39.0, 45.8)	42.9 (36.7, 43.5)	42.9 (38.2, 45.1)
Iowa	21.8 (20.5, 23.4)	22.3 (21.0, 23.9)	21.5 (21.4, 24.3)	21.1 (20.1, 23.0)	21.5 (19.4, 22.2)	21.7 (20.0, 22.9)
Kansas	19.0 (16.5, 19.8)	19.5 (17.1, 20.4)	19.0 (17.8, 21.1)	19.7 (17.6, 20.9)	19.6 (18.2, 21.4)	19.0 (18.1, 21.4)
Kentucky	33.4 (32.1, 36.3)	34.9 (31.8, 36.0)	32.1† (33.1, 37.2)	32.6 (30.7, 34.8)	33.2 (30.4, 34.5)	32.6 (30.9, 35.0)
Louisiana	55.0 (46.6, 54.8)	50.8 (49.5, 57.7)	47.9 (46.8, 55.0)	47.2 (43.4, 51.6)	50.1† (41.8, 50.0)	50.2 (44.3, 52.5)
Maine	9.41 (8,67, 10.3)	9.06 (8.80, 10.4)	8.20† (8.49, 10.1)	8.57 (7.59, 9.25)	8.51 (7.59, 9.52)	8.38 (7.56, 9.22)
Maryland	42.2 (39.0, 45.1)	42.8 (39.6, 45.6)	40.3 (40.3, 46.4)	39.6 (36.4, 42.5)	40.1 (35.6, 41.6)	39.3 (36.8, 42.8)
Massachusetts	33.0† (33.3, 36.3)	33.5 (31.6, 34.5)	33.4 (32.1, 35.1)	30.7† (32.0, 34.9)	30.8 (28.4, 31.3)	30.9 (28.4, 31.4)
Michigan	55.7 (52.1, 59.1)	55.3 (52.0, 59.0)	51.3† (51.6, 58.6)	49.9 (45.6, 52.6)	49.8 (44.5, 51.4)	48.6 (45.3, 52.3)
Minnesota	36.1 (34.9, 39.4)	36.5 (34.3, 38.8)	34.6 (34.4, 39.0)	32.2 (32.2, 36.7)	32.7 (29.1, 33.6)	32.3 (29.5, 34.0)

Table 3 (continued)

