TRANSPORTATION SUSTAINABILITY ON ECONOMIC AND ENVIRONMENTAL ASPECTS IN THE UNITED STATES: STATISTICAL AND QUANTITATIVE APPROACHES

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The Supervisory Committee certifies that this ***disquisition*** complies with North Dakota State University's regulations and meets the accepted standards for the degree of

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ABSTRACT

The dissertation consists of three essays: 1) Productivity growth in the transportation industries in the United States: An application of the DEA Malmquist productivity index; 2) how does a carbon dioxide emissions change affect transportation productivity? A case study of the U.S. transportation sector from 2002 to 2011; and 3) forecast of CO2 emissions from the U.S. transportation sector: Estimation from a double exponential smoothing model.

The first essay reviews productivity growth in the five major transportation industries in the United States (airline, truck, rail, pipeline, and water) and the pooled transportation industry from 2004 to 2011. The major findings are that the U.S. transportation industry shows strong and positive productivity growth except in the years of the global financial crisis in 2007, 2008, and 2010, and among the five transportation industries, the rail and water sectors show the highest productivity growth in 2011.

The second essay examines the effects of a carbon dioxide (CO2) emissions change on actual productivity in the U.S. transportation sector. This study finds that a CO2 emissions increase from 2002 to 2007 had a negative effect on actual productivity in the U.S. transportation sector, but the CO2 emissions reduction for 2008–2011 increases actual productivity. States mainly showing sustainable growth patterns (decrease in CO2 emissions concurrent with increasing actual productivity) experience higher technological innovation increase than an efficiency decrease. This finding suggests that fuel-efficient and carbon reduction technologies as well as alternative transportation energy sources may be essential factors to both grow transportation and slow global warming.

The third essay reviews whether the decreasing trend in U.S. CO_2 emissions from the transportation sector since the end of the 2000s is consistent 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 pseudo out-of-sample forecasts validity testing. This study concludes that the decreasing trend in transportation CO_2 emissions in the U.S. will continue in most states in the future.

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CHAPTER 1. STUDY MOTIVATIONS AND OBJECTIVES

For a long time now, the sustainability of the environment has been recognized as a major issue worldwide in terms of the coexisting needs of both the current and future generations, along with an increased awareness of environmental pollution. Among a variety of sources of environmental pollution, the transportation sector of a nation plays a pivotal role in emitting greenhouse gases; at the same time, transport is a key foundation for successful economic growth at all stages, and the sector's CO2 emissions mainly result from its fossil fuel consumption. The greenhouse effect caused by increased CO2 emissions has caused temperatures to rise globally, which in turn is causing more frequent occurrences of natural disasters and a change of the Earth's ecosystems, thereby threatening its prosperity and even survival.

This doctoral dissertation started to research how the transport sector has impacted on economic and environmental changes, using as a case study the U.S. Since my graduate research assistantship during the Ph.D. study period was supported by the Mountain-Plains Consortium, which is sponsored by the Department of Transportation through its university transportation centers program, I thought that it would be most opportune if I could have an opportunity to research the U.S. transportation sector. The structure of this dissertation consist of three essays: 1) Productivity growth in the transportation industries in the United States: An application of the DEA Malmquist productivity index; 2) How does a carbon dioxide emissions change affect transportation productivity? A case study of the U.S. transportation sector from 2002 to 2011; and 3) Forecast of CO2 emissions from the U.S. transportation sector: Estimation from a double exponential smoothing model.

For the first essay, the objective is to measure productivity growth in the five major transportation industries, as well as in the pooled transportation industry in 51 U.S. states between 2004 and 2011. The study motivation is twofold: 1) There are a number of separate studies to measure productivity growth in each transportation industry, but not all together; and 2) The study is expected to provide each state's transport policy planners with the state-level findings. The second essay reviews how actual productivity in the U.S. transportation sector has been affected by the CO2 emissions change from 2002–2011, since no research has been conducted in the transportation sector to evaluate the effects of a CO2 emissions change (GHG emissions change) on actual productivity. For the third essay, the objectives are 1) to forecast national and state-level CO2 emissions from 2012 to 2021; and 2) to review whether the decreasing trend in U.S. transportation CO2 emissions is likely to be consistent across all states during this period. The motivation behind this study is 1) to provide a CO2 emission forecast; and 2) to provide administrators and state policy planners with detailed CO2 emissions changes in the future. Although similar forecasting efforts preceded this one, the previous literature lacks validity testing, while the current effort uses pseudo out-of-sample forecasts for validity testing.

CHAPTER 2. PRODUCTIVITY GROWTH IN THE TRANSPORTATION INDUSTRIES IN THE UNITED STATES: AN APPLICATION OF THE DEA MALMQUIST PRODUCTIVITY INDEX

2.1. Introduction

Transportation is an important part of development and growth in economic activities. When a transportation industry is efficient, it can provide more economic and social benefits to residents, businesses, and the government through the decrease of congestion, just-in-time business work, and environmental pollution caused by an inefficient transportation mode. When a transportation industry is deficient, however, it leads to unexpected opportunity costs or lost business opportunities. In many developed countries, the proportion of transportation to Gross Domestic Product (GDP) ranges from 6% to 12% (Rodrigue & Notteboom, 2013). The transportation industry in the United States has long had a major effect on growth at the city, region, and state levels.

The U.S. transportation industry is one of the largest in the world. The U.S. Department of Transportation explains in its freight shipments report that the transportation industry brings together more than seven million domestic businesses and 288 million citizens with the employment of one out of seven U.S. workers. It is noted that “more than $1 out of every $10 produced in the U.S. GDP is related to transportation activity” (The United States Department of Transportation, 2014).

The increase in productivity in an industry occurs when growth in output is proportionately greater than growth in inputs. In the transportation industry, the measure of productivity growth has been an important issue for both transportation economists and transportation policymakers for centuries. A number of attempts have been made to solve this issue, with Data Envelopment Analysis (DEA) popular for the analysis of productivity gains. DEA has three main advantages: 1) the number of empirical applications is very large; 2) it does not place any restrictions on the assumption of the inefficiency term and technology; and 3) a production relationship regarding the form of the frontier between inputs and outputs is not restricted (Färe, et al., 1992; Färe & Grosskopf, 1994; Färe, et al., 1994A; Färe, et al., 1994B; Hjalmarsson, et al., 1996; Celen, 2013).

The productivity growth of efficiency and technological change in various industries including transportation has been studied. For example, Farrell (Farrell, 1957) measured productive efficiency based on price and technical efficiencies in U.S. agricultural production for the 48 states in 1952. The two key concepts used to measure a farmer's success were choosing the best set of inputs and producing the maximum output from a given set of inputs, respectively. Unlike Farrell (1957), Charnes et al. (1978) provided a nonlinear programming model to define efficiency and thus evaluated the performance of nonprofit public entities. In 1982, Caves et al. (1982) developed an index number procedure for input, output, and productivity, while Sueyoshi (1992) provided an effectively designed algorithmic procedure for the measurement of technical, allocative, and overall efficiencies. These were provided as a basis to construct a Malmquist productivity index, which was later developed by Färe et al. (1992), Färe and Grosskopf (1994), and Färe et al. (1994A; 1994B). In 1992, Färe et al. (1992; 1994A) developed the

Malmquist input-based productivity index to measure productivity growth in Swedish pharmacies and in 1994 used the Malmquist output-based productivity index to analyze productivity growth in industrialized countries and Swedish hospitals.

Following Färe and Grosskopf (1994), a unified theoretical explanation of three productivity indexes (Malmquist, Fisher, and Törnqvist, undated) was provided. In the 2000s, research started to compare the conventional Malmquist productivity index with an environmentally sensitive Malmquist productivity index in applications of the U.S. agricultural industry, the U.S. trucking industry, and 10 OECD countries (Ball, et al., 2004; Heng, et al., 2012; Sueyoshi & Goto, 2013).

Nevertheless, the conventional Malmquist productivity index has still been used to measure productivity growth. For example, Chen and Ali (2004) employed it for the productivity measurement of seven computer manufacturers in the Fortune Global 500 from 1991 to 1997, while Liu and Wang (2008) applied it to Taiwan's semiconductor industry during 2000 to 2003. Recently, the high-tech industry in China and Turkish electricity distribution industry have been analyzed to measure efficiency performance by Qazi and Yulin (2012) and Celen (2013), respectively.

The growth of the U.S. transportation industry has been led by the five major transportation modes: truck, rail, airline, pipeline, and water. For the past ten years, their growth patterns have been more complicated in the age of limitless competition based on the needs of the times, obtainable output profits from the input resources available, and levels of technological advances in each industry. The objective of this study utilizes the conventional Malmquist productivity index to measure productivity growth in these five major transportation industries in 51 U.S. states as well as the pooled transportation industry between 2004 and 2011. The state-level findings from this study are expected to be used to evaluate whether each state's transport policies have sufficiently functioned to enhance productivity growth at its boundary. The structure of the remainder of this paper is as follows. Section 2 explains the methodology and Section 3 describes the data. In Section 4, the results of the empirical analysis are shown and Section 5 concludes the study.

2.2. Methodology

Let I define:

x^t = Input vector from time period, t = 1, …, T.

y^t = Output vector from time period, t = 1, …, T.

S^t = Production technology that x^t can produce y^t.

Four output distance functions are required to calculate the output-based Malmquist productivity index, and the first distance function is defined as follows (Färe, et al., 1992; Färe, et al., 1994A; Färe, et al., 1994B):

$$D_0^t\,(x^t, y^t) = \inf\,\{\theta\colon (x^t, y^t/\theta) \in S^t\}. \quad (2\text{-}1)$$

The first distance function means the maximum change in outputs using a set of given inputs with the technology at t, and it should be less than or equal to 1 if and only if $(x^t, y^t) \in S^t$. If $D_0^t\,(x^t, y^t)$ = 1, then it means that (x^t, y^t) is on the technology frontier.

The mixed-period distance function in Equation 2-2 evaluates the maximum change in outputs using a set of $\mathrm{t}+1$ inputs compared with the t benchmark technology:

$$D_0^t\,(x^{t+1}, y^{t+1}) = \inf\,\{\theta\colon (x^{t+1}, y^{t+1}/\theta) \in S^t\}. \quad (2\text{-}2)$$

In Equation 2-3, the mixed-period distance function for the maximum change in outputs using a set of t inputs with the benchmark technology at $t+1$ is evaluated:

$$D_0^{t+1}\,(x^t, y^t) = \inf\,\{\theta: (x^t, y^t/\theta) \in S^{t+1}\}. \tag{2-3}$$

The fourth distance function evaluates the maximum change in outputs using a set of $t+1$ inputs compared with the $t+1$ benchmark technology:

$$D_0^{t+1}\,(x^{t+1}, y^{t+1}) = \inf\,\{\theta: (x^{t+1}, y^{t+1}/\theta) \in S^{t+1}\}. \tag{2-4}$$

Following Färe et al. (1992) and Färe et al. (1994A; 1994B), the output-based Malmquist productivity index is defined as

$$M_0^{t+1}\,(x^{t+1}, y^{t+1}, x^t, y^t) = \left[\frac{D_0^t\,(x^{t+1},y^{t+1})}{D_0^t\,(x^t,y^t)}\frac{D_0^{t+1}\,(x^{t+1},y^{t+1})}{D_0^{t+1}\,(x^t,y^t)}\right]^{1/2}. \tag{2-5}$$

The equivalent index is redefined as

$$M_0^{t+1}\,(x^{t+1}, y^{t+1}, x^t, y^t) = \frac{D_0^{t+1}\,(x^{t+1},y^{t+1})}{D_0^t\,(x^t,y^t)}\left[\frac{D_0^t\,(x^{t+1},y^{t+1})}{D_0^{t+1}\,(x^{t+1},y^{t+1})}\frac{D_0^t\,(x^t,y^t)}{D_0^{t+1}\,(x^t,y^t)}\right]^{1/2}. \tag{2-6}$$

The output-oriented method measures how much output quantities can proportionally increase without increasing input quantities (Coelli, 1996). Equation 2-5 is the geometric mean of two Malmquist productivity indexes, and in Equation 2-6, the output-based Malmquist productivity index is converted into two terms: the first term out of the square brackets indicates the efficiency change between two periods, t and $t+1$, while the geometric mean of the second term in the square brackets captures technical progress in period $t+1$ and t. If the value of the output-based Malmquist productivity index in Equation 2-6 is equal to one, then no productivity growth occurs between these two periods, whereas if it is more (less) than one, there is positive (negative) productivity growth between these two periods. Efficiency and technological change have the same interpretation. For example, zero means nothing happens; however, if greater (less) than one, there is positive (negative) change (Färe, et al., 1992; Färe, et al., 1994A; Färe, et al., 1994B).

2.3. Data

The data in this study consist of three proxies for inputs and one proxy for output in the five major transportation industries in the U.S. between2004 and 2011. The output-based Malmquist productivity index requires only data for inputs and output(s): input data[1] are yearly intermediate inputs such as energy, materials, and purchased-service inputs and output data is represented by annual GDP, which is equivalent to value added. The Bureau of Economic Analysis (BEA) defines the composition of gross output by industry as the summation of intermediate inputs and value added (The United States Bureau of Economoic Analysis, 2013). The BEA, however, only provides to the public yearly intermediate inputs data at the national level for each industry, not by state. Therefore, the extent of taxes that each state collected in the transportation industries from 2004 to 2011 were used to estimate the best-possible approximation for intermediate inputs by state over time. This is based on the assumption that more taxes paid by a transportation industry in a state means more purchased inputs to produce output. For example, if the state of North Dakota collected $4 billon in its air transportation industry in 2004 compared with $10,229 billion in the U.S. airline transportation industry, then each energy, materials, and purchased-service input for the airline transportation industry in North Dakota is calculated by multiplying the proportion of $\frac{4}{10{,}229}$ by the national level of each intermediate input. All

[1] There exists a data disparity by state or by industry. For example, airline data are usually provided by each airline company, not state. But the BEA provides each transportation industry GDP by state.

data were obtained from the online database of the BEA in 2013, and they are measured in millions of dollars (The United States Department of Commerce, 2014).

Table 2-1 shows that the values of output produced have been proportionally increasing with those of the intermediate inputs used in the airline, truck, rail, and water transportation industries from 2004 to 2011 excluding 2009, which shows a slight decrease in output values; the pipeline transportation industry has been decreasing in terms of the input values used. The value of gross output in each transportation industry is occupied in order for the truck, airline, rail, water, and pipeline transport modes. Truck transportation is the largest transportation industry in terms of GDP, almost equal to the sum of the production values of the other four industries. The truck and airline transportation industries show much more intensive usages of energy and service inputs compared with materials inputs; that might be attributed to their fundamental industry structures. The pooled transportation industry summarizes the change in the three intermediate inputs utilized: materials inputs consist of much lower amounts compared with energy and purchased-service inputs.

