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

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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 reduction in GDP and jobs lost 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 a production technology with one intended output 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 of by-production formulated by Murty, Russell, and Levkoff (2012) and modified by Ray, Mukherjee, and Venkatesh (2018) is employed.

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

JEL Codes: Q52, C61

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1 Introduction

A broad consensus in the scientific community about the potentially catastrophic impact of global warming due to unrestrained greenhouse gas emission upon plant and animal life in this planet has forced the leadership across countries to recognize the need and urgency of an internationally coordinated policy for environmental pollution reduction. The United States, the United Kingdom, Canada, and Japan have all promised to reduce CO_2 emission. The U.S. has rejoined the Paris Accord and has set a target of curbing CO_2 emission by 50-52% by 2030 (based on 2005 levels); Canada has increased its goal from 30% to 40%-45% (based on 2005 levels); Japan has raised the reduction target from 26% to 46%-50% by 2030 (based on 2013 levels); the United Kingdom has pledged to shrink CO_2 emission by 78% by 2035 (based on 1990 levels). The U.S. President Biden argued at the 2021 Leaders' Summit on Climate, 'nations that work together to invest in a cleaner economy will reap the rewards for their citizens' as he called upon the participating governments to collaborate on preventing global warming through CO_2 emission reduction. In fact, 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 reduction in GDP and jobs lost will be different for different countries and across different industries. 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 significant reduction in income and employment resulting from policies encouraging alternative and renewable sources of energy.

There exists a considerable volume of literature in environmental economics and also in the production efficiency literature specifically directed towards 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 (OM) 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 using 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 holding the level of inputs unchanged. 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.

Färe, 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). Färe, Grosskopf, and Pasurka (2016) measured the opportunity cost of abatement of SO_2 for coal-fired plants with particular focus on the impact of pollution regulation on technical change.

Examples of using the shadow price derived from parametrically specified distance functions can be found in Färe, Grosskopf, Lovell, and Yaiswarang (1993), Coggins and Swinton (1996), Swinton (2002), Lee, Park, and Kim (2002), and Hailu and Veeman (2003), among others. Färe, 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 tons of paper produced 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 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.[1] Ray and Mukherjee (2007) used country-level data on GDP as the good output and CO_2 emission as the bad output to 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.

As noted by Färe, 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. The shadow prices from DEA linear programming models are very unstable 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 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. Ray, Mukherjee, and Venkatesh (2018) used a DEA formulation of the production technology incorporating the by-production model of Murty, Russell, and Levkoff (2012) assuming 'joint disposability' of pollution and 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 opportunity cost of a 15% reduction in CO_2 emission for individual countries along a non-parametric frontier

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

constructed using the output directional distance function.

While using the opportunity cost measure of carbon emission reduction cost, this paper extends the literature in several directions. First, instead of looking at an aggregate measure of lost GDP due to CO_2 emission reduction for the entire economy, we examine the loss of desirable output due to a targeted pollution reduction for a number of major industries for different countries. This allows us to highlight the differential cost of pollution control that is imposed upon different industries. Side by side, we can also compare how this opportunity cost varies across countries even for the same industry. Such information should be helpful in setting industry-specific pollution reduction targets while trying to meet an overall pollution reduction goal for the country as a whole. At the same time, inter-country differences can be taken account of in any global agreement on emission reduction. Second, instead of estimating the effect of pollution reduction on employment as Färe, Grosskopf, and Pasurka (2018),[2] we estimate the effect of a particular reduction target on labor demand by applying the opportunity cost model as Ray, Mukherjee, and Venkatesh (2018).[3] The flexibility of the reduction target enable one to compare the effect of different emission reduction targets on labor demand.

The main contributions of the paper can be summarized as follows:

- We conceptualize the overall production technology and estimate pollution-oriented efficiency score using a by-production approach through a directional distance function across thirty-six countries and four manufacturing sectors, including basic metals, coke and refined petroleum products, chemical products, and paper products.

- We measure the cost of emission reduction in terms of foregone revenue based on the by-production approach through a opportunity cost model similar to RMV (2018). The cost of emission reduction is estimated in the minimum dollar amount of good output that would have to be sacrificed when the emission is required to be reduced by 25%.

[2] This effect of emission reduction on labor is measured by comparing labor demand with and without pollution regulation through an input-oriented distance function.

[3] In this study, the reduction target can be exogenously assigned by researcher incorporating with different emission reduction requirements.

- The reduction in the value of intended output is more likely to over estimate the opportunity cost because it does not reflect cost savings from reduction in fuel and (possibly) other inputs. Alternatively, we calculate the cost of emission reduction in terms of foregone profit for selected countries based on the projected input-output bundles, given the CO_2 emission is to be reduced by 25%.

- With the proposed opportunity cost model, we estimate the effect of this particular emission reduction on employment through the proposed method.

The rest of the paper is organized as follows. Section 2 conceptualizes the production possibility set which includes the production process 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 3 describes the collection and construction of the dataset. Section 4 presents and analyzes the results of pollution-oriented efficiency score, cost of emission reduction and effect of the particular emission reduction target on employment. Section 5 offers conclusions.

