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Optimal Profits under Environmental Regulation: The Benefits from Emission Intensity Averaging

Benjamin Hampf · Kenneth Løvold Rødseth

Abstract In this paper we analyze the economic effects of implementing EPA's newly proposed regulations for carbon dioxide (CO_2) on existing U.S. coal-fired power plants using nonparametric methods on a sample of 144 electricity generating units. Moreover, we develop an approach for evaluating the economic gains from averaging emission intensities among the utilities' generating units, compared to implementing unit-specific performance standards. Our results show that the implementation of flexible standards leads to up to 2.7 billion dollars larger profits compared to the uniform standards. Moreover, we find that by adopting best practices, current profits can be maintained even if an intensity standard of 0.88 tons of CO_2 per MWh is implemented. However, our results also indicate a trade-off between environmental and profit gains, since aggregate CO_2 emissions are higher with emission intensity averaging than with uniform standards.

JEL classification D24, L50, Q54

Keywords Environmental regulation, profit maximization, emission intensity averaging, nonparametric efficiency analysis

Corresponding author (B. Hampf): Tel.: +49 6151 165319, Fax: +49 6151 163897, E-mail: hampf@vwl.tu-darmstadt.de, Department of Law and Economics, Darmstadt University of Technology, Hochschulstraße 1, D-64289 Darmstadt, Germany · (K. L. Rødseth): Department of Economics and Logistics, Institute of Transport Economics, Gaustadalléen 21, NO-0349 Oslo, Norway

1 Introduction

In the summer of 2013, President Obama asked the U.S. Environmental Protection Agency (EPA) to design carbon dioxide (CO_2) regulations for new and existing power plants. In response to the President's request, the EPA proposed a new rule on June 18th, 2014, under the authority of the Clean Air Act (CAA).[1] According to the EPA's projections, the new rule would by 2030 reduce the power sector's CO_2 emissions by 30 percent relative to 2005-levels.

In their proposal, the EPA calculates CO_2 performance standards for each state, depending on their power sectors' perceived capabilities to reduce CO_2 emissions. The standards are determined based on a number of variables, including existing strategies to improve the efficiency of fossil-fuel power plants, existing programs to spur investments in low-emitting energy, demand-side energy savings programs, and the states' current fuel mixes.

While the state-level CO_2 performance standards are specific, the EPA does not direct measures which the states should implement to reach their emission targets. Instead, each state or a collaboration of states must develop plans on how they will achieve the EPA standards. The states must establish emission performance levels for affected electricity generating units that are equivalent to the state-specific CO_2 performance standards proposed by the EPA. These performance levels could be in the form of the performance standards set by the EPA, or the state-specific performance standards could be translated into mass-based goals as long as the translated goals achieve the same degree of emission limitation as the EPA performance standards.

This paper evaluates the economic implications of performance standard regulations using production analysis. In particular, we analyze optimal profits of decision making units (DMUs) taking into account potential productive inefficiencies. Previous studies which analyze the efficiency of DMUs in the presence of environmental regulation can be divided into two different strings of literature.[2] The first string of literature evaluates the technical efficiency of DMUs in the presence of regulation using distance functions. For example, Ramli et al. (2013) modify and apply the directional distance function by Chung et al. (1997) to analyze the eco-efficiency of the Malaysian manufacturing sector taking into account CO_2 emissions, while Zofio and Prieto (2001) apply the hyperbolic distance function by Färe et al. (1989) to measure the effects of CO_2 regulations on OECD countries.[3] A second string of literature analyzes the economic (e.g. cost or profit) efficiency of DMUs in the presence of environmental regulation taking into account price data. For example, Brännlund et al. (1995) present an analysis of the profit efficiency in the Swedish pulp and paper industry given a fixed quota on the emission of biological oxygen demand and chlorinated compounds. The profit effects of tradable quotas are examined e.g. in Brännlund et al. (1998) and Nielsen (2012). An analysis of profit efficiency in the presence of a tradable quota on CO_2 emissions is presented in Oude Lansink and van der Vlist (2008). Note that all aforementioned studies use nonparametric methods to evaluate the economic effects of environmental regulation. For a more detailed and broader survey accounting e.g. for parametric approaches see Ambec and Barla (2006).

In contrast to the previous literature we do not analyze the effect of a fixed or tradable quota (e.g. an absolute upper boundary on total emissions) but the effects of emission standards (e.g. the ratio of the produced good output to pollution). Although our approach is general and thus applicable to a wide range of environmental policy cases, the paper and its empirical case are motivated by EPA's recent proposal. Our modelling strategy builds on Rødseth and Romstad (2014). We assume that the DMUs under consideration (the electricity generating units) maximize profits and apply microeconomic production models to estimate maximal profits with and without environmental regulation. We consider environmental performance standards that either are DMU-specific or implemented for a group of DMUs (e.g., all DMUs belonging to an electric utility),

[1] See `https://www.federalregister.gov/articles/2014/06/18/2014-13726/carbon-pollution-emission-guidelines-for-existing-stationary-sources-electric-utility-generating#h-9` for details.

[2] See Song et al. (2012) for a detailed review of the literature on nonparametric analysis of environmental efficiency.

[3] Zhang and Choi (2014) provide a survey on the use of directional distance functions in environmental efficiency analysis.

where the group-averaging approach builds on the model by Brännlund et al. (1998). By comparing the different profit maxima, we are able to identify the economic gains from averaging emission intensities across DMUs.

Our approach also allows examining changes in pollution between the three scenarios, i.e. profit maximization in the cases i) without environmental regulation, ii) with DMU-specific performance standards, and iii) with averaging of emission intensities across groups of DMUs. In the case of the EPA standards, the resulting CO_2 emissions when emission intensities are averaged across electricity generating units provide valuable information for state plan designers. First, it will allow them to identify the DMU-specific performance standards that together minimize the profit losses related to the implementation of a certain state-specific standard. Second, knowledge about the level of regulatory induced emission reductions is also important for converting EPA's performance standards into mass-based goals that achieve comparable emission reductions.

It has long been recognized that different types of environmental policy instruments may affect the rates and direction of technological change differently (Jaffe et al. 2002). The strand of literature which argues that performance standards reduce incentives to invest in "clean" technologies (see e.g. Mohr 2006) is particularly relevant to our case. However, our paper examines a different aspect of performance standards, namely their potential to spur efficiency improvements given the state of the technology. Our approach builds on microeconomic production analysis, and consequently offers the possibility to examine forgone profits and excess pollution due to productive inefficiency. This is beneficial for at least three reasons. First, the analysis describes the potential for performance standards to induce efficiency improvements for affected DMUs. Second, the analysis allows identifying profit loss minimizing performance standards for affected DMUs under the assumption that all units have adopted best practices, rather than calculating optimal performance standards based on their current emission rates. In the latter case, the scope for reducing pollution may be largely underestimated. Third, by also identifying economic losses due to inefficiency, our approach may reveal that profit losses from environmental regulation - when compared to current profits - may be low. If the measures that are implemented influence the DMUs to become more efficient, the economic gains from efficiency improvements can partly or fully crowd out economic losses resulting from environmental compliance. Furthermore, our approach allows for net benefits of the environmental regulation by accounting for the possibility that the profits under the regulation exceed the actual business-as-usual profits due to the adaption of best-practices. Empirical evidence of net benefits would be supportive of the so-called Porter hypothesis (Porter and van der Linde 1995).

We illustrate our approach with an empirical example from the U.S. power sector. Rather than providing a complete assessment for all electricity generating units belonging to a state or several states, covering a wide range of fuel types, we emphasize CO_2 performance standards for bituminous-fired generating units. According to the U.S. Energy Information Administration (EIA), bituminous coal generates on average 2,236.8 kilograms of CO_2 per short ton, and is therefore among the most CO_2-intensive fuels. Hence, the implementation of CO_2 standards will therefore strongly affect the bituminous coal using generating units. Our sample selection strategy also ensures the homogeneity of the units under consideration to a much larger degree than most comparable studies.

We analyze the economic implications of performance standards for a sample of 144 bituminous-fired generating units that were in operation in 2011 using a modification of the nonparametric Free Disposable Hull (FDH) model by Deprins et al. (1984). Moreover, we evaluate benefits from averaging emission intensities across multiple electricity generating units. Therefore, we propose a new methodological approach which is similar to the idea of a central planner which optimally divides resources (see Nasrabadi et al. 2012) or costs and revenues (see Khodabakhshi and Aryavash 2014) among subunits. Our analysis is comparable to other studies which use production analysis techniques to analyze the economic benefits of emission trading (see Brännlund et al. 1998, Färe et al. 2013b, and Färe et al. 2014). However, while the mentioned studies emphasize emission trading, our paper is, to our knowledge, the first to present a detailed treatment on analyzing benefits from emission intensity averaging under a performance standard regime.

Our results show that the generating units under consideration are profit inefficient, and could potentially increase their combined profits by 27.5 percent in the case of no CO_2 regulation. Performance standards higher or equal to 1.03 tons of CO_2 per Megawatt-hour are found not to lead to profit losses given the adoption of best practices, while standards below 0.85 tons per Megawatt-hour lead to a complete shutdown of the bituminous electricity generating units. We find that a state-wise electric utility-specific averaging of emission intensities reduces profit losses relative to uniform generating unit-specific performance standards, but at the expense of increased CO_2 emissions.[4] Moreover, we find that profit efficiency improvements can allow the units to experience net economic gains for some performance standards, but possibly at the expense of increased CO_2 emissions compared to current emissions.

