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EWI Working Paper, No 17/03

Januar 2017

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ISSN: 1862-3808

Competition and Regulation as a Means of Reducing CO_2 Emissions: Experience from U.S. Fossil Fuel Power Plants

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Abstract

Levels of CO_2 emissions from electricity generation in the U.S. have changed considerably in the last decade. This development can be attributed to two factors. First, the shale gas revolution has reduced gas prices significantly, leading to a crowding out of the more CO_2-intensive coal for electricity generation. Secondly, environmental regulations have been tightened at both the federal and the state level. In this article, we analyze the relative CO_2 emission performance across 48 states in the U.S. using a two-stage empirical approach. In the first stage, we identify the states that followed best practice between 2000 and 2013, by applying nonparametric benchmarking techniques. In the second stage, we regress our CO_2 emission performance indicators on the state-specific national gas prices, the states' CO_2 regulatory policies and a number of other state-specific factors in order to identify the main drivers of the developments. We find that the CO_2 emission performance improved on average by 15% across all states from 2000 to 2013. Furthermore, our second-stage results support the argument that decreasing natural gas prices and stringent regulatory measures, such as cap-and-trade programs, have a positive impact on the state-specific CO_2 emission performance.

Keywords: Carbon dioxide emission performance, data envelopment analysis, global Malmquist index, environmental regulation

JEL classification: C61, D24, L94, Q58

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[1]The authors would like to thank Marc-Oliver Bettzüge, Van Anh Vuong and Hannah Schwind, as well as the participants of the EWEPA 2013 in Helsinki and the OR 2015 in Vienna, for their helpful support, comments, and discussions. We also thank Maria Novikova who provided excellent research assistance. The responsibility for the content of this publication lies solely with the authors.

1. Introduction

During the last decade, the electricity sector in the U.S. has undergone considerable change. On the supply side, the plummeting of gas prices induced by the so-called shale gas revolution has created incentives for power producers to increase gas usage and even to switch investment decisions in new capacity from coal to gas. As natural gas emits less than 50% of the CO_2 per kwh that coal does, emissions might have dropped as a result of fuel competition. Policy-wise, greenhouse gas emissions from the generating fleet have become a nationwide concern: in 2013, U.S. electricity generation accounted for more than 2,000 million tons of carbon dioxide (CO_2) emissions, or about 38% of the total U.S. energy-related emissions. About 70% of the electricity generated in 2013 was produced from fossil fuels (U.S. Energy Information Administration (EIA), 2016*b*).

Recently, the U.S. government has announced that it will pursue CO_2 reduction strategies to cut CO_2 emissions by 26-28% by 2025 compared to 2005 levels.[2] One important measure for achieving this aim is the so-called Clean Power Plan. As part of this, the U.S. Environmental Protection Agency (EPA) has suggested regulations to require existing power plants to reduce power sector emissions by 32% from their 2005 levels by 2030 (U.S. Environmental Protection Agency (EPA), 2015). Prior to these new guidelines, the rules were also tightened to permit fewer carbon emissions from electricity generation. States have introduced different means of regulation, from CO_2 performance standards (e.g. in Washington) to regional cap-and-trade programs (e.g. the Regional Greenhouse Gas Initiative (RGGI)). Both trends, inter-fuel competition and regulation, seem to have significantly decreased electricity-related CO_2 emissions. From their peak in 2007, CO_2 emissions from electricity generation dropped by about 16% between 2007 and 2013 (U.S. Energy Information Administration (EIA), 2016*b*). Whether the main reason for CO_2 reduction was competition or regulation remains an empirical question.

In this article, we analyze the success of the U.S. states in reducing CO_2 emissions from fossil fuel power plants. We identify CO_2 emission performance at the state level over time, and drivers that may have contributed to changing CO_2 developments. Faced with these developments, we argue that an overall fuel switching from high emitters like coal-fired power plants to cleaner technologies like natural gas combustion has occurred. To examine whether or not state-specific fuel price developments and/or CO_2 regulations also drove down emissions, we follow a two-step approach. First, we employ nonparametric data envelopment analysis techniques that allow us to measure the relative CO_2 emission performance across states considering the multiple-input and multiple-output production structure of electricity generation. As inputs, we use fuel consumption and nameplate capacity, and, as outputs, the electricity produced and CO_2 emissions. In doing so, we are able to provide a more comprehensive picture of each state's fossil fuel electricity generation process and its relative CO_2 emission performance, compared to a simple output-oriented CO_2 intensity measure, such as CO_2 emissions per unit of electricity produced. Comprehensive reviews of data envelopment analysis applications in energy and environmental studies can be found in Zhou et al. (2008) and Zhang and Choi (2014). Furthermore, a number of studies have addressed the measurement of the environmental efficiency of U.S. power plants (see, e.g., Färe et al., 2013; Hampf and Rødseth, 2015; Sueyoshi et al., 2010; Sueyoshi and Goto, 2013; Welch and Barnum, 2009).

[2]Press statement released by the Office of the Press Secretary, The White House, accessible at www.whitehouse.gov/the-press-office/2015/03/31/fact-sheet-us-reports-its-2025-emissions-target-unfccc.

In a second stage, we regress the performance indicators we have obtained on the state-specific natural gas prices, the states' CO_2 regulatory policies and a number of other state-specific factors in order to identify the main drivers of the development. This approach allows us not only to answer the question of whether fuel price competition and/or emissions regulation have proven to be successful in comprehensively reducing greenhouse gases but also to evaluate the impact of regulatory reforms at the state level.

The remainder of this article is organized as follows. Section 2 provides a short overview of U.S. electricity generation from fossil fuels, and its trends. Section 3 describes the empirical approach. Section 4 presents and discusses the results and Section 5 concludes.

2. U.S. electricity generation from fossil fuels 2000 - 2013

U.S. electricity generation has undergone substantial changes since the early 2000s. Electricity generation from fossil fuels does not rely today on the same power generation technology mix that used to prevail within the U.S. fossil fuel market. The reasons for this can be found on the regulatory as well as on the market side. On the market side, one of the most prominent drivers has been the development of U.S. shale gas production. In less than a decade, the production of shale gas in the U.S. has managed to make U.S. gas imports irrelevant and has made the national gas industry self-sufficient (Wang et al., 2014). As a consequence, the price structure of fossil fuel inputs for electricity generation has changed significantly.

Figure 1 shows the cost of fossil fuel receipts at electricity generating plants in dollars per million British thermal units (MMBtu) (U.S. Energy Information Administration (EIA), 2016*a*).[3] We observe that, until 2008, fuel prices increased for all fuel types shown. Interestingly, coal and petroleum prices started to increase again after 2009, while the natural gas price declined. We partly link this gas price development to the additional shale gas production volumes that submerged the supply side of the gas market. This development not only affected the U.S. natural gas prices but, as a consequence, also boosted the role of natural gas-fired plants in electricity generation (Krupnick et al., 2013).

In this context, Figure 2 shows the shares of net electricity generation from fossil fuels including coal, natural gas, petroleum and other gases over the same time horizon (U.S. Energy Information Administration (EIA), 2015*a*). Here, we observe that the share of net electricity generation from coal was 73% in 2000 and more than three times higher than the share (22%) of net generation from natural gas in that year. However, net generation from natural gas steadily increased over time while net generation from coal significantly decreased supporting our argument that decreasing gas prices made gas-fired generation more attractive. In 2013, 58% of total U.S. net electricity generated from fossil fuels was generated from coal, and 41% from natural gas.

