Opportunity Cost and Employment Effect of Targeted Emission Reduction: An Inter-Industry Comparison Across Countries

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Abstract

All nations stand to benefit from addressing the problem of global warming caused by greenhouse gas emissions. However, the economic impact of pollution reduction in the form of a reduction in industry production and jobs loss will be different for different countries and across different industries. In this paper, we estimate the opportunity cost of emission reduction in terms of the loss of intended output and, collaterally, the effect on employment that would result from a reduction in the consumption of fuel for various industries of different countries by using the data constructed from the World Input-Output Database. We conceptualize industry-specific production technology for a number of manufacturing sectors with one intended output (industry gross production) and one undesirable output (CO_2 emission) produced from labor, capital, and materials (treated as neutral input) and fuel (treated as the polluting input). The nonparametric Data Envelopment Analysis model following a by-production is employed. The results show that the cost of emission reduction in the basic metals industry is generally the lowest across countries in our sample, and the cost is generally high in coke and refined petroleum products among the observed countries.

Key Words: *CO_2 Emission, Opportunity Cost, DEA, Efficiency*

JEL Codes: Q52, C61

Highlights:

- CO_2 emission is a by-product of the energy input used in manufacturing production.
- Opportunity cost of emission reduction is the resulting loss of output of a firm.
- Opportunity cost varies across industries and countries.
- Fuel mix of the energy input can account for differences in ecological efficiency
- There is potential for significant CO_2 reduction in many industries in the U.S.

1 Introduction

There is now a broad consensus in the scientific community about the potentially catastrophic impact of global warming due to unrestrained greenhouse gas emissions upon plant and animal life on this planet. This has forced the leadership across countries to recognize the need and urgency of an internationally coordinated policy for environmental pollution reduction. All nations stand to benefit from addressing the problem of global warming caused by greenhouse gas emissions. However, the economic impact of pollution reduction in the form of a reduction in GDP and jobs lost will be different for different countries and across different industries within a country. While the benefits from pollution reduction are generally recognized by all, resistance to measures penalizing the use of fossil fuels (mainly coal and oil) that account for the biggest share of atmospheric pollution comes primarily from nations (and regions within nations) that face the prospect of a significant reduction in income and employment resulting from policies encouraging alternative and renewable sources of energy.

Three main approaches to emission control are (a) some form of 'end of the pipe' treatment like carbon capture and storage (CCS) of the carbon already generated from combustion of fossil fuels, (b) switching from high carbon (or 'dirty') to lower carbon-intensive (or 'cleaner') fuels, and (c) economizing on the industrial consumption of the energy input reducing thereby consumption of fossil fuels and the resulting emission of CO_2 into the atmosphere.

Despite its promise as a major weapon in the fight against CO_2 emission, as yet, widespread adoption of CCS is nowhere in sight. As per a report released by the Congressional Budget Office from December 2023, there were only 15 CCS facilities in operation in the entire US with a total capacity to capture a meagre 0.4% of the total carbon emission in the nation. Another 121 CCS

facilities were under construction and if all of them became operational, the total capacity to capture and store CO_2 would still be only 3% of total emission.

As for transition from high carbon fuels (like coal) to low carbon fuel (like natural gas), while firms can be incentivized to build natural gas-fired combined cycle (NGCC) plants as older coal-fired plants are retired, converting existing coal-fired plants into gas-fired ones would involve repurposing the existing infrastructure to enable such transition. As noted in (Seimens-Energy 2003), a full repowering implies replacing an old steam generator fired by coal (or oil) with gas turbines with downstream heat generators. This will be especially costly for industries in countries like China and India where coal is the principal fuel. For all practical purposes, therefore, reducing the fuel input remains the principal approach to emission reduction in the short run.

The opportunity cost of emission reduction can play an important role in emission reduction related policies. The focus of this paper is to provide a method of measuring the opportunity cost of emission reduction and present an inter-industry comparison across different countries. In their attempt to curtail emission, many countries have adopted two main policies: imposition of a carbon tax and/or setting an upper limit or a 'cap' on emission (in the form of limited emission permits) while allowing firms to exchange or trade such permits between themselves. While many countries have imposed carbon taxes, more countries are gradually adopting the cap-and-trade system because it is flexible and provides corporations with an incentive to find and invest in clean alternatives. Starting from 2005, countries from the European Union (plus Iceland, Norway, Liechtenstein, and the United Kingdom), New Zealand, the United States, Japan, Switzerland, Canada, Kazakhstan, South Korea, and China have established nationwide or regional emission trading systems (ETS). Each emission mitigation policy is designed based on the specific circumstances of a country or region and therefore differs in respect of overall reduction targets, covered industries, strategies of allowance allocation, trade mechanisms, etc.

Two major questions before the policymakers are

a) which sectors should be targeted for emission mitigation when the impact on the economy is the primary concern and

b) how to allocate emission reduction across firms within a specific industry or across various selected industries.

For instance, more than 2,200 enterprises from the power sector were regulated in China starting in 2021. Instead of pooling all the pollution-intensive industries together into the ETS, the EU ETS considers establishing separate ETS for different industries. It is preparing to expand the scope of covered industries by including pollution-intensive manufacturing industries such as petrochemical, chemical, building materials, steel, nonferrous metals, and paper sectors; In July 2021, along with a set of policy proposals targeting the "Fit for 55" (emission reductions of at least 55% below 1990 levels by 2030), the European Commission proposed establishing separate ETS for buildings and road transport sectors etc.

While the cap-and-trade system can effectively address the question of inter-firm allocation of emission quota through a market exchange mechanism, prioritizing selected industries for emission control should be guided by the (opportunity) cost of cutting back on the use of fossil fuels. In order to minimize the adverse impact on output and employment, industries with lower cost of emission reduction, should be targeted first. Practically, inclusion of specific industries in an ETS would depend on many factors including (but not limited to) the complexity and feasibility of data monitoring, policy implementation and the demand and supply across different sectors. Never the less, the idea of starting with the lowest-cost industry could still serve as a conceptual baseline and has served as such in different ETS programs. For example, EU ETS started in 2005 with the energy intensive sectors like power, steel, cement, refining, and chemical industries and is working on incorporating maritime, buildings and road transport fuels in separated ETS under

its “Fit for 55” reforms. China started the ETS with Power sector firstly in 2021 and has been working on including Steel, Cement, Aluminum, and Chemicals sectors into the ETS during 2021-2025. Besides those conventional pollution intensive sectors, UK is exploring the feasibility of maritime, and New Zealand has setup the plan to price carbon emission from agriculture starting from 2025. Because the opportunity cost of emission reduction is different across countries and sectors, properly estimating the cost of emission across industries is an essential question for emission reduction policy instruments.

In this study we try to identify the sectors that should be prioritized for emission mitigation in order to minimize the economy-wide adverse impact on output and employment. We formulate and estimate the opportunity cost of emission reduction across countries and industries.

The main contributions of this paper are twofold.

At the conceptual level,

- we extend the by-production approach by clearing up some confusion about the ‘joint disposability’ assumption about the bad output and the polluting input while at the same time pointing out some shortcomings in both Murty, Russell and Levkoff (MRL) (2012) and Ray, Mukherjee, and Venkatesh (RMV) (2018).
- In particular, we argue that so long as the fuel mix is left unchanged, there is no room for disposability (free or costly) as claimed by MRL (2012) and Murty and Russell (MR) (2022).
- We also show that the use of different sets of weight vectors in the construction of the sub-technologies for good output production and emission generation is not valid. This also applies to the so called “decentralized” models in RMV (2018).

Further, irrespective of the nature of returns to scale (variable or constant) in good output production, the pollution generation technology will always exhibit constant returns to scale.

As an empirical application,

- ours is the first such study that we are aware of that measures and compares the opportunity cost of emission reduction for different industries in a cross-country analysis.

We believe that a model like ours should provide valuable guidance to policy makers in deciding which sectors within an economy should be prioritized for emission reduction. Also, it should help in assessing the differential burden imposed on different countries as they agree to curtain carbon emission.

The rest of the paper is organized as follows. Section 2 provides a brief review of the relevant literature on measuring the opportunity cost of emission reduction. Section 3 conceptualizes the production possibility set which includes the production processes for both intended and undesirable outputs through the by-production approach, defines a pollution-oriented distance function for efficiency estimation, and provides the method for estimating the cost of emission reduction and its effect on employment. Section 4 describes the collection and construction of the dataset. Section 5 presents and analyzes the results of the pollution-oriented efficiency score, cost of emission reduction, and effect of the particular emission reduction target on employment. Section 6 offers the main conclusions.

2 Literature Review

There is a considerable volume of literature in environmental economics and production efficiency literature specifically directed toward measuring the cost of pollution abatement. However, the studies differ significantly in respect of how the cost of pollution abatement is measured. The three main alternative measures of the cost of pollution abatement can be identified as (a) reported abatement cost, (b) shadow price, and (c) opportunity cost.