This paper is structured as follows: Section 2 presents our methodological approach to optimal profits. Section 3 presents the analysis of optimal profits for U.S. coal-fired power plants, while section 4 concludes the paper.

2 Theory

In this section we present the methodological background of our analysis. We start by discussing the definition and estimation of environmental production technologies. Building upon the theoretical concepts, we present nonparametric methods to calculate optimal profits and propose a new approach to evaluate flexible performance standards based on the averaging of emission intensities.

2.1 Modeling and estimating environmental technologies

In our empirical analysis we consider the optimal short-run profits for coal-fired power plants in the United States. The electricity generation is modeled as a production process in which a single polluting input (bituminous coal) and a single non-polluting input (capacity) are used to produce a single good output (electricity) and a single bad output (CO_2).[5] This specification of the electricity generating process follows previous studies on the efficiency of U.S. power plants, see e.g. Mekaroonreung and Johnson (2012) and Hampf and Rødseth (2015). Defining $x^P \in \mathbb{R}_+$ as the polluting input, $x^{NP} \in \mathbb{R}_+$ as the non-polluting input and $y \in \mathbb{R}_+$ as the good output, the conventional technology which does not account for the production of emissions comprises all technically feasible combinations of inputs and good outputs and reads as:

$$T^{Conv} = \left\{ \left(x^P, x^{NP}, y\right) \in \mathbb{R}^3_+ : \left(x^P, x^{NP}\right) \text{ can produce } y \right\}. \tag{2.1}$$

From the definition of the technology it is obvious that, when derived from empirical data, all observations belong to the technology since their input-output combinations are observed and, thus, technically feasible. To construct a technology set based on empirical observations which satisfies several economically and technically reasonable characteristics (e.g. inactivity) specific axioms have to be imposed on the technology. For conventional technologies, a neoclassical axiomatic system has been proposed by Shephard (1970). These axioms are (see Färe and Primont (1995) for a detailed discussion):

1. Inactivity: $(0, 0, 0) \in T^{Conv}$.
   It is possible to shut down operations.

[4] In our analysis we refer to each generator located at coal-fired plants as a generating unit. Electric utilities are the companies which own the plants and may therefore be owning and operating multiple generating units.

[5] Note that our theoretical discussion can be easily extended to the case of more than two inputs and two outputs. For the sake of notational simplicity we restrict this presentation to our empirical specification.

2. No free-lunch: $(0, 0, y) \notin T^{Conv}$ if $y > 0$.
   It is not possible to produce positive amounts of good outputs without using any inputs.
3. Strong disposability of inputs:
   If $\left(x^P, x^{NP}, y\right) \in T^{Conv}$ then $\left(\tilde{x}^P \geq x^P, \tilde{x}^{NP} \geq x^{NP}, y\right) \in T^{Conv}$.
   It is always possible to produce the same amount of output using more inputs.
4. Strong disposability of good outputs:
   If $\left(x^P, x^{NP}, y\right) \in T^{Conv}$ then $\left(x^P, x^{NP}, \tilde{y} \leq y\right) \in T^{Conv}$.
   It is always possible to produce less output for a given input mix.
5. Closeness: T^{Conv} is a closed set.
   The boundary of the technology is thus also part of the technology.

In addition to inputs and good outputs, environmental technologies also account for the unintended by-production of bad outputs (in our application CO_2). Defining $b \in \mathbb{R}_+$ as the bad output, the environmental technology reads as:

$$T^{Env} = \left\{ \left(x^P, x^{NP}, y, b\right) \in \mathbb{R}^4_+ : \left(x^P, x^{NP}\right) \text{can produce} \, (y, b) \right\}. \tag{2.2}$$

In contrast to conventional technologies, the axioms by Shephard (1970) cannot readily be imposed on environmental technologies since it would lead to physically infeasible technology sets (Färe and Grosskopf 2003). For example, assuming free disposability of bad outputs would imply that all DMUs can reduce their emissions to zero at no costs (Førsund 2009). To overcome this issue various alternative axiomatic systems have been proposed (see Scheel (2001) for an overview). In most empirical analyses the joint production (JP) or weak disposability model by Färe et al. (1989) is applied (see e.g. Zhou et al. (2008) for a survey on empirical environmental efficiency studies). Färe et al. (1989) proposed two additional axioms for modeling environmental technology sets: weak disposability and null-jointness of good and bad outputs (for a more thorough discussion of these axioms see Färe and Grosskopf 2004).

JP.1 Weak disposability of bad outputs:
If $\left(x^P, x^{NP}, y, b\right) \in T^{Env}$, then $\left(x^P, x^{NP}, \theta y, \theta b\right) \in T^{Env}$ with $0 \leq \theta \leq 1$.
Bad outputs can only be reduced if the good ouputs are reduced by the same proportion. Therefore, the reduction of bad outputs is costly (in terms of reduced good outputs).

JP.2 Null-jointness: If $\left(x^P, x^{NP}, y, b\right) \in T^{Env}$ and $b = 0$, then $y = 0$.
It is not possible to produce positive amounts of the good output without producing positive amounts of the bad output.

An alternative approach to modeling environmental technologies has been introduced by Rødseth (2014) which is based on the materials balance (MB) condition. The MB, introduced in the economic literature by Ayers and Kneese (1969), states that the amount of materials bound in polluting inputs is equal to the amount of materials bound in good and bad outputs. That is, materials can not vanish during the production process (see Lauwers (2009) for a justification of applying the MB in economic models). Rødseth (2014) proposes an axiomatic approach to environmental technologies which explicitly accounts for the restrictions imposed by the MB.

MB.1 Weak g-disposability:
If $\left(x^P, x^{NP}, y, b\right) \in T^{Env}$ and $s_x g_x + s_y g_y = g_b$, then $\left(x^P + g_x, x^{NP}, y - g_y, b + g_b\right) \in T^{Env}$.
For a given input-output combination within T only changes which are in line with the MB are valid to remain within T.

MB.2 Output essentiality:
If $\left(x^P, x^{NP}, y, b\right) \in T^{Env}$ and $b = 0$, then $x^P = 0$.
It is not possible to produce zero bad outputs given positive amounts of the polluting input.

In the weak g-disposability axiom (MB.1) g_x, g_y, and g_b represent changes in the inputs, the good output, and the bad output, respectively, when inputs and outputs are disposed. Choosing the g_x, g_y, and g_b (e.g., by allowing them to be determined ex ante by the researcher or, as in this paper, by allowing the empirical production model to endogenously determine them) is equivalent to choosing the direction in which inputs and outputs are disposable (also known as the G-direction). The summary constraint $s_x g_x + s_y g_y = g_b$ restricts the direction in which inputs and outputs are disposable. Let s_x and s_y represent the exogenous emission factor for the polluting input and the recuperation factor for the good output.[6] Then the weak G-disposable enforces disposal in line with the materials balance principle, ensuring that changes in emissions g_b equal the sum of changes in emissions due to disposal of the inputs ($s_x g_x$) and the good output ($s_y g_y$). In our example of the electricity generation, $s_y = 0$ because the output electricity does not contain any materials. For a more detailed comparison of the JP and the MB model, as well as an empirical application, see Hampf and Rødseth (2015).

To estimate the technology sets from empirical data we use nonparametric frontier methods. In contrast to parametric methods (e.g. Stochastic Frontier Analysis), the nonparametric approach does not assume a specific functional form of the production function enveloping the technology or impose assumptions on the inefficiency distribution. Moreover, it is not restricted to a single output.[7] Given a sample of $i = 1, \ldots, n$ decision making units (DMUs) the nonparametric estimation of the JP model reads as:

$$\begin{aligned} T^{JP} = \Big\{ \Big(x^P, x^{NP}, y, b\Big) \in \mathbb{R}^4_+ :\ & x^{NP} \geq \sum_{i=1}^{n} x_i^{NP}\lambda_i, x^P \geq \sum_{i=1}^{n} x_i^P \lambda_i, y \leq \sum_{i=1}^{n} y_i\lambda_i\theta, \\ & b = \sum_{i=1}^{n} b_i\lambda_i\theta, 0 \leq \theta \leq 1, \sum_{i=1}^{n}\lambda_i = 1, \lambda_1, \ldots, \lambda_n \in \{0,1\}\Big\}. \end{aligned} \tag{2.3}$$

In this formulation x_i^{NP} (x_i^P, y_i, b_i) refers to the amount of non-polluting inputs (polluting inputs, good outputs, bad outputs) of DMU i, with the inequalities for the inputs and the good output indicating strong disposability while the equality on b implies weak disposability.[8] θ denotes the weak disposability factor to be endogenously determined for each DMU. λ_i represents the weighting factor of DMU i. The summing-up condition on the λ-factors, as well as restricting them to be either equal to zero or equal to one, implies the non-convexity of the technology. Therefore, our approach to the technology estimation is an adaption of the Free Disposal Hull (FDH) estimator by Deprins et al. (1984) to an analysis including weak disposable outputs. We use this model since the test of convexity by Simar and Wilson (2011) rejects the hypothesis of a convex technology set (p-value: 0.053).[9]

The nonparametric estimation of the MB model reads as:

$$\begin{aligned} T^{MB} = \Big\{ \Big(x^P, x^{NP}, y, b\Big) \in \mathbb{R}^4_+ :\ & x^{NP} \geq \sum_{i=1}^{n} x_i^{NP}\lambda_i, x^P = \sum_{i=1}^{n} x_i^P \lambda_i + \epsilon_x, \\ & y = \sum_{i=1}^{n} y_i\lambda_i - \epsilon_y, b = \sum_{i=1}^{n} b_i\lambda_i + \epsilon_b, \\ & s_x\epsilon_x + s_y\epsilon_y = \epsilon_b, \sum_{i=1}^{n}\lambda_i = 1, \\ & \lambda_1, \ldots, \lambda_n \in \{0,1\}, \epsilon_x, \epsilon_y, \epsilon_b \geq 0\Big\}. \end{aligned} \tag{2.4}$$

In addition to the variables defined above, ϵ_x, ϵ_y and ϵ_b refer to the slacks in the inputs and outputs which have to satisfy the materials balance condition.