2 Methodology

Consider an industry using *n* inputs $x \in \mathbf{R}_+^n$ to produce *m* outputs $y \in \mathbf{R}_+^m$. A production plan is feasible if an input vector x can produce an output vector y . The production technology of this specific industry can be characterized by the production possibility set

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

Assume further that the output vector includes some 'bad' or undesirable output(s) along with the 'good' or intended outputs. The production technology must appropriately characterize the production process of both the good and the bad outputs. There are several ways of modeling bad output, specifically as: (a) a conventional input in the production process (Baumol and Oates

(1988), Cropper and Oates (1992)),[4] (b) a joint product with the good output (Färe et al. (1989)), 2005), Førsund (2009), etc.),[5] or (c) an incidental by-production resulting from the use of some or all inputs into the production process (Førsund (2009), Murty, Russel, and Levkoff (2012) (MRL), Lozano (2015), Dapko et al. (2016), and Ray, Mukherjee, and Venkatesh (2018) (RMV).

The joint production approach captures the production technology well in industries like livestock and pharmaceutical, where multiple inputs could not be clearly separated as polluting or non-polluting inputs. For manufacturing industries like non-metallic minerals and basic metals, polluting inputs and non-polluting inputs can be separated. For example, one of the most polluting manufacturing industries, non-metallic mineral products, includes the production of cement, lime, ceramics, and glass. The emission of the non-metallic mineral products comes from two input factors: 1) the calcination process for limestone, where limestone is heated and decomposed into calcium oxide and CO_2; and 2) the heating process from the use of fossil fuels for this calcination. In the iron and steel industry, capital, labor, iron ore, and fossil fuels are utilized to produce steel. CO_2 emission is generated during the smelting process from the use of fossil fuels. In summary, the reduction of pollution is physically tied with the reduction of polluting input in these manufacturing industries. Therefore, estimating the production technology of manufacturing sectors requires one to 1) adequately define the technology which includes the production process of both the good and the bad outputs; 2) capture the relationship between pollution and polluting input.

MRL (2012), therefore, models the overall technology as the intersection of two sub-technologies for producing good and bad outputs; the two sub-technologies are estimated through two separated problems of maximizing desirable and minimizing undesirable outputs. Lozano (2015) addresses the problem that the polluting inputs involved in both of the sub-problems of MRL (2012) are not guaranteed to be equal and had this problem fixed by imposing restrictions. RMV (2018) propose

[4]The approach by Baumol and Oates (1988), and Cropper and Oates (1992), which consider the undesirable outputs as inputs, starts from the positive relationship of desirable and undesirable outputs. However, as explained in RMV (2018), the approach is conceptually invalid because "First, an input exists even before the production process starts. Second, an input is depleted in stock as production is carried out. Third, an input is subject to some processing by the producer."

[5]This method regards undesirable output as an unintended output tied with the production of desirable output. More intended outputs are produced only if undesirable output increases, which means bad outputs are weakly disposable with good outputs.

to analyze the production technology through unified or decentralized by-production models, to address the concern of different intensity vectors used by Lozano (2015) and MRL (2012). The pollution-generating technology in RMV (2018) characterizes the exact proportional change of polluting inputs and pollution. In this study, we employed the approach and assumption in RMV (2018) to define the production technology.

To adequately define the production technology which includes the production process of both the intended and undesirable outputs for manufacturing sectors, we partition the input vector $x = (x_1, x_2)$ including *n-1* types of non-polluting inputs $x_1 \in \mathbf{R}_+^{n-1}$ and only one type of polluting input x_2. The inputs (x_1, x_2) are used to produce one good output y and one bad output b. The production technology is viewed as an intersection of the production for intended output T_{BP}^y and pollution generating process T_{BP}^b. Based on RMV (2018), we assume that the overall production technology under the by-production approach satisfies:

(A_1) Strong disposability of inputs: if $(x_1, x_2; y) \in T_{BP}^y$, and $(x_1', x_2') \geq (x_1, x_2)$ then $(x_1', x_2'; y) \in T_{BP}^y$;

(A_2) Strong disposability of desirable output: if $(x_1, x_2; y) \in T_{BP}^y$, and $y' \leq y$ then $(x_1, x_2; y') \in T_{BP}^y$;

(A_3) Joint disposability between pollution and polluting input: if $(x_2; b) \in T_{BP}^b$, for any $0 \leq \theta \leq 1$, then $(\theta x_2, \theta b) \in T_{BP}^b$.