Taken together, these observations may lead to the conclusion that low gas prices have triggered alterations in the use of fuels and the investment in coal or gas-fired plants. However, such a conclusion is strongly dependent on the time horizon of the study: as power plant capacity is assumed to be quasi-fixed in the short run, an instantaneous fuel switch from coal to natural gas that alters the technology mix can only be achieved if capacity is idle and favorable fuel prices trigger a quick response of gas-fired generation. Contrary to this short-run response, the portfolio

[3] The annual cost for fossil fuel receipts is calculated from the averages of monthly values, weighted by quantities, in Btu across all U.S. states.

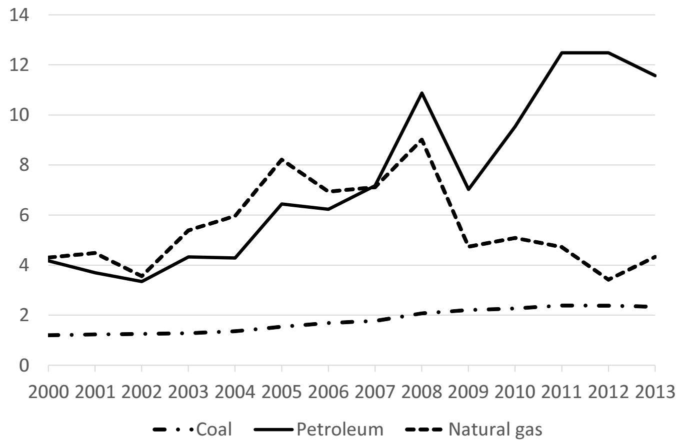

Figure 1: Cost of fossil fuel receipts at electricity generating plants in USD per million Btu

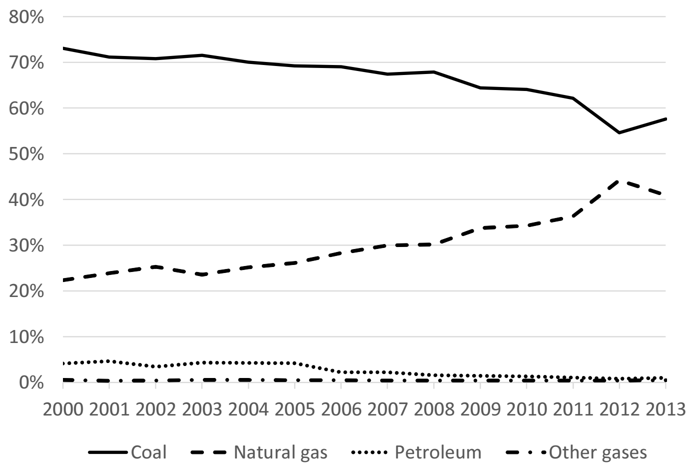

Figure 2: Shares of total U.S. net electricity generation from fossil fuels in %

of power generation technologies is subject to change in the long run. The addition of capacity depends on the current and expected technology-specific investment cost and fuel prices.

Besides the influence of shale gas on the market side, past and future regulations also affect the portfolio of power generation technologies. As an example, stricter regulation of CO_2 provides incentives for an increased usage of gas-fired power plants. Since generating electricity from natural gas produces nearly half as much CO_2 per kilowatt-hour as coal, such a stricter regulation of CO_2 may decrease emissions. However, to date there have been no nation-wide standards that require power plants to reduce their CO_2 emissions. State-specific regulatory policies include overall greenhouse gas (GHG) reduction targets and, CO_2 performance standards related to power plants, as well as regional CO_2-cap-and-trade systems related to power plants. Some states adopted one or all of these measures in the early years of this century, while others have not yet adopted any measures.[4]

[4] A detailed overview on state-specific CO_2 regulations is given in Section 3.3.

Hence, given the developments in fuel prices and the various state-specific CO_2 regulations, the CO_2 emission performance in a state may be influenced by a fuel switch from coal to gas in the short run. Such a switch is, however, constrained by the availability of capacity. In the long run, however, a state can influence its CO_2 emission performance by re-designing regulations and making certain power generation technologies more favorable than others. In this way, a state's portfolio of power generation technologies is, for instance, altered by building new gas-fired power plants and retiring old coal-fired power plants, and thus the capacity share of gas-fired power plants increases, and more natural gas can be used for electricity production.

3. Empirical approach

3.1. Benchmarking model

In order to analyze the state-specific CO_2 emission performance of U.S. fossil fuel power plants we model a production technology that includes both desirable and undesirable outputs. If we assume that $x = (x_1, \ldots, x_N) \in \Re_+^N$ denotes a vector of inputs, $y = (y_1, \ldots, y_M) \in \Re_+^M$ denotes a vector of desirable or good outputs, and $b = (b_1, \ldots, b_I) \in \Re_+^I$ denotes a vector of undesirable or bad outputs, the production technology set can be modeled as:

$$P(x) = \{(y, b) : x \text{ can produce } (y, b)\}, \tag{1}$$

where $P(x)$ represents all the combinations of desirable and undesirable outputs (y, b) that can be produced using the input vector x. $P(x)$ is a convex and compact set and satisfies the standard properties of "no free lunch", the possibility of inaction, and strong or free disposability of inputs and good outputs (see e.g. Färe and Primont, 1995).

Furthermore, in order to account for the joint production of desirable and undesirable outputs we follow Zhou et al. (2010) and impose two additional assumptions. First, we assume the desirable and the undesirable outputs to be together weakly disposable:

$$\text{if } (y, b) \in P(x) \text{ and } 0 \leq \lambda \leq 1, \text{ then } (\lambda y, \lambda b) \in P(x). \tag{2}$$

This assumption reflects the opportunity cost of abatement activities. In other words, a reduction of undesirable outputs is not costless, and negatively influences the production level of the desirable outputs.[5]

Second, the desirable and the undesirable outputs are considered as being null-joint:

$$\text{if } (y, b) \in P(x) \text{ and } b = 0, \text{ then } y = 0. \tag{3}$$

This means that no desirable outputs can be produced without producing some undesirable outputs.[6]

A production technology that seeks the maximal decrease of undesirable outputs and satisfies the above assumptions can be represented by an input distance function. Introduced by Shephard (1953), such a function can be formally defined as:

$$D(x, y, b) = \sup \{\theta : (y, b/\theta) \in P(x)\} \geq 1, \tag{4}$$

[5] The concept of weak disposability was introduced by Shephard (1970).
[6] The null-jointness assumption was introduced by Shephard and Färe (1974).

where θ represents the proportion by which the undesirable output b is scaled to reach the boundary or frontier of the production technology set $P(x)$. The distance function value θ is bounded below by one. A value of one identifies the observed output vector as located on the frontier, whereas values greater than one belong to output vectors below the frontier. When CO_2 emissions are the only undesirable output, Zhou et al. (2010) label this function as the Shephard carbon distance function. Furthermore, the inverse of the function is closely related to Farrell's 1957 measure of input-oriented technical efficiency (TE), that is:

$$TE(x, y, b) = [D(x, y, b)]^{-1} \leq 1. \tag{5}$$

This measure is a pure technical measure of efficiency, focusing on how much good and bad output is produced from a given quantity of inputs. In our case, efficiency among the states can differ, in the sense that the same amount of fossil fuel and the same amount of capacity can produce the same amount of electricity but fewer CO_2 emissions. This can be the result of using a better input quality, that is, by a higher share of the state's electricity output being produced from natural gas-fired power plants that are less carbon-intensive. This share, in turn, is influenced by the capacity share of natural gas-fired power plants in the state's electricity generating portfolio, and its utilization rate.