[6] Emission (recuperation) factors indicate the amount of materials bound in one unit of inputs (outputs).

[7] See e.g. Greene (2008) for a discussion on issues with parametric models containing multiple outputs.

[8] A formal proof of that the equality constraint implies weak disposability of the technology can be found in Färe and Grosskopf (2004, p. 49-51).

[9] See Färe and Grosskopf (2004) and Hampf and Rødseth (2015) for discussions on convex, variable returns to scale versions of the production models.

The presented estimations of the technology sets are non-convex versions of the estimators presented in Färe et al. (1989) and Hampf and Rødseth (2015). However, when estimated from empirical observations these technology estimates do not necessarily satisfy axiom 1 (inactivity).[10] To allow for the inactivity of the generating units, which implies the possibility to shut down operations, the dataset needs to be modified. Inactivity is particularly important in our application since firms will not continue to operate generators if they cannot cover their variable costs. Following Tulkens and Vanden Eeckaut (1995) we add a zero observation, an artificial observation with $\left(x_0^P, x_0^{NP}, y_0, b_0\right) = (0,0,0,0)$, to the dataset to allow for inactivity.

2.2 Estimating optimal profits

Based on the nonparametric estimation of the technology sets we calculate the optimal profits for the DMUs which in our application correspond to the electricity generating units (see e.g. Thanassoulis et al. (2008) for a discussion on profit maximization subject to nonparametric technology estimation). We assume that the DMUs maximize their short-run profits by considering the non-polluting input (capacity as a proxy for the capital stock) as fixed.[11] Furthermore, we assume that the profit optimization is restricted by an exogenously given constraint on the maximal ratio of bad to good outputs (the performance standard(s)). For example, such a regulation is given by EPA's initial proposal for carbon dioxide standards which restricts the maximal emission intensity to 1000 pounds of CO_2 per MWh of produced electricity, as well as the recently proposed state-specific standards.

In this setting both axiomatic approaches (the joint production and the materials balance model) lead to the same results.[12] A proof of this equivalence and a derivation of the following binary programming problems can be found in the appendix. The unconstrained short-run profit optimization problem for DMU i reads as:

$$\begin{array}{ll} \max\limits_{\lambda_1,\ldots,\lambda_n} & p_i \sum_{j=1}^n y_j\lambda_j - q_i \sum_{j=1}^n x_j^P \lambda_j \\ \text{s.t.} & x_i^{NP} \geq \sum_{j=1}^n x_j^{NP}\lambda_j \\ & \sum_{j=1}^n \lambda_j = 1 \\ & \lambda_1,\ldots,\lambda_n \in \{0,1\}. \end{array} \tag{2.5}$$

This programming problem estimates the maximal profit of DMU i assuming that no environmental regulation is imposed. $p_i \in \mathbb{R}_+$ denotes the exogenously given price for the good output (in our application electricity) while $q_i \in \mathbb{R}_+$ denotes the price for the polluting input (in our case bituminous coal). Note that we allow the prices to differ among the DMUs.

Adding the regulatory constraint on the maximal feasible emission to output ratio ($b/y \leq s$, where s is predetermined) leads to the modified, restricted binary programming problem

$$\begin{array}{ll} \max\limits_{\lambda_1,\ldots,\lambda_n} & p_i \sum_{j=1}^n y_j\lambda_j - q_i \sum_{j=1}^n x_j^P \lambda_j \\ \text{s.t.} & x_i^{NP} \geq \sum_{j=1}^n x_j^{NP}\lambda_j \\ & \sum_{j=1}^n b_j\lambda_j - s\sum_{j=1}^n y_j\lambda_j \leq 0 \\ & \sum_{j=1}^n \lambda_j = 1 \\ & \lambda_1,\ldots,\lambda_n \in \{0,1\}. \end{array} \tag{2.6}$$

In this model we assume that each generating unit independently optimizes its profit subject to a fixed, exogenous regulatory constraint. This constraint is the same for all DMUs located in the same state. Hence,

[10] The estimated technologies only satisfy the inactivity axiom if an inactive unit is part of the dataset, which is rarely the case given empirical data.

[11] See Welch and Barnum (2009) for a similar methodological approach to a cost and environmental analysis of power plants.

[12] Moreover, due to an optimization approach which is not based on distance functions, the problems discussed by Chen (2014) for the JP model do not arise.

the EPA standard, which was discussed in the introduction, is implemented uniformly across all generating units located in a state. To evaluate the benefits of a more flexible regulatory regime which allows the utilities to average the emission to electricity ratio across their electricity generating units, we propose a modified optimization approach. We assume that each utility simultaneously optimizes the profit for all its generating units, subject to the constraint that the average ratio satisfies the given regulatory standard. For example, this approach is in line with the NO_x regulations under the Acid Rain Program. Moreover, in line with the EPA's recently proposed performance standards, we allow averaging emission intensities across the generators located in the same state.

Therefore, the short-run profit is optimized given the constraint $\bar{b}/\bar{y} \leq s$ where $\bar{b}$ ($\bar{y}$) denotes the average emissions (average amount of produced electricity) of all DMUs belonging to a utility in a particular state. Note that we use the ratio of averages $\left(\frac{(1/n)\sum_{i=1}^n b_i}{(1/n)\sum_{i=1}^n y_i}\right)$ as the constraint for this aggregated optimization. This is done to avoid infeasible solutions which would occur if the average ratio $\left((1/n)\sum_{i=1}^n b_i/y_i\right)$ is evaluated and some of the generating units shut down operations ($y_i = b_i = 0$). Moreover, even if we account for this problem by adding a non-archimedean constant to the denominator of the ratios, the average of ratios can lead to problematic results since it favors corner solutions. Consider a utility with 4 efficient and one (relatively) inefficient generating unit. If the inefficient unit has access to less costly coal it could be economically optimal to use solely the inefficient unit under the constraint $\frac{1}{5}\left(\frac{b_i}{y_i}\right) \leq s$. Hence, this approach is likely to lead to environmental hotspots which should not be generated by regulatory actions (see e.g. Gruenspecht and Lave (1989) for a discussion of this issue). In the light of these arguments we decided to use the ratio of averages to quantify the economic benefits of emission intensity averaging.[13]

Assuming that the n DMUs can be attributed to $l = 1, \ldots, k$ utilities with n_l denoting the number of DMUs belonging to a utility in a given state, the optimization problem for the aggregated profit of a utility l in this state reads as:

$$\begin{aligned}
\max_{\lambda_{1,1},\ldots,\lambda_{n,n_l}} \quad & \sum_{z=1}^{n_l} \left(p_z \sum_{i=1}^n y_i \lambda_{i,z} - q_z \sum_{i=1}^n x_i^P \lambda_{i,z} \right) \\
\text{s.t.} \quad & \left.\begin{aligned} x_{lz}^{NP} &\geq \sum_{i=1}^n x_i^{NP} \lambda_{i,z} \\ \sum_{i=1}^n \lambda_{i,z} &= 1 \\ \lambda_{1,z}, \ldots, \lambda_{n,z} &\in \{0,1\} \end{aligned}\right\} z = 1, \ldots, n_l \\
& \sum_{z=1}^{n_l} \left(\sum_{i=1}^n b_i \lambda_{i,z} - s \sum_{i=1}^n y_i \lambda_{i,z} \right) \leq 0.
\end{aligned} \tag{2.7}$$

In this formulation, the objective function represents the sum of profits of all n_l generating units belonging to utility l. The first three restrictions model the technology constraints for the generating units. Note that the reference DMUs and hence the λ-values may differ for all units. Hence, the optimization problem contains $n \times n_l$ λ-values.[14] The last constraint restricts the ratio of average emissions to average electricity not to be larger than the exogenous standard s. To obtain results for each of the n DMUs this programming problem has to be solved for each of the k utilities and for each state. Note that if the averaging is allowed across all n units of all k utilities in all states, our model collapses into a non-convex version of the model by Brännlund et al. (1998).

To estimate the optimal profits based on equations (2.6) and (2.7) we use our own programmings for the statistical software R. The programming problems are solved using the R package lpSolve by S. Buttrey. The solver provided by this package uses a "'branch-and-bound"-algorithm to solve integer programming problems. For a more detailed description of the solver and the package see `http://cran.r-project.org/web/packages/lpSolve/lpSolve.pdf`.

[13] Note that if the ratio of averages is equal to c the average ratio can not be smaller than s since by Jensen's inequality it follows that $E(b/y) = E(b) \cdot E(1/y) \geq E(b) \cdot 1/E(y) = E(b)/E(y)$.

[14] For more detailed discussions on network technologies modeling subunits see e.g. Färe and Grosskopf (2000).