The reported cost is a direct measure of pollution abatement cost and expenditure (PACE) obtained from the EIA-767 survey of manufacturing plants conducted by the US Department of Commerce that requests information on operation and maintenance (O&M) expenditures associated with both collection and disposal of fly ash, bottom ash, and flue gas desulfurization. The shadow price approach uses a distance function including one or more environmental pollutants as bad outputs alongside one or more good outputs and performs a comparative static analysis to measure the marginal rate of transformation between the good and the bad outputs holding the distance function constant at a given level. In non-parametric models using Data Envelopment Analysis (DEA), the ratio of the values of the dual variables (or multipliers) at the optimal solution (with the price of the desirable output set equal to its market price) provides the marginal cost of reducing an undesirable output. In a parametrically specified output distance function, one uses the ratio of the partial derivatives obtained from the fitted model. Finally, the opportunity cost measure of pollution abatement is the reduction in the desired output that must be accepted if the level of pollution is to be lowered by a targeted amount without increasing the amount of inputs. Note that this trade-off between producing the good output and reducing the bad output is meaningful only when one compares points along the frontier of the production possibility set. Fare, Grosskopf, and Pasurka (2003) used the EIA-767 and PACE 1996 survey data to compute the opportunity cost

comparing the maximum producible output with and without pollution regulation and to compare (what they described as) the revealed cost with the survey estimates for coal-fired power plants in 1994-95. The abatement was for SO_2 and PM10. Their marginal pollution abatement cost was measured by the loss of good output (kwh of electricity). Fare, Grosskopf,¨ and Pasurka (2016) measured the opportunity cost of abatement of SO_2 for coal-fired plants with a particular focus on the impact of pollution regulation on technical change.

Examples of using the shadow price derived from nonparametric distance functions can be found in Fare, Grosskopf, Lovell, and Yaiswarang¨ (1993), Coggins and Swinton (1996), Swinton (2002), Lee, Park, and Kim (2002), Hailu and Veeman (2001), Ray and Mukherjee (2007), Wang et al. (2017) and Xie et al (2017). Fare, Grosskopf, Lovell, and Yaiswarang¨ (1993) specified a deterministic translog output distance function for a sample of 30 pulp and paper mills. The good output was the quantity of produced paper while the bad outputs were biochemical oxygen demand (BOD), total suspended solids (TSS), particulates, and SO_x. Coggins and Swinton (1996) estimated a deterministic translog output distance function to measure the shadow price of SO_2 emission allowance using 42 observations for 14 power plants in Wisconsin. Swinton (2002) used a deterministic translog output distance function for power plants with electricity as the good output and SO_2 as the bad output. Hailu and Veeman (2001) estimated a parametric input distance function for the Canadian pulp and paper industry using plant-level data with four good outputs (pulp, newsprint, other paper, and paperboard) and two bad outputs (BOD and total TSS). Shadow prices of NO_x, SO_x, and total suspended particulates (TSP) derived from non-parametric DEA models were computed by Lee, Park, and Kim (2002) for Korean power plants.[2] Ray and Mukherjee (2007) used country-level data on GDP as the good output and CO_2 emission as the bad output to

[2] Instead of projecting observations on to the frontier, the authors allowed inefficiency but held it constant while deriving their shadow prices.

empirically approximate a non-parametric directional distance function and computed the shadow price of carbon emission measured in purchasing power parity adjusted US dollars for individual countries. Wang et al. (2017) estimated the energy use efficiency and emission reduction cost of urban cities in China from a dataset of 285 cities in China during 2008–2012, using a shadow price approach with a slacks-based joint-product DEA method. Xie et al (2017) estimated the shadow prices of fossil energy and non-fossil energy through an input oriented distance function and their results of the substitutability of non-fossil energy for fossil energy indicated an improving energy structure in China during 1980-2014.

As noted by Fare, Grosskopf, and Pasurka (2003) direct measures of pollution abatement costs have the typical shortcomings of survey based estimates. Moreover, such data are much more difficult to gather. On the other hand, the shadow prices from DEA linear programming models are often quite and may not be unique. Even those obtained from partial derivatives of the parametrically estimated distance functions are local measures and using these shadow prices to compute the cost of a discrete change in the level of emission can lead to inaccurate results. By contrast, the opportunity cost approach of measuring the loss of the desired output required for a targeted reduction in the undesirable output provides a more reliable estimate of the cost of pollution control. He (2015) measured the regional differences in China's CO2 abatement cost through the opportunity cost approach with an output-orient distance function.

Recognizing that the joint production approach may not clearly capture the connection between pollution and polluting inputs, Ray, Mukherjee, and Venkatesh (RMV) (2018) used a DEA formulation of the production technology incorporating the by-production model of Murty, Russell, and Levkoff (MRL) (2012) but assumed 'joint disposability' of pollution and the polluting input implying that the bad output could be lowered only along with a simultaneous decrease in the polluting input. They treated GDP as the good output, CO_2 emission as the bad output, and fossil

fuel as the pollution generating input and measured the implied loss of GDP as the opportunity cost of a 15% reduction in CO_2 emission for individual countries along a non-parametric frontier constructed using the output directional distance function.

As noted above, to reduce emission effectively, policymakers need to consider two questions: 1) which sectors have to take action on emission mitigation; and 2) how to allocate emission reduction within a specific industry or across various selected industries. Several studies such as Mahdiloo (2018) (targets on electricity generation sector) and Yu et al.(2021) (focus on multiple manufacturing sectors) have proposed centralized abatement allocation mechanisms to address the question of how to allocate abatement targets. In this study, we address the question of which industry has the lowest opportunity cost of emission reduction (and therefore should be targeted for emission mitigation) among several manufacturing industries.

3 The Methodological Background

3.1 The Production Technology

Consider an industry producing a vector of m outputs $y \in R_+^m$ using a vector of n outputs $x \in R_+^n$. An input-output vector $(x, y) \in R_+^{m+n}$ is considered feasible if output y can be produced from the input x. The production technology of the industry can be characterized by the production possibility set

$$T = \{(x, y): x \text{ can produce } y\}. \quad (1)$$

Assume further that the output vector included some 'bad' or undesirable outputs along with the 'good' or intended outputs. The production technology needs to appropriately characterize the production of both good and bad outputs. In the existing literature there are three principal approaches to incorporate bad or undesirable outputs into the definition of the technology.

First, there is the input approach where the undesirable output is treated like a conventional input (Baumol and Oates (1988), Cropper and Oates (1992)) principally because of a positive relationship between the good and the bad outputs. However, as argued by Ray, Mukherjee, and

Venkatesh (RMV) (2018) and Ray (2022), the undesirable output lacks three defining characteristics of an input. "First, an input exists even before the production process starts. Second, any input is depleted in stock as production is carried out. Third, an input is subject to some processing by the producer". Clearly, none of these applies to an undesirable outcome like CO_2 emission.

The second approach popularized by Färe, Grosskopf, and their many coauthors (e.g., Färe et al (1989), (2005), Førsund (2009)), Shen et al (2009) treats the bad output as a joint product with the good output and invokes weak (as opposed to strong) disposability and 'null jointness' between them. Strong or free disposability of outputs implies that when a given input-output bundle is feasible, unilateral reduction in any output without a change in the other outputs or inputs would leave the altered input-output bundle feasible. Similarly, strong disposability of inputs implies that unilateral increase in any input does not render the new input-output bundle infeasible. By contrast, weak disposability between two outputs implies that when both outputs are reduced, the new input-output bundle would remain feasible although unilateral reduction in one (or both) of the outputs may not be feasible. Null jointness between the bad and the good output means that the bad output can be eliminated only if the good output is not produced at all.

For a clear understanding of these assumptions, consider an example of two outputs y (the good) and z (the bad) output produced from two inputs (x_1, x_2). Suppose, $(x_{10}, x_{20}; y_0, z_0)$ is a feasible input-output bundle. Then, free disposability of inputs implies that if $x^1 = (x_{11}, x_{21}) \geq x^0 = (x_{10}, x_{20})$, then $(x_{11}, x_{21}; y_0, z_0)$ is also feasible. Weak disposability of the outputs implies, that if $0 \leq \alpha < 1, (x_{10}, x_{20}; \alpha y_0, \alpha z_0)$ is feasible but $0 \leq \alpha < 1, (x_{10}, x_{20}; y_0, \alpha z_0)$ is not. Of course, if one assumes that the good output is freely disposable (as Färe et al (1989) do), $0 \leq \alpha < 1, (x_{10}, x_{20}; \alpha y_0, z_0)$ remains feasible. Null jointness implies that for any $(x_1, x_2), z = 0$ is feasible only if $y = 0$ as well. This is a logical corollary of weak disposability, setting α to 0.

While this joint production approach may suit well in the case of outputs which are 'technically joint' like corn and husk contained in the same crop or beef and methane gas (from the manure) embodied in the same animal in the herd, it does not describe the relation between the good and

bad outputs and the inputs involved in many other situations. The fact is that there is no 'one size fits all' model that applies to all cases of bad output production.

To be more specific, consider the present context where the good output is electric power generated, and the bad output is the carbon emission from combustion of fossil fuels. Clearly, power and emission are not technically joint. In fact, what links them together is fuel, the polluting input, which contains both heat that generates power and CO_2 that causes emission. This, of course, calls into question the assumption of weak disposability of the good and the bad output because if the inputs (including fuel, the polluting input) are left unchanged, how can one reduce carbon emission while consuming the same amount of fuel as before?