In order to measure efficiency changes over time, we combine the concepts of the Malmquist CO_2 emission performance index (MCPI) of Zhou et al. (2010) and the global Malmquist productivity index (GPI) of Pastor and Lovell (2005). The derived index represents the state-specific CO_2 emission performance over time and is termed the global Malmquist CO_2 emission performance index (GMCPI).

Compared to a conventional contemporaneous Malmquist productivity index that constructs the reference technology in period t from the observations in that period only, the GMCPI incorporates information from all observations in all periods. By doing this, the GMCPI provides a single measure of productivity change, is circular, and does not suffer from any infeasibility problems, thus avoiding the three well-known problems of conventional contemporaneous Malmquist productivity indices (Pastor and Lovell, 2005).

First, in order to define the GMCPI, we consider two benchmark technologies: a contemporaneous benchmark technology and a global benchmark technology. Following Pastor and Lovell (2005), the contemporaneous benchmark technology is defined as:

$$P^t(x) = \{(y^t, b^t) : x^t \text{ can produce } (y^t, b^t)\}, \text{with } t = 1 \ldots, T, \tag{6}$$

and the global benchmark technology as:

$$P^G(x) = conv\{P^1(x) \cup \ldots \cup P^T(x)\}. \tag{7}$$

The two technologies are graphically illustrated in Figure 3. The vertical axis shows the desirable output y and the horizontal axis shows the undesirable output b, i.e., CO_2 emissions. P^t and P^{t+1} represent the areas of all feasible combinations of the desirable and the undesirable output that can be produced by the input vector x in periods t and $t+1$, respectively. These technologies are enveloped by the global technology P^G that represents the area of all feasible input-output combinations in all periods.

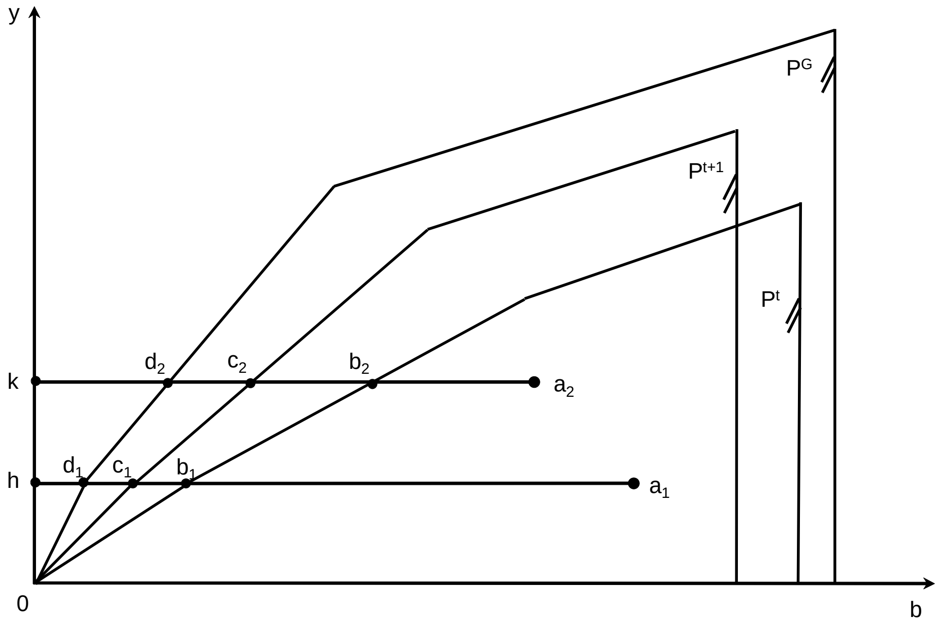

Figure 3: Global Malmquist CO_2 emission performance index (GMCPI)

Given Equation 4, and with $D^G(t) = D^G(x^t, y^t, b^t)$ and $D^G(t+1) = D^G(x^{t+1}, y^{t+1}, b^{t+1})$, the GMCPI between period t and period $t+1$ can now be defined as:[7]

$$GMCPI = \frac{D^G(t)}{D^G(t+1)}, \tag{8}$$

A value equal to one indicates no change in the CO_2 performance between period t and period $t+1$. If the value is less than one, the CO_2 performance decreased, while a value greater than one represents an increase.

Furthermore, the GMCPI can be decomposed into two components: efficiency change EC and best practice change BPC. That is,

$$GMCPI = EC \times BPC, \tag{9}$$

where

$$EC = \frac{D^t(t)}{D^{t+1}(t+1)}, \tag{10}$$

and

$$BPC = \frac{D^G(t)/D^t(t)}{D^G(t+1)/D^{t+1}(t+1)}. \tag{11}$$

EC captures the change in the distance of an observation to its respective frontier in periods t and $t+1$. Considering points a_1 and a_2 in Figure 3 as the production points of a decision making

[7] For notational convenience, we abbreviate the distance functions $D^G(x^t, y^t, b^t)$, $D^G(x^{t+1}, y^{t+1}, b^{t+1})$, $D^t(x^t, y^t, b^t)$ and $D^t(x^{t+1}, y^{t+1}, b^{t+1})$, respectively, to $D^G(t)$, $D^G(t+1)$, $D^t(t)$ and $D^{t+1}(t+1)$ in the following equations.

unit (DMU) in periods t and $t+1$, EC is equal to $(\overline{ha_1}/\overline{hb_1})/(\overline{ka_2}/\overline{kc_2})$. $EC > 1$ indicates a decrease in the distance and hence efficiency progress, whereas $EC < 1$ represents an increase in the distance and hence efficiency regress. Similarly, a shift of the contemporaneous frontier away from or towards the global frontier between period t and period $t+1$ is captured by BPC. In Figure 3 BPC is calculated as $BPC = ((\overline{ha_1}/\overline{hd_1})/(\overline{ha_1}/\overline{hb_1}))/((\overline{ka_2}/\overline{kd_2})/(\overline{ka_2}/\overline{kc_2}))$. $BPC > 1$ indicates technical progress, while $BPC < 1$ shows technical regress.

In order to determine the required global and contemporaneous distance functions, we employ data envelopment analysis techniques. With $s = t, t+1$ and $k = 1, \ldots, K$ observations, the contemporaneous distance function for each observation k' in each period s can be obtained by solving the following linear program:

$$\begin{aligned}
\left[D^s\left(x^s, y^s, b^s\right)\right]^{-1} &= \min_z \theta \\
s.t. \sum_{k=1}^{K} z_k^s y_{km}^s &\geq y_{k'm}^s, \qquad m = 1, \ldots, M, \qquad (i) \\
\sum_{k=1}^{K} z_k^s x_{kn}^s &\leq x_{k'n}^s, \qquad n = 1, \ldots, N, \qquad (ii) \\
\sum_{k=1}^{K} z_k^s b_{ki}^s &= \theta b_{k'i}^s, \qquad i = 1, \ldots, I, \qquad (iii) \\
z_k^s &\geq 0, \qquad k = 1, \ldots, K, \qquad (iv)
\end{aligned} \tag{12}$$

where z_k^s are intensity variables assigning a weight to each observation k when constructing the best-practice frontier. The inequality constraints in (i) and (ii) guarantee that observation k' does not produce more desirable outputs or use fewer inputs than the efficient benchmark on the frontier. The equality constraints in (iii) impose weak disposability, and the non-negativity constraints in (iv) indicate that the reference technology exhibits constant returns to scale.