In the following empirical analysis we evaluate and compare the optimal profits for different standards. Moreover, the economic benefit of averaging emission intensities is compared to the environmental effects as quantified by the aggregated emissions.

3 Empirical analysis

In this section we present the data and results of our analysis of U.S. power plants. We start by describing the construction of the dataset, highlighting our strategy to ensure that the generating units under consideration are homogeneous. This description is followed by a presentation and discussion of the results for the profit optimizations. We present results on the effects of emission intensity averaging evaluating a grid of exogenously given performance standards, as well as for specific standards proposed by the EPA.

3.1 Constructing the dataset

As explained in the theory section, we model a production process assuming that the electricity generating units use two inputs (fuel and capacity) to produce a single good (electricity) and a single bad (carbon dioxide) output. The short-run costs of the units are given by their fuel consumption times the fuel price while their revenues consist of the produced electricity times the price of electricity. We define the differences in the units' revenues and the short-run costs as their short-run profits.[15] The selection of the analyzed units is based on the file EIA-860 by the U.S. Energy Information Administration (EIA) which provides data on the input variable capacity. Data on the fuel input, the electricity generation as well as the CO_2 emissions are collected from the Clean Air Markets database provided by the U.S. Environmental Protection Agency (EPA). Finally, data on fuel prices are obtained from file EIA-923, while data on sales prices for electricity are obtained from file EIA-861. Following Färe et al. (2005), the sales price is equal to the average of the retail and resale prices for electricity. Our sample covers generating units which were in operation during 2011.

Following Mekaroonreung and Johnson (2012) we restrict our sample to those generating units that only use bituminous coal (measured in million british thermal units, MMBtu). With this selection criterion we assure that the generating units are evaluated against a reference set which only contains units operating under the same technological conditions. In contrast, previous studies (see e.g. Färe et al. 2007) which include generating units that use different coal types and moreover additional fuel types (e.g. oil, natural gas) are likely to lead to efficiency estimates which are biased, since they capture efficiency differences as well as technological differences among the generating units.[16] In our analysis we assume that the fuel consumption is a variable input. Hence, it is endogenously determined by profit maximization. As a second input we include the capacity of the generating units (measured in megawatts) as a proxy of their capital stock. We use a proxy variable since studies which estimate the capital stock directly by using data from the Federal Energy Regulatory Commission (FERC) are faced with significant reductions in the number of observations leading to results which are questionable in terms of their generalizability (see e.g. Hampf (2014) for such an analysis with a limited number of observations). For the same reason we do not include labor in our analysis.[17] However, Welch and Barnum (2009) argue that the labor input of a plant is proportional to its generating capacity. Therefore, by including the capacity of the plants we indirectly account for the labor

[15] Note that in line with the literature on profit efficiency we assume that the prices are not affected by the profit optimization. If demand and supply functions are known, endogenous models (see Johnson and Ruggiero 2011) could be estimated.

[16] See Heshmati et al. (2012) for a discussion of the issues when estimating power plant efficiency with heterogeneous technology sets.

[17] See Färe et al. (2013a) for a discussion on the reduction of the number of observations due to missing data from U.S. power plants.

input. In our analysis we assume that the capacity and hence the capital stock is fixed in the short run. Hence, the capacity of the generating units is an exogenous variable. In addition to the inputs, we include the good output electricity (measured in megawatt hours, MWh) and the bad output carbon dioxide (measured in tons), which are assumed to be variable and hence endogenously determined factors.

The total sample comprises 160 generating units operating in the United States in 2011.[18] From this sample we have to remove 16 observations due to missing data on the fuel or electricity prices. Hence, the final analyzed sample contains 144 generating units (excluding the artificial "zero observation"). These units can be attributed to 29 utilities as well as to 15 states where the plants are located. Descriptive statistics of the analyzed sample are presented in table 1.

Table 1 Descriptive statistics of the data (144 units)

Variable	Min.	Mean	Max.	St.dev.
Capacity (MW)	112.50	345.42	1425.60	233.31
Fuel (MMBtu)	57417.69	16570772.62	74900000.00	14829299.04
Electricity (MWh)	5884.10	1754698.85	8541295.90	1632501.37
CO_2 (tons)	5890.97	1702688.82	7686116.00	1521278.43
Electricity price ($ per MWh)	42.12	68.40	99.67	10.03
Fuel price ($ per MMBtu)	1.50	3.16	5.19	0.74

3.2 Aggregated results for the generating units

The aggregated results for the total sample of 144 generating units are depicted in figure 1 which consists of two panels. The upper panel presents the sum of optimal profits of all generating units (in billion dollars) calculated using programming problems (2.6) and (2.7) for a grid of emission standards ranging from 0.8 to 1.25 tons of CO_2 per MWh of produced electricity.[19] The maximal observed emission intensity in the sample is 1.23 tons per MWh. Therefore, standards larger than 1.23 tons per MWh are equal to a situation without any standards since the restriction on the emission intensity is not binding for any of the evaluated generating units. In contrast, the minimal observed emission intensity in the sample is 0.85 tons per MWh. Hence, imposing a standard lower than 0.85 tons per MWh leads to a shutdown of all units in the sample. Thus, the effective interval of the performance standards is given by $[0.85, 1.23]$ tons per MWh.

The solid line in the upper panel of figure 1 indicates the optimal profits for different performance standards if they are fixed for each generating unit, hence if the optimal profit for each generator cannot be associated with an emission intensity larger than the imposed standards. The dashed line indicates the optimal profits if intensity averaging is allowed. In this setting the ratio of average emissions to average produced electricity of all generating units owned by a utility in a state has to be lower than or equal to the defined standard. Finally, the horizontal dotted line represents the actual (or business-as-usual) short-run profits of the generating units, which amount to 10.46 billion dollars.[20] Note that to be able to generate this figure we have assumed that each state implements the same standard. If standards differ across the states, the optimal profits will change. However, since we assume that utilities cannot average the intensities across states, the benefits of the averaging will not be biased in this situation.

From the figure it is obvious that without regulation (or with a standard larger than 1.23 tons per MWh) considerable potentials to increase profits exist. The maximal aggregated profit in this setting amounts to 13.31 billion dollars. Therefore, the profit efficiency is equal to $(13.31/10.46) \times 100\% = 127.25\%$ indicating

[18] See Hampf and Rødseth (2015) for more details on the data.
[19] Note that the grid is evaluated for steps of 0.01 tons per MWh.
[20] We define the profits of the generating units given their inefficiencies as the business-as-usual profits.

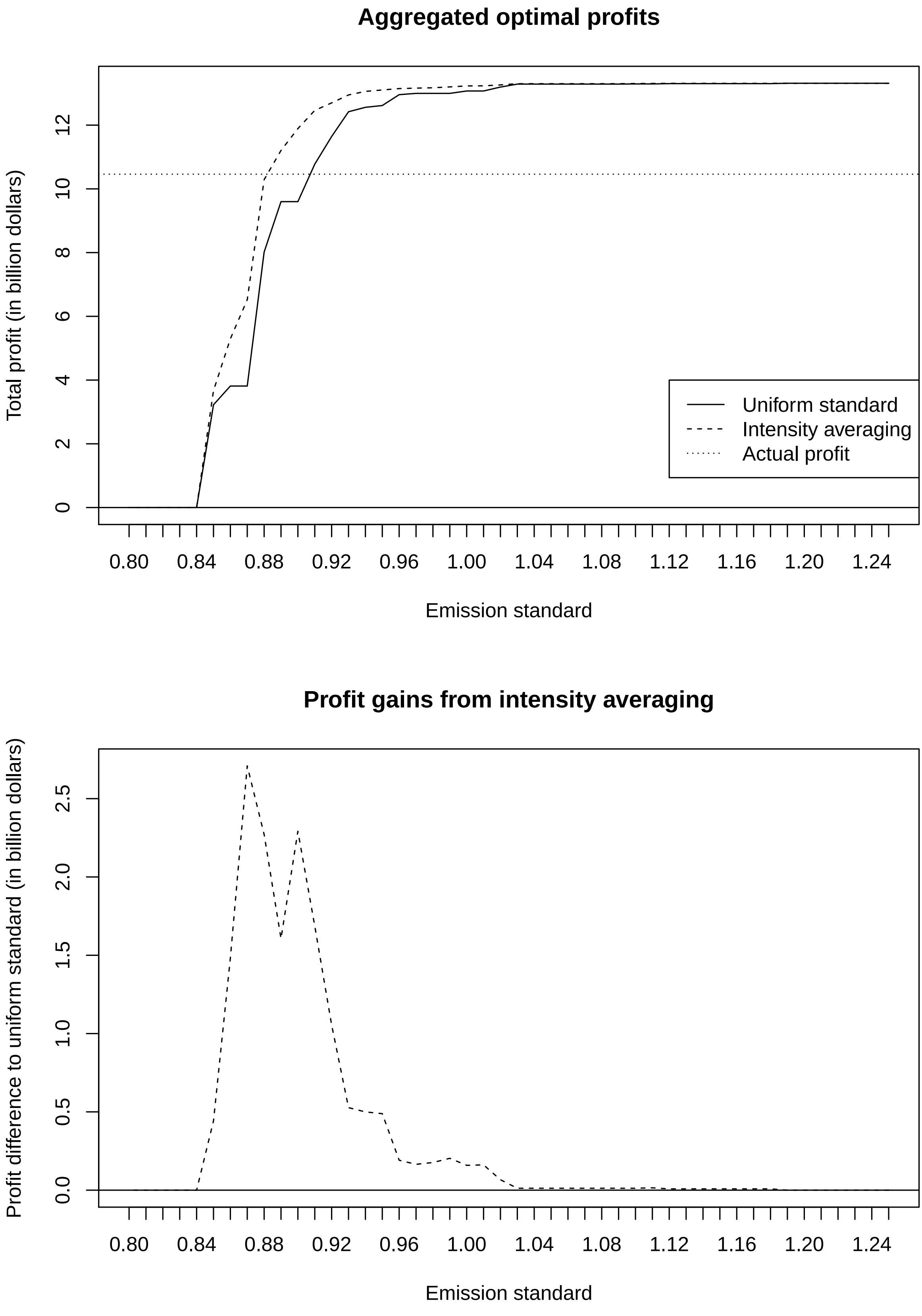

Fig. 1 Aggregated results of the profit maximization

that the generating units' combined profits could be increased by 27.25% if best practices would be adopted and efficiency improvement potential would be exploited.