(A_4) $T_{BP} = T_{BP}^y \cap T_{BP}^b$

where strong disposability assumptions of inputs and good output hold only for T_{BP}^y. Strong disposability assumption holds for polluting input in the production process of good output, as all inputs could be inappropriately or inefficiently utilized for the production process of good output. However, strong disposability does not hold for polluting input in pollution generation process, as polluting input could not be arbitrarily increased without changing the pollution. Therefore, for the process of pollution generation T_{BP}^b, we assume the polluting input and the pollution are jointly disposable in the way that the pollution reduction must come from the same proportional reduction of corresponding polluting input. This assumption from RMV (2018) reflects the transformation between polluting input and pollution based on two major facts:

- The polluting input that has entered the transformation process generates a certain amount of pollution primarily based on the carbon content and net calorific value. In other words, the emission factors across different types of fuels determine the transformation rate between energy and emission.
- The data of the pollution is measured mostly based on the product of emission factors of different types of polluting inputs and the amounts of those polluting inputs.[6]

Additionally, the method of RMV (2018) addresses the problem of the uncoordinated amount of polluting input between T^y_{BP} and T^b_{BP} in the work of MRL (2012). Therefore, we use the by-production approach of RMV (2018) to conceptualize and estimate the technology with the imposed relationship between the pollution and polluting input. The production possibility set following the by-production approach and constant return to scale in the non-parametric form can be approximated as:

$$T^y_{BP} = \Bigg\{(x_1, x_2; y) : \sum_{j=1}^{N} \lambda_j y_j \geq y; \sum_{j=1}^{N} \lambda_j x_1^j \leq x_1; \sum_{j=1}^{N} \lambda_j x_2^j \leq x_2; \lambda_j \geq 0; (j = 1, 2, \dots, N)\Bigg\} \tag{2}$$

$$T^b_{BP} = \Bigg\{(x_2; b) : 0 \leq \theta \leq 1, \sum_{j=1}^{N} \lambda_j x_2^j = \theta x_2, \sum_{j=1}^{N} \lambda_j b_j = \theta b_j; \lambda_j \geq 0; (j = 1, 2, \dots, N)\Bigg\} \tag{3}$$

$$T_{BP} = \left\{(x_1, x_2; y, b) : (x_1, x_2; y) \in T^y_{BP} \wedge (x_2; b) \in T^b_{BP}\right\} \tag{4}$$

[6]Real-time CO_2 emission monitoring has not been widely adopted among most polluting industries. The emission data generally relies on the amount of polluting inputs and emission factors.

We propose to characterize the overall production technology and estimate pollution-oriented efficiency through the following directional distance function.

$$\begin{aligned}
&\vec{D}\left(x_1, x_2; y, b; g^{x_1}, g^{x_2}, g^y, g^b\right) \\
&= \{\max \beta : \left(x_1, x_2 - \beta g^{x_2}; y, b - \beta g^b\right) \in T; \\
&\quad 0 \leq \beta \leq 1; g^{x_2} = x_2, g^b = b, g^{x_1} = g^y = 0\}
\end{aligned} \tag{5}$$

where $\left(g^{x_1}, g^{x_2}, g^y, g^b\right)$ is the pre-specified direction vectors. We maximize the reduction of pollution and polluting input in this directional distance function, as we focus on producing the current amount of desirable output with the least amount of pollution. Thus, $g^{x_2} = x_2$, $g^b = b$ and $g^{x_1} = g^y = 0$. Here, the proportional reduction of pollution and polluting input are $\beta = 1 - \theta$. In this study, the model include one type of good output y in dollar amount; pollution and polluting input are CO_2 emission b and fuels f; non-polluting inputs x_1 include capital k, materials m and labor l. As the focus is emission reduction, relaxation of the strong disposablity of labor enables one to find the maximal emission reduction allowing variation of labor; therefore, we propose a pollution-oriented DEA model allowing the variation of labor as following,

$$\begin{aligned}
\vec{D}\left(x_1, x_2; y, b; g^{x_1}, g^{x_2}, g^y, g^b\right) = max\ \beta & \\
s.t \qquad & \textstyle\sum_j^N \lambda_j y_j \geq y^0 \\
& \textstyle\sum_j^N \lambda_j m_j \leq m^0 \\
& \textstyle\sum_j^N \lambda_j k_j \leq k^0 \\
& \textstyle\sum_j^N \lambda_j l_j = l^* \\
& \textstyle\sum_j^N \lambda_j f_j = (1-\beta) f^0 \\
& \textstyle\sum_j^N \lambda_j b_j = (1-\beta) b^0 \\
& \lambda_j \geq 0,\ \forall j \in N
\end{aligned} \tag{6}$$

where β is the proportion reduction of CO_2 and fuels for a specific observation, *N* is the number of observations and λ_j are the intensity variables. The objective is to maximize the pollution reduction without decreasing the quantity of desirable output y^0 under the proposed by-product approach. As mentioned above, strong disposability assumptions hold for materials, capital, fuel, and desirable output only in T^y_{BP}. The strong disposability of polluting input does not hold for the overall technology, as the overall technology is an intersection of both T^y_{BP} and T^b_{BP}. Therefore, fuel is jointly disposable with CO_2, and if the pollution is reduced by β proportionally, the amount of fuel has to be reduced by the same proportion. The fourth constraint in (6) denotes that labor is projected in the direction of minimizing emission reduction and is adjusted by the corresponding intensity variables without having the observed level of labor as an upper bound. 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 variation of labor. Eventually, solving the problem of (6) for each industry of all the countries provides the efficiency score $(1 - \beta^*)$ and the corresponding input-output bundle at efficient level for ith observation is $(y^*, b^*, f^*, m^*, k^*, l^*)$.

Färe and Grosskopf (1998) provides a theoretical model[7] 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[8] 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 is usually unstable and cannot be adequately approximated for efficient observations.