Table 2-1. Annual GDP (Value Added) and Intermediate Inputs in Each Transportation Industry and the Pooled Transportation Industry, 2004–2011

Airline transportation	2004	2005	2006	2007	2008	2009	2010	2011
GDP	56.1	55.7	59.7	60.2	59.9	59.4	66.1	69.6
Intermediate inputs	66.4	74.5	80.5	89.6	101	72.1	79.8	92.1
Energy inputs	18.1	27.1	29.6	40.1	49.6	25.6	33	41.8
Materials inputs	2.1	1.5	1.8	2.6	2.7	1.9	1.9	2.3
Purchased-service inputs	46.2	46	49.1	46.9	48.7	44.6	44.8	48
Truck transportation	2004	2005	2006	2007	2008	2009	2010	2011
GDP	110.7	119.6	125.3	127.2	122.3	114.8	119.8	126
Intermediate inputs	122	136.8	148.4	153.7	162.1	116.2	128.5	149.1
Energy inputs	30.1	41.1	46.8	50.9	60.4	35.5	35.1	50
Materials inputs	13.3	13.8	14.7	18.5	17.6	13.8	13.6	16
Purchased-service inputs	78.6	81.9	86.9	84.2	84.1	67	79.7	83.1
Rail transportation	2004	2005	2006	2007	2008	2009	2010	2011
GDP	24.3	27	30.6	31.7	35.1	31	32.2	36.7
Intermediate inputs	26.4	32	36.6	38	43.4	32.4	43.7	49.1
Energy inputs	3.5	5.7	6.8	7.7	11.2	4.9	8.4	10.8
Materials inputs	5.5	6	6.7	7.7	9.6	6.9	8.9	9.8
Purchased-service inputs	17.4	20.3	23.1	22.6	22.6	20.7	26.4	28.5
Pipeline transportation	2004	2005	2006	2007	2008	2009	2010	2011
GDP	8.3	8.9	11.7	12.8	14.3	13.9	13.8	14.5
Intermediate inputs	11.9	12.8	13.6	14.1	14.1	10.3	8.3	6.4
Energy inputs	1	1.1	1.2	1.1	1.5	0.5	0.7	0.6
Materials inputs	2.2	2.2	2.4	2.4	2.3	1.4	1.3	1
Purchased-service inputs	8.7	9.4	10.1	10.6	10.4	8.4	6.3	4.8
Water transportation	2004	2005	2006	2007	2008	2009	2010	2011
GDP	31.3	34.8	36.6	39.6	41.3	42.8	43.5	45.6
Intermediate inputs	22.4	21.7	19.2	21.6	23.3	21.5	23.3	25.4
Energy inputs	7.7	9.1	7.3	10.1	11.1	6.9	9.9	12.7
Materials inputs	1.7	1.3	1.4	1.9	1.8	1.8	1.3	1.5
Purchased-service inputs	13	11.2	10.5	9.7	10.4	12.8	12.1	11.2
Pooled transportation	2004	2005	2006	2007	2008	2009	2010	2011
GDP	230.7	246	263.9	271.5	272.9	261.9	275.4	292.4
Intermediate inputs	249.1	277.8	298.3	317	343.9	252.5	283.6	322.1
Energy inputs	60.4	84.1	91.7	109.9	133.8	73.4	87.1	115.9
Materials inputs	24.8	24.8	27	33.1	34	25.8	27	30.6
Purchased-service inputs	163.9	168.8	179.7	174	176.2	153.5	169.3	175.6

2.4. Results

The traditional Malmquist productivity indexes for each transportation industry as well as the pooled transportation industry are estimated in Tables 2-3 to 2-9, by using DEA Programming (DEAP) 2.1. First, in Tables 2-3 to 2-8, the average productivity for the eight years by state for each transportation industry is shown. Second, Table 2-9 provides the annual average productivities for the transportation industries over time. In these tables, the sources of productivity growth are decomposed into an efficiency change component and a technological change component. Färe et al. (1994A) defined efficiency change as catching up, that is how much closer a state can approach the ideal frontier in a transportation industry, and technological change as an innovation, namely how much the ideal frontier shifts because of the existing technology.

In Table 2-2, the three non-parametric statistical tests such as Median test, Kruskal-Wallis test, and Van der Waerden test are tested to evaluate the validity of the Malmquist productivities in each transportation industry and the pooled transportation industry. Their null hypothesis of the six population distribution functions (airline, truck, rail, pipeline, water, and pooled transportation industries) are identical is rejected at the 1% significance level. This implies that the Malmquist productivities by state in the five major transportation industries and the pooled transportation industry show significantly different (Daniel, 1990).

Table 2-2. Non-Parametric Statistical Tests to Assess the Validity of the Malmquist Productivities

Statistical tests	P values
Median test	<0.001***
Kruskal-Wallis test	<0.001***
Van der Waerden test	<0.001***

Notes: the null hypothesis of the three tests is that the six population distribution functions are identical; *** indicates significance at 1%.

Table 2-3 shows the Malmquist productivity and its decomposition in the pooled model of the U.S. transportation industry from 2004 to 2011. On average, a positive productivity growth of 0.5% by state is shown, which is attributed to a 4.6% efficiency growth and a technological decline of 3.9%. This finding means that the transportation industry in a state has marginally increased growth on average, while its innovation movement is far below the efforts of catching up to the frontier. All states experience negative growth in technological change on average; therefore, if productivity growth in a state is positive, this suggests that its technological decline is offset or surpassed by an efficiency gain. Altogether, 28 states show positive productivity growth, and of these, the Malmquist productivity changes in the following 17 states average at least 10%: New York, North Carolina, North Dakota, Ohio, Oklahoma, Oregon, South Carolina, South Dakota, Tennessee, Texas, Utah, Vermont, Virginia, Washington, West Virginia, Wisconsin, and Wyoming. Figure 1 depicts the geographic representation of average productivity for the eight years by state in the pooled transportation industry: Malmquist productivity < 1, productivity decline; Malmquist productivity = 1, no change in productivity; Malmquist productivity > 1, productivity growth.

Table 2-3. Malmquist Productivity and Its Decomposition in the Pooled Model of the U.S. Transportation Industry, 2004–2011

State	Efficiency change	Technological change	Productivity
Alabama	0.914	0.951	0.869
Alaska	0.927	0.959	0.889
Arizona	0.918	0.969	0.890
Arkansas	0.969	0.967	0.937
California	0.970	0.959	0.930
Colorado	0.972	0.947	0.921
Connecticut	0.914	0.967	0.884
Delaware	0.940	0.964	0.906
District of Columbia	1.013	0.975	0.988
Florida	1.052	0.972	1.022
Georgia	1.035	0.961	0.994
Hawaii	0.988	0.978	0.966
Idaho	0.964	0.972	0.937
Illinois	0.922	0.955	0.880
Indiana	0.876	0.959	0.840
Iowa	0.859	0.948	0.814
Kansas	1.119	0.956	1.070
Kentucky	1.108	0.960	1.063
Louisiana	1.102	0.958	1.056
Maine	1.101	0.966	1.064
Maryland	1.116	0.960	1.072
Massachusetts	1.084	0.954	1.034
Michigan	1.047	0.964	1.010
Minnesota	1.051	0.952	1.000
Mississippi	0.839	0.957	0.803
Missouri	0.858	0.968	0.830
Montana	0.846	0.950	0.803
Nebraska	0.984	0.964	0.949
Nevada	0.976	0.953	0.930
New Hampshire	0.968	0.961	0.931
New Jersey	0.959	0.955	0.916
New Mexico	0.961	0.941	0.905
New York	1.179	0.944	1.113
North Carolina	1.188	0.969	1.151
North Dakota	1.184	0.969	1.148
Ohio	1.177	0.963	1.134
Oklahoma	1.192	0.957	1.141
Oregon	1.159	0.950	1.101
Pennsylvania	1.114	0.960	1.069
Rhode Island	1.127	0.961	1.083
South Carolina	1.166	0.957	1.115
South Dakota	1.170	0.965	1.129
Tennessee	1.155	0.973	1.123
Texas	1.239	0.970	1.201
Utah	1.195	0.963	1.151
Vermont	1.182	0.951	1.125
Virginia	1.179	0.962	1.135
Washington	1.206	0.962	1.160
West Virginia	1.190	0.963	1.147
Wisconsin	1.165	0.971	1.131
Wyoming	1.161	0.972	1.128
Average	1.046	0.961	1.005

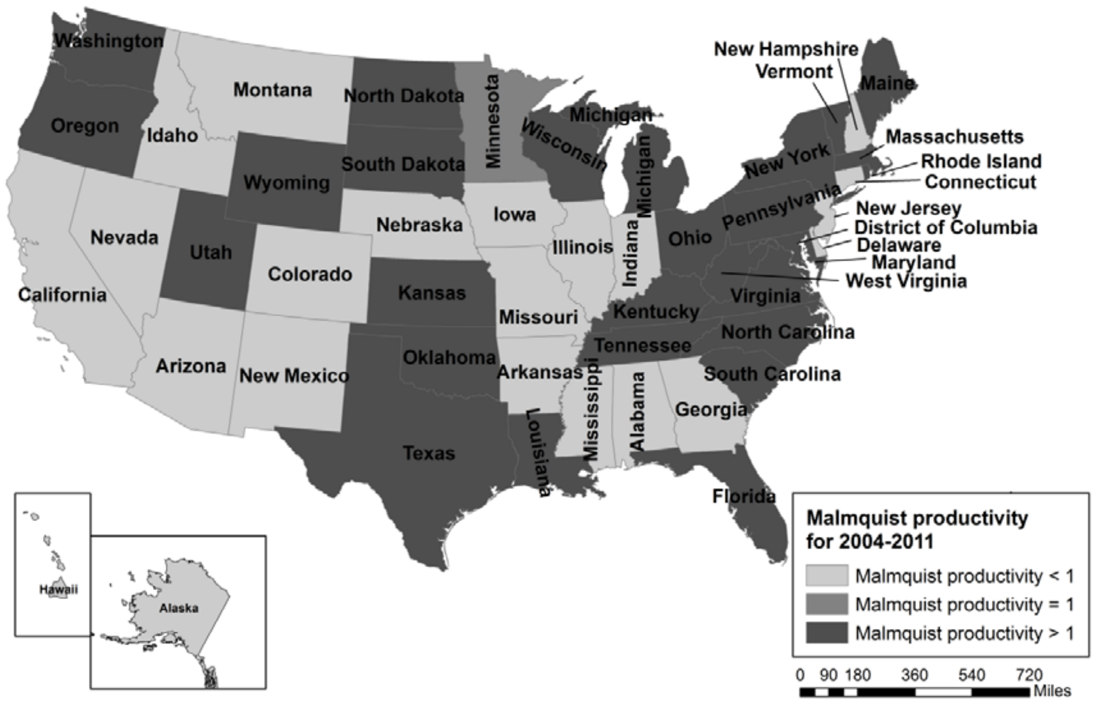

Figure 2-1. Geographic Representation of Average Malmquist Productivity for 2004–2011 by State in the Pooled Transportation Industry

The productivity measurement in the U.S. transportation industry by state is now described more in detail with the results of the five major transportation industries. Table 2-4 shows the changes in Malmquist productivity, efficiency, and technology in the airline transportation industry between 2004 and 2011. Productivity growth by state averages close to zero due to the increase of 1% in efficiency change and the decrease of 1.1% in technological change; therefore, the airline transportation industry by state on average shows that growth itself might be stuck at zero or at worst showing a slight decline during the study period. Nevertheless, 27 of the 51 states show positive productivity growth, with Texas and Wyoming having the highest growth of 10.3%. Figure 2-2 depicts the geographic representation of average productivity for 2004–2011 by state in the airline transportation industry.

Table 2-4. Malmquist Productivity and Its Decomposition in the Airline Transportation Industry in the U.S., 2004–2011

State	Efficiency change	Technological change	Productivity
Alabama	1.031	0.979	1.009
Alaska	1.013	0.995	1.008
Arizona	1.030	1.039	1.070
Arkansas	1.070	0.967	1.034
California	1.046	0.944	0.988
Colorado	0.996	1.007	1.003
Connecticut	0.934	0.991	0.925
Delaware	0.944	0.983	0.927
District of Columbia	0.941	0.979	0.922
Florida	0.908	0.995	0.903
Georgia	0.908	1.039	0.943
Hawaii	1.056	0.967	1.021
Idaho	1.005	0.944	0.950
Illinois	0.953	1.007	0.960
Indiana	0.953	0.991	0.944
Iowa	0.964	0.983	0.947
Kansas	0.999	0.979	0.978
Kentucky	0.998	0.995	0.993
Louisiana	1.013	1.039	1.052
Maine	1.112	0.967	1.075
Maryland	1.076	0.944	1.016
Massachusetts	1.000	1.007	1.007
Michigan	0.980	0.991	0.971
Minnesota	0.991	0.983	0.974
Mississippi	0.942	0.979	0.922
Missouri	0.961	0.995	0.956
Montana	0.971	1.039	1.009
Nebraska	1.026	0.967	0.992
Nevada	1.018	0.944	0.961
New Hampshire	0.952	1.007	0.959
New Jersey	0.914	0.991	0.905
New Mexico	0.928	0.983	0.912
New York	0.971	0.979	0.950
North Carolina	1.099	0.995	1.093
North Dakota	1.055	1.039	1.097
Ohio	1.133	0.967	1.095
Oklahoma	1.093	0.944	1.032
Oregon	1.023	1.007	1.030
Pennsylvania	1.014	0.991	1.005
Rhode Island	1.041	0.983	1.023
South Carolina	0.997	0.979	0.976
South Dakota	0.996	0.995	0.991
Tennessee	0.963	1.039	1.001
Texas	1.141	0.967	1.103
Utah	1.129	0.944	1.066
Vermont	1.048	1.007	1.055
Virginia	1.026	0.991	1.017
Washington	1.079	0.983	1.061
West Virginia	1.041	0.979	1.020
Wisconsin	1.045	0.995	1.040
Wyoming	1.061	1.039	1.103
Average	1.01	0.989	0.998