The results for standards below 1.23 tons per MWh show that the introduction of the environmental regulation does not necessarily lead to profit reductions if efficiency improvements are taken into account. By adopting best practices the generating units can decrease their emission intensity and thus are able to maintain a profit very close to the optimal profits down to a standard of 1.03 tons per MWh if a uniform standard is imposed. In case of a regulation which allows for averaging among generating units, these profits can be obtained even for standards smaller than 1.03 tons per MWh. The dashed line indicates only small changes down to standards of 0.93 tons per MWh. If the standards are further reduced, the optimal profits start to decline even if efficiency improvements are exploited. The intersections of the profit curves with the dotted line indicate the standard which is associated with an optimal profit that is equal to the business-as-usual profits without any regulation. The figure shows that if a fixed standard is imposed a restriction of approximately 0.91 tons per MWh would lead to this equality of profits while the averaging approach leads to an intersection for a lower standard of approximately 0.88 tons per MWh. This highlights the possibility to obtain larger profits if the utilities are allowed to average emission intensities.

To visualize in more detail the additional profits due to emission averaging, the lower panel in figure 1 presents the differences in maximal profits between the averaging approach compared to the uniform standard, hence depicts $\sum_{l=1}^{k} \left(\pi_{l,\text{avg}} - \pi_{l,\text{unif}}\right)_s \geq 0$, where $\pi_{l,\text{avg}}$ denotes the profit of utility l given the possibility to average intensities while $\pi_{l,\text{unif}}$ represents the profit under a uniform standard. s denotes the analyzed standard. Similar to the upper panel, this figure shows that due to the adaption of best-practices there are profit decreases close to zero caused by the regulation and hence nearly no profit gains from the intensity averaging for standards larger than 1.03 tons per MWh. For standards smaller than 1.03 tons per MWh the averaging approach leads to additional profits compared to the uniform standard with a maximal gain for a standard of 0.87 tons per MWh. Given this standard the averaging leads to additional profits of 2.7 billion dollars. Stated differently, the averaging approach leads to additional profits of approximately 26% of the business-as-usual profits of 10.46 billion dollars. These numbers show that large economic benefits can be obtained when allowing utilities to average their emission intensities.

In order to analyze the sensitivity of our results we have calculated the optimal profits for three alternative model specifications. Table 2 presents the correlation coefficients comparing the results of the above specified model with those obtained from an analysis allowing for convexity (Data Envelopment Analysis, DEA) given two different assumptions regarding the returns to scale (constant returns to scale (CRS) and variable returns to scale (VRS)). The results show that the optimal profits for uniform standards and intensity averaging as well as the profit gains from intensity averaging are highly correlated with the results obtained in our specification. However, the results for an analysis of a non-convex (FDH) model excluding the capacity variable (as proposed by Welch and Barnum (2009)) show that the profit gains from intensity averaging are only weakly correlated to those obtained from our model. This follows because in the alternative model all inputs and outputs are variable and therefore the benefits from the more flexible emission intensity averaging approach decrease. However, by removing the capacity as a variable in the model it is implicitly assumed that the size of the plants can be changed instantaneously without any costs. Since this assumption is rather implausible our chosen model specification represents a more realistic view on the potential benefits from emission averaging.

Table 2 Results of the sensitivity analysis (optimal profits)

	Uniform standard	Intensity averaging	Profit gains
DEA (CRS)	0.9993	0.9993	0.9180
DEA (VRS)	0.9993	0.9975	0.9062
FDH (excl. capacity)	0.9042	0.9042	0.1600

Note: The table presents the Spearman rank correlation coefficients.

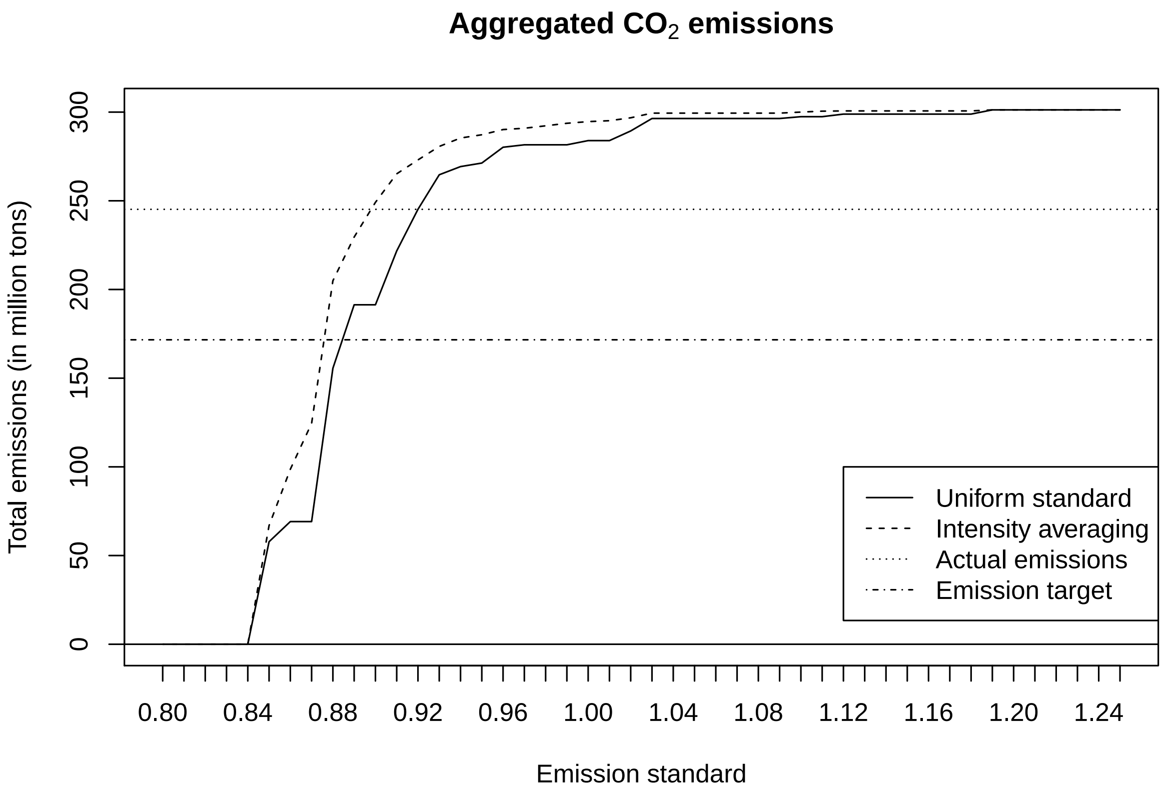

Fig. 2 Aggregated carbon dioxide emissions

Comparing the aggregate CO_2 emissions for different standards, we find a trade-off between the economic benefits and the environmental damages of the two regulatory approaches. Figure 2 depicts the aggregated carbon dioxide emissions (in million tons) for different standards given the profit optimization of the generating units. The two different curves indicate the emissions associated with the uniform standard and the averaging approach, while the horizontal dotted line indicates the aggregate CO_2 emissions resulting in the (non-optimized) business-as-usual production situation. In addition, the horizontal dotdashed line represents the amount of emissions resulting if the actual emissions are reduced by 30%. This emission reduction is expected to result from the implementation of the regulatory plans of the EPA for the coal-fired power plants in the United States as presented in the introduction.

The emission curves in this figure show very similar patterns to the profit curves in the upper panel of figure 1. Therefore, the additional profits resulting from both the adoption of best practices and the possibility to average emission intensities are associated with an increase in the total emissions. Hence, our results indicate a trade-off between the environmental damages and the economic benefits from profit optimization as well as intensity averaging. Furthermore, the figure highlights that the implementation of standards may not lead to lower, but higher emissions if the generating units react to the regulation by adopting best practices. In such a situation very tight standards of 0.92 (0.89) tons per MWh in case of a fixed (averaging) standard would have to be imposed to be able to maintain the current emission level, given that the electricity generating units reduce their inefficiencies. Moreover, to achieve the reduction projections of the EPA even more restrictive standards of 0.88 (0.87) tons per MWh have to be imposed if the DMUs exploit their efficiency enhancements possibilities.

The discussion of efficiency effects induced by the implementation of a regulation connects our analysis to the economic discussion on potential positive effects of regulation for the regulated firms known in the literature as the "Porter-Hypothesis" based on Porter and van der Linde (1995). This hypothesis states that flexible environmental regulations can have positive economic implications for firms if the economic gains by activities required to satisfy the regulations (e.g. by investing in new production methods which reduce resource usage and therefore pollution) offset the costs associated with the regulation (e.g. the payment for emission taxes). In our application the implementation of performance standards could encourage the utilities to increase their efficiency by adopting best-practices to achieve lower emission intensities and hence increase their profits. However, although the emission intensities may improve, our results also suggest that the overall emissions can increase compared to the ex-ante emissions.