As the technology of capturing and offsetting CO_2 is not widely accepted, the emission re-

[7]There is a large amount 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 established based on the assumption that the observed input-output bundles are always on the production frontier.

[8]Abatement technologies aimed at capturing and offsetting CO_2 is too costly to be widely adopted. Thus, the reported abatement cost of CO_2 mitigation is not considered here.

duction of CO_2 of a specific industry relies on the reduction in the use of polluting inputs in the short run.[9] Any reduction in the intended output caused by a reduction of the polluting input is the opportunity cost of pollution reduction in terms of desirable output. We apply the opportunity cost model as RMV (2018) to analyze the trade-off between pollution reduction and desirable outputs across different manufacturing sectors and different countries. The opportunity cost model is set up to find the minimum dollar amount of good output that would have to be sacrificed if CO_2 emission is to be reduced by some proportion $\bar{\gamma}$ decided by the analyst. We propose the following opportunity cost model,

$$\begin{aligned} & min\ \eta \\ s.t \quad & \textstyle\sum_j \mu_j y_j^* \geq (1-\eta) y^* \\ & \textstyle\sum_j \mu_j m_j^* \leq m^* \\ & \textstyle\sum_j \mu_j k_j^* \leq k^* \\ & \textstyle\sum_j \mu_j l_j^* = l^{**} \\ & \textstyle\sum_j \mu_j f_j^* = (1-\bar{\gamma}) f^* \\ & \textstyle\sum_j \mu_j b_j^* = (1-\bar{\gamma}) b^* \\ & \mu_j \geq 0,\ \forall j \end{aligned} \tag{7}$$

The purpose of this model is to find the minimum loss of the desirable output, where pollution must be decreased by a further $100 \cdot \bar{\gamma}\%$, from the efficient level of ith observation obtained from (6). From the efficient projections obtained in (6) and (7), we compare the variation of desirable output in dollar amount $\eta^* y^*$ vis-à-vis the change of pollution $\bar{\gamma} b^*$ along the frontier. Then the trade-off between good and bad outputs along the frontier as

$$\frac{\Delta y}{\Delta G} = \frac{\eta^* y^*}{\bar{\gamma} b^*} \tag{8}$$

is the per unit opportunity cost of pollution reduction in terms of dollar amount of good output. Additionally, The model in (7) provides the maximal desirable output $(1-\eta^*)y^*$ and also the

[9] 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.

corresponding variable input bundle (m^{**}, f^{**}, l^{**}), given that the emission and the polluting input is required to be decreased to $(1-\bar{\gamma})f^*$ and $(1-\bar{\gamma})b^*$. It is important to notice that the emission reduction affects both revenue and the production cost. Therefore, the reduction in the value of intended output is more likely to over estimate the opportunity cost because it does not reflect cost savings from reduction in fuel and (possibly) other inputs.[10] If we assume the inputs and intended output prices are exogenously given and the intended output is measured in value terms, denoting the input prices as $\mathbf{w} = (w_m, w_F, w_l)$, the non-parametric method presented in (6) and (7) enables one to further estimate the cost of emission reduction in terms of change in variable profit

$$\frac{\Delta\pi}{\Delta b} = \frac{\eta^* y^* - \mathbf{w}(m^* - m^{**}, f^* - f^{**}, l^* - l^{**})'}{\bar{\gamma} b^*} \tag{9}$$

We propose to measure the cost of emission reduction alternatively in terms of foregone revenue and foregone variable profit, given that emissions must be further reduced by $\bar{\gamma} = 25\%$ from the level of the pollution-oriented projection in (6) for selected countries including China, Germany, India, Japan, Mexico and the United States.[11]

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 on 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. Färe, Grosskopf, Pasurka (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. In this study, we focus on measuring the factor shift effect following the concept proposed in Morgenstern, Pizer, and Shih (2002). The factor shift effect is the change of labor

[10] Especially when the abatement technology for CO_2 is not widely accepted, therefore, not considered in this study, the foregone revenue is over-estimating the cost of emission reduction based on theories of environmental economics.

[11] The lack of all the input quantities and input prices impedes the estimation of emission reduction cost in terms of foregone profit for all the observations.

due to the variation of inputs shares before and after the regulation (associate with the possible substitution among different inputs along the frontier) . Because abatement technologies aimed at CO_2 offsetting and capturing has not been widely accepted and applied, the cost effect is not considered. Our model could be extended to incorporate the labor change due to the reduced demand of intended output if a panel dataset is employed.

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 (6) and (7). 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. The labor change in percentage is denoted as

$$\frac{l^{**}-l}{l} = \frac{l^{**}-l^{*}}{l} + \frac{l^{*}-l}{l} \tag{10}$$

where l is observed level of employment, l^* is the projected level of labor after the observation has been projected onto the frontier, and l^{**} 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 the emission reduction target is decomposed to the change due to the efficiency improvement $\frac{l^{*}-l}{l}$ and the change due to the factor shift effect $\frac{l^{**}-l^{*}}{l}$.

3 Data

We construct industry-level data from the World Input-Output Database[12], including good output, intermediate input, capital stock, and employment from Socioeconomic Accounts of 2014.[13] Energy consumption and CO_2 emission data are from Environmental Accounts WIOD.[14] The

[12]We would like to thank Surender Kumar at Delhi School of Economics, for offering help with the WIOD dataset.