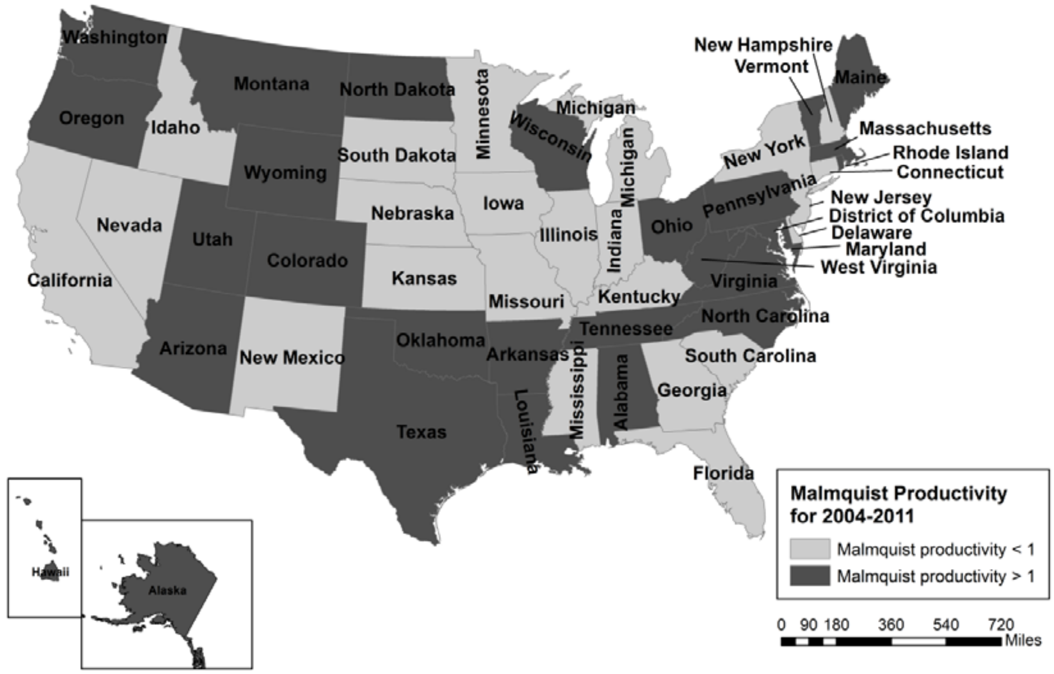

Figure 2-2. Geographic Representation of Average Malmquist Productivity for 2004–2011 by State in the Airline Transportation Industry

Table 2-5 shows the Malmquist productivity and its decomposition in the truck transportation industry from 2004 to 2011. On average, a negative productivity growth of 2.2% per state is shown and this is decomposed into an efficiency gain of 0.6% and a technological decline of 2.7%. The truck industry in each state shows all negative technological changes, implying that innovation has declined over time on average; however, the productivity growth changes in the 20 states on average show non-zero growth due to the high levels of catching up. It is noted that productivity growth in Kansas, Kentucky, and Louisiana is much higher than that in the other 20 states with positive growth (19.1%, 16.7%, and 16.5%, respectively). Figure 2-3 depicts the geographic representation of average productivity for 2004–2011 by state in the truck transportation industry.

Table 2-5. Malmquist Productivity and Its Decomposition in the Truck Transportation Industry in the U.S., 2004–2011

State	Efficiency change	Technological change	Productivity
Alabama	0.981	0.971	0.953
Alaska	0.961	0.98	0.942
Arizona	0.964	0.975	0.939
Arkansas	0.974	0.972	0.946
California	0.956	0.977	0.934
Colorado	0.94	0.974	0.915
Connecticut	0.924	0.968	0.894
Delaware	0.955	0.965	0.921
District of Columbia	1.004	0.971	0.975
Florida	0.991	0.98	0.971
Georgia	1.008	0.975	0.983
Hawaii	1.039	0.972	1.009
Idaho	0.992	0.977	0.969
Illinois	0.97	0.974	0.944
Indiana	0.982	0.968	0.95
Iowa	0.996	0.965	0.961
Kansas	1.226	0.971	1.191
Kentucky	1.19	0.98	1.167
Louisiana	1.195	0.975	1.165
Maine	1.117	0.972	1.086
Maryland	1.116	0.977	1.09
Massachusetts	1.075	0.974	1.047
Michigan	1.103	0.968	1.068
Minnesota	1.09	0.965	1.051
Mississippi	0.843	0.971	0.819
Missouri	0.827	0.98	0.811
Montana	0.828	0.975	0.807
Nebraska	0.971	0.972	0.944
Nevada	0.962	0.977	0.94
New Hampshire	0.956	0.974	0.931
New Jersey	0.966	0.968	0.935
New Mexico	0.968	0.965	0.934
New York	1.062	0.971	1.032
North Carolina	1.084	0.98	1.063
North Dakota	1.089	0.975	1.061
Ohio	1.068	0.972	1.038
Oklahoma	1.076	0.977	1.051
Oregon	1.047	0.974	1.02
Pennsylvania	1.059	0.968	1.025
Rhode Island	1.065	0.965	1.028
South Carolina	1.049	0.971	1.019
South Dakota	1.042	0.98	1.021
Tennessee	1.038	0.975	1.011
Texas	0.947	0.972	0.92
Utah	0.942	0.977	0.92
Vermont	0.918	0.974	0.894
Virginia	0.969	0.968	0.938
Washington	0.965	0.965	0.931
West Virginia	0.992	0.971	0.964
Wisconsin	0.981	0.98	0.962
Wyoming	0.989	0.975	0.964
Average	1.006	0.973	0.978

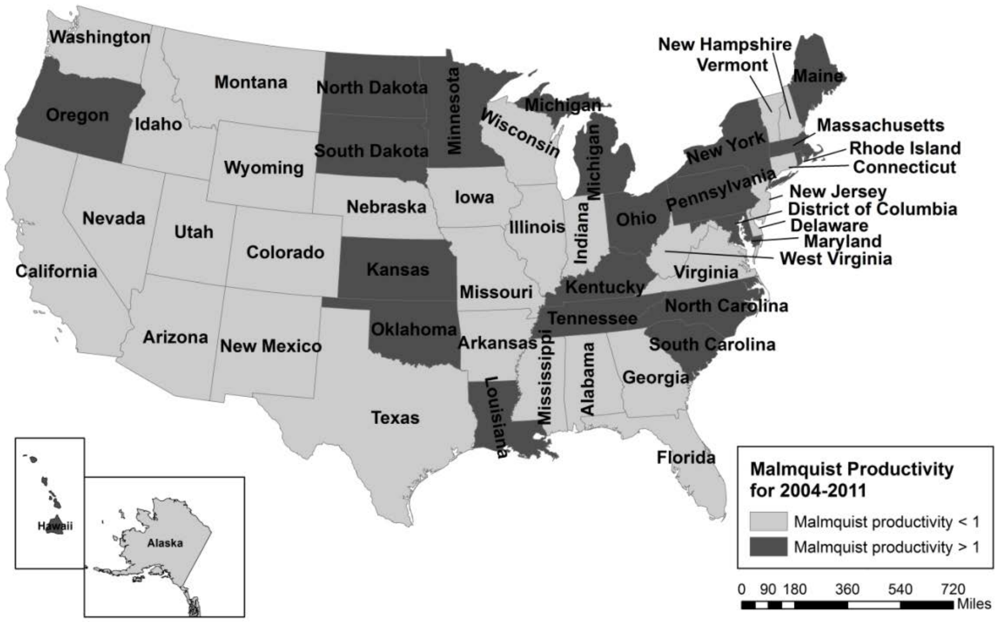

Figure 2-3. Geographic Representation of Average Malmquist Productivity for 2004–2011 by State in the Truck Transportation Industry

In Table 2-6, the changes in Malmquist productivity, efficiency, and technology in the rail transportation industry are shown between 2004 and 2011. On average, the rail transportation industry by state shows a negative productivity growth of 1.1% based on a decrease of 5.2 % in efficiency change and an increase of 4.3% in technological change. The results of the rail industry are interesting in two regards. First, the 16 states showing positive productivity growth had been growing with a high average productivity growth of 7% to 54.9%. In particular, the productivity growth rates in West Virginia, Texas, Utah, Vermont, Washington, Wyoming, and Wisconsin reach 54.9%, 47.7%, 46.9%, 41.9%, 37.1%, 37.1%, and 36.8%, respectively. Second, all 49 states show at least 0.8% annual average innovation growth, meaning that innovation has been continuously shifting on average. Figure 2-4 depicts the geographic representation of average productivity for 2004–2011 by state in the rail transportation industry.

Table 2-6. Malmquist Productivity and Its Decomposition in the Rail Transportation Industry in the U.S., 2004–2011

State	Efficiency change	Technological change	Productivity
Alabama	0.885	1.031	0.912
Arizona	0.772	1.026	0.793
Arkansas	0.762	1.072	0.817
California	0.768	1.052	0.808
Colorado	0.763	1.008	0.769
Connecticut	0.786	1.037	0.816
Delaware	0.811	1.064	0.862
District of Columbia	0.793	1.059	0.839
Florida	0.835	1.031	0.861
Georgia	0.845	1.026	0.867
Idaho	0.812	1.072	0.870
Illinois	0.823	1.052	0.865
Indiana	0.813	1.008	0.819
Iowa	0.828	1.037	0.859
Kansas	0.867	1.064	0.922
Kentucky	0.835	1.059	0.884
Louisiana	0.796	1.031	0.821
Maine	0.847	1.026	0.869
Maryland	0.843	1.072	0.904
Massachusetts	0.871	1.052	0.915
Michigan	0.844	1.008	0.851
Minnesota	0.815	1.037	0.845
Mississippi	0.836	1.064	0.889
Missouri	0.821	1.059	0.869
Montana	0.907	1.031	0.935
Nebraska	1.043	1.026	1.070
Nevada	1.023	1.072	1.097
New Hampshire	1.072	1.052	1.127
New Jersey	1.084	1.008	1.092
New Mexico	1.111	1.037	1.152
New York	1.152	1.064	1.226
North Carolina	1.076	1.059	1.139
North Dakota	0.942	1.031	0.971
Ohio	0.916	1.026	0.940
Oklahoma	0.898	1.072	0.963
Oregon	0.901	1.052	0.948
Pennsylvania	0.879	1.008	0.886
Rhode Island	0.890	1.037	0.923
South Carolina	0.903	1.064	0.961
South Dakota	0.893	1.059	0.945
Tennessee	1.161	1.031	1.197
Texas	1.439	1.026	1.477
Utah	1.370	1.072	1.469
Vermont	1.349	1.052	1.419
Virginia	1.279	1.008	1.289
Washington	1.322	1.037	1.371
West Virginia	1.457	1.064	1.549
Wisconsin	1.292	1.059	1.368
Wyoming	1.330	1.031	1.371
Average	0.948	1.043	0.989

Note: Rail transportation information for Alaska and Hawaii is not available in the BEA online database, so 49 states are used for this productivity analysis.

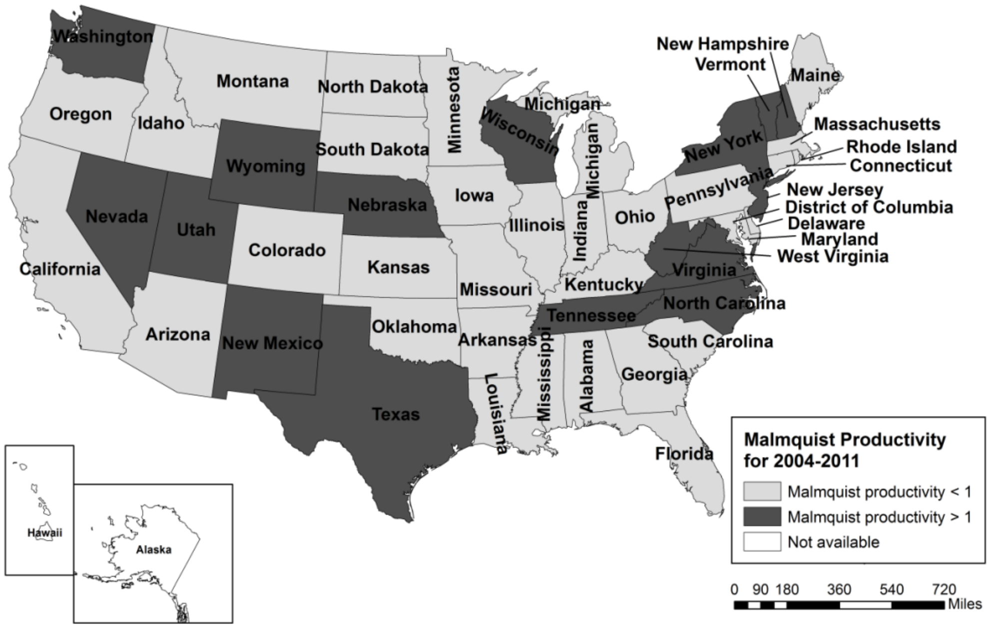

Figure 2-4. Geographic Representation of Average Malmquist Productivity for 2004–2011 by State in the Rail Transportation Industry

Table 2-7 shows the change in Malmquist productivity and its decomposition in the pipeline transportation industry by state from 2004 to 2011. On average, the productivity decline by state in this industry is the highest of the five major transportation industries, showing -11.2%. This is explained by the severe annual average technological decline of 18.3% and the 10% increase in efficiency change. Excluding the seven states of Maryland, Massachusetts, Michigan, Minnesota, Mississippi, Missouri, and Ist Virginia, the productivity change in the remaining states averages much less than zero. Innovation in all states had been declining with much lower technological change, with some states even showing decreases in both efficiency and technological change: Florida, Louisiana, North Dakota, Ohio, Oklahoma, Pennsylvania, South Carolina, and Tennessee. Figure 2-5 depicts the geographic representation of average productivity for 2004–2011 by state in the pipeline transportation industry.

Table 2-7. Malmquist Productivity and Its Decomposition in the Pipeline Transportation Industry in the U.S., 2004–2011

State	Efficiency change	Technological change	Productivity
Alabama	1.047	0.815	0.854
Alaska	1.107	0.816	0.903
Arizona	1.122	0.815	0.915
Arkansas	1.078	0.820	0.884
California	1.211	0.821	0.994
Colorado	1.061	0.815	0.865
Connecticut	1.061	0.815	0.865
Florida	0.896	0.815	0.730
Georgia	1.106	0.815	0.902
Idaho	1.122	0.816	0.916
Illinois	1.123	0.815	0.915
Indiana	1.079	0.820	0.885
Iowa	1.202	0.821	0.987
Kansas	1.037	0.815	0.846
Kentucky	1.080	0.815	0.880
Louisiana	0.930	0.815	0.758
Maine	1.208	0.815	0.984
Maryland	1.253	0.816	1.022
Massachusetts	1.265	0.815	1.032
Michigan	1.233	0.820	1.011
Minnesota	1.431	0.821	1.174
Mississippi	1.232	0.815	1.004
Missouri	1.337	0.815	1.089
Montana	1.171	0.815	0.954
Nebraska	1.097	0.815	0.894
Nevada	1.126	0.816	0.919
New Hampshire	1.144	0.815	0.933
New Jersey	1.081	0.820	0.887
New Mexico	1.170	0.821	0.960
New York	1.036	0.815	0.844
North Carolina	1.055	0.815	0.860
North Dakota	0.846	0.815	0.689
Ohio	0.964	0.815	0.785
Oklahoma	0.984	0.816	0.803
Oregon	1.013	0.815	0.826
Pennsylvania	0.995	0.820	0.816
Rhode Island	1.145	0.821	0.939
South Carolina	0.992	0.815	0.808
South Dakota	1.012	0.815	0.824
Tennessee	0.883	0.815	0.720
Texas	1.103	0.815	0.899
Utah	1.141	0.816	0.931
Virginia	1.162	0.815	0.947
Washington	1.137	0.820	0.933
West Virginia	1.242	0.821	1.019
Wisconsin	1.094	0.815	0.892
Wyoming	1.143	0.815	0.931
Average	1.100	0.817	0.898

Note: Pipeline transportation information for District of Columbia, Delaware, Hawaii, and Vermont is not available in the BEA online database, so 47 states are used for the productivity analysis.