For decades, this joint production conceptualization of the technology became the standard analytical format for efficiency and productivity measurement incorporating bad outputs. However, Murty, Russell, and Levkoff (MRL)(2012) offered a third and alternative formulation where the bad output is regarded as a by-product of the good output production process rather than a joint product. In their formulation, there are two sub-technologies for the production of the good and the bad outputs within the overall production possibility set. Continuing with the 2-output 2-input example, both inputs $x_1$and $x_2$contribute positively to the production of the good output y. The sub-technology for the production of the good output is

$$T_{BP}^{y} = \{(x_1, x_2; y): (x_1, x_2)\text{can produce } y\}. \qquad (2)$$

The standard assumptions of free disposability of both inputs and the output are retained for this sub-technology. Thus,

$$(x_{10}, x_{20}; y_0) \in T_{BP}^{y}, (x_{11}, x_{21}) \geq (x_{10}, x_{20}) \Rightarrow: (x_{11}, x_{21}, y_0) \in T_{BP}^{y}. (3)$$

Also,

$$(x_{10}, x_{20}; y_0) \in T_{BP}^{y}, y_1 < y_0 \Rightarrow: (x_{11}, x_{21}, y_1) \in T_{BP}^{y}. \quad (4)$$

For bad output production, the sub-technology is

$$T_{BP}^{z} = \{(x_2, z): x_2 \text{ can produce } z\} \quad (5)$$

MRL (2012) assume what they describe as 'costly' (as opposed to 'free' disposability of the bad output and the polluting input. Thus,

$$(x_{20}, z_0) \in T_{BP}^{z}, x_{21} < x_{20}, z_1 > z_0 \Rightarrow (x_{21}, z_1) \in T_{BP}^{z}. (6)$$

In other words, the same amount of the bad output can be produced from less of the polluting input or the same amount of the polluting input can generate more pollution.

Their overall production possibility set is

$$T_{BP} = T_{BP}^{y} \cap T_{BP}^{z} = \{(x_1, x_2, y, z): (x_1, x_2, y, z) \in T_{BP}^{y}; (x_2, z) \in T_{BP}^{z}\}. \quad (7)$$

RMV (2018) also adopt the by-production formulation of MRL (2012) as the appropriate analytical model. However, they assume that the polluting input and the bad output can only be reduced proportionately. Given its similarity with weak disposability between the outputs in the joint production approach they call it *joint disposability* between the bad output and the polluting input. This, of course, means that neither the bad output nor the polluting input is freely disposable. More explicitly,

$$(x_{20}, z_0) \in T_{BP}^{z}, z_1 > z_0 \Rightarrow (x_{20}, z_1) \notin T_{BP}^{z}. \quad (8a)$$

$$\text{Also, } (x_{20}, z_0) \in T_{BP}^{z}, x_{21} < x_{20} \Rightarrow (x_{21}, z_0) \notin T_{BP}^{z}. \quad (8b)$$

$$\text{However, } (x_{20}, z_0) \in T_{BP}^{z}, \alpha \geq 0 \Rightarrow (\alpha x_{20}, \alpha z_0) \in T_{BP}^{z}. \quad (8c)$$

Assumption (8c) above implies that the by production sub-technology will always exhibit constant returns to scale due to the proportional relation between CO_2 and the energy input for any given fuel mix. This is unrelated to the nature of returns to scale in good output production. Further, convex combinations of feasible pairs of x_2 and z are feasible so long as it is proportional to some feasible pair. Hence, the bad output (CO_2 emission) can be reduced only by proportionately reducing the quantity of the polluting input directly or through the convex combinations of other feasible pairs of x_2 and z. Due to its apparent similarity with the weak disposability of outputs (but actually between the polluting input and the bad output) RMV (2018) call it joint disposability.

It should be noted, however, that unlike strong or weak disposability of conventional inputs and outputs, the so-called joint disposability does not signify technical inefficiency. That is because T_{BP}^{z} represents 'nature's technology' which allows no inefficiency. Burning a given quantity of

fuel will inevitably release exactly its carbon content – neither more nor less without any proactive abatement activities. Thus, every feasible pair of (x_2, z) is technically efficient.[3]

This, in its turn, calls into question the disposability assumption (6) above in MRL (2012) and Murty and Russell (MR) (2022). In fact, the production possibility set for the bad output should be only the ray through the origin shown in Figure 4(b) in Murty and Russell (MR) (1922, p 507) and should not include the points above the line.

This proportional relationship between the heat and carbon contents of fuel claimed above seems to be in direct conflict with the empirical evidence that firms with the same amount fuel measured in btu (British Thermal Unit) emit different quantities of carbon and in many cases less carbon from more btu. The clue to this apparent puzzle lies in the fact that often firms in the same industry (and more frequently, from different industries) use different kinds and combinations of fuels. These different fuels have different physical units of measurement. For example, coal is measured in tons, oil in gallons, natural gas in cubic feet, and so on. For aggregation of different quantities of fuel and also for inter-fuel comparison, the physical quantities of fuel are measured in their heat content (Btu) typically expressed as tonnes[4] of oil equivalent (toe). But the constituent fuels differ in their carbon to heat proportions. For example, natural gas contains 52.91 kg of CO_2 per 1 million Btu of heat. By contrast, the carbon to heat ratio for coal is 95.99 kg of CO_2 per 1 million Btu.[5] Thus, the carbon to energy ratio for any observed data point will depend on the fuel mix. One can lower or increase the CO_2 to heat ratio only by changing the fuel mix. If, however, the fuel mix is held unchanged, carbon emission can be reduced only by scaling down the use of fuel.

The conceptualization of the by production technology in this paper is best explained using the following diagram in Figure 1. For the good output (y) we have the standard production function $y \leq f(x_1, x_2)$, where x_1 is the neutral input and x_2 is the polluting input (fuel). A number of isoquants in the northeast quadrants are shown for the output levels y_0 , y_1, and y_2. The point A_0

[3] The corresponding author thanks Victor Podinovski for some valuable insights in this context in a recent conversation.
[4] A tonne (or a metric ton) is 2205 lbs. as opposed to a short ton which is 2000 lbs.
[5] Source: Carbon Dioxide Emission Coefficients, https//www.eia.gov/environmemt/emissions/co2

on the y_0 isoquant corresponds to the input bundle (x_{10}, x_{20}). Similarly, A_1 on the y_1 isoquant corresponds to the input bundle (x_{10}, x_{21}). With input 1 held unchanged at x_{10}, appropriate increase in input 2 leads to the increase in intended output from y_1 to y_2 and so on.

The diagram in southeast quadrant in Figure 1 shows the production of the bad output (CO_2) from the polluting input (fuel). As argued above, there is a proportional relationship between the quantity of fuel of a given mix (or CO_2 to btu ratio) and the emission generation function is shown by the ray $z = a_0 x_2$. The point B_0 shows the combination (x_{20}, z_0). Similarly, B_1 corresponds to (x_{21}, z_1). But recall that in the good output production, when combined with x_{10}, x_{20} produces y_0 and x_{21} produces y_1. The points B_0, B_1, B_2 correspond to the bad output levels z_0, z_1, and z_2 shown along the downward segment of the vertical axis. These ultimately lead to the good-bad pairs (y_0, z_0), (y_1, z_1), and (y_2, z_2) shown by the points P_0, P_1, and P_2 on the curve $y = g(z|a_0; x_{10})$ shown in the southwest quadrant in Figure 1.