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

[14]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.

dataset covers 28 EU countries and 14 other major countries in the world for 2014. To construct a means of measuring the material input, we convert the polluting input (energy) to barrels of oil equivalent. We use barrels of oil equivalent to obtain the cost of energy using the 2014 average price of the Brent oil. The cost of material is separated by subtracting the cost of energy from the total dollar amount of the intermediate input.

In this dataset, pollution from all the 19 manufacturing sectors accounts for 30.09% of the total pollution among all the industries. We select four major manufacturing industries: 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 the emission generating processes within these sectors largely depend on the burning of fossil fuels. 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, since the emission generation process of this industry involves emission from the decomposition of limestone and emission from the heating process through fossil fuels, and data on limestone is not available. The total emissions in tons, emission percentage across all the manufacturing industries, good outputs in dollar amount, and the 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 and chemicals and chemical products, which involve processes requiring a large amount of fuels burned for heating. Summary statistics for the inputs and outputs of different industries across all countries of 2014 are provided in Table 2.

Heterogeneity of emission-related inputs measured in TJ is a part of the embedded variation. As summarized by the U.S. Energy Information Administration, one million Btu of coal emits 228.6 pounds of CO_2, while natural gas emits only 117 pounds. In this situation, 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 the fuel mixture.[15] 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.

4 Results

The technology of different industries defined according to the by-production approach is captured by the environmental-oriented DEA model in (6). Solving the problem in (6) 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 3 for selected countries, including China, Germany, India, Japan, Mexico, and the U.S. We provide details for other countries in Appendix Table 1. In Table 3, for example, the score of 0.71 for Germany's paper industry means that it could have scaled down the emission to 71% of the current level. Mexico and Germany performed generally well across all of these four industries. The production process of Mexico is pollution-oriented efficient for those four sectors. Germany has relatively high performance scores (no lower than 0.6). The chemical products industry of India is efficient, while the paper products and basic metals industries of India did poorly and could have reduced CO_2 emission by more than 50%. Basic metals in the U.S. performed well and only 30% of the emission could be reduced; by contrast, a large proportion of emission could be reduced in coke and petroleum and chemical products industries of the United States. China could have reduced about 50% of the emission for all the selected industries. Japan did poorly for all the emission intensive industries including basic metals, chemical products and coke and petroleum sectors. Particularly, coke and petroleum industry in Japan could have reduced more

[15]To separate out the effects of heterogeneous inputs on pollution-oriented performance, it is necessary to utilize a dataset 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.

than 70% of the CO_2 emission.

The optimal solution of the problem (6) yields the input-output bundles at the efficient level. Starting with these efficient bundles, one can determine new projected input-output bundles when emission is required to be further reduced by $\bar{\gamma}$ =25% by solving the problem in (7). We calculated the opportunity cost of emission reduction in terms of the foregone revenue (in dollars per ton of emission reduction) as (8). The result is presented in Table 4a for selected countries and in Appendix Table 2 for more countries.

The cost of emission reduction in terms of foregone revenue 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 \$582 for the U.S. and by \$1,542 for Japan in the basic metals industries, and the comparable figures in the paper products industries are \$1,042 for the U.S and \$1,360 for Japan . 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 \$14,724 and \$18,211 in coke and petroleum sectors of the U.S and Japan, respectively. International comparison by sectors shows that: China has the highest costs in both paper products and coke and petroleum industries; India has the lowest cost in paper products, and Germany has the lowest in coke and petroleum; Japan (the U.S.) has the highest (lowest) cost in the chemical products, and India (China) has the highest (lowest) cost in the basic metals.

As mentioned earlier, the reduction in the value of intended output is more likely to overestimate the opportunity cost of emission reduction as it does not reflect cost savings from the reduction in fuel and (possibly) other inputs. We alternatively calculate the cost of emission reduction in terms of foregone variable profit. Foregone variable profit based on the difference between the foregone revenue and the change of variable cost is calculated using (9). The change of the variable cost consists of the cost change in materials, labor, and fuel. The cost change in materials and fuel are straightforward to measure because materials are in dollar amount, and the cost change in fuel could be calculated based on the Brent oil price and the quantity change in the fuel.

In addition, we collect the labor price for the selected countries from different sources to calculate the change in production cost.[16] The opportunity cost of emission reduction in terms of foregone variable profit (in dollars per ton of emission reduction) for selected countries is presented in Table 4b. We also provide Fig 1. for comparing the variation between foregone revenue and foregone profit across industries for selected countries.