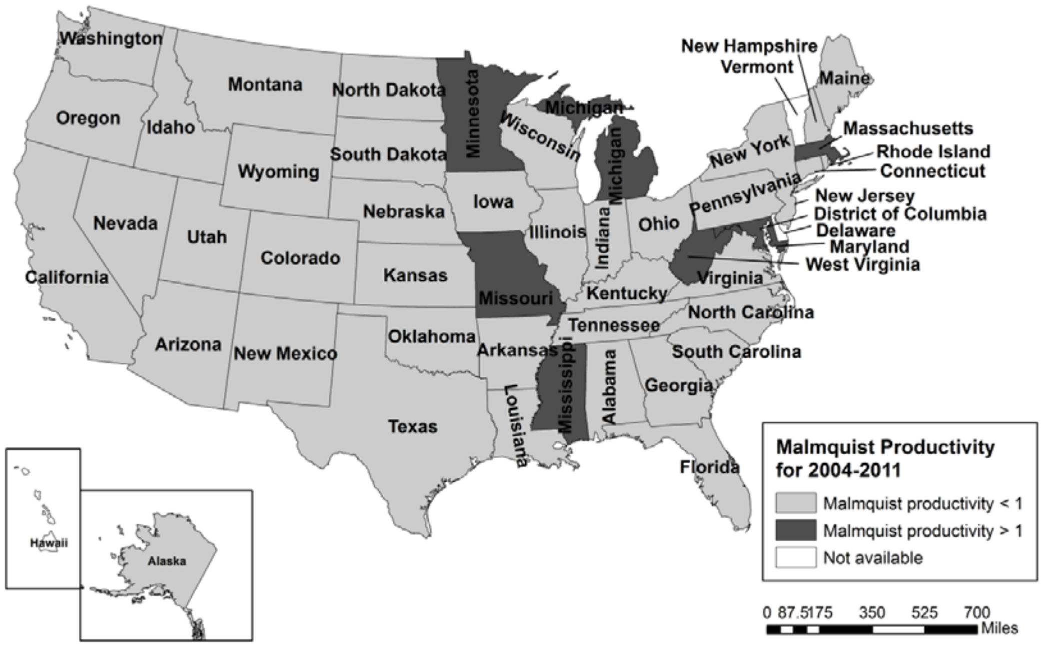

Figure 2-5. Geographic Representation of Average Malmquist Productivity for 2004–2011 by State in the Pipeline Transportation Industry

In Table 2-8, Malmquist productivity and its decomposition in the water transportation industry are shown between2004 and 2011. Average productivity growth in the water transportation industry in each state shows close to zero growth or a slight increase. On average, productivity growth is 0.1%, which is decomposed into an increase of 2.3% in efficiency change and a decrease of 2.2% in technological change. Like the truck transportation industry, each water transportation industry in the 38 states shows all negative technological changes, but the productivity changes in the 18 states show growth. The following states having an average productivity growth of more than 10%: Arizona (18.1%), North Carolina (16.4%), South Carolina (15.3%), Pennsylvania (13.9%), Connecticut (13.9%), Rhode Island (13.2%), Ohio (11.1%), and Alaska (10.9%). Figure 2-6 depicts the geographic representation of average productivity for 2004–2011 by state in the water transportation industry.

Table 2-8. Malmquist Productivity and Its Decomposition in the Water Transportation Industry in the U.S., 2004–2011

State	Efficiency change	Technological change	Productivity
Alabama	1.087	0.978	1.063
Alaska	1.147	0.967	1.109
Arizona	1.197	0.987	1.181
Arkansas	1.115	0.977	1.090
California	1.082	0.978	1.058
Connecticut	1.150	0.991	1.139
District of Columbia	1.051	0.969	1.018
Florida	1.078	0.980	1.056
Georgia	1.111	0.978	1.086
Hawaii	1.057	0.967	1.021
Illinois	1.031	0.987	1.017
Indiana	1.010	0.977	0.988
Iowa	1.000	0.978	0.978
Kentucky	1.000	0.991	0.991
Louisiana	0.849	0.969	0.822
Maine	0.864	0.980	0.846
Maryland	1.035	0.978	1.012
Massachusetts	1.002	0.967	0.968
Michigan	0.947	0.987	0.934
Mississippi	0.999	0.977	0.977
Missouri	0.973	0.978	0.952
New Jersey	0.915	0.991	0.907
New Mexico	0.993	0.969	0.962
New York	0.997	0.980	0.977
North Carolina	1.191	0.978	1.164
Ohio	1.149	0.967	1.111
Oregon	1.092	0.987	1.077
Pennsylvania	1.165	0.977	1.139
Rhode Island	1.158	0.978	1.132
South Carolina	1.164	0.991	1.153
Tennessee	0.974	0.969	0.943
Texas	0.992	0.980	0.972
Utah	0.951	0.978	0.930
Vermont	0.942	0.967	0.910
Virginia	0.918	0.987	0.906
Washington	0.883	0.977	0.864
West Virginia	0.891	0.978	0.871
Wisconsin	0.904	0.991	0.896
Average	1.023	0.978	1.001

Note: Water transportation information for Colorado, Delaware, Idaho, Kansas, Montana, Nebraska, Nevada, New Hampshire, Minnesota, North Dakota, Oklahoma, South Dakota, and Wyoming is not available in the BEA online database, so 38 states are used for the productivity analysis.

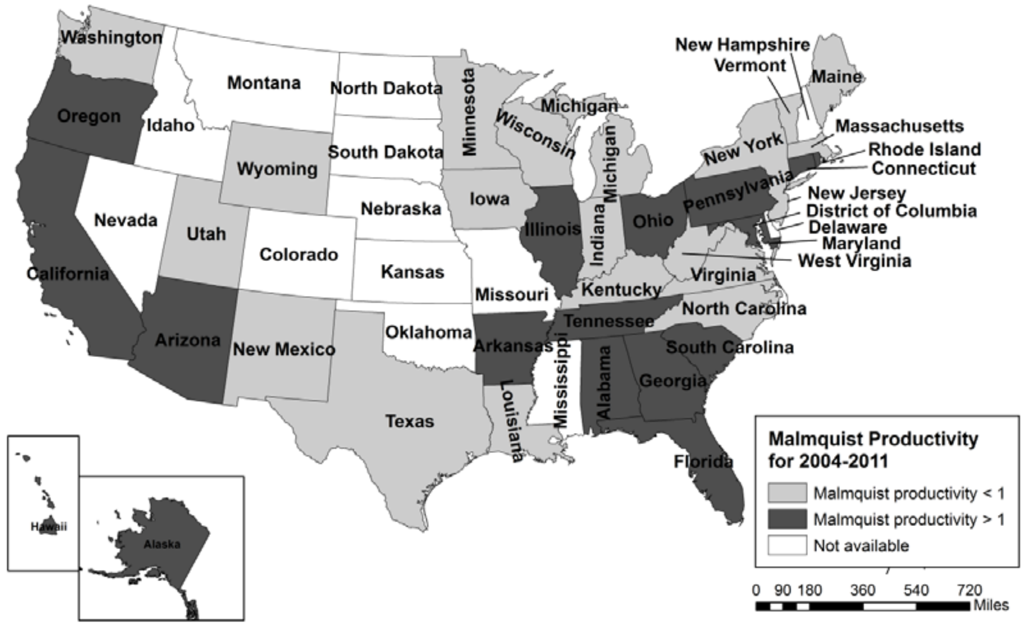

Figure 2-6. Geographic Representation of Average Malmquist Productivity for 2004–2011 by State in the Water Transportation Industry

Table 2-9 summarizes the annual average productivity and efficiency and technological change in the five major transportation industries and the pooled transportation industry for 2004 to 2011. As is known, an unexpected global financial crisis occurred in 2007, 2008, and 2010, which negatively affected U.S. industry. As a result, each transportation industry had been growing at different rates corresponding to the U.S. economic recovery.

The major findings are as follows. First, the pooled transportation representing the U.S. transportation industry shows productivity growth of 21.7% in 2011 as well as a strong and positive trend except in the years of 2007, 2008, and 2010. Second, the airline transportation industry shows a severe drop in productivity growth during the years of the global financial crisis, but high productivity growth in 2005, 2009, and 2011. Third, the truck transportation industry grew in 2007 and 2010, but recently shows a decrease in productivity growth and even a decline in 2011 at 16.4%. Fourth, productivity growth in the rail transportation industry exponentially increased except in those three years. Indeed, the distinct productivity growth levels of 50.2% in 2006, 81.5% in 2009, and 91.6% in 2011 are surprising. Fifth, the pipeline transportation industry grew sharply until 2008, but after that point, productivity declines drifted. This industry show a productivity decline with the truck transportation industry in 2011. Finally, the water transportation industry on average shows at least 10% productivity growth out of the years of the financial crisis, but particularly almost close to zero in 2009. It is also ranked the second highest productivity growth in 2011 (37%). Overall, efficiency and technological change shows a mixed increase or decrease over time in each industry and the pooled transportation industry, but their productivities have predictable increasing or decreasing trends. Figure 2-7 depicts the productivities of each transportation industry and the pooled transportation industry for 2005, 2006, 2009, and 2011.

Table 2-9. Productivity and Efficiency and Technological Change in Each Industry and the Pooled Industry during the Period of 2004 to 2011

Productivity	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**Average**
Airline transportation	1.389	0.862	0.783	0.836	1.327	0.840	1.132	0.998
Truck transportation	0.642	1.322	1.039	0.872	1.208	1.105	0.836	0.978
Rail transportation	0.476	1.502	1.216	0.660	1.815	0.464	1.916	0.989
Pipeline transportation	0.494	1.035	1.087	1.921	0.752	0.829	0.707	0.898
Water transportation	1.176	1.121	0.870	0.917	0.990	0.708	1.370	1.001
Pooled transportation	0.662	1.485	0.831	0.951	1.291	0.848	1.217	1.005

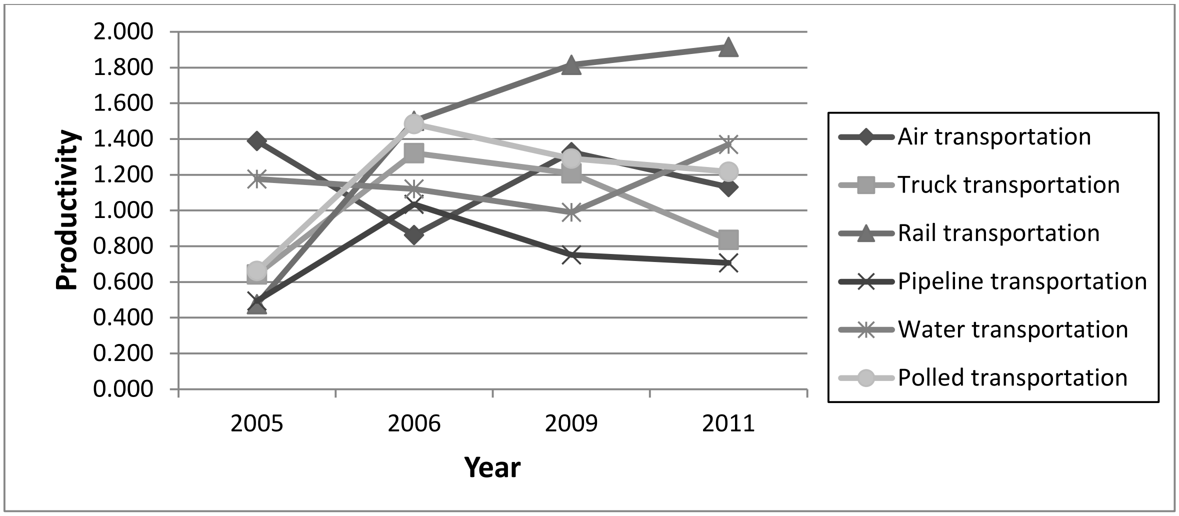

Figure 2-7. Annual Average Malmquist Productivities of Each Transportation Industry and the Pooled Transportation Industry for 2005, 2006, 2009, and 2011

2.5. Conclusions

The U.S. transportation industry contributes over one-tenth of U.S. GDP, and thus its productivity growth is importantly connected to the growth of the entire U.S. economy. In this study, I measured productivity growth in the five major transportation industries of airline, truck, rail, pipeline, and water as well as the pooled transportation industry for 2004–2011 and decomposed this growth into efficiency and technological change to provide its fundamental driving forces. This study separately finds the results of average productivity for the eight years by state in each transportation industry and the annual average productivities for the transportation industries themselves. Although the average productivity growth by state in these transportation industries is on average close to zero or slightly increasing, the overall U.S. transportation industry grew with a strong and positive trend with notable productivity growth of 21.7% in 2011, except in the years of the global financial crisis in 2007, 2008, and 2010. The rail and water transportation industries had the first and second highest productivity growth in 2011, which might have been as a result of the growth in sustainable transport modes globally.

This study has a limitation based on the data used. The intermediate inputs for each state were estimated to find the best-possible approximation through the extent of taxes that each state collected; if original data on energy, materials, and purchased-service inputs in the BEA were available to the public, I could estimate more accurate results for productivity growth in the U.S. transportation industry.

CHAPTER 3. HOW DOES A CARBON DIOXIDE EMISSINS CHANGE AFFECT TRANSPORTATION PRODUCTIVITY? A CASE STUDY OF THE U.S. TRANSPORTATION SECTOR FROM 2002 TO 2011

3.1. Introduction

The concentrations of greenhouse gases (GHGs) in the atmosphere made by human activities have increased since the Industrial Revolution and they have led to significant global warming compared with the past two centuries (Intergovernmental Panel on Climate Change, 2013). Rising temperature globally is contributing to a rise in sea level caused by melting ice in the North and South Poles, more frequent occurrences of natural disasters (floods, droughts, etc.), and a change of ecosystems on Earth, thereby threatening its survival and prosperity (Barth & Boriboonsomsin, 2008; Intergovernmental Panel on Climate Change, 2007A; The U.S. Environmental Protection Agency, 2014A).