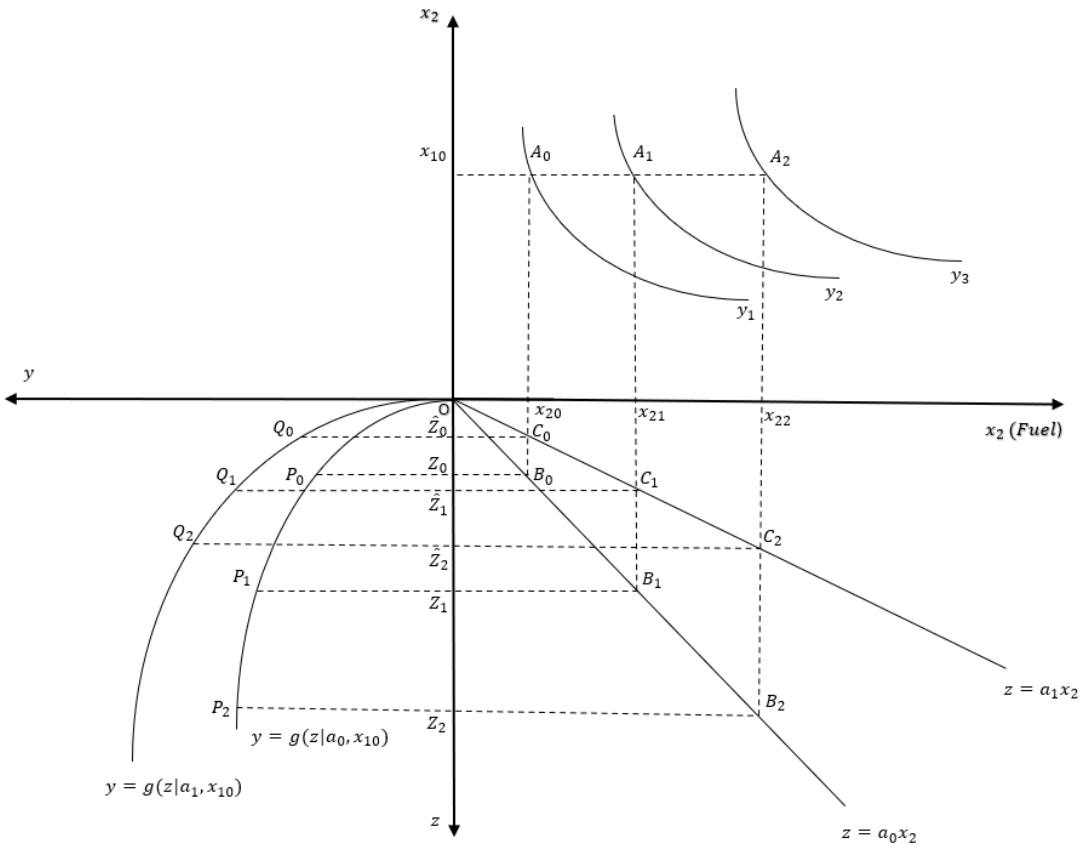


Figure 1

In drawing the pollution generation function we assumed a certain quality of fuel. Now suppose that the heat input (btu) relevant for the good output was generated from a fuel mix with a lower CO_2-to-btu ratio. In this case with cleaner energy, the same level of btu will be associated with a lower emission of CO_2. That is shown by the ray $z = a_1 x_2$. The corresponding combinations of x_2 and z are now shown by the points C_0 through C_2. Because the same quantities of btu ($x_{20}$and x_{21}) result in lower emission levels- ($\hat{z}_0, \hat{z}_1$) while producing good output y_0 and y_1, this results in an upward shift in the good-bad frontier$y = g(z, a_1; x_{10})$ in the diagram in the southwest quadrant of Figure 1.

3.2 Empirical Approximation to the Production Possibility Set

Suppose that the data on inputs and the good and bad outputs are available for *N* firms from an industry. Denote the set of observed data points as *J* where the individual elements of the set are $(x_{1j}, x_{2j}, y_j, z_j)$ $(j = 1,2, \ldots, N)$. Then, under the assumptions of convexity and free disposability, the sub-technology for good output production can be approximated as

$$S_{BP}^{y} = \begin{Bmatrix} (x_1, x_2, y): x_{1k} \geq \sum_{j \in J} \lambda_j x_{1j}; x_{2k} \geq \sum_{j \in J} \lambda_j x_{2j}; \\ y_k \leq \sum_{j \in J} \lambda_j y_j;\ j\ and\ k \in J; \lambda_j \geq 0 (j = 1, 2, \ldots,\ N) \end{Bmatrix} \quad (9)$$

However,

$$S_{BP}^{z} =$$

$$\begin{Bmatrix} (x_2, z): \sum_{j \in J} \lambda_j x_{2j} = \alpha x_{2k}; \sum_{j \in J} \lambda_j z_j = \alpha z_k;\ j\ and\ k \in J\ ; \lambda_j \geq 0\ (j = 1, 2, \ldots, N) \end{Bmatrix} \quad (10)$$

3.3 The Empirical DEA Problem for Reducing the Bad Output

In this study, $\boldsymbol{x_1}$ (l, k, m) include non-polluting inputs such as labor, capital, and non-energy materials whereas only one polluting input/energy x_2 and only one bad output/CO_2 emission as z_0. For any observed data point $(\boldsymbol{x_{10}}, x_{20}, y_0, z_0)$ the relevant minimization problem is

$max\ \beta_0$

$$s.t. \sum_{j=1}^{N} \lambda_j \boldsymbol{x_{1j}} \leq \boldsymbol{x_{10}};$$

$$\sum_{j=1}^{N} \lambda_j x_{2j} = (1-\beta_0)x_{20};$$

$$\sum_{j=1}^{N} \lambda_j y_j \geq y_0;$$

$$\sum_{j=1}^{N} \lambda_{1j} z_j = (1-\beta_0)z_0;$$

$$\sum_{j=1}^{N} \lambda_j = 1; \lambda_j \geq 0 (j = 1,2,\ldots,N); \quad (11)$$

The optimization problem is explained graphically in Figures 2(a)-2(b). Suppose that there are three firms each producing output y_0. Their input bundles along with the isoquant for the good output level y_0 are shown by points A, B, and C in Figure 2 (a). While points B and C are on the frontier, A is in the interior of the input set for y_0 and its horizontal projection A^* on to the isoquant shows that it is possible to reduce the polluting input x_2 to $(1-\beta)x_2^0$ while keeping the other input unchanged at $\boldsymbol{x_{10}}$. This is going to have its repercussions in Figure 2(b) as well, where the energy and carbon combinations of the observed inputs are shown. As the energy input is reduced while the actual carbon-to energy ratio of unit A is maintained, the observed point A in Figure 2(b) has to be moved to the point A^* on the ray *OA* through the origin. Consider two alternative ways to reduce carbon without changing the carbon-to-energy ratio. One could simply scale point A by a factor of $(1-\beta_0)$ so that the new point is $((1-\beta_0)x_2^0, (1-\beta_0)z_0)$ or create a convex combination of the points B and C in Figure 1(b) which leads the same projection. In creating the convex combination we choose the weights to be $\omega_B = \frac{BA^*}{BC}$ and $\omega_C = (1-\omega_B) = \frac{CA^*}{BC}$. This would ensure that the resulting output will remain y_0 as required. If on the other hand, we simply

scaled observation A by a factor of $(1-\beta_0)$, the resulting projection in Figure 1(a) would become point D, which is below the isoquant for y_0 so that the good output constraint would be violated.

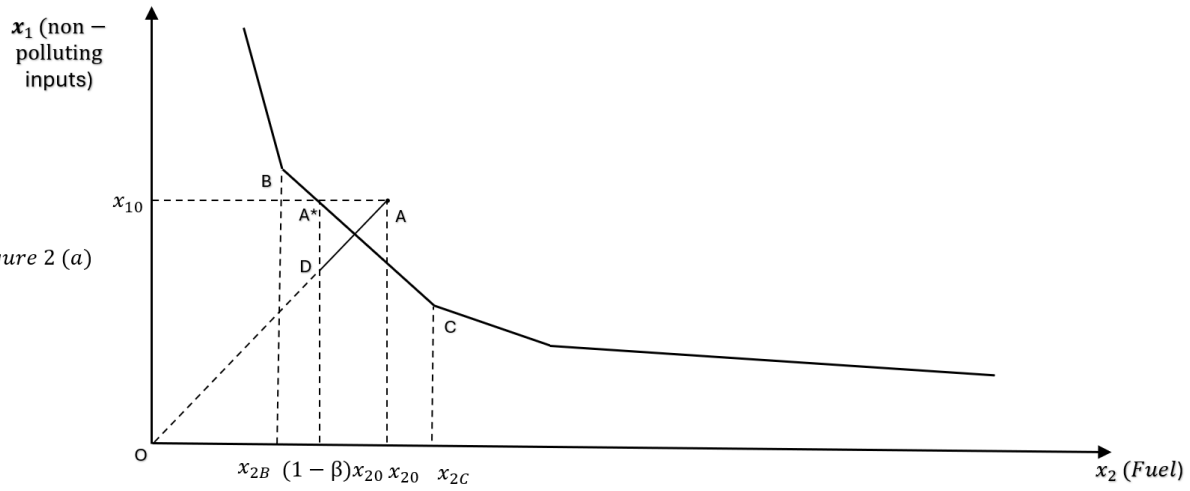


Figure 2 (a)

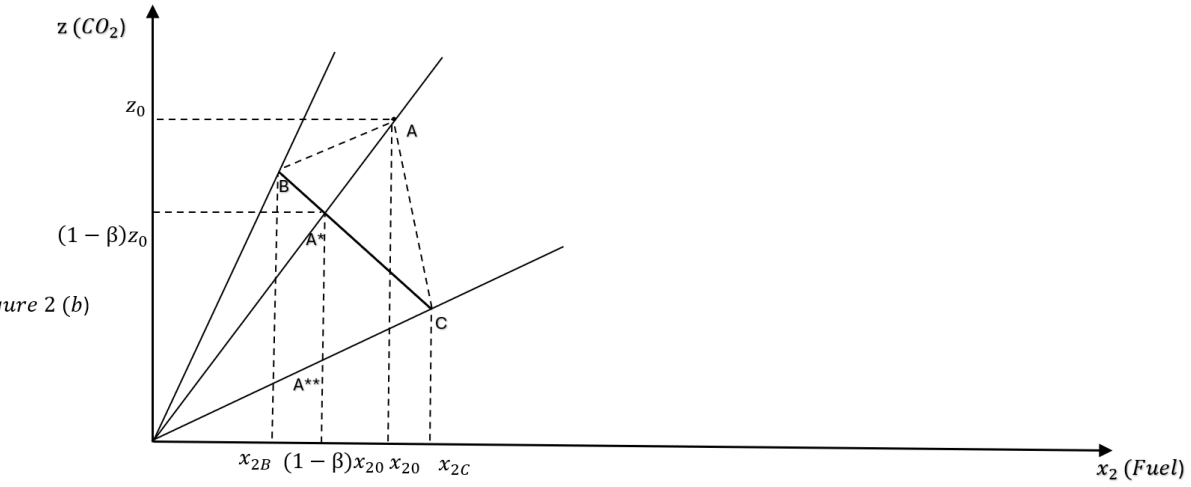


Figure 2 (b)

Another point needs to be emphasized here. The benchmark for the point A in Figure 1(a) is a convex combination of the points B and C with weights $\lambda_B = \frac{BA^*}{BC}$ and $\lambda_C = \frac{CA^*}{BC}$. To reach the corresponding benchmark point A^* on the ray OA we must be the exact same convex combinations of the point B and C on the rays OB and OC.