Note that, with only one undesirable output, the optimal solutions to the linear program under the assumption of weak disposability and the linear program under the assumption of strong disposability are identical. In other words, with $I = 1$ the equality constraint in (iii) can be replaced by the inequality constraint $\sum_{k=1}^{K} z_k^s b_{ki}^s \leq \theta b_{k'i}^s$ (Oggioni et al., 2011).

Finally, with $t = 1, \ldots, T$, the global distance function for each observation k' in each period s can be obtained by solving the following linear program:

$$\begin{aligned}
\left[D^G\left(x^s, y^s, b^s\right)\right]^{-1} &= \min_z \theta \\
s.t. \sum_{t=1}^{T}\sum_{k=1}^{K} z_k^t y_{km}^t &\geq y_{k'm}^s, \qquad m = 1, \ldots, M, \qquad (i) \\
\sum_{t=1}^{T}\sum_{k=1}^{K} z_k^t x_{kn}^t &\leq x_{k'n}^s, \qquad n = 1, \ldots, N, \qquad (ii) \\
\sum_{t=1}^{T}\sum_{k=1}^{K} z_k^t b_{ki}^t &= \theta b_{k'i}^s, \qquad i = 1, \ldots, I, \qquad (iii) \\
z_k^t &\geq 0, \qquad k = 1, \ldots, K, \qquad (iv)
\end{aligned} \tag{13}$$

As before, in the case of a single undesirable output, the equality constraint in (iii) can be replaced by the respective inequality constraint.

3.2. Benchmarking data

We conduct our analysis using state-level panel data for 48 out of the 50 federal states in the U.S. for a 13-year period starting in 2000 and ending in 2013.[8] The data come from the survey forms EIA-860 and EIA-923 of the U.S. Energy Information Administration (EIA), which provide detailed information on the inputs and outputs of U.S. power plants (U.S. Energy Information Administration (EIA), 2015*a*,*b*).

As inputs we include aggregated fuel consumption measured in billion British thermal units (Bn Btu)[9] and aggregated nameplate capacity measured in gigawatts (GW) for all coal- and natural gas-fired power plants in each state.[10] Fuel consumption directly influences power plant usage and therefore the desirable and undesirable output (net generation and CO_2 emissions, respectively). Nameplate capacity serves as a proxy for the capital input. In the short run, too much capacity is inefficient, since idle capacity will not be used for generation. However, in the medium and long run a higher capacity offers more flexibility for switching fuels. Hence, the capacity variable in our model reflects the trade-off between optimal capacity in the short run and optimal flexibility in the medium and long run.

Table 1 provides descriptive statistics based on state-level data for the two input variables, fuel consumption and generation capacity, and the two output variables, CO_2 emissions measured in million tons and net generation measured in gigawatt-hours (GWh), for the 48 U.S. states from 2000 to 2013.[11] Emissions and net generation from coal and gas are used as outputs in order to reflect the link and trade-offs between production and pollution.

The descriptive statistics shown in Table 1 reflect a wide range of values, since power generation sizes and technologies differ across the states. Therefore, the table primarily shows the size of the U.S. fossil fuel power generation sector. The depicted minimum and maximum values can be directly linked to certain U.S. states.

Table 1: Descriptive statistics: state-level data 2000 to 2013

	Unit	Mean	SD	Min value	Max value
Net generation from coal and gas	GWh	57,254.3	56,237.2	1,194.2	358,396.7
CO_2 emissions	million t	48.6	44.5	0.8	266.4
Fuel consumption	Bn Btu	546,921.7	512,824.3	8,392.0	3,159,475.0
Nameplate capacity	GW	15.9	16.1	0.7	101.5

[8] Vermont is excluded because it has zero electricity production from coal or gas over this time period, and so is Hawaii because of its geographic isolation from the mainland.

[9] We account for the state-specific heat values of coal by using the EIA's State Energy Data System (SEDS). The coal consumed by the electrical power sector in each state is calculated by dividing the total heat content of coal received at the electrical power plants by the total quantity consumed in physical units, which is collected on Form EIA-923 for each year.

[10] As the amount of electricity generated from petroleum is very small in the U.S. (cf. Figure 2) we do not include petroleum-fired power plants in our analysis.

[11] Because of some suspicious changes in one or more of the in- and outputs from one year to the other (changes higher than 100%) we exclude the observations for Idaho and New Hampshire in the years 2000 to 2002, as well as the observation for Maine in the year 2000, from our data set.

Over the whole period, Texas is by far the largest CO_2 emitter across all U.S. states in the electrical power sector. With a peak value of 266 million tons of emitted CO_2 in 2011, "Texan" CO_2 emissions are more than twice the CO_2 emissions of Ohio, which rank in second place. At the same time, Texas also ranks highest in terms of overall electricity generated and fuel consumed. Peak annual electricity generation was equal to 358,397 GWhs and peak annual fossil fuel amounted to 3,159,475 billion Btu, both values occurring in the year 2011. In 2011 Texas had an installed gas and coal-fired capacity of 101.5 GW. The minimum values shown in Table 1 all belong to Idaho in 2000 and 2011.

3.3. Second-stage regression

In order to test which factors determine the differences in the CO_2 emission performances of the states over time, we regress their cumulative GMCPI obtained in the first step of our analysis on several state-specific factors, in a second step. The cumulative GMCPI until period t, rather than the GMCPI for each two-year period, is used in order to account for all CO_2 emission performance changes until that period. That is:

$$\begin{aligned} CumGMCPI_{it} = \alpha_0 &+ \alpha_1 GasPrice_{it} + \alpha_2 Target_{it} + \alpha_3 Standards_{it} + \alpha_4 Cap_{it} \\ &+ \alpha_5 \ln GDPPC_{it} + \alpha_6 NucShare_{it} + \alpha_7 HydroShare_{it} \\ &+ \alpha_8 WindShare_{it} + \alpha_t Dum_t + \alpha_i Dum_i + \epsilon_{it}, \end{aligned} \tag{14}$$

where $GasPrice_{it}$ is the annual state-specific natural gas electrical power price that reflects the price of gas used by electricity generators. $Target_{it}$, $Standards_{it}$ and Cap_{it} are dummy variables equal to one if in state i and year t greenhouse gas emissions targets, CO_2 performance standards or a cap-and-trade program, respectively, are in place and equal to zero otherwise. $GDPPC_{it}$ is the annual real gross domestic product (GDP) per capita by state. $NucShare_{it}$, $HydroShare_{it}$ and $WindShare_{it}$ are state i's share of nuclear, hydroelectric and wind energy in state i's total nameplate capacity in year t. Dum_t and Dum_i denote year and state fixed effects and the α's and ϵ_{it} are parameters to be estimated.

Data for the annual state-specific natural gas electrical power price are drawn from the EIA Natural Gas Summary. The data originally come from the Federal Energy Regulatory Commission (FERC), Form-423, and are in nominal dollars per thousand cubic feet. The price index for GDP from the US Bureau of Economic Affairs (BEA) is used to transform the nominal prices into constant prices based on the year 2009. Data on the real GDP per capita are also taken from the BEA and are in 2009-dollars.