3.3 Distributive effects

In the following we present the distributive effects of this regulation. That is, we examine how many utilities will suffer decreases in their profits ($\pi_{l,s}$) compared to their business-as-usual profits ($\pi_{l,act}$) and whether these decreases are offset by utilities which obtain larger profits due to efficiency improvements. Therefore, we divide for each standard $s \in [0.8, 1.25]$ the $k = 29$ utilities of our sample into two groups: $W_s = \left\{l|\pi_{l,s} - \pi_{l,act} \geq 0\right\}$ and $L_s = \left\{l|\pi_{l,s} - \pi_{l,act} < 0\right\}$. The group W_s denotes all "winners" for the standard s and contains all firms which do not suffer losses compared to their actual profits if they adopt the best-practice under the regulatory standard s. Firms which face decreased profits under this regulation, and hence can be considered as the "losers" of the regulation, are collected in the set L_s. Moreover, we define

$$\pi_{W,s} = \sum_{l \in W_s} \left(\pi_{l,s} - \pi_{l,act}\right) \geq 0 \tag{3.1}$$

$$\pi_{L,s} = \sum_{l \in L_s} \left(\pi_{l,s} - \pi_{l,act}\right) < 0 \tag{3.2}$$

as the total wins and losses due to the regulatory standard s. Note that the wins and losses are defined relative to the (non-optimized) actual profits. Negative short-run profits $\left(\pi_{l,s} < 0\right)$ are not possible in our model since inactivity $\left(\pi_{l,s} = 0\right)$ is always a feasible option.

Based on these wins and losses we define the loser share as the number of utilities with losses due to the regulation s divided by the total number of utilities in our sample (29). Furthermore, we define a profit index I_s as:

$$\begin{aligned} I_s &= \frac{\pi_{W,s}}{\pi_{W,s} + |\pi_{L,s}|} \\ &= \frac{2\pi_{W,s}}{2\left(\pi_{W,s} + |\pi_{L,s}|\right)} = \frac{\pi_{W,s} + |\pi_{L,s}|}{2\left(\pi_{W,s} + |\pi_{L,s}|\right)} + \frac{\pi_{W,s} - |\pi_{L,s}|}{2\left(\pi_{W,s} + |\pi_{L,s}|\right)} \\ &= \frac{1}{2} + \frac{1}{2} \cdot \frac{\pi_{W,s} - |\pi_{L,s}|}{\left(\pi_{W,s} + |\pi_{L,s}|\right)} \end{aligned} \tag{3.3}$$

where $\pi_{W,s} - |\pi_{L,s}|$ can be interpreted as the net profit effect of the regulatory standard s with $\pi_{W,s} - |\pi_{L,s}| < 0$ (> 0) indicating a net loss (win) compared to the current profit level. This index is bound in the interval $[0, 1]$ and takes the value 0 if all firms loose due to the regulation $\left(\pi_{W,s} = 0\right)$ and the value 1 if all firms achieve profit gains compared to their business-as-usual profits $\left(\pi_{L,s} = 0\right)$. Moreover, a value of 0.5 indicates that the profit gains of the "winners" are equally large as the profit losses of the "losers". An additional interpretation of the index can be derived by calculating:

$$\begin{aligned} \frac{I_s}{1 - I_s} &= \frac{\pi_{W,s}}{\pi_{W,s} + |\pi_{L,s}|} \cdot \left(1 - \frac{\pi_{W,s}}{\pi_{W,s} + |\pi_{L,s}|}\right)^{-1} \\ &= \frac{\pi_{W,s}}{\pi_{W,s} + |\pi_{L,s}|} \cdot \left(\frac{|\pi_{L,s}|}{\pi_{W,s} + |\pi_{L,s}|}\right)^{-1} \\ &= \frac{\pi_{W,s}}{|\pi_{L,s}|}. \end{aligned} \tag{3.4}$$

Hence, $I_s/(1 - I_s) \cdot 100\%$ indicates how much of the losses of the loosing utilities are gained by the winning utilities with values larger (lower) than 100% indicating net wins (losses) of the regulation.

Figure 3 depicts the loser share (solid line) and the profit index I_s for each $s \in [0.8, 1.25]$. The upper panel presents the results assuming a uniform standard, while the lower panel presents the results given the possibility to average emission intensities.

For the uniform standard, we find that the loser share is zero down to a standard of 1.19 tons per MWh. This indicates that no utility will make smaller profits than its business-as-usual profit if efficiency improvement potentials are exploited. Down to a standard of 0.94 tons per MWh this share increases only slightly to 14%. Moreover, although some of the utilities suffer losses, the aggregated result is a net win of the regulation with an I_s value of 0.97 indicating that the winning firms gain $0.97/(1 - 0.97) \cdot 100\% = 3233.3\%$ of the losses. However, further tightening of the standard leads to a sharp increase in the loser share with 70% of the utilities suffering losses compared to their current profits for a standard of 0.89 tons per MWh. For this standard the I_s is 0.17 which indicates that the winner only gain 20.5% of the losses experienced by the losers. Hence, this fixed standard leads to net losses. Interestingly, the profit index and the loser share curves cross at a value of 0.5. This indicates that if a standard is chosen which leads to the same number of utilities winning from the regulation as the number of utilities loosing from the regulation, then the regulation also leads to net losses of zero which means the aggregated business-as-usual profits can be maintained in this situation.

The economic benefits from the intensity averaging approach are clearly visible from the lower panel of figure 3. The loser share is 0% up to a standard of 1.11 tons per MWh indicating that compared to a fixed standard tighter regulations can be imposed without leading to utility profits below the actual profits. Moreover, the figure shows that the curves do not cross for a value of 0.5 for each curve. If the regulator aims at implementing a standard which leads to the same number of winners and losers ($s_l = 0.5$), the index I_s takes a value of 0.7. Therefore, for this standard the winners obtain larger profit gains than the losses of the losers (233.3%) and hence this regulation would lead to net profits.

Furthermore, if a standard is implemented to achieve emission reductions of the EPA proposal (30% reduction of CO_2 emissions) a standard of 0.88 tons per MWh has to be imposed given a uniform standard if efficiency improvement potential are taken into account (see the discussion above) and of 0.87 tons per MWh standard if emission intensity averaging is allowed. In case of a uniform standard this leads to a loser share of nearly 90% and an I_s of 0.08, indicating that a large net loss will occur due to this regulation. In case of the possibility to average intensities, the loser share reduces to 82% and the index increases to 0.1. The difference in the I_s values shows that although both regulations lead to net losses, the winners can gain 11.1% of the losses given an averaging approach compared to only 8.7% if a fixed standard is implemented. This shows that the reduction target can be achieved with smaller losses if the utilities are allowed to average emission intensities.

3.4 Results for EPA standards

While the above discussed results are based on the evaluation of a grid of possible performance standards which were assumed to be equal for all states, we now present the results for EPA's state-specific standards. These standards are calculated based on the output-weighted historical emission rates of different fossil fuels, with the weights adjusted for future increase in natural gas, renewable, and nuclear power capacity, as well as demand side energy reductions. The average EPA standard is 0.5 tons of CO_2 per MWh produced, which according to our previous results implies that all bituminous generating units in our sample would shut down (see Kotchen and Mansur (2014) and Hampf and Rødseth (2015) for further evaluations of the