State/Year	2006	2007	2008	2009	2010	2011
Mississippi	26.8 (23.8, 26.9)	26.6 (25.4, 28.5)	25.6 (25.4, 28.5)	25.0 (24.1, 27.2)	25.2 (23.2, 26.2)	24.6 (23.4, 26.5)
Missouri	42.2 (39.0, 45.1)	42.8 (39.6, 45.6)	40.3 (40.3, 46.4)	39.6 (36.4, 42.5)	40.1 (35.6, 41.6)	39.3 (36.8, 42.8)
Montana	8.5 (7.5, 9.0)	9.0 (7.9, 9.4)	8.3† (8.4, 9.9)	7.9† (8.0, 9.5)	8.1 (7.5, 9.0)	8.2 (7.4, 8.9)
Nebraska	12.4 (11.3, 13.4)	12.6 (11.5, 13.6)	12.3 (11.7, 13.8)	12.5 (11.2, 13.3)	14.6 (11.4, 13.6)	14.1 (14.8, 17.0)
Nevada	18.0 (16.8, 18.0)	18.2 (18.1, 19.3)	16.3† (18.4, 19.6)	14.8† (15.9, 17.1)	13.9 (13.6, 14.8)	13.3 (12.4, 13.6)
New Hampshire	7.2 (6.8, 7.8)	7.4 (6.6, 7.6)	7.2 (6.9, 7.8)	7.2 (6.7, 7.7)	7.2 (6.6, 7.6)	7.0 (6.6, 7.6)
New Jersey	68.8 (65.7, 73.4)	72.6 (66.5, 74.2)	73.5 (69.9, 77.6)	62.2† (71.5, 79.2)	63.7 (61.1, 68.8)	65.9 (58.9, 66.6)
New Mexico	16.0 (14.0, 16.9)	15.5 (14.5, 17.4)	14.2† (14.3, 17.1)	14.0 (13.0, 15.8)	13.6 (12.3, 15.2)	14.1 (11.9, 14.7)
New York	74.8 (69.4, 82.4)	74.6 (69.6, 82.7)	74.3 (69.2, 82.2)	72.3 (68.6, 81.6)	72.3 (66.5, 79.5)	66.9 (65.7, 78.7)
North Carolina	53.1 (53.0, 56.9)	54.9 (51.2, 55.1)	53.4† (54.1, 58.1)	48.9† (50.8, 54.8)	49.2† (43.7, 47.6)	47.7 (46.2, 50.1)
North Dakota	6.2 (5.8, 7.0)	7.1† (5.7, 6.9)	6.3† (6.4, 7.6)	6.0† (6.1, 7.2)	6.9† (5.6, 6.8)	8.0† (6.2, 7.3)
Ohio	72.1 (67.6, 75.7)	72.9 (68.6, 76.6)	69.0† (69.5, 77.6)	64.5 (63.2, 71.2)	65.9† (57.0, 65.0)	65.2 (60.9, 69.0)
Oklahoma	31.7 (28.0, 33.0)	32.5 (29.2, 34.2)	32.3 (30.3, 35.3)	31.0 (30.3, 35.3)	32.2 (28.9, 33.9)	31.9 (29.6, 34.6)
Oregon	23.9 (22.4, 25.2)	24.5 (23.0, 25.8)	22.7† (23.7, 26.4)	22.9 (21.1, 23.8)	22.1 (21.1, 23.9)	21.2 (20.3, 23.0)
Pennsylvania	72.4 (70.1, 78.2)	72.2 (68.3, 76.4)	67.4† (67.9, 76.0)	66.4 (59.5, 67.6)	66.0† (60.7, 68.8)	64.4 (61.4, 69.5)
Rhode Island	4.4 (4.0, 4.5)	4.3 (4.1, 4.6)	4.1 (4.1, 4.6)	4.2 (3.8, 4.3)	4.2 (3.9, 4.4)	4.0 (3.9, 4.4)
South Carolina	32.0 (30.2, 33.7)	32.2 (31.1, 34.6)	30.6† (31.3,34.8)	31.2 (29.7, 33.2)	31.2 (29.7, 33.2)	30.8 (29.6, 33.1)
South Dakota	6.1 (5.6, 6.6)	6.4 (5.6, 6.7)	6.0 (5.9, 7.0)	6.2 (5.5, 6.6)	6.5 (5.7, 6.8)	6.5 (6.1, 7.1)
Tennessee	45.8 (43.8, 48.4)	46.2 (44.0, 48.6)	42.9† (44.3, 48.9)	41.5 (39.9, 44.5)	43.1† (37.9, 42.5)	43.1 (40.1, 44.8)
Texas	202 (186, 206)	205 (194, 214)	197 (198, 218)	190† (190, 210)	194 (179, 199)	195 (182, 201)
Utah	18.5† (16.2, 17.9)	18.5 (18.3, 20.0)	17.0† (18.3, 20.0)	16.4 (16.2, 17.9)	16.3 (15.1, 16.8)	17.4 (15.1, 16.8)
Vermont	3.8 (3.7, 4.1)	3.8 (3.7, 4.1)	3.5 (3.6, 4.0)	3.6 (3.2, 3.6)	3.5 (3.3, 3.7)	3.4 (3.2, 3.6)
Virginia	56.9 (55.4, 60.1)	57.2 (56.3, 61.0)	52.7 (56.0, 60.7)	50.8 (49.7, 54.3)	50.4 (46.7, 51.4)	48.3 (46.6, 51.2)
Washington	44.8 (40.3, 46.7)	47.8 (41.8, 48.1)	42.9 (45.1, 51.5)	42.1 (41.0, 47.3)	41.2 (38.9, 45.2)	41.1 (37.5, 43.8)

Table 3 (continued)

State/Year	2006	2007	2008	2009	2010	2011
West Virginia	12.5 (11.6, 13.6)	12.4 (11.6, 13.6)	11.0† (11.5, 13.5)	11.3 (9.8, 11.9)	11.6 (9.9, 12.0)	11.2 (10.4, 12.5)
Wisconsin	30.8 (28.9, 31.9)	31.1 (29.5, 32.6)	30.1 (29.8, 32.9)	29.5 (28.3, 31.3)	30.3 (27.4, 30.4)	29.1 (28.8, 31.9)
Wyoming	8.6 (7.5, 9.3)	8.8 (7.8, 9.6)	8.6 (8.1, 9.9)	8.3 (7.9, 9.7)	8.4 (7.5, 9.3)	7.7 (7.5, 0.3)
U.S. Total	2028 (1962, 2106)	2045 (1990, 2133)	1929† (1998, 2141)	1867 (1807, 1950)	1891† (1731, 1874)	1862 (1801, 1944)

Note: † indicates that actual CO_2 emissions are not within the 95% forecast confidence interval. Actual CO_2 emissions are out of the parentheses, and 95% forecast confidence intervals are in the parentheses.