The summary statistics on the second-stage variables depicted in Table 2 reflect the high heterogeneity among the states. The maximum real gas price of $11.56 per thousand cubic feet is observed for Georgia in 2005. In the same year, the price in Alaska was only $3.72 per thousand cubic feet. As for real GDP per capita, the maximum value of $70,918 is found for Alaska in 2009. This value is more than twice the minimum value, which is found for Mississippi in 2001.

Similar differences can be seen for the shares of the three most common CO_2-free electricity generation technologies in the states' total nameplate capacity.[12] The low mean and standard

[12] As the share of solar thermal and photovoltaic in total nameplate capacity is far below 1% for almost all states in the time period of the observations, it is not included in the analysis. Only Arizona, California, North Carolina, New Jersey, Nevada, and New Mexico show values above 1%. The maximum value is 4.3% in California in 2013. A similar argument applies to geothermal energy and pumped storage. While in a limited number of states these technologies play a minor role, they are not installed at all in the vast majority of states.

Table 2: Determinants of CO_2 emission performance: summary statistics

	Unit	Mean	SD	Min value	Max value
Gas price	2009 $	6.14	2.12	2.16	11.55
Real GDP per capita	2009 $	45 648	8 519	28 957	70 918
Nuclear share in nameplate capacity	%	8.45	8.78	0	41.30
Hydroelectric share in nameplate capacity	%	10.33	17.85	0	87.12
Wind share in nameplate capacity	%	2.40	4.77	0	30.02
GHG emissions targets	0/1	0.24	0.43	0	1
CO_2 performance standards	0/1	0.07	0.25	0	1
Cap and trade	0/1	0.07	0.25	0	1

deviation values for the share of wind show that the generation of electricity from wind is of low relevance in many states in the time period of the observations. In fact, in 37 of the 48 states the wind share in the nameplate capacity is below 10% in all years. Noteworthy exceptions are Iowa, with a share of about 30%, and North Dakota, with a share of about 27% in 2013. The nuclear and hydroelectric share in nameplate capacity is about 10% on average. Exceptions here are Idaho, with a hydroelectric share of about 87% in 2000, and New Hampshire with a nuclear share of about 41% in 2000 and 2001.

Information on state-specific regulatory policies is taken from the website of the Center for Climate and Energy Solutions (C2ES).[13] The C2ES collects a variety of data on state and regional climate actions within the U.S. Table 3 lists the states that have adopted the state-specific regulatory policies to be tested and the dates when these policies were put in place in each state. The most common policy is the definition of GHG emissions targets. By 2013, 18 of the 48 states included in the study had set emission reduction targets, to be achieved by a certain date. The baseline and target years, as well as the reduction levels, vary among the states. The most common short-term targets, to be met by 2020, are the reduction of emissions to 1990 levels (four states) and to 10% below 1990 levels (eight states). In the long-term, the targets vary between 50% and 85% below the 1990 and 2005 levels. Most states have a long-term target year of 2050.

In addition to GHG emissions targets, six states have adopted CO_2 performance standards. The standards and their area of application differ considerably among the states. While in some states the standards only apply to specific (e.g. baseload) or new power plants, in others they apply to all power plants. Furthermore, standards might require generators to reduce emissions from power plants directly to a given emissions rate per output unit, or they might also allow indirect measures such as, payments to third-party mitigation projects. Overall, no consistent pattern in the design of state-level CO_2 performance standards is observable.

The last regulatory policy included in our analysis is the implementation of a cap-and-trade program. Cap-and-trade is a system that sets a decreasing limit on emissions from one or multiple economic sectors. Below the cap there is a market in which the entities convered by the program can trade carbon allowances. An entity that emits less than its allocated limit can sell its allowances to an entity that emits more, and vice versa. The less an individual entity emits, the less it pays. Hence, there is an economic incentive to reduce emissions.

Within the observed period a cap-and-trade system was only implemented in the north and Mideast of the U.S. and in California. In its first control period from 2009-2011 the Regional

[13]http://www.c2es.org/us-states-regions, last accessed 29.02.2016.

Table 3: State-specific regulatory policies

Year	GHG emissions targets	CO_2 performance standards	Cap and trade
2000		OR	
2001	CT, MA, ME, NH, RI	OR	
2002	CT, MA, ME, NH, RI, NY	OR	
2003	CT, MA, ME, NH, RI, NY	OR	
2004	CT, MA, ME, NH, RI, NY	OR, WA	
2005	CT, MA, ME, NH, RI, NY, CA, NM	OR, WA	
2006	CT, MA, ME, NH, RI, NY, CA, NM, AZ	OR, WA, CA	
2007	CT, MA, ME, NH, RI, NY, CA, NM, AZ, FL, IL, MN, NJ, OR, WA	OR, WA, CA, MT	
2008	CT, MA, ME, NH, RI, NY, CA, NM, AZ, FL, IL, MN, NJ, OR, WA, CO	OR, WA, CA, MT	
2009	CT, MA, ME, NH, RI, NY, CA, NM, AZ, FL, IL, MN, NJ, OR, WA, CO, MD, MI	OR, WA, CA, MT, IL	CT, DE, MA, MD, ME, NH, NJ, NY, RI
2010	CT, MA, ME, NH, RI, NY, CA, NM, AZ, FL, IL, MN, NJ, OR, WA, CO, MD, MI	OR, WA, CA, MT, IL	CT, DE, MA, MD, ME, NH, NJ, NY, RI
2011	CT, MA, ME, NH, RI, NY, CA, NM, AZ, FL, IL, MN, NJ, OR, WA, CO, MD, MI	OR, WA, CA, MT, IL	CT, DE, MA, MD, ME, NH, NJ, NY, RI
2012	CT, MA, ME, NH, RI, NY, CA, NM, AZ, FL, IL, MN, NJ, OR, WA, CO, MD, MI	OR, WA, CA, MT, IL, NY	CT, DE, MA, MD, ME, NH, NY, RI
2013	CT, MA, ME, NH, RI, NY, CA, NM, AZ, FL, IL, MN, NJ, OR, WA, CO, MD, MI	OR, WA, CA, MT, IL, NY	CT, DE, MA, MD, ME, NH, NY, RI, CA

Note: Arizona (AZ), California (CA), Colorado (CO), Connecticut (CT), Delaware (DE), Florida (FL), Illinois (IL), Maine (ME), Maryland (MD), Massachusetts (MA), Michigan (MI), Minnesota (MN), Montana (MT), New Hampshire (NH), New Jersey (NJ), New Mexico (NM), New York (NY), Oregon (OR), Rhode Island (RI), Washington (WA).

Greenhouse Gas Initiative (RGGI) included fossil fuel electricity generation in ten northern and mid-eastern states (cf. Table 3: Vermont is one of the ten but is not included in our data set.). All fossil fuel power plants with 25 megawatts or greater capacity had to comply with the cap, with the aim of stabilizing emissions between 2009 and 2014 and achieving a 10% reduction by 2019. New Jersey withdrew from the system before the start of the second control period in 2012. Furthermore, in 2013 California implemented an overall emission cap that applies to all major industrial sources and electric utilities. By 2015 the system was enlarged to distributors of transportation fuels, natural gas, and other fuels. Each year the total amount of allowances is reduced by 3% in order to reduce emissions.