As expected, the opportunity cost in terms of the foregone profit is less than the cost in terms of foregone revenue except for paper products industry. The basic metals industry has the lowest cost of emission reduction in terms of foregone profit than other sectors (except for India). For example, per ton emission reduction will reduce the profit by only \$116 for the U.S and \$216 for Japan in the basic metals industry. The cost of emission reduction in coke and refined petroleum products is generally higher than in other sectors. For instance, per ton of CO_2 reduction reduces the profit by \$2,851 and \$6,577 in coke and petroleum industry in the U.S. and Japan. The inter-country comparison of the costs in terms of foregone variable profit among these four sectors is similar to the one in terms of foregone revenue, except that Germany has the lowest cost of emission reduction in the chemical products industry and the U.S has the lowest cost in the basic metals industry. In general, promoting emission reduction policies in the basic metal industry will have a significant effect on the emission reduction at a lower cost, since the basic metal industry is a top-polluting industry across the selected countries, and it is also less costly to implement emission reduction in the basic metal industry than in others. By contrast, coke and petroleum industry is less likely to be included in a environmental policy based on its high emission-reduction cost.

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 revenue with the ratio of the intended output to the CO_2 emission (the inverse of emission intensity) in Table 4a and Table 5. Noticeably, the measure by this simple ratio is larger than the cost of emission reduction in terms of foregone revenue in basic metals industry except Mexico and India, whereas it is smaller in paper products industry. The

[16] We use OECD annual wage dataset for OECD members; the wage data of India is from Labour Bureau of India; for China, we employ the data from the National Bureau of Statistics of China.

simple ratio generally can not 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 the emission, and b) mostly the simple ratio measure is not along the production frontier but within the frontier, which does not consider any inefficiency.[17]

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 the 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 empirical finding 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 the sharply rising carbon price of EU Emissions Trading System 62.4 € per tonne, the recent allowance price in California was $24.3 per ton and $9.3 per ton in the market of the Regional Greenhouse Gas Initiative (RGGI) in the U.S. in September 2021. Based on our findings, there is considerable room for California and RGGI 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 polices leads to unemployment. In this study, we find that the effect of achieving a particular emission reduction target on employment is not always negative. The estimate of labor changes as in (10) is provided in Table 6 and presented in Figure 2 for selected countries.

It is noteworthy that the overall labor changes are equal to the sum of change due to the efficiency improvement $l^* - l$ and change due to the factor shift effect $l^{**} - l^*$. The factor shift effects are negative for selected countries, except for paper products industry. In paper products industry, labor demand at pollution-oriented efficient level is larger than the actual level except in China and

[17] 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.

India. The factor shift effects are positive except in China. In consequence, the overall effect of the particular emission reduction target on the employment of paper product industry is positive in Germany (47.78%), Japan (183.73%), Mexico (89.68%), and the U.S. (268%). In 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 factor shift effect 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 coke and refined petroleum, and chemical products industries. Labor demand increases in multiple industries of different countries especially in paper products industry.

5 Conclusion

Studies estimating the shadow price of undesirable output along production possibility frontier typically rely on the trade-off between the pollution reduction and the loss of desirable output. Analysis focusing on this trade-off requires conceptualizing a production technology which 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-product if the polluting input 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 revenue 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 the emission reduction. The results show that imposing environmental policy on basic metals industry will reduce the overall employment level for all the selected countries, but in other sectors, especially in paper products industry, implementing emission reduction plans may increase the 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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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

Table 1. Summary of Selected Polluting Manufacturing Industries

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

Table 2a. Summary Statistic: Manufacture of Basic Metals

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 2b. Summary Statistic: Manufacture of Chemicals and Chemical Products

Coke and Refined 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 2c. Summary Statistic: Manufacture of Coke and Refined Petroleum Products

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_2emission (in kt)	35	4298.82	43601.30	60.62	8909.65

Table 2d. Summary Statistic: Manufacture of Paper and Paper Products

Efficiency	Paper Products	Coke and Petroleum	Chemicals	Basic Metals
Country	C17	C19	C20	C24
CHN	0.44	0.41	0.51	0.52
DEU	0.71	1.00	0.65	0.60
IND	0.40	0.67	1.00	0.46
JPN	0.66	0.27	0.37	0.44
MEX	1.00	1.00	1.00	1.00
USA	0.66	0.35	0.47	0.70

Table 3. Environmental-Oriented Efficiency Score

	Paper Products	Coke and Refined Petroleum Products	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

Table 4a. Cost of Emission Reduction in terms of Foregone Revenue ($/ton)

	Paper Products	Coke and Refined Petroleum Products	Chemical Products	Basic Metals
Country	C17	C19	C20	C24
CHN	3751	7357	1523	283
DEU	2114	174	629	464
IND	634	8224	1299	960
JPN	3647	6577	4808	216
MEX	4249	506	1243	719
USA	2217	2851	2448	116

Table 4b. Cost of Emission Reduction in terms of Foregone Profit ($/ton)

	Paper Products	Coke and Refined Petroleum Products	Chemical 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

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

Paper Products	$(l^* - l)/l$	$(l^{**} - l^*)/l$	$(l^{**} - l)/l$
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 6a. Labor Changes in Paper Products Industry (in proportion)

Coke and Refined Petroleum Products	$(l^* - l)/l$	$(l^{**} - l^*)/l$	$(l^{**} - l)/l$
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 6b. Labor Changes in Coke and Refined Petroleum Products Industry (in proportion)

Chemical Products	$(l^* - l)/l$	$(l^{**} - l^*)/l$	$(l^{**} - l)/l$
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 6c. Labor Changes in Chemical Products Industry (in proportion)