An implication of this is that the use of two different sets of weights in the two sub-technologies for the good and bad outputs as in MRL (2012 p 130, problem (6a-b)) or Murty and Russell (2022,

p 529, problem (28)) is inappropriate. For the same reason, the so called 'decentralized' problems in RMV (2018) invalid. It should be noted in this context that contrary to what is claimed by Murty and Russell (2022, p 529, fn. 51) adjusting for slacks will not ensure that the same benchmark quantity of the polluting input will be obtained for the good and bad output production technologies with two different sets of weights.

3.2 Opportunity Cost of Emission Reduction

Fare and Grosskopf (1998) provides a theoretical model[6] for shadow pricing undesirable outputs in terms of loss of good output under the output-oriented distance function assuming that the undesirable output is weakly-disposable with the desirable output. Studies measuring shadow prices of undesirable outputs are generally through (a) reported abatement cost, (b) shadow price, and (c) opportunity cost methods. Rather than investigating the reported abatement cost[7] or applying the shadow price approach for estimating the cost of emission reduction, we apply the opportunity cost model as proposed in RMV (2018) which measures the opportunity costs of a targeted emission reduction in terms of the loss of good output in dollar amounts. The advantage of this method is that it circumvents the problem of the DEA dual approach, where the opportunity cost based on the dual variables is usually unstable and cannot be adequately approximated for efficient observations. Although the shadow price provides an exact local measure for cost of emission reduction ensuring the observation is already on production frontier compared to directly using the pollution intensity, calculating the cost of certain amount of emission reduction using the

[6] There is a large body of literature on how to conceptualize and estimate the cost of emission reduction using computable general equilibrium models (Yang et al. (1996), Ellerman and Decaux (1998), Klepper and Peterson (2002)) and how to achieve emission reduction efficiently using policy instruments based on the theory of environmental economics (Montgomery (1972), Hahn (1984) and Stavins (1995). However, these studies are based on the assumption that the observed input-output bundles are always on the production frontier.

[7] Abatement technologies aimed at capturing and offsetting CO_2 is too costly to be widely adopted. As pointed out by Robertson and & Mousavian (2022), based on their case study on the 13 flagship cases of carbon capturing projects, it is found that the carbon capturing method is a significant financial and technical risk to enterprises across different industries. Thus, the reported abatement cost of CO_2 mitigation is not considered here.

same shadow price multiplying pollution reduction would underestimate the cost because it ignores the concavity of the production function in inputs, thereby, pollution as well. As shown in the figure below, if an efficient unit located at point D is required to reduce the pollution proportionally by β, then Y_2 of point E will be the maximal output given the pollution reduced from Z_d to $(1-\beta)Z_d$. The correct opportunity cost with such an emission reduction target is $Y_0 - Y_2$. However, the opportunity cost measurement would be inaccurate if it measured by the local shadow price at point D, i.e., $Y_0 - Y_1$, or by pollution intensity at point D, i.e., $Y_0 - Y_3$, where the cost measured by pollution intensity could have been more misleading if point D was an interior point.

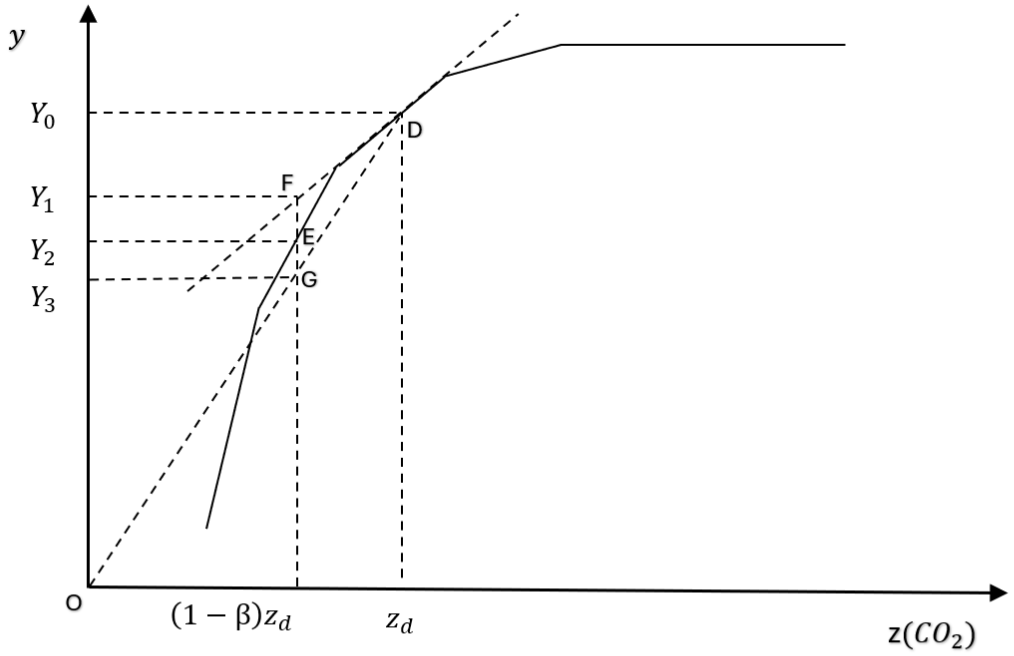


Figure (3)

Because the technology of capturing and offsetting CO_2 is not widely accepted, reduction of CO_2 emission in a specific industry relies on reduction in the use of polluting inputs in the short run.[8] The following opportunity cost model is set up to find the minimum amount of good output

[8] In the long run, the intended output would be less affected by the reduction of polluting inputs, if the transitioning from coal to natural gas or other sources of cleaner energy is accepted by more and more countries or if the technology of carbon capturing becomes more achievable financially and technically.

that would have to be sacrificed if CO_2 emission is to be reduced by some proportion $\bar{\gamma}$ targeted by analysts.

$$min\ \eta_0$$
$$s.t. \sum_{j=1}^{N} \mu_j \boldsymbol{x_{1j}} \leq \boldsymbol{x_{10}^*};$$
$$\sum_{j=1}^{N} \mu_j x_{2j} = (1-\bar{\gamma}) x_{20}^*;$$
$$\sum_{j=1}^{N} \mu_j y_j \geq (1-\eta_0) y_0^*;$$
$$\sum_{j=1}^{N} \mu_j z_j = (1-\bar{\gamma}) z_0^*;$$
$$\sum_{j=1}^{N} \mu_j = 1; \mu_j \geq 0 (j = 1,2,\ldots,N)\ (12);$$

The model finds the minimum loss of the desirable output, where pollution must be decreased by a further $\bar{\gamma}$ percent, from the efficient level of j^{th} observation obtained from (11). From the efficient projections obtained in (11) and (12), we compare the variation of desirable output in dollar amount $\eta_0 y_0^*$ vis-a-vis the change of pollution $\bar{\gamma}\, z_0^*$ along the frontier. Then the trade-off between good and bad outputs along the frontier below is the per unit opportunity cost of pollution reduction in terms of the dollar amount of good output.

$$\frac{\Delta y}{\Delta z} = \frac{\eta_0 y_0^*}{\bar{\gamma}\, z_0^*} \qquad (13)$$

3.3 Employment Effect

Berman and Bui (2001) and Morgenstern, Pizer, and Shih (2002) are two well-cited papers proposing structural models for estimating the effect of environmental regulation on employment. Morgenstern, Pizer, and Shih (2002) decomposed the emission reduction effect on employment into cost, factor shift, and demand effects. Specifically, the cost effect is generally positive for the increment in labor due to the additional abatement activities (cost); the demand effect is that labor

demand goes down because the increased production cost lowers the supply of intended output. Fare, Grosskopf, Pasurka, and Shadbegian (2018) estimated the effect of emission reduction of SO_2 using Data Envelopment Analysis for the US power plants incorporating the concepts of cost effect and factor shift effect. Their strategy is to measure the radial input-oriented distance function from two LP models: one including a restriction on the quantity of the bad output allowed and the other without any such restriction. Comparison of the labor input at the technically optimal projection onto the two isoquants (restricted and unrestricted) yields the change in employment due to emission regulation. It may be noted that the imposition of the restriction will only cause an outward shift of the isoquant and the optimal level of employment can only increase. By contrast, we allow the level of the desired output to decline (along the efficient frontier) as the targeted level of emission is lowered. This, we feel, would present a more accurate measure of the employment effect of emission reduction. To the extent that there is a substitution possibility between labor and other inputs, the optimal level of employment could either rise or fall. In the present study, because abatement technologies aimed at CO_2 offsetting and capturing have not been widely accepted and applied, we focus on the labor change due to the variation of the intended output caused by the change in fossil fuel.