4. Results

4.1. Benchmarking results

Table 4 reports the CO_2 emission efficiency scores for each state for the years 2000, 2006 and 2013, obtained from the linear program given in Equation 13. In 2013 the best results are achieved by the New England states Maine (1.00), Rhode Island (0.95) and Connecticut (0.94), as well as California (0.87) and Oregon (0.80). Considering the other years, this ranking is stable only for Maine and Rhode Island. In all years, Maine and Rhode Island are ranked either first or second, reflecting their exceptionally high shares of electricity generated from natural gas (more than 95% and 100% in all years, for Maine and Rhode Island respectively).

Table 4: CO_2 emission efficiency scores per state

State	2000	2006	2013	Rank 2013	State	2000	2006	2013	Rank 2013
Alabama	0.44	0.47	0.57	18	Nebraska	0.41	0.41	0.40	44
Alaska	0.47	0.50	0.51	27	Nevada	0.57	0.69	0.78	8
Arizona	0.48	0.55	0.54	22	New Hampshire		0.64	0.70	13
Arkansas	0.40	0.47	0.48	29	New Jersey	0.54	0.57	0.80	6
California	0.68	0.78	0.87	4	New Mexico	0.47	0.46	0.49	28
Colorado	0.49	0.48	0.46	32	New York	0.56	0.59	0.77	9
Connecticut	0.53	0.73	0.94	3	North Carolina	0.44	0.44	0.54	21
Delaware	0.42	0.43	0.64	14	North Dakota	0.46	0.47	0.45	33
Florida	0.53	0.64	0.73	11	Ohio	0.44	0.44	0.47	30
Georgia	0.44	0.46	0.58	17	Oklahoma	0.47	0.53	0.53	24
Idaho		0.64	0.73	10	Oregon	0.76	0.79	0.80	5
Illinois	0.38	0.39	0.39	46	Pennsylvania	0.44	0.46	0.55	20
Indiana	0.43	0.43	0.43	35	Rhode Island	0.90	0.97	0.95	2
Iowa	0.36	0.37	0.37	48	South Carolina	0.46	0.46	0.51	26
Kansas	0.40	0.40	0.39	47	South Dakota	0.42	0.40	0.42	38
Kentucky	0.45	0.42	0.42	41	Tennessee	0.42	0.41	0.40	45
Louisiana	0.51	0.53	0.59	16	Texas	0.52	0.55	0.57	19
Maine		0.88	1.00	1	Utah	0.56	0.52	0.51	25
Maryland	0.48	0.44	0.41	42	Virginia	0.40	0.41	0.53	23
Massachusetts	0.55	0.70	0.78	7	Washington	0.50	0.55	0.60	15
Michigan	0.44	0.43	0.42	37	West Virginia	0.51	0.47	0.44	34
Minnesota	0.41	0.39	0.42	39	Wisconsin	0.37	0.39	0.42	40
Mississippi	0.45	0.53	0.72	12	Wyoming	0.51	0.49	0.47	31
Missouri	0.41	0.42	0.43	36	Mean	0.48	0.52	0.57	
Montana	0.48	0.44	0.41	43	Median	0.46	0.47	0.52	

Note: To conserve space, only the values for the first, the middle and the last year of sample are presented. The values for all years are available from the authors upon request.

The other top performer states show a rather heterogeneous development. For example, in 2000, Connecticut only reached an efficiency score of 0.53. In the years to 2013 Connecticut almost doubled this score, reaching a value of 0.94 in 2013. Interestingly, from 2000 to 2013, Connecticut increased the share of natural gas in the total electricity generated from coal and natural gas from 56% to 96%. In contrast, the natural gas shares in California and Oregon increased only slightly, from, respectively, 98% and 71% in 2000 to 99% and 79% in 2013. The rankings of California and Oregon vary between second and fifth place within these years.

The low performer states in 2013 are the Midwest states of Iowa (0.37), Kansas (0.39), Illinois (0.39), and Nebraska (0.40), as well as Tennessee (0.40). Interestingly, while the low performance states all show a high share for coal generation, other states with even higher shares perform better. For example, Wyoming, with a coal share of almost 100%, is ranked at place 31. These results show that, in addition to the coal and gas capacity mix, the CO_2 content of the burned coal and the overall capacity utilization also influence the efficiency rankings.

As the efficiency scores in Table 4 are obtained from a within-year comparison, they only present a static view of the CO_2 emission performance of the states. In order to evaluate the CO_2 emission performance over time, we calculate the GMCPI defined in Equation 8 for each two-year period and each state. The cumulative GMCPIs over the period 2000-2013 are reported in Table 5.

The results show that, on average, the states improved their CO_2 emission performance from 2000 to 2013 by about 15%. Furthermore, for 34 of the 48 states a positive development in the CO_2 emission performance is shown. The top five performers are Connecticut (1.76), Mississippi (1.62), Delaware (1.54), New Jersey (1.47), and Massachusetts (1.53). The low performers are Montana (0.86), Maryland (0.86), West Virginia (0.88), Utah (0.92), and Kentucky (0.92). On average, the CO_2 emission performance of the low performers decreased by about 11% from 2000 to 2013.

Table 5: Cumulative GMCPI per state over the period 2000-2013 (2000 = 1)

State	CumGMCPI	Rank	State	CumGMCPI	Rank
Alabama	1.31	12	Nebraska	0.99	36
Alaska	1.09	25	Nevada	1.37	8
Arizona	1.13	22	New Hampshire	1.20	16
Arkansas	1.19	18	New Jersey	1.47	4
California	1.28	13	New Mexico	1.02	33
Colorado	0.95	42	New York	1.38	7
Connecticut	1.76	1	North Carolina	1.21	15
Delaware	1.54	3	North Dakota	0.97	39
Florida	1.40	6	Ohio	1.07	27
Georgia	1.32	10	Oklahoma	1.12	24
Idaho	1.33	9	Oregon	1.06	28
Illinois	1.04	30	Pennsylvania	1.26	14
Indiana	0.98	37	Rhode Island	1.06	29
Iowa	1.01	34	South Carolina	1.13	23
Kansas	0.98	38	South Dakota	0.99	35
Kentucky	0.92	44	Tennessee	0.96	41
Louisiana	1.15	20	Texas	1.08	26
Maine	1.16	19	Utah	0.92	45
Maryland	0.86	47	Virginia	1.31	11
Massachusetts	1.53	5	Washington	1.20	17
Michigan	0.97	40	West Virginia	0.88	46
Minnesota	1.03	32	Wisconsin	1.15	21
Mississippi	1.62	2	Wyoming	0.93	43
Missouri	1.03	31	Mean	1.15	
Montana	0.86	48	Median	1.11	

As shown in Equations 9-11, the GMCPI can be decomposed into two components. Table 6 depicts the cumulative efficiency change and the cumulative best practice change. First, referring to the cumulative best practice change, the results indicate a positive rate of technological change over time, on average and for 44 of the 48 states. The average rate of cumulative best practice change is 13%. While this result suggests technological improvements for almost all input mixes and levels, it does not indicate whether all states have implemented these improvements. A state's positive rate of cumulative best practice change simply indicates a shift of the state's relevant portion of the contemporaneous frontier towards the global frontier, between the first period and the last period. However, it does not indicate whether the state actually operates on that frontier or causes its own outward shift (Färe et al., 1994). For example, the highest rate of cumulative best practice change is shown for Louisiana, and is about 79%. However, we also observe a cumulative efficiency decrease for Louisiana of about 36%. This means that, for Louisiana's production technology, CO_2 reducing innovations occurred over time, but Louisiana was not able to follow these innovations. Graphically speaking, over the observed period Louisiana was not able to catch-up to the outwardly shifting contemporaneous frontier towards the global frontier. Overall, Louisiana's cumulative GMCPI indicates an increase in its CO_2 emission performance of about 15%.