Basic Metals	$(l^* - l)/l$	$(l^{**} - l^*)/l$	$(l^{**} - l)/l$
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

Table 6d. Labor Changes in Basic Metals Industry (in proportion)

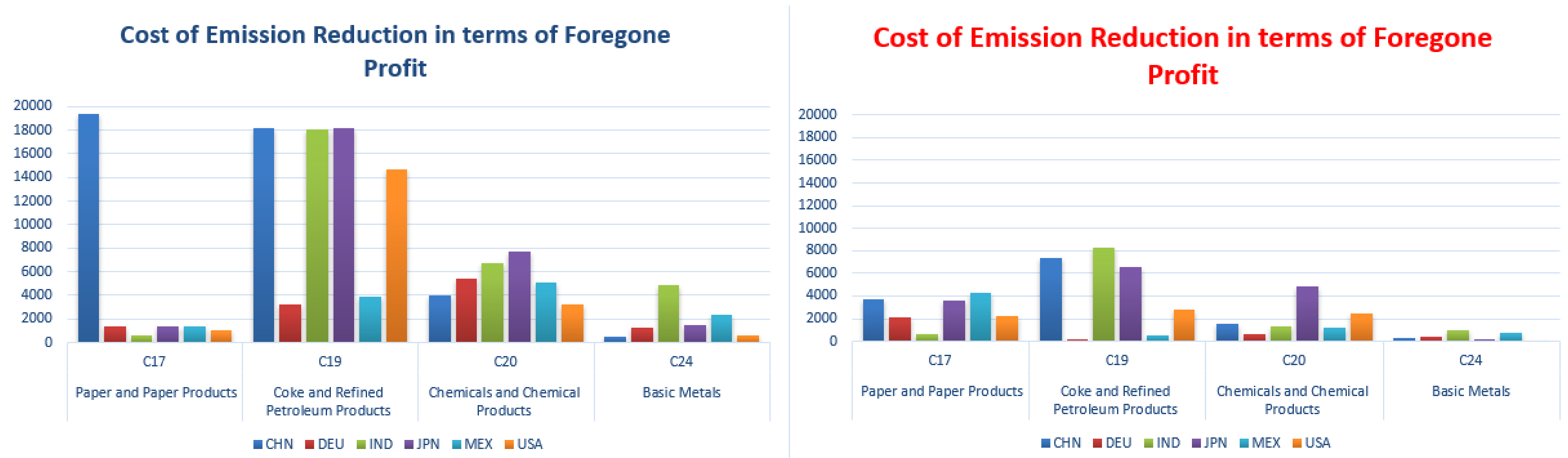

Figure 1. Comparison of Cost of Emission Reduction in terms of Foregone Revenue and Profit ($/ton)