CONCLUSIONS

The increase in CO_2 emissions in the world has adversely affected sustainable development for human life and the Earth's ecosystems, resulting in global warming and climate change; therefore, the recent decrease in CO_2 emissions from the U.S. transportation sector and its long-term decreasing trend found in this study are meaningful for the world's efforts to reduce CO_2 emissions. This study found that the decreases in CO_2 emissions in most states are not temporary, but rather will continuously occur for the next decade. By 2021, the U.S. is projected to emit CO_2 of 1664 MMT from the transportation sector, a reduction of 198 MMT compared with 2011. This reduced amount in 2021 will account for almost all the CO_2 emissions from California in 2011, which emitted the most CO_2 emissions in the nation.

A major finding from the empirical results is that while CO_2 emissions by most of the U.S. states for the next 10 years will show a downward pattern, 10 states are projected to show an increasing tendency of transportation CO_2 emissions. One possible hypothesis to explain this difference across states is probably related to whether a state has a GHG emissions reduction plan in place or not. Looking at these 10 states, eight of them have not actually completed any climate change action plan within their boundaries, compared with most of the other states trying to address GHG emissions. This could imply much more importance needs to be placed on environmental policies for CO_2 emissions reduction in the transportation sector, not only at national but at state level, too. One caveat, nevertheless, is that from this finding, the policymakers should really aim at those areas where the policy might be warranted, i.e., by the Lucas Critique,[6] if a policy changes, the outcomes of sample forecasts will be wrong.

This study has a limitation based on the data used. The CO_2 emissions data from 1960 to 1989 for each state and the U.S. were estimated from motor gasoline consumption data to find the best possible approximation; if original data during the period were available from the EPA, we could have estimated more accurate results for our CO_2 emissions forecasts from the U.S. transportation sector.

Table 4: Parameter Estimates, a Measure of Accuracy, and Goodness of Fit for Projections of CO_2 Emissions by State, the District of Columbia, and the U.S. for 2012–2021

State	Smoothed Level	Smoothed Trend	Smoothing Weight	RMSE	R^2
Alabama	33.59	-0.12	0.56 ***	1.06	0.97
Arizona	31.80	-0.63	0.83 ***	0.77	0.99
Arkansas	20.28	-0.13	0.51 ***	0.78	0.95
Alaska	14.64	-0.50	0.53 ***	1.13	0.93
California	211.74	-5.31	0.59 ***	6.43	0.97
Colorado	29.27	-0.37	0.57 ***	0.84	0.98
Connecticut	16.05	-0.35	0.58 ***	0.51	0.94
Delaware	4.46	-0.21	0.51 ***	0.20	0.94
District of Columbia	1.17	0.02	0.57 ***	0.10	0.94
Florida	105.33	-0.33	0.56 ***	3.47	0.98
Georgia	65.41	-0.04	0.52 ***	1.99	0.98
Hawaii	10.10	-0.19	0.55 ***	0.90	0.87
Idaho	9.15	0.04	0.51 ***	0.34	0.96
Illinois	67.44	-1.06	0.62 ***	3.25	0.85
Indiana	42.84	-0.22	0.48 ***	1.72	0.91
Iowa	21.69	0.16	0.71 ***	0.71	0.91
Kansas	19.31	0.004	0.44 ***	0.80	0.84
Kentucky	32.88	-0.12	0.47 ***	1.04	0.96
Louisiana	49.85	-0.20	0.43 ***	2.20	0.95
Maine	8.50	-0.08	0.43 ***	0.41	0.91
Maryland	29.78	-0.87	0.70 ***	1.50	0.98
Massachusetts	31.04	-0.38	0.61 ***	0.85	0.96
Michigan	49.05	-1.00	0.73 ***	1.76	0.94
Minnesota	32.63	-0.59	0.58 ***	1.13	0.96
Mississippi	24.97	-0.32	0.55 ***	0.78	0.97
Missouri	39.60	-0.44	0.70 ***	1.50	0.94
Montana	8.23	-0.004	0.41***	0.39	0.89
Nebraska	14.05	0.44	0.63 ***	0.62	0.91
Nevada	13.48	-0.69	0.87 ***	0.49	0.98
New Hampshire	7.15	-0.07	0.59 ***	0.23	0.98
New Jersey	65.91	-0.57	0.42 ***	2.63	0.93
New Mexico	14.13	-0.21	0.45 ***	0.71	0.93
New York	70.25	-1.59	0.48 ***	3.21	0.80
North Carolina	48.29	-1.25	0.71 ***	1.26	0.98
North Dakota	7.10	0.26	0.36 ***	0.38	0.84
Ohio	65.38	-0.55	0.77 ***	2.03	0.94
Oklahoma	31.91	0.08	0.47 ***	1.23	0.93
Oregon	21.61	-0.72	0.66 ***	0.72	0.96
Pennsylvania	64.78	-1.30	0.83 ***	2.08	0.93