Table 6: Cumulative GMCPI decomposition per state over the period 2000-2013 (2000 = 1)

State	CumEC	CumBPC	State	CumEC	CumBPC
Alabama	1.10	1.19	Nebraska	0.87	1.14
Alaska	1.02	1.07	Nevada	1.08	1.27
Arizona	0.90	1.25	New Hampshire	1.13	1.06
Arkansas	1.14	1.05	New Jersey	1.35	1.09
California	1.24	1.04	New Mexico	0.88	1.17
Colorado	0.76	1.25	New York	1.28	1.08
Connecticut	1.67	1.05	North Carolina	1.13	1.07
Delaware	1.43	1.08	North Dakota	1.16	0.84
Florida	1.31	1.07	Ohio	0.93	1.16
Georgia	1.25	1.06	Oklahoma	1.05	1.07
Idaho	0.78	1.66	Oregon	0.86	1.23
Illinois	0.96	1.08	Pennsylvania	1.34	0.94
Indiana	0.84	1.17	Rhode Island	1.00	1.06
Iowa	0.88	1.15	South Carolina	0.96	1.17
Kansas	0.92	1.07	South Dakota	0.89	1.12
Kentucky	0.76	1.21	Tennessee	0.83	1.16
Louisiana	0.64	1.79	Texas	1.03	1.05
Maine	1.10	1.06	Utah	0.99	0.94
Maryland	0.68	1.27	Virginia	1.23	1.06
Massachusetts	1.31	1.08	Washington	0.95	1.26
Michigan	0.91	1.06	West Virginia	0.83	1.05
Minnesota	0.85	1.21	Wisconsin	1.08	1.06
Mississippi	1.49	1.09	Wyoming	1.00	0.93
Missouri	0.98	1.06	Mean	1.03	1.13
Montana	0.85	1.02	Median	0.99	1.08

An opposing picture is shown for, for example, Rhode Island. The cumulative efficiency change value of 1 and the equal cumulative best practice change and GMCPI values of 1.06 suggest that Rhode Island in all years operated on the best practice frontier and pushed it's relevant portion outwards towards the global frontier by technological innovations. Overall, Rhode Island realized an increase in its CO_2 emission performance of about 6% as a result of technological innovations.

A third example is given by North Dakota. North Dakota is one of the four states for which we observe a negative rate of technological change over time, namely −16%. This result indicates an inward shift of North Dakota's relevant portion of the contemporaneous frontier away from the global frontier. Such a result occurs if the states that determine this portion of the frontier experience a deterioration of their technological performance over time. In fact, Wyoming's cumulative efficiency change value of 1 and its cumulative best practice change value of 0.93 suggest that Wyoming is one of these states. Other states may have also belonged to this group in some years, but have been able to compensate for this in other years by input adjustments.

Altogether, our results on cumulative efficiency change and cumulative best practice change suggest that some innovative states shifted the contemporaneous frontier towards the global frontier by implementing technological innovations. However, the decline in cumulative efficiency change for 24 of the 48 states shows that half of the states were not able to follow these innovations and to catch-up to the new best practice frontier.

A better view of the CO_2 emission performance over time is shown in Figure 4, which depicts the cumulative GMCPI trends for the top and bottom performers for the period 2000-2013. While the lower part of the figure shows a relatively steady decline in the CO_2 emission performance of the bottom performers over time, the upper part indicates a relatively strong increase in the CO_2 emission performance of the top performers, particularly after 2008. This may be a first indication that the significant decrease in the natural gas price after 2008 is a major driver of CO_2-reduced electricity generation from fossil fuel power plants, although this is yet to be proven.

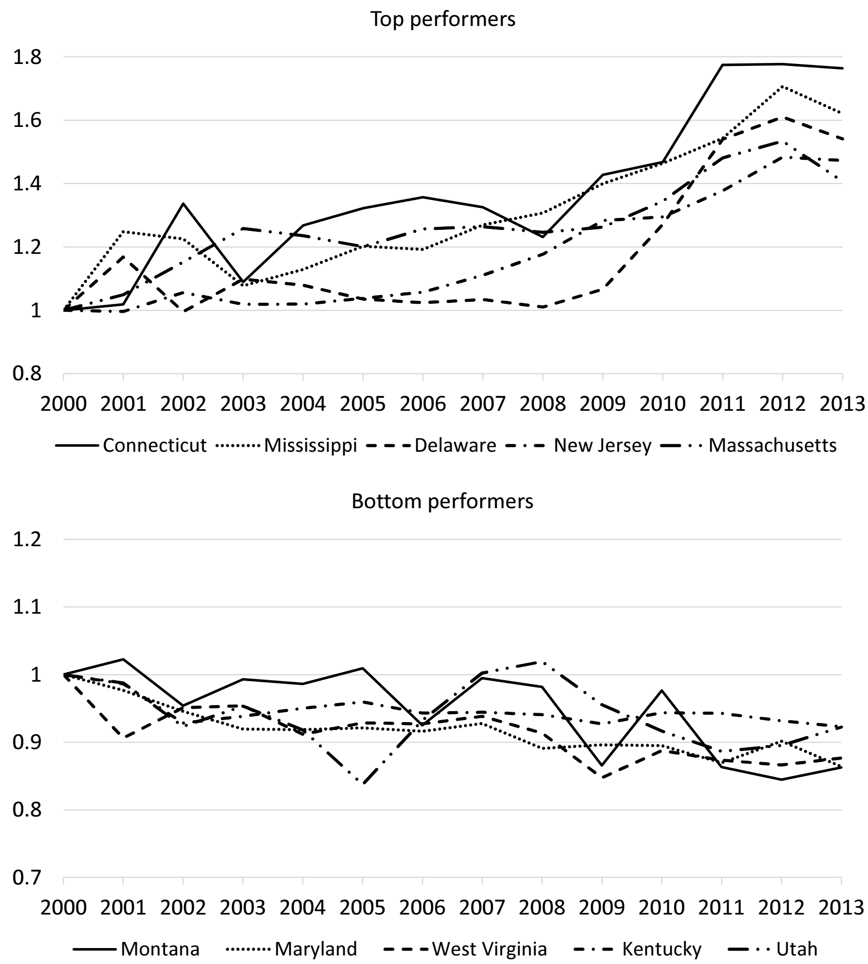

Figure 4: Cumulative GMCPI trends for the top and bottom performers for the period 2000-2013

4.2. Second-stage regression results

Table 7 present the estimation results for Equation 14. As reverse causality, that is, not only regulation has an impact on the CO_2 emission performance but the CO_2 emission performance also has an impact on the regulation, might be a problem, we first conduct a test of endogeneity. The test provides moderate evidence against the null hypothesis that the regulatory variables are exogenous (p=0.031). Therefore, we estimate two model specifications: one treating the regulatory variables as exogenous, and one treating the regulatory variables as endogenous. In the latter we apply the two-stage least squares (2SLS) estimator and instrument the regulatory variables with their first lags as well as with a dummy variable equal to one in the case of a governor from the democrat party, and zero otherwise. Both specifications include state and year fixed effects.