In our discussion so far, the environmental (in)efficiency is being measured by the potential reduction in the undesirable output achievable without increasing any of the inputs – polluting or neutral. In many cases, a secondary objective of the policy makers is to minimize emission while allowing increase in the use of some preferred input to (make up to the extent possible) for the decrease in the use of the polluting input. To be more specific, it would be desirable to cut down on pollution while at the same time to minimize the loss of (and, if possible to increase) employment. Because the focus is on emission reduction, removing the upper bound on labor enables one to find the maximal emission reduction allowing increasing in labor, if needed. We propose a pollution-oriented DEA model allowing variation of labor as follows:

$$max\ \beta_0^{UR}$$

$$\sum_{j=1}^{N} \lambda_j^{UR} m_j \leq m_0;$$

$$\sum_{j=1}^{N} \lambda_j^{UR} k_j \leq k_0;$$

$$\sum_{j=1}^{N} \lambda_j^{UR} l_j = l;$$

$$\sum_{j=1}^{N} \lambda_j^{UR} x_{2j} = (1-\beta_0) x_{20};$$

$$\sum_{j=1}^{N} \lambda_j^{UR} y_j \geq y_0;$$

$$\sum_{j=1}^{N} \lambda_j^{UR} z_j = (1-\beta_0) z_0;$$

$$\lambda_j^{UR} \geq 0 (j = 1,2,\ldots,N) \quad (14)$$

Note that in this revised DEA problem, labor (l) is now a choice variable. The third constraint in (14) denotes that labor is adjusted by the corresponding intensity variables without having the observed level of labor as an upper bound, i.e., l is unrestricted and could be any positive value according to the intensity vector. In this way, the production frontier represents the technology where the good output is produced through the corresponding inputs with the least amount of pollution, allowing possible increase in labor, if needed. The optimal solution for problem (14) is denoted as $(m_0^{UR*}, k_0^{UR*}, l_0^{UR*}, x_{20}^{UR*}, z_0^{UR*}, y_0^{UR*})$.

The corresponding opportunity cost model as the problem (15) is set up to find the minimum amount of good output that would have to be sacrificed if CO_2 emission is to be reduced by some proportion $\bar{\gamma}$ targeted by analysts allowing possible variation in labor, if needed. The optimal solution for problem (14) is denoted as $(m_0^{UR**}, k_0^{UR**}, l_0^{UR**}, x_{20}^{UR**}, z_0^{UR**}, y_0^{UR**})$.

$$min\ \eta_0^{UR}$$

$$s.t. \sum_{j=1}^{N} \mu_j^{UR} m_j \leq m_0^{UR*};$$

$$\sum_{j=1}^{N} \mu_j^{UR} k_j \leq k_0^{UR*};$$

$$\sum_{j=1}^{N} \mu_j^{UR} l_j = l;$$

$$\sum_{j=1}^{N} \mu_j^{UR} x_{2j} = (1-\bar{\gamma}) x_{20}^{UR*};$$

$$\sum_{j=1}^{N} \mu_j^{UR} y_j \geq (1-\eta_0) y_0^{UR*};$$

$$\sum_{j=1}^{N} \mu_j^{UR} z_j = (1-\bar{\gamma}) z_0^{UR*};$$

$$\sum_{j=1}^{N} \mu_j^{UR} = 1; \mu_j^{UR} \geq 0 (j = 1,2,\dots,N)\ (15);$$

As in the problem (15), in (150 also labor is a choice variable without a prespecified upper bound. The opportunity cost of emission reduction by $\bar{\gamma}$ proportionally from the efficient level allowing variation of the labor could be calculated by

$$\frac{\Delta y}{\Delta z} = \frac{\eta_0 y_0^{UR*}}{\bar{\gamma}\, z_0^{UR*}}\ (16)$$

One advantage of estimating the cost of emission reduction through the non-parametric opportunity cost model is that the efficient input-output bundles before and after achieving a particular emission reduction target are provided in (14) and (15). Not only can we compare labor change due to efficiency improvement in pollution generation, but we can also investigate the labor

change due to the possible substitution among different inputs along the frontier before and after achieving a particular emission reduction target. Without an upper bound on labor, the labor change in proportion is denoted as

$$\frac{l_0^{UR**}-l_0}{l_0} = \frac{l_0^{UR**}-l_0^{UR*}}{l_0} - \frac{l_0^{UR*}-l_0}{l_0} \quad (17)$$

where l_0 is the observed level of employment; $l_0^{UR*}$is the level of labor after the observation has been projected onto the frontier, and $l_0^{UR**}$is the labor quantity when the emission is required to be further reduced by $\bar{\gamma}$ proportionally along the frontier. The labor change due to imposing emission reduction target is decomposed to the change due to the efficiency improvement $\frac{l_0^{UR*}-l_0}{l_0}$ and the change due to the variation of the intended output caused by the decrease of pollution and fossil fuel is $\frac{l_0^{UR**}-l_0^{UR*}}{l_0}$.

4 Data

We construct industry-level data from the World Input-Output Database, including good output, intermediate input, capital stock, and employment from Socioeconomic Accounts of 2014.[9]Emission-related energy consumption and the direct CO_2 emission data of each sector from Environmental Accounts WIOD.[10] The dataset covers 28 EU countries and 14 other major countries in the world for 2014. It is worth noting that the data mentioned above only includes intermediate input in dollars and the polluting input (fuel) in TJ but does not explicitly provide the measure of non-polluting inputs. We use barrels of oil equivalent to obtain the cost of energy using

[9] Desirable output, capital stocks, and intermediate inputs presented in current purchasers' prices (in millions of local currency) are converted to US dollars by purchasing power parity (PPP). We use the number of persons engaged as a measure of labor.

[10] There is WIOD 2016 Release (http://www.wiod.org/home), and we use 2014 data which is provided by Timmer et al. (2015) because it is the latest year for which all the inputs and outputs information is available for countries and industries. Polluting input and pollution are measured in terajoule (TJ) of energy and tons of emission.

the 2014 average price of Brent crude oil. The cost of material is separated by subtracting the cost of energy from the total dollar amount of the intermediate input.

Table 1 Summary of Selected Polluting Manufacturing Industries

Sectors	Total Emission (kt)	Total Output (m$)	Emission Percentage (within manufacturing)	Emission Intensity (Emission/Total Output)
Basic Metals	2614419.84	5484380.85	29.94	0.48
Chemicals and Chemical Products	1317254.50	4989441.63	15.09	0.26
Coke and Refined Petroleum Products	707646.67	4681440.07	8.10	0.15
Paper and Paper Products	152293.57	1171890.09	1.74	0.13

In this dataset, the fossil fuel related pollution from all 19 manufacturing sectors accounts for 30.09% of the total pollution among all the industries. We select four major manufacturing industries for our analysis: basic metals, coke and petroleum, chemicals and chemical products, and paper and paper products industry. These four industries account in total for 54.87% of the total CO_2 emission across all manufacturing industries. These four are the top polluting manufacturing industries, and emission-generating processes within these sectors largely depend on the combustion of fossil fuels.[11]

The total emissions (in tons), emission percentage across all the manufacturing industries, good outputs (in dollar amount), and emission intensities (emission per dollar of good output) of these four polluting industries are summarized in Table 1. The CO_2 emission intensity is higher in basic metals (0.48) and chemicals and chemical products (0.26), which involve processes requiring a large number of fuels burned for heating. Summary statistics for the inputs and outputs of different industries across all countries in 2014 are provided in Table 2.

[11] The non-metallic mineral products industry generates 32% of the total emission in the manufacturing industries in this dataset. However, it is not included in this study, because the emission in this industry comes from decomposition of limestone and emission from the heating process through fossil fuels, and data on limestone is not available.

The heterogeneity of emission-related inputs measured in terajoule (TJ) is a part of the embedded variation in emission. As noted by the U.S. Energy Information Administration, one million British thermal unit (Btu) of coal emits 228.6 pounds of CO_2, while the same Btu from natural gas emits only 117 pounds. In light of this, observations that have the best performance in pollution generation and have produced desirable outputs with the most environmental-friendly polluting input like natural gas will be on the production frontier. Therefore, in this study, the efficiency of an industry depends on its operational performance in producing intended output with the minimum required quantity of energy input and also on the fuel mix.[12] As the firm-level data is only minimally available across different industries, we apply the industry-level data presented above to conduct the analysis for estimating the cost of emission reduction and the impact of emission reduction on employment across basic metals, coke and refined petroleum products, chemical products, and paper products industries through a modified opportunity cost model using Data Envelopment Analysis described above.