Table 4 (continued)

State	Smoothed Level	Smoothed Trend	Smoothing Weight	RMSE	R^2
Rhode Island	4.11	-0.08	0.56 ***	0.12	0.93
South Carolina	31.04	-0.07	0.49 ***	0.90	0.98
South Dakota	6.49	0.09	0.54 ***	0.26	0.89
Tennessee	43.03	0.005	0.64 ***	1.28	0.97
Texas	195.03	-0.34	0.53 ***	5.22	0.98
Utah	17.13	0.22	0.62 ***	0.59	0.97
Vermont	3.47	-0.08	0.61 ***	0.11	0.97
Virginia	48.99	-1.64	0.73 ***	1.38	0.98
Washington	41.78	-0.67	0.48 ***	1.76	0.96
West Virginia	11.43	-0.14	0.50 ***	0.54	0.89
Wisconsin	29.47	-0.43	0.68 ***	0.78	0.97
Wyoming	8.14	-0.17	0.49 ***	0.44	0.90
U.S. Total	1869	-19.81	0.75 ***	41.10	0.98

Note: *** indicate significance at the 1% level. The smoothed level and trend are not related to the hypothesis tests. The smoothed level and trend and smoothing weight use a unit of MMT CO_2.

Table 5: Forecasted Values of CO_2 Emissions from the Transportation Sector by State, the District of Columbia, and the U.S. from 2012 to 2021 (Unit: MMT)

State/Year	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
Alabama	33.4	33.2	33.1	33.0	32.9	32.8	32.6	32.5	32.4	32.3
Arizona	31.0	30.4	29.8	29.1	28.5	27.9	27.2	26.6	26.0	25.3
Arkansas	20.0	19.9	19.8	19.6	19.5	19.4	19.2	19.1	18.9	18.8
Alaska	13.7	13.2	12.7	12.2	11.7	11.2	10.7	10.2	9.7	9.2
California	202.8	197.5	192.2	186.9	181.5	176.2	170.9	165.6	160.3	155.0
Colorado	28.6	28.2	27.9	27.5	27.1	26.7	26.4	26.0	25.6	25.2
Connecticut	15.4	15.1	14.7	14.4	14.0	13.7	13.3	12.9	12.6	12.2
Delaware	4.0	3.8	3.6	3.4	3.2	3.0	2.8	2.6	2.3	2.1
District of Columbia	1.2	1.2	1.3	1.3	1.3	1.3	1.3	1.4	1.4	1.4
Florida	104.7	104.4	104.0	103.7	103.4	103.0	102.7	102.4	102.1	101.7
Georgia	65.3	65.2	65.2	65.2	65.1	65.1	65.0	65.0	64.9	64.9
Hawaii	9.7	9.5	9.3	9.1	8.9	8.8	8.6	8.4	8.2	8.0
Idaho	9.2	9.2	9.3	9.3	9.4	9.4	9.5	9.5	9.5	9.6
Illinois	65.7	64.6	63.6	62.5	61.4	60.4	59.3	58.3	57.2	56.1
Indiana	42.3	42.1	41.9	41.7	41.5	41.2	41.0	40.8	40.6	40.3
Iowa	21.9	22.0	22.2	22.4	22.5	22.7	22.9	23.0	23.2	23.4
Kansas	19.3	19.3	19.3	19.3	19.3	19.3	19.3	19.3	19.3	19.3
Kentucky	32.6	32.4	32.3	32.2	32.0	31.9	31.8	31.7	31.5	31.4
Louisiana	49.3	49.1	48.9	48.7	48.5	48.3	48.1	47.9	47.7	47.5
Maine	8.3	8.2	8.1	8.0	7.9	7.8	7.7	7.6	7.5	7.4
Maryland	28.4	27.5	26.6	25.7	24.9	24.0	23.1	22.2	21.4	20.5
Massachusetts	30.4	30.0	29.6	29.2	28.8	28.4	28.1	27.7	27.3	26.9
Michigan	47.6	46.6	45.6	44.6	43.6	42.6	41.6	40.6	39.6	38.6
Minnesota	31.6	31.0	30.4	29.8	29.2	28.6	28.0	27.4	26.8	26.2
Mississippi	24.3	24.0	23.7	23.4	23.1	22.7	22.4	22.1	21.8	21.4
Missouri	38.9	38.5	38.0	37.6	37.1	36.7	36.3	35.8	35.4	34.9
Montana	8.2	8.2	8.2	8.2	8.2	8.1	8.1	8.1	8.1	8.1
Nebraska	14.7	15.1	15.6	16.0	16.5	16.9	17.3	17.8	18.2	18.7
Nevada	12.6	11.9	11.3	10.6	9.9	9.2	8.5	7.8	7.1	6.4
New Hampshire	7.0	6.9	6.8	6.8	6.7	6.6	6.5	6.5	6.4	6.3
New Jersey	64.5	63.9	63.3	62.8	62.2	61.6	61.0	60.5	59.9	59.3
New Mexico	13.6	13.4	13.2	13.0	12.8	12.6	12.4	12.1	11.9	11.7
New York	66.7	65.1	63.5	61.9	60.3	58.7	57.1	55.5	53.9	52.3
North Carolina	46.5	45.2	44.0	42.7	41.4	40.2	38.9	37.7	36.4	35.2
North Dakota	7.8	8.0	8.3	8.6	8.8	9.1	9.4	9.6	9.9	10.1
Ohio	64.6	64.1	63.5	63.0	62.4	61.8	61.3	60.7	60.2	59.6
Oklahoma	32.0	32.1	32.2	32.3	32.4	32.5	32.6	32.7	32.8	32.9
Oregon	20.5	19.8	19.0	18.3	17.6	16.9	16.2	15.4	14.7	14.0
Pennsylvania	63.2	61.9	60.6	59.3	58.0	56.7	55.4	54.1	52.8	51.5
Rhode Island	3.9	3.8	3.7	3.6	3.6	3.5	3.4	3.3	3.2	3.1