Table 7: Determinants of CO_2 emission performance: estimation results

		Fixed effects		2SLS	
Variable	Parameter	Coef.	Std. err.	Coef.	Std. err.
Constant	α_0	2.356^{**}	(1.191)	–	
Gas price	α_1	-0.011^{**}	(0.004)	-0.011^{***}	(0.004)
GHG emissions targets	α_2	0.003	(0.018)	0.040	(0.029)
CO_2 performance standards	α_3	0.043	(0.029)	0.022	(0.038)
Cap-and-trade system	α_4	0.077^{***}	(0.026)	0.137^{***}	(0.042)
Real GDP per capita (log)	α_5	-0.097	(0.110)	-0.126	(0.119)
Nuclear share in nameplate capacity	α_6	-0.014^{**}	(0.006)	-0.014^{**}	(0.006)
Hydroelectric share in nameplate capacity	α_7	-0.010^{**}	(0.004)	-0.009^{**}	(0.004)
Wind share in nameplate capacity	α_8	-0.008^{***}	(0.001)	-0.007^{***}	(0.001)
State fixed effects	α_i	yes		yes	
Year fixed effects	α_t	yes		yes	
R-squared	R_2	0.802		0.490	
Adjusted R-quared	R_2(adj.)	0.767		0.400	
Endogeneity test	P-value	–		0.071	
Underidentification test	P-value	–		0.000	
Overidentification test	P-value	–		0.500	
Kleinbergen-Paap	F-statistic	–		15.258	
Observations	N	437		436	

Notes: Robust standard errors in parentheses. Instruments for 2SLS: First lags of regulatory variables and dummy variable for party of the governor. ***, ** and *: significant at the 1%-, 5%-, and 10%-level. All estimations were performed in Stata 13.1 using the official areg command and the user-written xtivreg2 command developed by Schaffer (2012).

The results of the two specifications are very similar. The regression diagnostics for the 2SLS specification suggest that the instrumental variables used for the regulatory variables are sufficient. The under-identification test rejects the null hypothesis that the model is not identified ($p<0.01$), the over-identification test fails to reject the null hypothesis that the instruments are not valid ($p>0.50$), and the Kleinbergen-Paap F-statistic is greater than the rule of thumb of 10 (15.258), indicating that weak instruments are no problem.

The results in Table 7 indicate a statistically significant impact of the natural gas price, and a regional cap-and-trade-system, as well as the state's shares of nuclear, hydroelectric and wind energy in total nameplate capacity, on the state's CO_2 emission performance of fossil fuel power plants. As expected, an increase in the natural gas price has a negative impact on the cumulative GMCPI. In both specifications the estimated coefficient of -0.011 suggests that a \$1 increase in the price decreases the cumulative GMCPI by one percentage point. Similar results are shown for the shares of the most common CO_2-free electricity generation technologies in the state's total nameplate capacity. The estimated coefficients of between -0.007 and -0.014 suggest that an additional percentage point in the shares decreases the cumulative GMCPI by between 0.7 and

1.4 percentage points. This result can be explained by a lower incentive for states with a high share of CO_2-free electricity generation capacity to reduce the $C0_2$ emissions from their fossil fuel generation capacity.

Finally, among the regulatory variables we only find a statistically significant impact for a regional cap-and-trade system. The estimated coefficients indicate that the implementation of such a system increases the cumulative GMCPI by 7.7 and 13.7 percentage points, respectively, for the two specifications. This result emphasizes that stringent regulation is the most important driver of the states' CO_2 emission performance.

5. Conclusions

CO_2 emissions from fossil-fueled electricity generation in the U.S. have dropped considerably in the last decade. As U.S. states seem to show varying success in reducing these CO_2 emissions, the objective of this article was to compare the relative CO_2 emission performance of fossil fuel power plants across the states for the period 2000-2013. In particular, we analyzed whether or not the inter-fuel competition induced by the shale gas revolution and/or state-specific CO_2 regulations have contributed to the developments over time.

For a better understanding of the state-specific CO_2 emission performance over time we first applied a nonparametric benchmarking approach. In doing this, we did not just consider a simple measure of CO_2 intensity, such as CO_2 emissions per unit of electricity produced, but we also took other factors, such as fuel consumption and nameplate capacity, into account. This approach allowed us to measure the relative CO_2 emission performance across states, considering both the input and the output dimension of the states' fossil fuel electricity generation profiles, and hence provided a more comprehensive picture of the states' relative CO_2 emission performance than a simple output-oriented CO_2 intensity measure.

In particular, we used a 'global' Malmquist CO_2 performance index (GMCPI) to measure each state's performance against a global benchmarking technology. The cumulative GMCPI obtained can be interpreted as a total factor CO_2 emission performance index between 2000 and 2013. Overall, we find that the CO_2 emission performance across all states improved, on average, by 15% from 2000 to 2013. Decomposing the performance index into its elements, efficiency change and technological change, revealed that this development was mainly due to technological progress. However, the observed efficiency decline in 24 of the 48 states shows that half of the states were not fully able to implement the technological improvements introduced in some innovative states.

To test whether fuel competition and/or emissions regulations led to an improvement in the CO_2 emission performance over time, we regressed the cumulative GMCPI on natural gas prices, regulatory policies and a number of other state-specific factors. Altogether, the results support the argument of increased inter-fuel competition induced by the shale gas revolution and the positive impact of this on electricity-related CO_2 emissions. That is, lower natural gas prices come with a higher state-specific CO_2 emission performance over time. Furthermore, considering state-level regulatory policies, the results suggest a positive impact of regional cap-and-trade programs on the state-specific CO_2 emission performance over time.

As for the other two regulatory policies considered, there may be several reasons why we do not find them to have a statistically significant impact on the states' CO_2 emission performance. First, the setting of a GHG emissions target does not necessarily come with a set of concrete actions. In most states there is a long period between the announcement of a target and the implementation of mandatory regulations within the individual sectors. Hence, GHG emissions targets can be seen as a soft type of regulatory policy rather than a stringent set of actions. Second, the design of CO_2 performance standards varies enormously among the states. While some standards may have an impact, others may not. In all likelihood, this heterogeneity prevents us from finding a statistically significant impact of state-specific CO_2 performance standards in general.

Altogether, we conclude that lower gas prices and stringent CO_2 regulations are suitable means to reduce electricity-related CO_2 emissions. However, although the effect of lower natural gas prices is statistically significant, it should be carefully interpreted. Taken literally, a $5 drop in the natural gas price, as observed on the national level between 2008 and 2013, is estimated to increase a state's CO_2 emission performance by about 5 percentage points. Whether or not this effect is small or large in environmental terms cannot be clearly answered within our framework. A more comprehensive evaluation should include all the economic and environmental costs (and benefits): in the case of natural gas, this also incorporates the environmental costs resulting from shale gas exploitation. A similar argument applies to our estimated effect of cap-and-trade regulation. While regional cap-and-trade programs seem to be very effective in reducing CO_2 emissions, policy makers should carefully weigh the costs and benefits of such programs before considering a regional and sectoral expansion.

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