Table 2 (a) Summary Statistic for Basic Metals Sector

Basic Metals	Obv	Mean	Max	Min	Sdv
Labor (thousand people)	35	422.99	6093.07	2.79	1125.52
Capital (in million $)	35	100275.72	1518803.38	135.89	268014.75
Materials (in million $)	35	116300.30	2273773.83	342.70	386062.41
Polluting Input (in TJ)	35	802697.78	14519441.97	8559.75	2466841.05
Desirable Output (in million $)	35	156601.61	2960988.60	869.31	502315.06
CO_2 Emission (in kt)	35	73697.14	1354870.67	211.60	231197.27

[12] To separate out the effects of heterogeneous inputs on pollution-oriented performance, it is necessary to utilize datasets at firm-level, including the record of types and percentages of different fuels used. Hampf and Rødseth (2019) addressed the environmental-oriented efficiency with the heterogeneity of polluting input specifically for the coal-fired power plants in the US.

Table 2 (b) Summary Statistic for Chemical Products Sector

Chemical Products	Obv	Mean	Max	Min	Sdv
Labor (thousand people)	33	388.95	7597.27	5.07	1306.13
Capital (in million $)	33	100024.76	1295086.37	619.47	245410.04
Materials (in million $)	33	102250.69	1735822.71	1213.46	295205.65
Polluting Input (in TJ)	33	489333.68	8016698.07	6075.22	1393576.07
Desirable Output (in million $)	33	142274.30	2224903.65	1701.53	384000.88
CO_2 Emission (in kt)	33	36898.88	690717.89	333.07	117746.09

Table 2 (c) Summary Statistic for Coke and Petroleum Products Sector

Coke and Petroleum Products	Obv	Mean	Max	Min	Sdv
Labor (thousand people)	35	62.48	929.54	1.00	170.54
Capital (in million $)	35	52468.29	554248.03	420.11	116342.18
Materials (in million $)	35	113875.68	1171700.96	264.53	229307.03
Polluting Input (in TJ)	35	369363.93	3213581.48	1950.88	684881.45
Desirable Output (in million $)	35	141436.14	1404637.59	545.28	281678.13
CO_2 Emission (in kt)	35	21116.81	188447.01	562.06	38680.14

Table 2 (d) Summary Statistic for Paper and Paper Products Sector

Paper and Paper Products	Obv	Mean	Max	Min	Sdv
Labor (thousand people)	35	223.09	3765.06	2.40	654.13
Capital (in million $)	35	31303.02	286015.51	199.91	58584.72
Materials (in million $)	35	21379.34	275179.55	248.93	48438.33
Polluting Input (in TJ)	35	211623.31	1970829.10	2516.40	401024.87
Desirable Output (in million $)	35	33411.94	372025.62	394.01	68590.10
CO_2 Emission (in kt)	35	4298.82	43601.30	60.62	8909.65

5 The Empirical Finding

The technology of different industries defined according to the by-production approach is captured by the environmental-oriented DEA model in (11). Although the LP models specified in the sections above are designed for variable return to scale technology, because that the data is reported as country and industry aggregates, we opted for a constant return to scale technology in our empirical analysis. Solving the problem in (11) for all the observations sector by sector provides the estimates of the pollution-oriented efficiency scores measured by possible minimum emission as a proportion of the observed emission, which is summarized in Table 3a for the selected countries, including China, Germany, India, Japan, Mexico, and the U.S. For example, the score of 0.92 for Germany's paper industry means that it could have scaled down emissions by 8% of the current level without reducing the level of the intended output. United States and Mexico performed generally excellent across all these four industries. Germany has relatively high-performance scores (no lower than 0.6). The chemical products and Coke and Petroleum sectors of India are efficient, while the paper products and basic metals industries of India did poorly and could have reduced CO_2 emission by more than 50%. China could have reduced about 40% of the emissions for all the selected industries. Japan did poorly in basic metals and chemical products where emission could have been reduced by more than 30% of the CO_2 emission. When countries

reduce pollution reduction taking employment impact into consideration, the labor unrestricted model (14) finds its rightful place and the results of the efficiency allowing potential labor increase is presented in Table 3b from Appendix. As expected, the efficiency score in labor unrestricted model (14) is lower as it relaxes the labor restriction in problem (11).

Table 3 (a) Environmental-Oriented Efficiency Score Labor Restricted

Efficiency	Paper Products	Coke and Petroleum	Chemicals	Basic Metals
Country	C17	C19	C20	C24
CHN	0.42	0.57	0.51	0.52
DEU	0.92	1.00	0.65	0.75
IND	0.30	1.00	1.00	0.46
JPN	0.82	1.00	0.43	0.46
MEX	1.00	1.00	1.00	1.00
USA	1.00	1.00	1.00	0.99

Starting with these efficient bundles from (11), one can determine new projected input-output bundles when the emission is required to be further reduced by $\bar{\gamma}$ =25% by solving the problem in (15). We calculated the opportunity cost of emission reduction in terms of the foregone output (in dollars per ton of emission reduction) as (13). The result is presented in Table 4a for selected countries.

As presented in Table 4a, the cost of emission reduction in terms of foregone output varies across industries and countries. Compared to other sectors, the costs in basic metals and paper products industries are generally lower for the selected countries. For instance, one ton reduction of emission reduces the value of the good output by $107 for the U.S. and by $559 for China in the basic metals industries. On the other hand, the cost is generally higher for coke and petroleum industry than other industries. For example, per ton emission reduction lowers the good output by $2,144 and $9,921 in coke and petroleum sectors of the U.S and China, respectively.

International comparison by sectors shows that: 1) in paper products industry, China has the highest cost as $20,114 and Japan has the lowest cost as $1,481; 2) in coke and petroleum products

industry, Japan has the highest cost, $10,393 and the U.S. has the lowest $2,144; 3) in chemical products industry, Japan has the highest cost $8,258 and the U.S has the lowest $1350; 4) in basic metals, the highest cost $4,856 is from India and the lowest cost $559 is from China. Similarly, like Table 3b, the corresponding opportunity cost of reducing the pollution by $\bar{\gamma}$ allowing possible increase in labor as (16) is reported in Table 4b from Appendix. It is worth pointing out that the opportunity cost measurements in (13) and (16) are calculated by assuming different production technology and different efficient benchmarks, thus, these results are not directly comparable.

Table 4 (a) Labor Restricted Foregone Output

	Paper and Paper Products	Coke and Refined Petroleum Products	Chemicals and Chemical Products	Basic Metals
Country	C17	C19	C20	C24
CHN	20114	9921	3975	559
DEU	1845	3185	5418	478
IND	5297	10393	6762	4856
JPN	1481	2261	8258	1177
MEX	2008	3911	5062	2385
USA	1737	2144	1350	107

Table 5 Ratio of Intended output verses CO_2 Emission ($/ton)

	Paper ProductsCoke and Refined Petroleum ProductsChemical Products			Basic Metals
Country	C17	C19	C20	C24
CHN	8532	7454	3221	2185
DEU	7363	5050	6641	2985
IND	5824	12045	6762	2643
JPN	6945	4886	4586	2107
MEX	12253	4199	5418	2385
USA	5977	6121	3720	2481

A simple ratio measure like emission intensity is also widely used in other studies as another direct measure for the trade-off between emission and intended output. We compare the cost of emission reduction in terms of foregone output with the ratio of the intended output to the CO_2

emission (the inverse of emission intensity) in Table 4a, 4b and Table 5. Noticeably, the measure by this simple ratio is larger than the cost of emission reduction in terms of foregone output in basic metals industry except Mexico and India, whereas it is larger than the cost in terms of foregone output in paper products industry (except for China). The simple ratio generally cannot correctly reflect the cost of emission reduction because: a) along the production frontier the intended output is not necessarily reduced by the same proportion as emission, and b) mostly the simple ratio measure is not along the production frontier but within the frontier, which does not consider any inefficiency.[13]

At present, more and more countries are trying to introduce a system of carbon pricing to address the underlying problem of the negative externality. For such a policy to be effective, the carbon price should be high enough to discourage emission by rational producers who will always compare the price with the opportunity cost of emission reduction measured by the loss of revenue or profit. Our findings show that the carbon prices of different markets in the U.S. are way below the opportunity cost to alter the producer emission behavior in any significant way. Unlike the sharply rising carbon price of EU Emissions Trading System 65 euro per ton, the allowance price in California was $38 per ton in 2024.[14] Based on our findings, there is considerable room for California to promote their environmental policies more aggressively.

Reducing production or shutting down factories that are pollution inefficient is a straightforward approach to emission reduction, and therefore is a common occurrence. However, these curtailment activities often cause people to think that promoting environmental policies necessarily leads to unemployment.

[13] As it is noticed that the estimate for basic metals industry of Mexico is the same, it is actually a perfect example supporting the extreme situation. The simple ratio measure will be the same as the non-parametric measure only when the observation is 1) environmental efficient; 2) the production frontier has a constant trade-off between the intended output and emission locally.