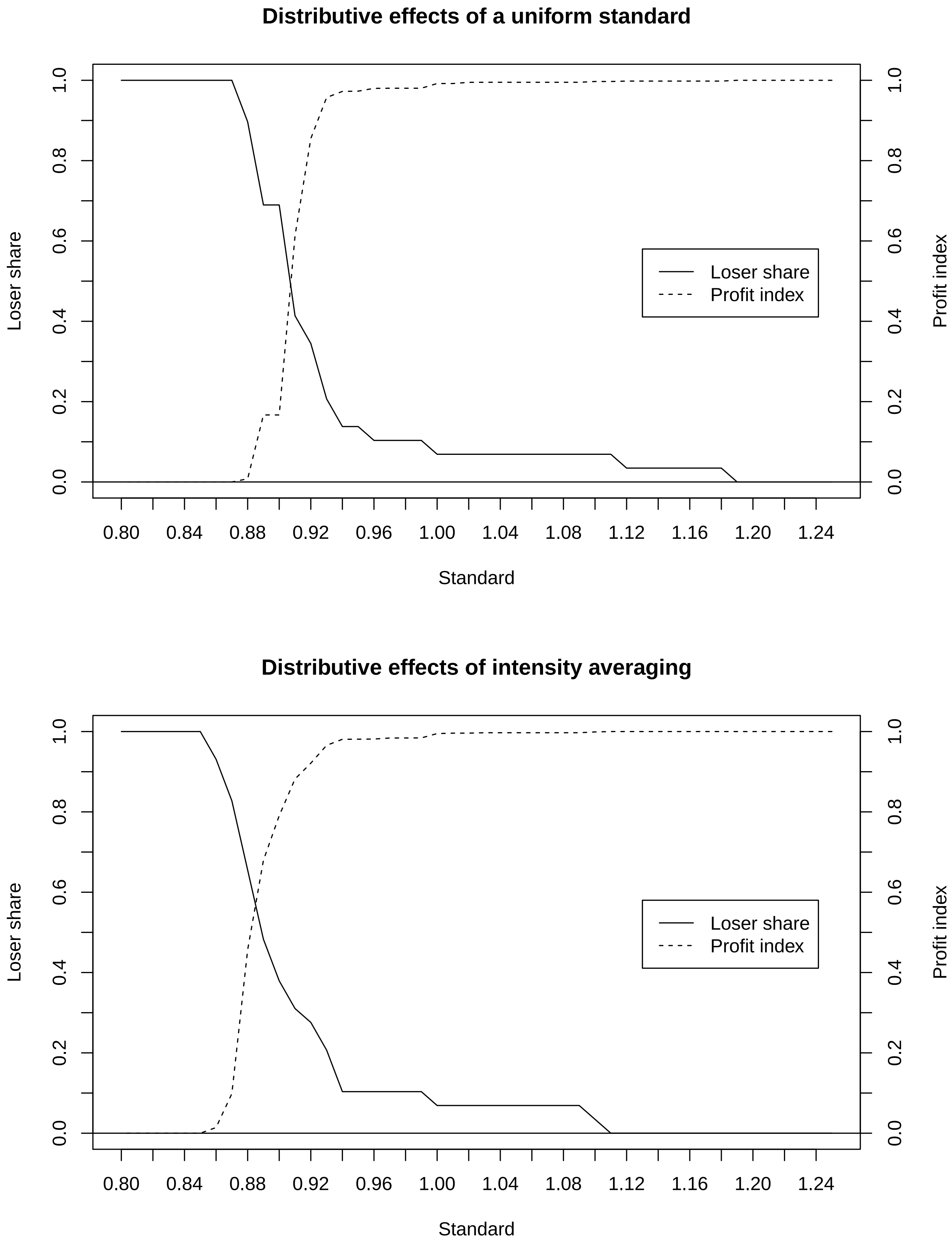

Fig. 3 Profit index and loser share

technical feasibility of this standard for coal-fired generating units). Hence, we do consider the final EPA standard to be an interesting case for our paper.[21]

The EPA standards are based on the so-called Best System of Emission Reduction, which involves considering a series of feasible measures for reducing carbon dioxide emission. One measure proposed by the EPA is a 6% improvement in the emission intensities of the existing coal fleet, relative to their current emission intensities. Our approach is well suited for evaluating the feasibility of this proposed efficiency improvement, as well as its economic implications. Moreover, the EPA calculates separate performance standards for each year between 2020 and 2030, under the assumption that the impact of renewable energy and demand-side energy efficiency measures will increase over time. Since our dataset contains generating units in operation in 2011 (i.e., long before the introduction of the renewables and demand-side improvements), it would be more reasonable to evaluate the economic consequences of the EPA 2020 standard, than the implications of its final standard in year 2030. By considering the EPA 2020 standard (a tight standard) and the standard concerning 6% emission intensity improvements of current emission rates for coal (a lax standard), we are readily able to evaluate the economic consequences of introducing performance standards of varying degrees of stringency.

The state-specific results are presented in table 3. The mass-based goals as well as the net profit changes are presented for both standards (EPA 6% target, EPA 2020 standard) and both approaches to performance standards (uniform, averaging). The mass-based goals refer to state-specific emission targets calculated as the sum of carbon dioxide pollution given the implementation of the EPA standards and our results for the profit maximization. The net profits changes are calculated as the state-specific sum of optimal profits minus the actual business-as-usual profits.

The difference in the stringency of the two EPA standards is clearly illustrated by table 3. Only three states (Indiana, Kentucky, and West Virginia) have bituminous-fired units in operation if the EPA 2020 standard is uniformly implemented for all fuel types, while there are bituminous units in operation in all states if the EPA 6% target is implemented. The 6% target appears to be unambitious for the coal fleet, as our results indicate that profit maximization leads to profit losses in only two states (Colorado and Utah). In contrast, all other states can achieve larger profits if the utilities exploit their efficiency enhancement potentials. Moreover, only few states show significant differences in their profit changes if the utilities are allowed to average emission intensities across their generating units compared to uniform standards. This also indicates that the emission standards under the EPA 6% target are rather lax since utilities do not have an incentive to reallocate production among their generating units to mininize compliance costs. However, for states where utilities exploit averaging possibilities, we again find that the larger profits due to emission intensity averaging are associated with an increase in aggregated emissions.

In contrast to the results for the EPA 6% target, the EPA 2020 standard results show that the strict standard leads to substantially higher profit gains due to emission intensitiy averaging. This can be seen from the results for Indiana and Kentucky, where Indiana's profit losses due to the regulation drop from 542 million to 395 million dollars while Kentucky's profits gains increase from 119 million to 151 million dollars.

To show in more detail the different effects of the averaging approach for both standards, figure 4 presents the density functions of emission intensities in the cases where an uniform standard is imposed and when utilities can average emission intensities. The panel to the left illustrates the emission intensities under the 6-% coal efficiency standard, while the panel to the right illustrates the emission intensities under the EPA 2020 standard. It is obvious that the emission intensities under the 6-% coal efficiency standard do not differ much across the two analyzed approaches. This result is caused by the fact that EPA's proposed efficiency improvement of 6% appears to be unambitious leading to ratios which are very similar to the ratios which

[21] In principle, cost minimization implies allocating different standards to different fossil fuel types (that on average amount to the EPA standards), in order to equalize marginal abatement costs across different fuel types. Hence, if the fuel-specific abatement costs were known, it would be possible to assign fuel specific performance standards. The emission standard for coal will intuitively be higher than the EPA standard.

Table 3 Results for proposed EPA standards

	Mass-based goal (tons CO_2)				Net gains ($)			
	EPA 6% target		EPA 2020 standard		EPA 6% target		EPA 2020 standard	
State	Uniform	Averaging	Uniform	Averaging	Uniform	Averaging	Uniform	Averaging
Alabama	13,757,992	14,400,083	0	0	161,373,240	167,122,576	-415,719,580	-415,719,580
Colorado	2,785,016	2,785,016	0	0	-5,521,532	-5,521,532	-180,194,613	-180,194,613
Florida	35,037,605	35,037,605	0	0	435,831,905	435,831,905	-1,367,386,369	-1,367,386,369
Illinois	1,165,956	1,165,956	0	0	8,577,372	8,577,372	-49,067,962	-49,067,962
Indiana	49,094,959	49,094,959	23,798,943	26,910,863	417,033,583	417,033,583	-542,871,479	-395,211,453
Kentucky	40,631,394	42,130,982	39,997,133	41,968,155	125,590,647	150,813,385	118,640,083	150,527,856
Mississippi	2,331,912	2,331,912	0	0	39,388,297	39,388,297	-55,208,006	-55,208,006
North Carolina	49,076,058	49,710,319	0	0	343,856,711	349,201,213	-1,514,770,618	-1,514,770,618
Nevada	1,843,929	1,843,929	0	0	26,896,269	26,896,269	-53,235,740	-53,235,740
Ohio	29,700,964	32,716,556	0	0	281,588,878	325,769,034	-1,673,796,932	-1,673,796,932
South Carolina	17,187,510	17,187,510	0	0	282,762,040	282,762,040	-400,313,422	-400,313,422
Tennessee	4,663,824	4,663,824	0	0	82,528,906	82,528,906	-71,584,495	-71,584,495
Utah	2,548,246	2,548,246	0	0	-30,801,720	-30,801,720	-167,301,329	-167,301,329
Virginia	25,013,321	25,655,412	0	0	357,337,985	358,606,201	-684,397,711	-684,397,711
West Virginia	14,606,495	15,084,496	14,151,422	14,151,422	142,582,561	157,832,393	128,769,560	128,769,560