Table 5 (continued)

State/Year	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
South Carolina	30.8	30.8	30.7	30.6	30.5	30.5	30.4	30.3	30.2	30.2
South Dakota	6.6	6.7	6.8	6.9	7.0	7.1	7.2	7.3	7.4	7.5
Tennessee	43.0	43.0	43.0	43.0	43.0	43.0	43.0	43.0	43.0	43.0
Texas	194.3	194.0	193.6	193.3	193.0	192.6	192.3	191.9	191.6	191.2
Utah	17.4	17.7	17.9	18.1	18.4	18.6	18.8	19.0	19.3	19.5
Vermont	3.3	3.2	3.1	3.0	2.9	2.8	2.8	2.7	2.6	2.5
Virginia	46.7	45.0	43.4	41.7	40.1	38.5	36.8	35.2	33.5	31.9
Washington	40.3	39.7	39.0	38.3	37.6	37.0	36.3	35.6	35.0	34.3
West Virginia	11.1	10.9	10.8	10.6	10.5	10.3	10.2	10.0	9.9	9.7
Wisconsin	28.8	28.4	27.9	27.5	27.0	26.6	26.2	25.7	25.3	24.9
Wyoming	7.7	7.6	7.4	7.2	7.0	6.9	6.7	6.5	6.3	6.1
U.S. Total	1843	1823	1803	1783	1763	1744	1724	1704	1684	1664

Endnotes

1. The EPA defines light-duty vehicles (i.e., passenger cars) as carrying a maximum Gross Vehicle Weight Rating of less than 8500 lbs (The U.S. Energy Information Administration 2014).

2. These variables are embodied in the trend of the change in CO_2 emissions. The change of CO_2 emissions in the transportation sector are highly related to these factors, so if we use those variables as explanatory variables with CO_2 emissions variable in a forecasting model, then it could result in multicollinearity. Also, DES models only use one variable that we are trying to forecast. For example, suppose we are interested in forecasting CO_2 emissions in the transportation sector. The dependent variable and independent variables using the DES model will be calculated through the mathematical formula of the DES model from only the one variable.

3. CO_2 emissions per kWh in electricity from coal-fired thermal power stations are reported higher than in CO_2 emissions per kWh from various other fuels (Hutton 2013).

4. CO_2 emissions are generated by both gasoline consumption and diesel consumption data. Due to the non-availability of diesel consumption data to the public, this study could only use gasoline consumption data.

5. Pseudo out-of-sample forecasting is generally used to test the real-time accuracy of a forecasting model. The mechanism is as follows: Select a date close to the end of the sample, estimate a forecasting model with data up to that date, utilize the estimated forecasting model to make a forecast after the date, and then compare the forecasted values corresponding to the original data (Stock and Watson 2011).

6. The Lucas Critique derived from his work on macroeconomic policymaking implies that evaluation of the effects of economic policy based on the historical data might not be appropriate (Lucas 1976).

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