At the global scale, carbon dioxide (CO_2), which was the largest GHG emissions source in 2004, consists of 60% of total GHG emissions, while transportation-sector CO_2 emissions represented 15% of total GHG emissions in 2010. Furthermore, global CO_2 emissions from transport increased by 45% in 1990–2007, and these are projected to increase by approximately 40% from 2007 to 2030 (Intergovernmental Panel on Climate Change, 2007B; The International Transport Forum, 2010). Hence, the transportation sector is a large and steadily growing source of GHG emissions (Krautzberger & Wetzel, 2012).

In the U.S., CO_2 emissions account for 82% of total U.S. GHG emissions, which is higher than the global average. Furthermore, the U.S. transportation sector emitted over one-third of total U.S. CO_2 emissions in 2012. U.S. CO_2 emissions, which are the second largest in the world, represented 1481 million metric tons (MMT) in 2010, which accounted for 19% of CO_2 emissions in the world, while China emitted 2259 MMT (23%) (The U.S. Department of Energy, 2010; The U.S. Environmental Protection Agency, 2014B). On the other hand, CO_2 emissions have reduced in the U.S. transportation sector since 2008, as a result of not only political support for more fuel-efficient vehicle standards and the development of cost-effective alternative energy, but also changes in consumer and producer preferences toward eco-friendly vehicles (Wang, et al., 1999; Barth & Boriboonsomsin, 2008; Karplus & Paltsev, 2012).

Figure 3-1 shows the changes in gross domestic product (GDP) and CO_2 emissions from 2002 to 2011 for the U.S. transportation sector (The U.S. Bureau of Economic Analysis, 2014; The U.S. Environmental Protection Agency, 2014D). The increasing trend in U.S. CO_2 emissions remained until 2007, but thereafter they fell compared with the period of 2002–2007. Although the U.S. experienced a global financial crisis at the end of the 2000s, the U.S. transportation sector grew consistently after a slight decrease in 2009, so that CO_2 emissions reduction entered a new phase.

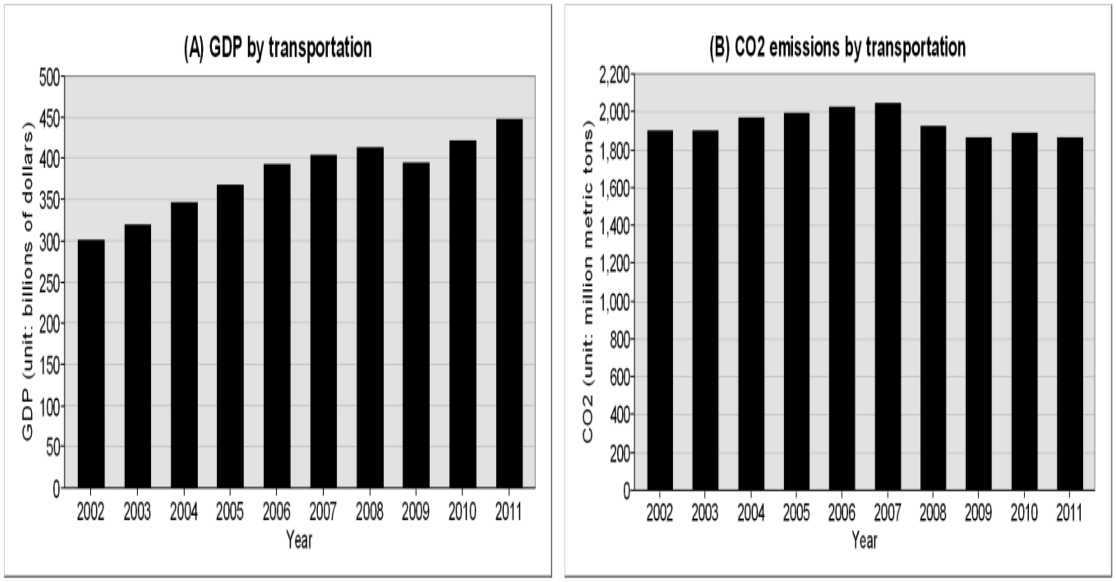

Figure 3-1. Changes in GDP and CO_2 emissions in the U.S. Transportation Sector from 2002 to 2011

A transport mode that operates only on electricity or hydrogen does not emit CO_2 emissions (The U.S. Environmental Protection Agency, 2014C). However, most transport modes (airlines, light- and heavy-duty vehicles, rail, and sea vessels) are today driven by the combustion of fossil fuels. However, CO_2 will be emitted less and less with newer carbon reduction technologies and by using carbon-neutral alternative fuels (Messa, 2006; Boriboonsomsin, et al., 2009; Bittner, et al., 2012; Nealer, et al., 2012; Winchester, et al., 2013; Rodrigues, et al., 2014; Buehler, Undated).

For the past couple of decades, a variety of studies have used the Data Envelopment Analysis Malmquist productivity index to measure productivity changes (Färe, et al., 1992; Färe & Grosskopf, 1994; Färe, et al., 1994A; Färe, et al., 1994B; Hjalmarsson, et al., 1996). However, but as a couple of authors have pointed out (Ball, et al., 2004; Heng, et al., 2012), this approach is limited to analyzing the relationship between output change(s) and non-environmental factors.

However, Ball et al. (2004) developed the Malmquist environmental productivity index to measure the effects of environmental pollution[2] on actual productivity change and this has been applied in various fields including transportation by several researchers (Ball, et al., 2004; Lansink & Silva, 2004; Managi, et al., 2005; Watjanapukka, 2006; Heng, et al., 2012; Shortalla & Barnesb, 2013). In 2004, Ball et al. (2004) used the Malmquist environmental productivity index to measure U.S. agriculture productivity for 1960–1996 with four environmental impact variables, and Lansink and Silva (2004) utilized it to calculate the environmental productivity of pesticides based on the shadow price of pesticides generated from a non-parametric method.

On the other hand, Managi et al. (2005) and Watjanapukka (2006) applied the Malmquist environmental productivity index to explain the interactions between environmental regulations, technological innovation, and productivity growth in the oil and gas industry in the Gulf of Mexico and productivity changes in U.S. electricity generation from environmental externalities (SO_2, NO_x, and CO_2), respectively. Similarly, Heng et al. (2012) used it to reveal the actual productivity change from an air pollution reduction in the U.S. trucking industry and Shortalla and Barnesb (2013) applied it to examine environmental efficiency, including the change in GHG emissions from milk ranches in Scotland.

[2] There are two point of views regarding whether an environmental pollution vector should be in input or output vectors from Fare et al. (1992, 1994A) and Ball et al. (2004). This study followed the perspective of which environmental pollution is in input vector according to Ball et al. (2004).

In the literature, however, even though a variety of research fields has analyzed actual productivity change from environmental pollution through the Malmquist environmental productivity index, to our best knowledge, no research has thus far been conducted in the transportation sector to evaluate the effects of a CO_2 emissions change (GHG emissions change) on actual productivity. To address this limitation, this study reviews how actual productivity in the U.S. transportation sector has been affected by the CO_2 emissions change for 2002–2012 and then reveals the driving forces behind it. From this study, state-level findings will be used to evaluate whether each state's CO_2 emissions reduction efforts have appropriately functioned at its boundary.

The second section of this study presents the study area and factors of CO_2 emissions changes and the third section explains the methodology. After the data and empirical results are presented, the conclusions discuss the relationship between actual productivity and the CO_2 emissions change in the U.S. transportation sector.

3.2. Study Area and Factors of the CO_2 Emissions Change

The transportation sector plays an important role in the growth in the U.S. economy, which showed spending of $1.33 trillion in 2012, accounting for 8.5 % of U.S. total GDP. While it is a major and large-scale sector to increase national wealth, the transportation sector is also a significant source of emitting CO_2 in the U.S. Indeed, it is the fastest-growing source of CO_2 emissions among other sectors (industry, commercial, residential, and agriculture), showing an approximately 17% net increase in total U.S. transportation CO_2 emissions between1990 and 2011 (The U.S. Bureau of Economic Analysis, 2014; The U.S. Department of Commerce, 2014).

To consider the significant CO_2 emissions in the U.S. transportation sector and to detect its micro-level change by state, the study area for this study was defined as all 49 states in the U.S. and Hawaii and Alaska. There exist many possible factors behind the CO_2 emissions change, but among them, this study largely demonstrates three main factors. First, there is a state policy change. For example, many states show their own strategies to simultaneously achieve a CO_2 emissions reduction and economic development goals in the transportation sector. States are doing exemplary actions to address CO_2 emissions activities within their states by making either 1) case studies lead by example activities[3], 2) a GHG inventory[4], or 3) climate change action plans[5] (The U.S. Environmental Protection Agency, 2014E).

Second, a total fuel consumption decline has been observed in the U.S. transportation sector since 2008 and this is projected to fall from 26.7 quadrillion Btu in 2012 to 25.5 quadrillion Btu in 2040. Because at least 99% of the carbon in a fuel is emitted as CO_2 through combustion, the recent CO_2 emissions reduction during the same period was directly led by the total fuel consumption decline. Such a decreasing trend in total fuel consumption was attributed to a variety of causes such as increases in vehicle fuel efficiency with improving CO_2 reduction technologies, oil price, biofuel production, and a

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[3] A state is leading by example to reduce CO2 emissions and encourage using clean energy in government facilities and operations (The U.S. Environmental Protection Agency, 2014E).

[4] An accounting method of GHG emitted to or removed from the atmosphere in a particular period (The U.S. Environmental Protection Agency, 2014E).

[5] Strategies such as particular policy recommendations that a state utilizes to reduce its GHG emissions (The U.S. Environmental Protection Agency, 2014E).

decrease in vehicle mileage travel from Light Duty Vehicles[6] exceeding growth in other transport modes (The U.S. Energy Information Administration, 2014A; The U.S. Environmental Protection Agency, 2014C).

Third, federal regulations in air pollution including GHG emissions have been stricter over time. For instance, under the Clean Air Act (1970) and Clean Air Act Amendments (1990), Energy Policy Act (2005) and Energy Independence and Security Act (2007), and Obama announcements of national policies to reduce GHG emissions in 2009–2011 and 2014, the U.S. Environmental Protection Agency has set stricter limits of how much CO_2 can be emitted in the transportation sector (The U.S. Environmental Protection Agency, 2014F; 2014G).

Figure 3-2 shows CO_2 emissions changes in the transportation sector by state for 2002–2011 (The U.S. Environmental Protection Agency, 2014D). During the period 2002–2011, 32 states among 51 emitted CO_2 in 2011 less than in 2002, but 19 states increased CO_2 emissions in 2011 compared with in 2002. The top five largest CO_2 emissions reductions between2002 and 2011 arose in California, Michigan, Pennsylvania, Louisiana, and Ohio, but the top five largest CO_2 emissions increases occurred with Illinois, Florida, Georgia, South Carolina, and Iowa. However, as noted, since 2008, all states excluding Nebraska, North Dakota, and South Dakota have decreased CO_2 emissions.

[6] Light Duty Vehicles mean that their maximum gross vehicle weight rating is less than 8,500 pounds (The U.S. Energy Information Administration, 2014A).

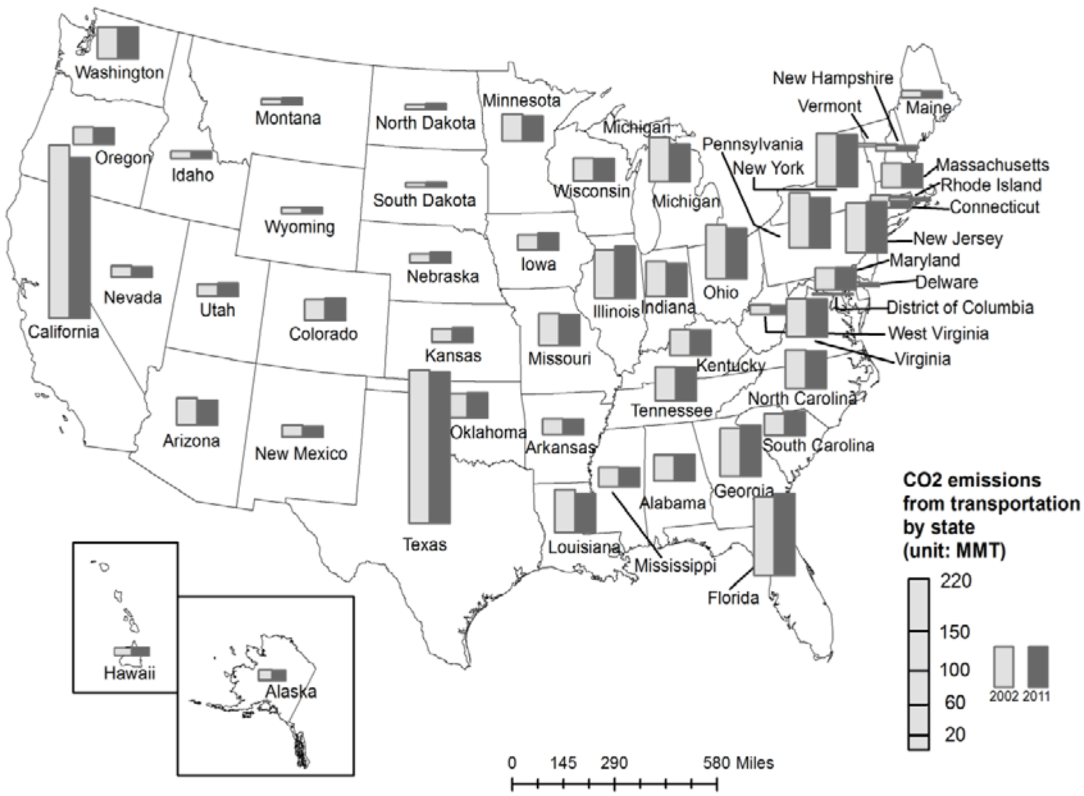

Figure 3-2. Changes in CO_2 Emissions from the U.S. Transportation Sector by State Between 2002 and 2011

3.3. Methodology

Let I define:

x^t = Input vector from time period, $t = 1, \ldots, \mathrm{T}$.

b^t = Environmental pollution vector from time period, $t = 1, \ldots, \mathrm{T}$.

y^t = Output vector from time period, $t = 1, \ldots, \mathrm{T}$.

S^t = Production technology that x^t can produce y^t.