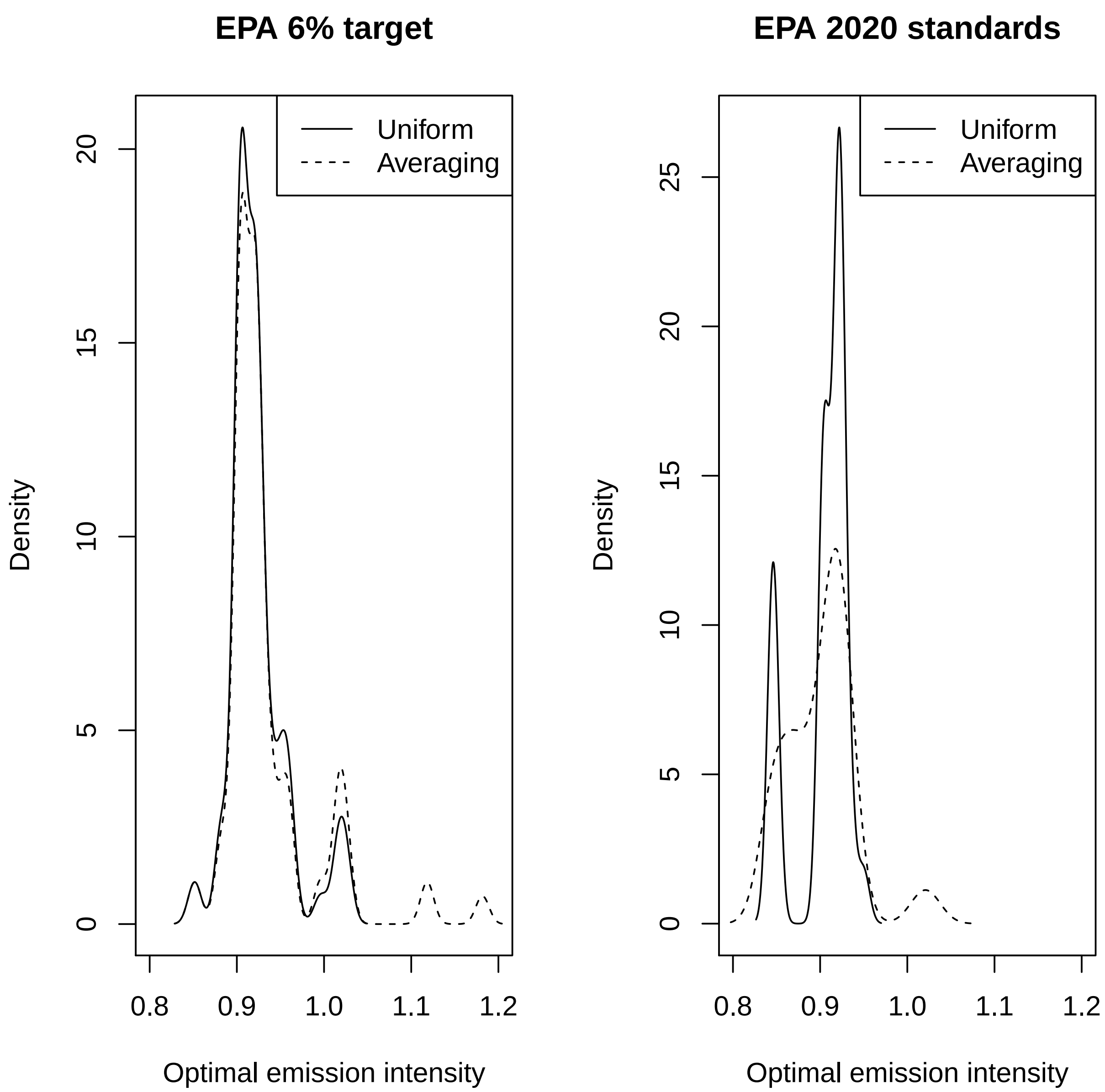

Fig. 4 Density functions of optimal emission intensities

result for optimal profits without any regulation (unconstrained optimization). The EPA 2020 standard is, on the other hand, far more restrictive, which leads to a larger difference in the distribution of emission intensities between the two approaches. This is intuitively reasonable, since by allowing for averaging, the optimal emission intensities are distributed across the utility's generating units such that their marginal profit from a change in the standard are equalized. Thus, when the generating-units' characteristics differ, the optimal standards will also differ widely across the generating units.

4 Conclusion

In this paper we have developed a production analysis approach which allows examining economic implications of environmental performance standards. By applying a modification of the FDH production model to a sample of 144 bituminous generating units, we have examined the economic implications of performance standards for CO_2 emissions on bituminous-fired electricity generating units in the U.S. Our results indicate that the economic consequences of CO_2 performance standards may be severe, as standards below 0.85 tons of CO_2 per MWh induce shut down of all units under consideration. However, for laxer standards there is even a potential for achieving profit increases if the electricity generating units exploit the identified potential to improve their productive efficiency. We also find that profit improvements generally lead to increases in CO_2 emissions, which indicates that an important environmental-economic trade-off exists. Moreover, our results for a regulatory regime that allows for averaging emission intensities among the generating units shows that considerably larger profits can be obtained compared to implementing uniform standards. However, these additional profits are associated with larger overall emissions of CO_2. Therefore, our results capture well the pros and cons of performance standards as compared to mass-based emission targets. Performance standards provide flexibility to accommodate changes in the overall quantities of electricity generated in response to shifts in electricity demand, while mass-based regulations make sure that absolute emission reductions are achieved by the regulation. This result shows that when comparing uniform standards to emission intensity averaging no unambiguously superior approach can be identified. If policy makers want to reduce the profit losses caused by environmental regulation then intensity averaging is a more suitable approach. However, if the reduction of emissions is the main objective without considering profit losses then fixed standards lead to larger reductions of emissions compared to intensity averaging.

While our empirical results offer insights to the economic consequences of performance standards for CO_2, additional research is needed to guide the development of the state plans recently commissioned by the EPA. We limit our analysis to generating units that only consume bituminous coal, and consequently leave out possibilities to average emissions among different coal types and among coal and other fossil fuels. This is an important consideration because these other fuel types differ in terms of their carbon intensities and prices, hence involving important environmental-economic trade-offs that must be taken into account when developing the state plans.

By focusing on only one fuel type, our paper differs widely from most other studies on the efficiency of U.S. power plants. The common practice is to account for a wide range of different fuel types and qualities in the production model, which we consider inconsistent with the goal of securing that the DMUs under consideration are homogeneous and, thus, comparable. In other words, we believe that the common practice leads to biased estimates. Future research may therefore model the overall energy supply using the fuel type-specific technologies as presented in this paper, but allow emission intensity averaging across the fuel-specific technologies using the network-technology approach of Färe and Grosskopf (2000).

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Appendix

Proof of the equivalence of the JP and the MB model:
To start consider the profit optimization subject to the non-convex JP model:

$$\begin{aligned}
\max_{y,x^P,b,\lambda_1,\ldots,\lambda_n} \quad & p_i y - q_i x^P \\
\text{s.t.} \quad & x_i^{NP} \geq \textstyle\sum_{j=1}^n x_j^{NP}\lambda_j \\
& x^P \geq \textstyle\sum_{j=1}^n x_j^P \lambda_j \\
& y \leq \textstyle\sum_{j=1}^n y_j\lambda_j\theta \\
& b = \textstyle\sum_{j=1}^n b_j\lambda_j\theta \\
& b - sy \leq 0 \\
& 0 \leq \theta \leq 1 \\
& \textstyle\sum_{j=1}^n \lambda_j = 1 \\
& \lambda_1,\ldots,\lambda_n \in \{0,1\}.
\end{aligned} \tag{A.1}$$

In the optimum $x^P = \sum_{j=1}^n x_j^P\lambda_j$ and $y = \sum_{j=1}^n y_j\lambda_j\theta$ hold since x^P and y can be freely chosen and $b = \sum_{j=1}^n b_j\lambda_j\theta$ by construction. Moreover, θ can be set equal to one since y and b can be freely chosen. Replacing the modified equalities in the objective function and the regulatory constraint leads to:

$$\begin{aligned}
\max_{\lambda_1,\ldots,\lambda_n} \quad & p_i \textstyle\sum_{j=1}^n y_j\lambda_j - q_i \sum_{j=1}^n x_j^P\lambda_j \\
\text{s.t.} \quad & x_i^{NP} \geq \textstyle\sum_{j=1}^n x_j^{NP}\lambda_j \\
& \textstyle\sum_{j=1}^n b_j\lambda_j - s\sum_{j=1}^n y_j\lambda_j \leq 0 \\
& \textstyle\sum_{j=1}^n \lambda_j = 1 \\
& \lambda_1,\ldots,\lambda_n \in \{0,1\}.
\end{aligned} \tag{A.2}$$

The optimization problem under the non-convex MB model is given by:

$$\begin{aligned}
\max_{y,x^P p,b,\epsilon_x,\epsilon_b,\lambda_1,\ldots,\lambda_n} \quad & p_i y - q_i x^P \\
\text{s.t.} \quad & x_i^{NP} \geq \textstyle\sum_{j=1}^n x_j^{NP}\lambda_j \\
& x^P = \textstyle\sum_{j=1}^n x_j^N\lambda_j + \epsilon_x \\
& y \leq \textstyle\sum_{j=1}^n y_j\lambda_j \\
& b = \textstyle\sum_{j=1}^n b_j\lambda_j + \epsilon_b \\
& s_x\epsilon_x = \epsilon_b \\
& b - sy \leq 0 \\
& x^P, y, b, \epsilon_x, \epsilon_b \geq 0 \\
& \textstyle\sum_{j=1}^n \lambda_j = 1 \\
& \lambda_1,\ldots,\lambda_n \in \{0,1\}.
\end{aligned} \tag{A.3}$$

In this formulation the slack on the good output ϵ_y is removed and the equality replaced by an inequality since the output in our analysis (electricity) does not contain any materials. In the optimum $\epsilon_x = \epsilon_b = 0$ since x^P and b can be freely chosen. Hence, $x^P = \sum_{j=1}^n x_j^P\lambda_j$ and $b = \sum_{j=1}^n b_j\lambda_j$. Moreover, $y = \sum_{j=1}^n y_j\lambda_j$ since y can be freely chosen. Replacing these equalities in the objective function and the regulatory constraint leads to:

$$\begin{aligned}
\max_{\lambda_1,\ldots,\lambda_n} \quad & p_i \textstyle\sum_{j=1}^n y_j\lambda_j - q_i \sum_{j=1}^n x_j^P\lambda_j \\
\text{s.t.} \quad & x_i^{NP} \geq \textstyle\sum_{j=1}^n x_j^{NP}\lambda_j \\
& \textstyle\sum_{j=1}^n b_j\lambda_j - s\sum_{j=1}^n y_j\lambda_j \leq 0 \\
& \textstyle\sum_{j=1}^n \lambda_j = 1 \\
& \lambda_1,\ldots,\lambda_n \in \{0,1\}.
\end{aligned} \tag{A.4}$$

Therefore, the JP and the MB model lead to the same results for the profit maximization.