[14] It is $9.3 per ton in the market of the Regional Greenhouse Gas Initiative (RGGI) for power sector in the U.S.

We first report the employment effects of targeted emission reduction for different industries across selected countries when the upper bound on labor is imposed as in models (11)-12). The labor impact with this restriction is presented below in Table 6.

Table 6 (a) Decomposition of Labor Change (in proportion) of Paper and Paper Products

Paper and Paper Products	$(l_0^* - l_0)/l_0$	$(l_0^{**} - l_0^*)/l_0$	$(l_0^{**} - l_0)/l_0$
CHN	-0.5174	-0.1207	-0.6380
DEU	0.0000	0.0000	0.0000
IND	-0.6151	-0.1478	-0.7629
JPN	0.0000	0.0000	0.0000
MEX	0.0000	0.0000	0.0000
USA	0.0000	0.0000	0.0000

Table 6 (b) Decomposition of Labor Change (in proportion) of Coke and Petroleum Products

Coke and Petroleum Products	$(l_0^* - l_0)/l_0$	$(l_0^{**} - l_0^*)/l_0$	$(l_0^{**} - l_0)/l_0$
CHN	0.0000	0.0000	0.0000
DEU	0.0000	-0.0878	-0.0878
IND	0.0000	0.0000	0.0000
JPN	0.0000	0.0000	0.0000
MEX	0.0000	-0.2514	-0.2514
USA	0.0000	0.0000	0.0000

Table 6 (c) Decomposition of Labor Change (in proportion) of Chemical Products

Chemical Products	$(l_0^* - l_0)/l_0$	$(l_0^{**} - l_0^*)/l_0$	$(l_0^{**} - l_0)/l_0$
CHN	-0.4583	-0.0113	-0.4696
DEU	-0.0026	-0.1810	-0.1835
IND	0.0000	-0.2500	-0.2500
JPN	0.0000	0.0000	0.0000
MEX	0.0000	-0.2514	-0.2514
USA	0.0000	0.0000	0.0000

Table 6 (d) Decomposition of Labor Change (in proportion) of Basic Metals

Basic Metals	$(l_0^* - l_0)/l_0$	$(l_0^{**} - l_0^{UR*})/l_0$	$(l_0^{**} - l_0)/l_0$
CHN	-0.2688	-0.1996	-0.4684
DEU	0.0000	0.0000	0.0000
IND	-0.3786	-0.4487	-0.8273
JPN	0.0000	0.0000	0.0000
MEX	0.0000	-0.2500	-0.2500
USA	0.0000	0.0000	0.0000

These results can be contrasted with our relaxed model (15) without the upper bound on labor. It can be seen (from Table (7) that the effect of achieving a particular emission reduction target on employment is not always negative when labor restriction is relaxed. The estimated labor changes as in (17) are provided in Table 7. It is noteworthy that the overall labor changes are equal to the sum of change due to the efficiency improvement $l_0^{UR*} - l_0$ and change due to the variation of the intended output $l_0^{UR**} - l_0^{UR*}$. The change due to the variation of the intended output is negative for selected countries, except for the paper products industry. In the paper products industry, labor demand at pollution-oriented efficient level (l_0^{UR*}) is larger than the actual level (l_0) except in China and India. The overall effect of the particular emission reduction target on the employment of the paper product industry is positive in Germany (47.78%), Japan (183.73%), Mexico (89.68%), and the U.S. (268%). In the coke and refined petroleum products industry, labor changes due to the efficiency improvement are all non-negative; the overall effect on labor is negative only in Germany (-8.78%) and Mexico (-25.14%). The labor changes due to efficiency improvement are negative for China and Germany in the chemical products industry; the overall effect in the chemical products industry is positive for Japan (66.31%) and the U.S. (116.27%). In the basic metals industries, the overall effect is negative for all the selected countries because the change due to the variation of the intended output caused by the change of fossil fuel dominates the change due to efficiency improvement. In summary, the overall change of employment is negative for the selected countries in the basic metals industry, while the overall change in labor varies across countries in the coke and refined petroleum, paper products, and chemical products industries.

Table 7 (a) Decomposition of Labor Change (in proportion) of Paper and Paper Products

Paper and Paper Products	$(l_0^{UR*} - l_0)/l_0$	$(l_0^{UR**} - l_0^{UR*})/l_0$	$(l_0^{UR**} - l_0)/l_0$
CHN	-0.5011	-0.1199	-0.6209
DEU	0.2696	0.2083	0.4778
IND	-0.7698	0.1592	-0.6106
JPN	1.4121	0.4251	1.8373
MEX	0.0000	0.8968	0.8968
USA	2.1310	0.5489	2.6800

Table 7 (b) Decomposition of Labor Change (in proportion) of Coke and Petroleum Products

Coke and Petroleum Products	$(l_0^{UR*} - l_0)/l_0$	$(l_0^{UR**} - l_0^{UR*})/l_0$	$(l_0^{UR**} - l_0)/l_0$
CHN	1.1254	-0.5314	0.5941
DEU	0.0000	-0.0878	-0.0878
IND	2.1035	-0.7759	1.3276
JPN	8.6984	-2.4246	6.2738
MEX	0.0000	-0.2514	-0.2514
USA	8.4316	-1.4855	6.9461

Table 7 (c) Decomposition of Labor Change (in proportion) of Chemical Products

Chemical Products	$(l_0^{UR*} - l_0)/l_0$	$(l_0^{UR**} - l_0^{UR*})/l_0$	$(l_0^{UR**} - l_0)/l_0$
CHN	-0.4583	-0.0113	-0.4696
DEU	-0.0026	-0.1810	-0.1835
IND	0.0000	-0.2500	-0.2500
JPN	1.0500	-0.3869	0.6631
MEX	0.0000	-0.2514	-0.2514
USA	1.4822	-0.3195	1.1627

Table 7 (d) Decomposition of Labor Change (in proportion) of Basic Metals

Basic Metals	$(l_0^{UR*} - l_0)/l_0$	$(l_0^{UR**} - l_0^{UR*})/l_0$	$(l_0^{UR**} - l_0)/l_0$
CHN	-0.2688	-0.1996	-0.4684
DEU	0.2546	-0.2830	-0.0284
IND	-0.3786	-0.4487	-0.8273
JPN	0.7654	-1.0111	-0.2457
MEX	0.0000	-0.2500	-0.2500
USA	0.1361	-0.2453	-0.1093

6 Conclusion and Policy Implications

Studies estimating the shadow price of undesirable output along the production possibility frontier typically rely on the trade-off between pollution reduction and the loss of desirable output. Analysis focusing on this trade-off requires conceptualizing a production technology that includes the production process of both the good and the bad outputs. Treating pollution as a joint product with desirable output or regarding it as an unavoidable by-production resulting from the use of polluting input into the production process are two alternative and well-founded ways. Although the appropriateness of one approach over one the other typically depends on the context, there is a growing realization that the by-production approach is better suited for environmental pollution analysis.

The estimates of pollution-oriented efficiency scores indicate that there is a significant potential for China, India, Japan, and the U.S. to produce the same amount of desirable outputs with less emission by improving their environmental efficiency and concentrating more on transitioning from coal to natural gas or other sources of cleaner energy. We estimated the cost of emission reduction in terms of foregone output and alternatively in terms of foregone variable profit through the by-production approach based on the fact that CO_2 must come from the burning of fossil fuels. The results show that the cost of emission reduction in the basic metals industry is generally the lowest, and the cost is generally high in coke and refined petroleum products among the observed countries.

Along with the opportunity cost of emission reduction, we also look at employment changes due to emission reduction. The results show that imposing environmental policy on the basic metals industry will reduce the overall employment level for all the selected countries, but in other sectors, especially in the paper products industry, implementing emission reduction plans may increase labor demand.

Finally, a remark on the levels of environmental inefficiency in the specific industries for the individual countries measured by our empirical analysis is in order. Excessive carbon emission for a given level of production of the intended output of any industry can result from a combination of inefficient and wasteful use of fuel in production (which can be addressed by improving efficiency in fuel consumption) and higher carbon content of the mix of different kinds of fuel used. To the extent that nations can transition away from conventional fossil fuels to 'cleaner' and renewable energy, environmental efficiency will also improve.

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Appendix

Table 3 (b) Environmental-Oriented Efficiency Score Labor Unrestricted

Efficiency	Paper Products	Coke and Petroleum	Chemicals	Basic Metals
Country	C17	C19	C20	C24
CHN	0.42	0.41	0.51	0.52
DEU	0.71	1.00	0.65	0.60
IND	0.30	0.67	1.00	0.46
JPN	0.64	0.27	0.37	0.44
MEX	0.84	1.00	1.00	1.00
USA	0.66	0.35	0.47	0.70

Table 4 (b) Labor Unrestricted Foregone Output

	Paper and Paper Products	Coke and Refined Petroleum Products	Chemicals and Chemical Products	Basic Metals
Country	C17	C19	C20	C24
CHN	19416	18193	3975	559
DEU	1427	3185	5418	1317
IND	642	18091	6762	4856
JPN	1360	18211	7658	1542
MEX	1362	3911	5062	2385
USA	1045	14724	3284	582