Conventional Malmquist productivity is calculated from four output distance functions, and these functions are defined as follows (Färe, et al., 1992; 1994A; 1994B; Färe & Grosskopf, 1994):

$$D_0^t\ (x^t, y^t) = \inf\ \{\theta: (x^t, y^t/\theta) \in S^t\}. \tag{3-1}$$

$$D_0^t\ (x^{t+1}, y^{t+1}) = \inf\ \{\theta: (x^{t+1}, y^{t+1}/\theta) \in S^t\}. \tag{3-2}$$

$$D_0^{t+1}\ (x^t, y^t) = inf\ \ \{\theta: (x^t, y^t/\theta) \in S^{t+1}\}. \tag{3-3}$$

$$D_0^{t+1}\ (x^{t+1}, y^{t+1}) = inf\ \ \{\theta: (x^{t+1}, y^{t+1}/\theta) \in S^{t+1}\}. \tag{3-4}$$

The first distance function in Equation 3-1 explains the maximum change in outputs from the input vector with the technology at t, and it is noted that it is less than or equal to 1 if and only if $(x^t, y^t) \in S^t$. If $D_0^t\ (x^t, y^t)$ = 1; then, (x^t, y^t) is on the technology frontier. The mixed-period distance function in Equation 3-2 means the maximum change in outputs from $t + 1$ inputs compared with the t technology. In Equation 3-3, the maximum change in outputs from t inputs with the technology at $t + 1$ is evaluated, and Equation 3-4 explains the maximum change in outputs by using a set of $t + 1$ inputs compared with the $t + 1$ technology.

Following Färe et al. (Färe, et al., 1992; 1994A; 1994B) and Färe and Grosskopf (Färe & Grosskopf, 1994), the output-based conventional Malmquist productivity is as follows:

$$M_O\ (x^{t+1}, y^{t+1}, x^t, y^t) = \frac{D_0^{t+1}\ (x^{t+1}, y^{t+1})}{D_0^t\ (x^t, y^t)} [\frac{D_0^t\ (x^{t+1}, y^{t+1})}{D_0^{t+1}\ (x^{t+1}, y^{t+1})} \frac{D_0^t\ (x^t, y^t)}{D_0^{t+1}\ (x^t, y^t)}]^{1/2}. \tag{3-5}$$

According to Ball et al. (2004), output-based environmentally sensitive Malmquist productivity is defined as

$$M_{OE}\ (x^{t+1}, y^{t+1}, b^{t+1}, x^t, y^t, b^t) = \frac{D_0^{t+1}\ (x^{t+1}, y^{t+1}, b^{t+1})}{D_0^t\ (x^t, y^t, b^t)} [\frac{D_0^t\ (x^{t+1}, y^{t+1}, b^{t+1})}{D_0^{t+1}\ (x^{t+1}, y^{t+1}, b^{t+1})} \frac{D_0^t\ (x^t, y^t, b^t)}{D_0^{t+1}\ (x^t, y^t, b^t)}]^{1/2}. \tag{3-6}$$

In Equation 3-6, with the presence of environmental pollution, the environmental efficiency change is shown with out of the square brackets between t and $t+1$ periods and is called a catching up, namely how much closer a state can approach the ideal frontier. On the other hand, environmental technical progress is the geometric mean of the second term in the square brackets in periods of t and $t+1$, and this means a technological innovation, namely how much the ideal frontier shifts from the existing technology. If $M(OE) = 1$, then there is no environmental productivity growth between t and $t+1$ periods, whereas if $M(OE) > 1$ ($M(OE) < 1$), there is positive (negative) environmental productivity growth between these two periods (Färe, et al., 1994A).

Following Ball et al. (2004), the Malmquist environmental productivity index is the ratio of environmentally sensitive and conventional Malmquist productivities as follows:

$$E_H\,(x^{t+1}, y^{t+1}, b^{t+1}, x^t, y^t, b^t) = \frac{M_{OE}\,(x^{t+1}, y^{t+1}, b^{t+1}, x^t, y^t, b^t)}{M_O\,(x^{t+1}, y^{t+1}, x^t, y^t)}. \tag{3-7}$$

$E(H)$, the Malmquist environmental productivity index, has three signs: if $E(H) = 1$, then it means that environmentally sensitive Malmquist productivity and conventional Malmquist productivity are the same, that is, environmental pollution does not have any impact on actual productivity change; if $E(H) > 1$, then it implies that environmentally sensitive Malmquist productivity is greater than conventional Malmquist productivity (actual productivity growth is affected by the change in environmental pollution), and; if $E(H) < 1$, then environmentally sensitive Malmquist productivity is less than conventional Malmquist productivity. Hence, the change in environmental pollution has an impact on the actual productivity decline (Heng, et al., 2012).

3.4. Data

The output distance function only needs data for inputs, output, and pollutions (Heng, et al., 2012), meaning that in our analysis state-level panel data of 51 states for the period of 2002–2011 were used. These consist of one proxy for output, three proxies for inputs, and one proxy for GHG effects in the U.S. transportation sector. The one output is GDP from the transportation sector in a state, which was measured in millions of dollars and derived from the U.S. Bureau of Economic Analysis (2014). For inputs, the number of workers, number of establishments, and all petroleum consumption by the transportation sector in a state were utilized: the first and second inputs are measured in ones and obtained from the U.S. Census Bureau (2014) and the third input, thousand barrels of oils, was derived from the U.S. Energy Information Administration (2014B). To be representative of the GHG effect, state CO_2 emissions by fuel combustion in the transportation sector were chosen and derived from the U.S. Environmental Protection Agency (2014D) and measured in MMT.

Table 3-1 shows the summary statistics for the data used in this study. The coefficient of variation in each variable that is calculated from the ratio of the standard deviation to the mean shows much less than 10, suggesting the dispersion of the variables is small (Mendenhall & Sincich, 2011); therefore, no input and output used in the data shows a high heterogeneity among the 51 states. California has the largest transportation industry in the data, while District of Columbia is the smallest transportation industry. In addition, in terms of output production and CO_2 emissions, California's transportation industry produces approximately 125 times more gross output and 168 times more CO_2 emissions than District of Columbia's transportation industry. During the study period,

CO_2 emissions from the U.S. transportation sector in 2011 decreased by 2% compared with 2002, but GDP from it in 2011 increased by 48% during the same period.

Table 3-1. Summary statistics for output and input variables from 2002 to 2011

Variable	Mean	SD	Min	Max	CV
GDP (million dollars)	7,489	8,369	302	47,457	1.12
Labor (ones)	81,185	86,323	3,110	468,916	1.06
Establishment (ones)	4,123	4,018	175	21,711	0.97
Petroleum (thousands of barrels)	97,643	107,158	2,853	615,649	1.10
CO_2 (MMT)	38.02	41.64	1.07	238.14	1.10

3.5. Empirical Results

To measure the effects of the CO_2 emissions change on U.S. transportation productivity for 2002–2011, the Malmquist environmental productivity index was calculated from a Data Envelopment Analysis (program 2.1) and decomposed into conventional and environmentally sensitive Malmquist productivities and their efficiency and technological components in the Malmquist summary of state means in Table 3-3. In Table 3-4, the index from the Malmquist summary of annual means was used to reveal the relationship betweenCO_2 emissions changes and actual productivity.

Before further discussions of the Malmquist environmental productivity index, the two non-parametric statistical tests in Table 3-2 were performed to assess the validity of conventional and environmentally sensitive Malmquist productivities. Even though the Sign test rejected the null hypothesis that the difference between them is equally positive or negative at the 10% significance level, there was insufficient evidence to show the difference in the two productivities was nonzero. Therefore, the Signed Rank test was additionally performed to compare the differences between conventional and environmentally sensitive Malmquist productivities with zeroes, and then the null hypothesis of indifference between them was rejected at 5%, showing that they were statistically different from each other (Daniel, 2000).

Table 3-2.Non-Parametric Statistical Tests between Conventional and Environmentally Sensitive Malmquist Productivities

Statistical test	Statistic and p-value
Sign test	-7 (0.064)*
Signed Rank test	-231.5 (0.023)**

Notes: the null hypothesis of the Sign test is that the difference between conventional and environmentally sensitive Malmquist productivities is equally positive or negative; the null hypothesis of the Signed Rank test is that the mean difference between conventional and environmentally sensitive Malmquist productivities is zero; * and ** indicate significance at 10% and 5%, respectively.

In Table 3-3, the effects of these CO_2 emissions changes were interpreted with the three distinct findings from the Malmquist environmental productivity index. First, among the 51 states, 17 states showed an actual productivity decline ($E(H) < 1$) with a decrease in CO_2 emissions, which suggests that a CO_2 emissions reduction in one-third of U.S. states from the transportation sector negatively affected actual productivity. Second, California, which had emitted the largest CO_2 but decreased CO_2 emissions from the transportation sector the most, demonstrated that conventional and environmentally sensitive Malmquist productivities were the same ($E(H) = 1$), which means a CO_2 emissions reduction had not changed actual productivity. Third, as the ideal case, 30 states, much more than half of the 51 states sampled, revealed actual productivity growth ($E(H) > 1$) with a decrease in CO_2 emissions.

Many states (22 in 30) with $E(H) > 1$ showed higher (lower) technological (efficiency) change scores in environmentally sensitive Malmquist productivity than in conventional Malmquist productivity, implying that the driving force of actual productivity growth from a CO_2 emissions reduction was attributed to a technological innovation increase exceeding an efficiency decrease. On the other hand, all states with $E(H) < 1$ experienced lower efficiency change scores when considering a CO_2 emissions reduction compared with conventional Malmquist productivity. These lowered inefficiency scores eventually resulted in an actual productivity decline since they were not offset by increased technological scores, and were aggravated in some states by decreased technological scores in environmentally sensitive Malmquist productivity.

Most states have emitted less and less CO_2 from the transportation sector since 2008, but as noted Nebraska and North Dakota have increased CO_2 emissions, leading to actual productivity growth. The reverse trend of these two states is not desirable to compare to a sustainable growing pattern found by the third finding above. A solution might be achieved by actively considering existing and upcoming transportation policies to reduce CO_2 emissions. However, these could cause an actual productivity decline once they negatively function as a heavy burden to reducing CO_2 emissions, as in the second case. Figure 3-3 geographically describes the summary of the Malmquist environmental productivity index with a CO_2 emissions change in the transportation sector by state means for 2002–2011.

Table 3-3. Conventional and Environmentally Sensitive Malmquist Productivities ($M(H)$, $M(EH)$), Their Efficiency and Technological Changes (Effch and Techch), and the Malmquist Environmental Productivity Index $E(H)$ in the U.S. Transportation Sector by State Means for 2002–2011

State	Effch	Techch	$M(H)$	Effch	Techch	$M(EH)$	$E(H)$
Alabama	1.079	0.955	1.030	1.097	0.951	1.043	1.013
Alaska	1.099	0.933	1.025	1.097	0.937	1.028	1.003
Arizona	1.095	0.951	1.041	1.092	0.955	1.043	1.002
Arkansas	1.092	0.948	1.035	1.089	0.949	1.033	0.998
California	1.093	0.946	1.034	1.090	0.948	1.034	1.000
Colorado	1.101	0.961	1.058	1.099	0.964	1.059	1.001
Connecticut	1.090	0.964	1.051	1.087	0.965	1.049	0.998
Delaware	1.108	0.959	1.063	1.103	0.960	1.059	0.996
District of Columbia	1.107	0.970	1.074	1.102	0.969	1.068	0.994
Florida	1.108	0.973	1.077	1.103	0.975	1.075	0.998
Georgia	1.040	0.959	0.997	1.040	0.962	1.001	1.004
Hawaii	1.009	0.959	0.968	1.009	0.963	0.972	1.004
Idaho	1.002	0.932	0.934	1.002	0.937	0.939	1.005
Illinois	1.020	0.934	0.952	1.020	0.940	0.959	1.007
Indiana	1.012	0.930	0.941	1.012	0.937	0.948	1.007
Iowa	1.009	0.931	0.940	1.009	0.936	0.945	1.005
Kansas	0.989	0.923	0.913	0.989	0.929	0.919	1.007
Kentucky	0.997	0.921	0.918	0.996	0.928	0.924	1.007
Louisiana	0.988	0.913	0.902	0.988	0.919	0.907	1.006
Maine	0.982	0.895	0.879	0.982	0.899	0.883	1.005
Maryland	1.120	0.923	1.034	1.117	0.929	1.038	1.004
Massachusetts	1.023	0.948	0.970	1.020	0.954	0.973	1.003
Michigan	1.016	0.951	0.966	1.015	0.957	0.971	1.005
Minnesota	1.020	0.945	0.964	1.014	0.954	0.968	1.004
Mississippi	1.022	0.951	0.972	1.017	0.958	0.975	1.003
Missouri	1.025	0.960	0.984	1.020	0.967	0.987	1.003
Montana	1.019	0.964	0.983	1.013	0.972	0.985	1.002
Nebraska	1.028	0.979	1.007	1.023	0.987	1.009	1.002
Nevada	1.022	0.966	0.988	1.014	0.974	0.987	0.999
New Hampshire	1.021	0.980	1.000	1.012	0.984	0.995	0.995
New Jersey	1.059	0.982	1.040	1.056	0.981	1.037	0.997
New Mexico	1.029	0.966	0.994	1.049	0.956	1.002	1.008
New York	1.032	0.973	1.004	1.051	0.963	1.013	1.009
North Carolina	1.025	0.974	0.998	1.044	0.965	1.008	1.010
North Dakota	1.026	0.971	0.996	1.047	0.964	1.01	1.014
Ohio	1.033	0.965	0.998	1.054	0.959	1.011	1.013
Oklahoma	1.030	0.958	0.987	1.049	0.949	0.996	1.009
Oregon	1.042	0.961	1.001	1.062	0.953	1.011	1.010
Pennsylvania	1.033	0.970	1.002	1.052	0.959	1.008	1.006
Rhode Island	1.024	0.944	0.966	1.042	0.936	0.976	1.010
South Carolina	1.087	0.929	1.009	1.106	0.922	1.02	1.011
South Dakota	1.086	0.946	1.027	1.079	0.949	1.024	0.997
Tennessee	1.070	0.967	1.034	1.063	0.966	1.027	0.993
Texas	1.070	0.974	1.042	1.062	0.971	1.032	0.990
Utah	1.071	0.981	1.051	1.065	0.976	1.039	0.989
Vermont	1.078	0.986	1.063	1.072	0.986	1.057	0.994
Virginia	1.086	0.997	1.083	1.079	1.001	1.08	0.997
Washington	1.090	0.992	1.081	1.083	0.993	1.075	0.994
West Virginia	1.072	0.990	1.061	1.064	0.990	1.054	0.993
Wisconsin	1.079	0.990	1.068	1.071	0.993	1.063	0.995
Wyoming	1.102	0.998	1.099	1.096	0.999	1.094	0.995

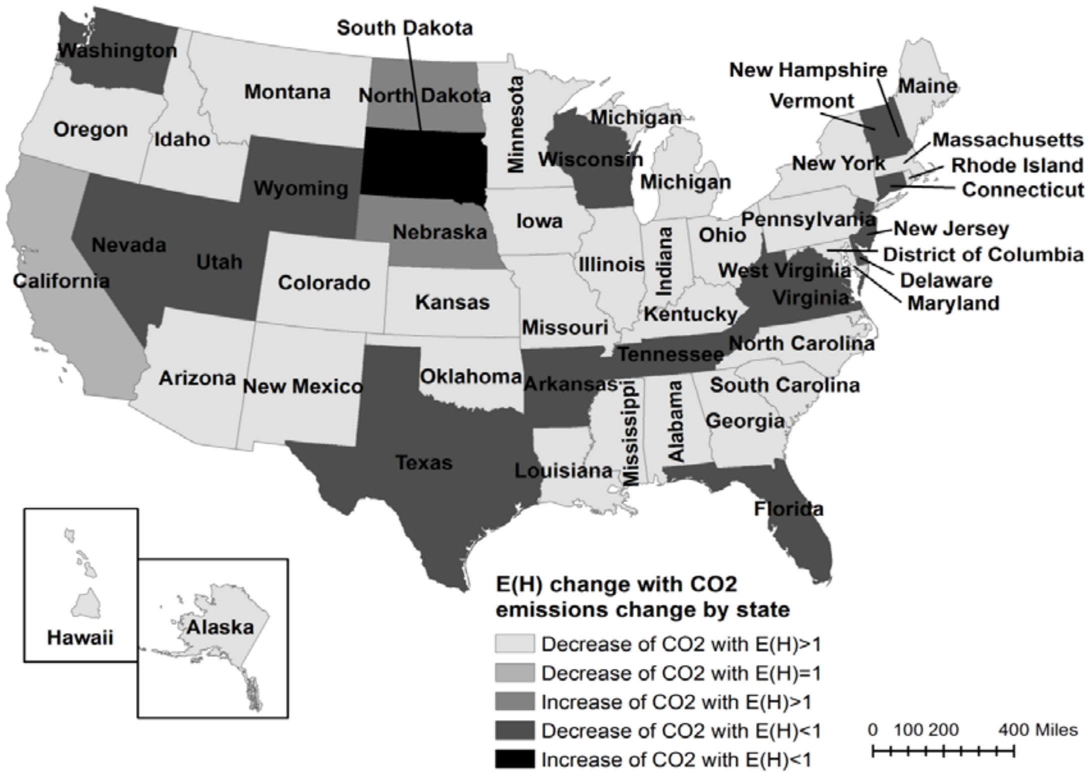

Figure 3-3. Malmquist Environmental Productivity Index ($E(H)$) with the CO_2 Emissions Change by State Means for 2002–2011

Unlike Table 3-3 (state means over the 10-year period), Table 4 shows the findings by annual means. During the period 2002–2011, there was a probability of approximately 67% (because of 2003, 2006, and 2007) that if average CO_2 emissions by state in year t increased (decreased) compared with $t-1$, then environmentally sensitive Malmquist productivity in year t was smaller (larger) than conventional Malmquist productivity in the same year. Thus, the average CO_2 emissions reduction since 2008 excluding 2010 by state in the transportation sector positively contributed to actual productivity growth. This finding was confirmed by the Malmquist environmental productivity indices showing more than or equal to one ($E(H) \geq 1$) during the same period.

Table 3-4. Conventional and Environmentally Sensitive Malmquist Productivities ($M(H)$, $M(EH)$) and the Malmquist Environmental Productivity Index $E(H)$ in the U.S. Transportation Sector by Annual Means for 2002–2011

Year	State mean CO2 emissions (unit: MMT)	$M(H)$	$M(EH)$	$E(H)$
2003	36.883	0.884	0.899	1.017
2004	37.554	1.116	1.115	0.999
2005	37.831	0.916	0.911	0.995
2006	38.136	0.945	0.951	1.006
2007	38.304	1.297	1.297	1.000
2008	37.168	0.850	0.851	1.001
2009	36.561	0.901	0.903	1.002
2010	36.793	1.148	1.146	0.998
2011	36.508	1.071	1.073	1.002

Notes: CO_2 emissions in 2002 is 36.877 MMT; 2002 does not have a base year to calculate M(H), M(EH), and E(H).

3.6. Conclusions

It can be assumed that CO_2 emissions reduction efforts in the transportation sector have a negative effect on productivity growth since reducing CO_2 emissions would lead to not only a decrease in fossil fuel consumption (mainly used to all transport modes), but also large-scale financial investments for developing CO_2 reduction technology and alternative energy.

By applying the Malmquist environmental productivity index in the U.S. transportation sector by state, this study, however, revealed that the effects of a CO_2 emissions reduction can positively affect actual productivity growth. Most states experiencing such sustainable growth showed technological innovation increases going beyond efficiency decreases. Activities to reduce CO_2 emissions evidently affected decision making and acted as a heavy burden to actual productivity. However, new technology developments, making possible more fuel-efficient and carbon reduction transport modes as well as alternative transportation energy sources in recent years, have moved the ideal frontier further from the existing out-of-date frontier.

This might make I question why in the same nation each state had no choice but to experience individual and different efficiency and technological changes. Although new carbon reduction and fuel-efficient technologies were developed in the market, the usage of these at the initial stage required the payment of high costs to producers as well as consumers. Thus, once I understand that each state has different political tendencies with regard to subsidies and environmental regulations, cultural understanding, and concerns about CO_2 emissions, the result in this study could make sense.

Given the advancing low-carbon and energy-efficient technology and increasing environmental policies for the CO_2 emissions reduction in the transportation sector in the world, it will be possible in the near future for CO_2 emissions reduction efforts in the transportation sector to positively affect productivity growth.

This study, nevertheless, could not estimate the individual and quantified effect on actual productivity of a change in environmental policy, fuel-efficient and CO_2 reduction technology development, or each input used. I could only decompose actual productivity change into efficiency and technological changes based on the Malmquist environmental productivity index, but those two factors might be two of many more possible driving forces. In addition, due to data confidentiality, this study had no choice but to focus on aggregate transportation sector data, not by each transport mode such as airlines, trucks, railways, sea vessels, pipelines, and so on. Thus, those limitations might be solved by a future study, if one can collect data by transport mode and use a multiple regression.

CHAPTER 4. FORECAST OF CO_2 EMISSIONS FROM THE U.S. TRANSPORTATION SECTOR: ESTIMATION FROM A DOUBLE EXPONENTIAL SMOOTHING MODEL

4.1. 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, CO2 emissions from U.S. transportation energy use increased up until 2008 due to the growth of the three factors of 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 the demand of vehicle mileage travel from passenger cars (The 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[7], which

[7] The USEPA 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).

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). Heavy-duty vehicles, airplanes, marine vessels, lubricants, and military use are expected to continue to increase fuel consumption for the next two decades, however (The 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 (The 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. Figure 4-1 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 (The U.S Energy Information Administration, 2013).

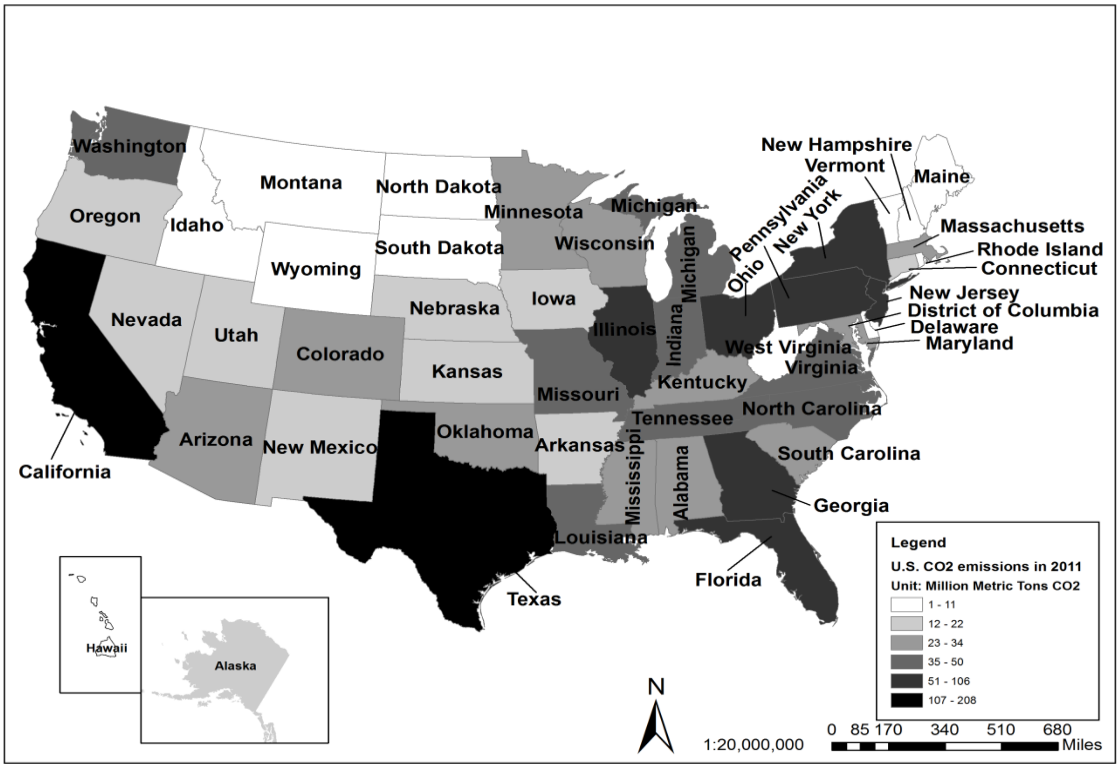

Figure 4-1. U.S. CO_2 Emissions by State and the District of Columbia in 2011

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, et al., 2012; Rentziou, et al., 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 started to forecast 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 CO2 emissions from 2012 to 2021 and ii) to review whether the decreasing trend in U.S. transportation CO2 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 CO2 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 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 U.S.

4.2. Discussions of Alternative Forecasting Techniques

There exist many mathematical forecasting models today. Among them, the autoregressive integrated moving average (ARIMA) technique and the seasonal autoregressive integrated moving average (S-ARIMA) technique that are statistically sophisticated and mathematically complex methods 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 number 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-ARIAM techniques compared to 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)

4.3. 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 (The 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 (The 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 Energy Policy Act (2005), Energy Independence and Security Act (2007), and Obama announcements of national policies (2009–2011 and 2014), stricter nation air quality standards have been established by the IEPA. For more detailed information, Table 4-1 provides each air pollution act and its key points regarding reducing air pollution and/or GHG emissions (The U.S. Environmental Protection Agency, 2014A, 2014B).

Table 4-1. 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 Ie 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 IEPA (2014A, 2014B).

4.4. Methodology

Let I 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.

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

$$Y_t = \mu_t + \varepsilon_t, \qquad t = 1, \ldots, T. \tag{4-1}$$

The smoothing equation is:

$$S_t = \alpha Y_t + (1 - \alpha) S_{t-1}. \tag{4-2}$$

The m-step prediction equation is:

$$\hat{Y}_t(m) = S_t. \tag{4-3}$$

The *m*-step prediction value $\hat{Y}_t(m)$ is estimated through Equation 4-1 and Equation 4-2 (Elliott & Timmermann, 2008; SAS 9.2 User's Book, 2013). Equation 4-1 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 Equation 4-2. 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 α. Exponential smoothing does not regard the effect of each past lag equally, and rather gives more weight to recent observations; hence, the smoothing weight α between0 and 1 is adjusted for this purpose. The smoothing process is backdated from time t to time 1 to determine the starting value of the smoothed state at time 0 (Chatfield & 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 S_t in Equation 4-3. Thus, a DES model is used to reflect the effect of a trend in the data.

The model equation for this is:

$$Y_t = \mu_t + \beta_t t + \varepsilon_t, \qquad t = 1, \ldots, T. \tag{4-4}$$

The smoothing equations are:

$$S'_t = \alpha Y_t + (1 - \alpha)S'_{t-1}. \tag{4-5}$$

$$S''_t = \alpha S'_t + (1 - \alpha)S''_{t-1}. \tag{4-6}$$

The m-step prediction equation is:

$$\hat{Y}_t(m) = \left(2 + \frac{\alpha m}{1-\alpha}\right)S'_t - (1 + \frac{\alpha m}{1-\alpha})S''_t. \tag{4-7}$$

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 Equation 4-5 and Equation 4-6. (Elliott & 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 Equation 4-5 and Equation 4-6. The DES method can extrapolate nonseasonal patterns and trends such that the time series is smooth and has a slowly time-varying mean.

4.5. Data

The data on CO_2 emissions[8] 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 U.S. Environmental Protection Agency (IEPA) for 1990–2011 (The 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

[8] CO2 emissions per kWh in electricity from coal-fired thermal power stations are reported higher than in CO2 emissions per kWh from various fuels (Hutton 2013).

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[9], 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 (IEIA) (The 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, I calculated the ratio of CO_2 emissions and motor gasoline consumption from 1990 to 2011 in a state. Second, I 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 between1990 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 4-2 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

[9] CO2 emissions are generally relevant with both gasoline consumption and diesel consumption data. Due to the nonavailability of diesel consumption data to the public, this study could only use gasoline consumption data.

recently increased their CO_2 emissions: Alabama, Alaska, Hawaii, Idaho, Iowa, Louisiana, Nebraska, New Jersey, North Dakota, Ohio, Oklahoma, Tennessee, Texas, and Utah.

Table 4-2. CO_2 Emissions from the Transportation Sector by State, the District of Columbia, and the U.S. from 1960 to 2011

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

Table 4-2. CO_2 Emissions from the Transportation Sector by State, the District of Columbia, and the U.S. from 1960 to 2011 (continued)

State/Year	1960	1970	1980	1990	2000	2007	2009	2011
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
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 IEIA (2013); the CO_2 emissions from 1990 to 2011 were obtained from IEPA (2013).

4.6. Empirical Results

Before beginning with 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), I assumed that motor gasoline consumption in the transportation sector will decrease in the next ten years even though the U.S. economic recovery will be shown, since a decrease in the demand of vehicle mileage travel from passenger cars which is the most possible cause to show recent decrease in CO_2 emissions in the U.S. transportation sector will 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[10] 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 4-3 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.

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[10] 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).

Table 4-3. 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	36.1	33.5†	32.6	33.7	33.5
	(33.7, 37.6)	(34.2, 38.1)	(34.7, 38.7)	(31.8, 35.7)	(30.1, 34.0)	(31.1, 35.1)
Arizona	38.2	37.9†	35.0†	33.1	32.0	31.7
	(36.7, 39.0)	(38.0, 40.4)	(37.3, 39.7)	(33.2, 35.6)	(30.4, 32.8)	(29.3, 31.7)
Arkansas	20.6	21.1	20.5	20.3	20.4	20.1
	(19.1, 22.4)	(19.1, 22.4)	(19.6, 22.8)	(19.0, 22.3)	(18.7, 21.9)	(18.7, 21.9)
Alaska	19.1	18.0†	15.4†	13.6†	15.0	14.2
	(17.9, 21.6)	(18.2, 22.0)	(17.3, 21.1)	(14.7, 18.5)	(12.1, 15.9)	(12.2, 16.0)
California	234	238	222†	217	215	207
	(221, 245)	(226, 250)	(230, 254)	(212, 237)	(202, 226)	(198, 223)
Colorado	30.7	31.5	30.1†	29.3	29.8	28.8
	(29.2, 32.3)	(30.1, 33.2)	(30.8, 34.0)	(29.3, 32.5)	(27.9, 31.1)	(28.1, 31.2)
Connecticut	17.6†	17.6	16.7	16.4	16.1	15.8
	(18.1, 20.0)	(17.0, 18.9)	(16.6, 18.6)	(15.7, 17.6)	(15.1, 17.0)	(14.7, 15.7)
Delaware	5.1	5.2	5.0	4.8	4.4	4.2
	(4.7, 5.6)	(4.8, 5.6)	(4.9, 5.7)	(4.6, 5.4)	(4.4, 5.2)	(4.0, 4.8)
District of Columbia	1.23	1.22	1.07	1.12	1.10	1.22
	(1.15, 1.56)	(0.94, 1.35)	(0.90, 1.32)	(0.77, 1.18)	(0.82, 1.24)	(0.83, 1.25)
Florida	116	115	105†	99	105†	105
	(111, 124)	(113, 127)	(111, 125)	(99, 113)	(89, 103)	(95, 109)
Georgia	68.3	67.0	61.2†	65.4†	66.7	65.0
	(68.2, 74.4)	(66.8, 73.0)	(64.4, 70.7)	(56.7, 62.9)	(61.2, 67.4)	(63.9, 70.1)
Hawaii	13.0	14.0	9.71†	9.44	9.65†	10.23†
	(12.5, 14.6)	(12.5, 14.6)	(13.6, 15.7)	(7.93, 10.0)	(7.14, 9.28)	(7.81, 9.95)
Idaho	9.30	9.63	8.78†	8.68	9.47†	9.13
	(8.17, 9.31)	(8.92, 10.06)	(9.36, 10.51)	(8.22, 9.36)	(7.94, 9.08)	(8.97, 10.12)
Illinois	73.3†	73.7	69.8	68.3	67.6	66.8
	(75.3, 87.9)	(68.9, 81.5)	(67.9, 80.5)	(62.1, 74.7)	(60.2, 72.8)	(60.0, 72.6)
Indiana	46.4	45.5	42.3†	40.8	42.9	42.9
	(42.2, 49.0)	(43.0, 49.9)	(42.4, 24.2)	(39.0, 45.8)	(36.7, 43.5)	(38.2, 45.1)
Iowa	21.8	22.3	21.5	21.1	21.5	21.7
	(20.5, 23.4)	(21.0, 23.9)	(21.4, 24.3)	(20.1, 23.0)	(19.4, 22.2)	(20.0, 22.9)
Kansas	19.0	19.5	19.0	19.7	19.6	19.0
	(16.5, 19.8)	(17.1, 20.4)	(17.8, 21.1)	(17.6, 20.9)	(18.2, 21.4)	(18.1, 21.4)
Kentucky	33.4	34.9	32.1†	32.6	33.2	32.6
	(32.1, 36.3)	(31.8, 36.0)	(33.1, 37.2)	(30.7, 34.8)	(30.4, 34.5)	(30.9, 35.0)
Louisiana	55.0	50.8	47.9	47.2	50.1†	50.2
	(46.6, 54.8)	(49.5, 57.7)	(46.8, 55.0)	(43.4, 51.6)	(41.8, 50.0)	(44.3, 52.5)
Maine	9.41	9.06	8.20†	8.57	8.51	8.38
	(8,67, 10.3)	(8.80, 10.4)	(8.49, 10.1)	(7.59, 9.25)	(7.59, 9.52)	(7.56, 9.22)
Maryland	42.2	42.8	40.3	39.6	40.1	39.3
	(39.0, 45.1)	(39.6, 45.6)	(40.3, 46.4)	(36.4, 42.5)	(35.6, 41.6)	(36.8, 42.8)
Massachusetts	33.0†	33.5	33.4	30.7†	30.8	30.9
	(33.3, 36.3)	(31.6, 34.5)	(32.1, 35.1)	(32.0, 34.9)	(28.4, 31.3)	(28.4, 31.4)
Michigan	55.7	55.3	51.3†	49.9	49.8	48.6
	(52.1, 59.1)	(52.0, 59.0)	(51.6, 58.6)	(45.6, 52.6)	(44.5, 51.4)	(45.3, 52.3)
Minnesota	36.1	36.5	34.6	32.2	32.7	32.3
	(34.9, 39.4)	(34.3, 38.8)	(34.4, 39.0)	(32.2, 36.7)	(29.1, 33.6)	(29.5, 34.0)
Mississippi	26.8	26.6	25.6	25.0	25.2	24.6
	(23.8, 26.9)	(25.4, 28.5)	(25.4, 28.5)	(24.1, 27.2)	(23.2, 26.2)	(23.4, 26.5)
Missouri	42.2	42.8	40.3	39.6	40.1	39.3
	(39.0, 45.1)	(39.6, 45.6)	(40.3, 46.4)	(36.4, 42.5)	(35.6, 41.6)	(36.8, 42.8)
Montana	8.5	9.0	8.3†	7.9†	8.1	8.2
	(7.5, 9.0)	(7.9, 9.4)	(8.4, 9.9)	(8.0, 9.5)	(7.5, 9.0)	(7.4, 8.9)
Nebraska	12.4	12.6	12.3	12.5	14.6	14.1
	(11.3, 13.4)	(11.5, 13.6)	(11.7, 13.8)	(11.2, 13.3)	(11.4, 13.6)	(14.8, 17.0)
Nevada	18.0	18.2	16.3†	14.8†	13.9	13.3
	(16.8, 18.0)	(18.1, 19.3)	(18.4, 19.6)	(15.9, 17.1)	(13.6, 14.8)	(12.4, 13.6)
New Hampshire	7.2	7.4	7.2	7.2	7.2	7.0
	(6.8, 7.8)	(6.6, 7.6)	(6.9, 7.8)	(6.7, 7.7)	(6.6, 7.6)	(6.6, 7.6)

Table 4-3. 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 (continued)

State/Year	2006	2007	2008	2009	2010	2011
New Jersey	68.8	72.6	73.5	62.2†	63.7	65.9
	(65.7, 73.4)	(66.5, 74.2)	(69.9, 77.6)	(71.5, 79.2)	(61.1, 68.8)	(58.9, 66.6)
New Mexico	16.0	15.5	14.2†	14.0	13.6	14.1
	(14.0, 16.9)	(14.5, 17.4)	(14.3, 17.1)	(13.0, 15.8)	(12.3, 15.2)	(11.9, 14.7)
New York	74.8	74.6	74.3	72.3	72.3	66.9
	(69.4, 82.4)	(69.6, 82.7)	(69.2, 82.2)	(68.6, 81.6)	(66.5, 79.5)	(65.7, 78.7)
North Carolina	53.1	54.9	53.4†	48.9†	49.2†	47.7
	(53.0, 56.9)	(51.2, 55.1)	(54.1, 58.1)	(50.8, 54.8)	(43.7, 47.6)	(46.2, 50.1)
North Dakota	6.2	7.1†	6.3†	6.0†	6.9†	8.0†
	(5.8, 7.0)	(5.7, 6.9)	(6.4, 7.6)	(6.1, 7.2)	(5.6, 6.8)	(6.2, 7.3)
Ohio	72.1	72.9	69.0†	64.5	65.9†	65.2
	(67.6, 75.7)	(68.6, 76.6)	(69.5, 77.6)	(63.2, 71.2)	(57.0, 65.0)	(60.9, 69.0)
Oklahoma	31.7	32.5	32.3	31.0	32.2	31.9
	(28.0, 33.0)	(29.2, 34.2)	(30.3, 35.3)	(30.3, 35.3)	(28.9, 33.9)	(29.6, 34.6)
Oregon	23.9	24.5	22.7†	22.9	22.1	21.2
	(22.4, 25.2)	(23.0, 25.8)	(23.7, 26.4)	(21.1, 23.8)	(21.1, 23.9)	(20.3, 23.0)
Pennsylvania	72.4	72.2	67.4†	66.4	66.0†	64.4
	(70.1, 78.2)	(68.3, 76.4)	(67.9, 76.0)	(59.5, 67.6)	(60.7, 68.8)	(61.4, 69.5)
Rhode Island	4.4	4.3	4.1	4.2	4.2	4.0
	(4.0, 4.5)	(4.1, 4.6)	(4.1, 4.6)	(3.8, 4.3)	(3.9, 4.4)	(3.9, 4.4)
South Carolina	32.0	32.2	30.6†	31.2	31.2	30.8
	(30.2, 33.7)	(31.1, 34.6)	(31.3,34.8)	(29.7, 33.2)	(29.7, 33.2)	(29.6, 33.1)
South Dakota	6.1	6.4	6.0	6.2	6.5	6.5
	(5.6, 6.6)	(5.6, 6.7)	(5.9, 7.0)	(5.5, 6.6)	(5.7, 6.8)	(6.1, 7.1)
Tennessee	45.8	46.2	42.9†	41.5	43.1†	43.1
	(43.8, 48.4)	(44.0, 48.6)	(44.3, 48.9)	(39.9, 44.5)	(37.9, 42.5)	(40.1, 44.8)
Texas	202	205	197	190†	194	195
	(186, 206)	(194, 214)	(198, 218)	(190, 210)	(179, 199)	(182, 201)
Utah	18.5†	18.5	17.0†	16.4	16.3	17.4
	(16.2, 17.9)	(18.3, 20.0)	(18.3, 20.0)	(16.2, 17.9)	(15.1, 16.8)	(15.1, 16.8)
Vermont	3.8	3.8	3.5	3.6	3.5	3.4
	(3.7, 4.1)	(3.7, 4.1)	(3.6, 4.0)	(3.2, 3.6)	(3.3, 3.7)	(3.2, 3.6)
Virginia	56.9	57.2	52.7	50.8	50.4	48.3
	(55.4, 60.1)	(56.3, 61.0)	(56.0, 60.7)	(49.7, 54.3)	(46.7, 51.4)	(46.6, 51.2)
Washington	44.8	47.8	42.9	42.1	41.2	41.1
	(40.3, 46.7)	(41.8, 48.1)	(45.1, 51.5)	(41.0, 47.3)	(38.9, 45.2)	(37.5, 43.8)
West Virginia	12.5	12.4	11.0†	11.3	11.6	11.2
	(11.6, 13.6)	(11.6, 13.6)	(11.5, 13.5)	(9.8, 11.9)	(9.9, 12.0)	(10.4, 12.5)
Wisconsin	30.8	31.1	30.1	29.5	30.3	29.1
	(28.9, 31.9)	(29.5, 32.6)	(29.8, 32.9)	(28.3, 31.3)	(27.4, 30.4)	(28.8, 31.9)
Wyoming	8.6	8.8	8.6	8.3	8.4	7.7
	(7.5, 9.3)	(7.8, 9.6)	(8.1, 9.9)	(7.9, 9.7)	(7.5, 9.3)	(7.5, 0.3)
U.S. Total	2028	2045	1929†	1867	1891†	1862
	(1962, 2106)	(1990, 2133)	(1998, 2141)	(1807, 1950)	(1731, 1874)	(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.

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 between0 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 4-4 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 & Porter, 2009).

In Table 4-4, 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 4-4. The levels of decreasing emissions will be different in each state, with California showing the largest CO_2 emissions decrease due to the largest negative smoothed trend value of -5.31.

Table 4-4. 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

Table 4-4. 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 (continued)

State	Smoothed Level	Smoothed Trend	Smoothing weight	RMSE	R^2
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
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 used a unit of MMT CO_2.

Table 4-5 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_2 emissions 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 4-4 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 4-5. Forecasted Values of CO_2 Emissions from the Transportation Sector by State, the District of Columbia, and the U.S. from 2012 to 2021

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

Table 4-5. Forecasted Values of CO_2 Emissions from the Transportation Sector by State, the District of Columbia, and the U.S. from 2012 to 2021 (continued)

State/Year	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
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
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

4.7. 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 ten years will show a downward pattern, 10 states are projected to show an increasing tendency of transportation CO_2 emissions across the nation. 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 to 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, 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 IEPA, I could have estimated more accurate results for our CO_2 emissions forecasts from the U.S. transportation sector.

CHAPTER 5. CONCLUSIONS

The U.S. transportation sector is one of the largest in the world. While it is a major and large-scale sector to increase national wealth, the transportation sector is also a significant source of emitting CO2 in the U.S. My doctoral dissertation started to answer how the transport sector in the U.S. has had an impact on economic and CO2 emissions changes using statistical and quantitative approaches. It consists of three essays: 1) Productivity growth in the U.S. transportation sector; 2) How does a carbon dioxide emissions change affect the U.S. transportation productivity?; and 3) Forecast of CO2 emissions from the U.S. transportation sector. From the three essays, this dissertation summarizes significant findings and conclusions as follows: 1) the average productivity growth by state in the five transportation industries is on average close to zero or slightly increasing; 2) the overall U.S. transportation industry grew with a strong and positive trend with notable productivity growth of 21.7% in 2011, except in the years of the global financial crisis in 2007, 2008, and 2010; 3) the rail and water transportation industries had the first and second highest productivity growth in 2011, which might have been as a result of the growth in sustainable transport modes globally; 4) many states (22 in 30) with $E(H)>1$ were attributed to a technological innovation increase exceeding an efficiency decrease; 5) all states with $E(H)<1$ experienced lower efficiency change scores than increased technological scores, and were aggravated in some states by decreased technological scores; 6) Nebraska and North Dakota have increased CO2 emissions, leading to actual productivity growth; 7) the average CO2 emissions reduction since 2008 by state in the transportation sector positively contributed to actual productivity growth with a probability of approximately 67%; 8) the overall forecasting accuracies by the DES models in the 47 states and the U.S. are high, which was checked by Pseudo out-of-sample forecasts; 9) 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; and 10) 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.

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