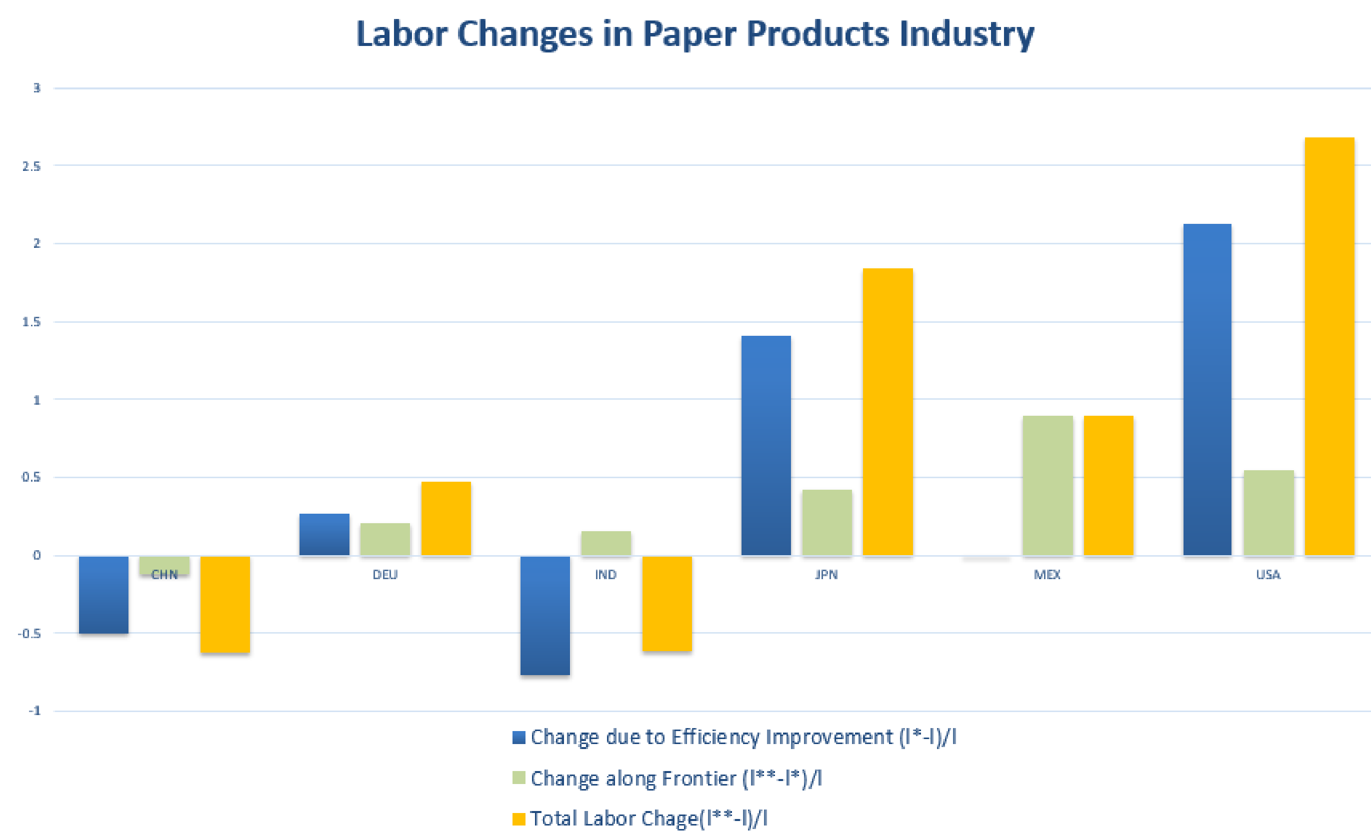

Figure 2a. Comparison of Labor Changes in Paper Products Industry (in proportion)

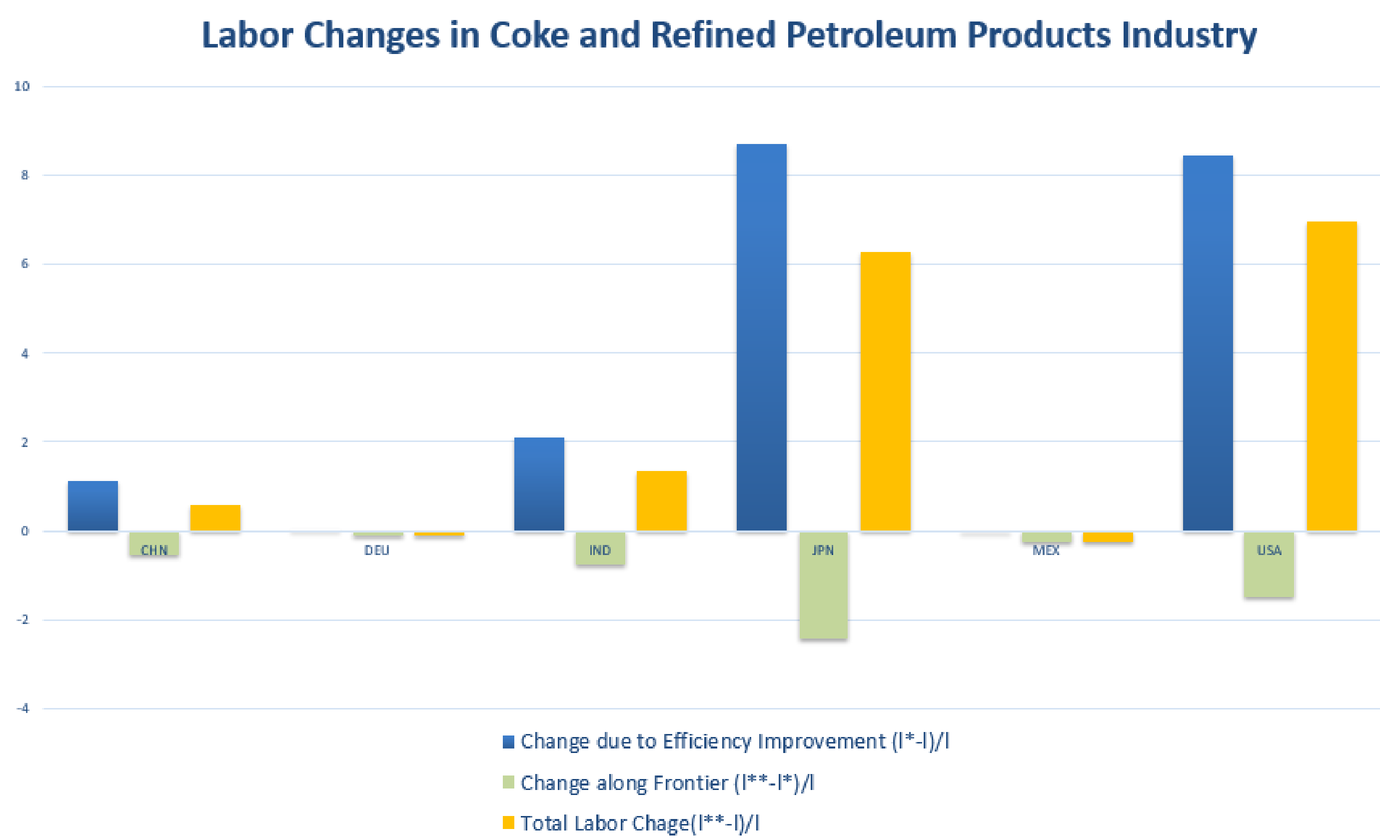

Figure 2b. Comparison of Labor Changes in Coke and Refined Petroleum Products Industry (in proportion)

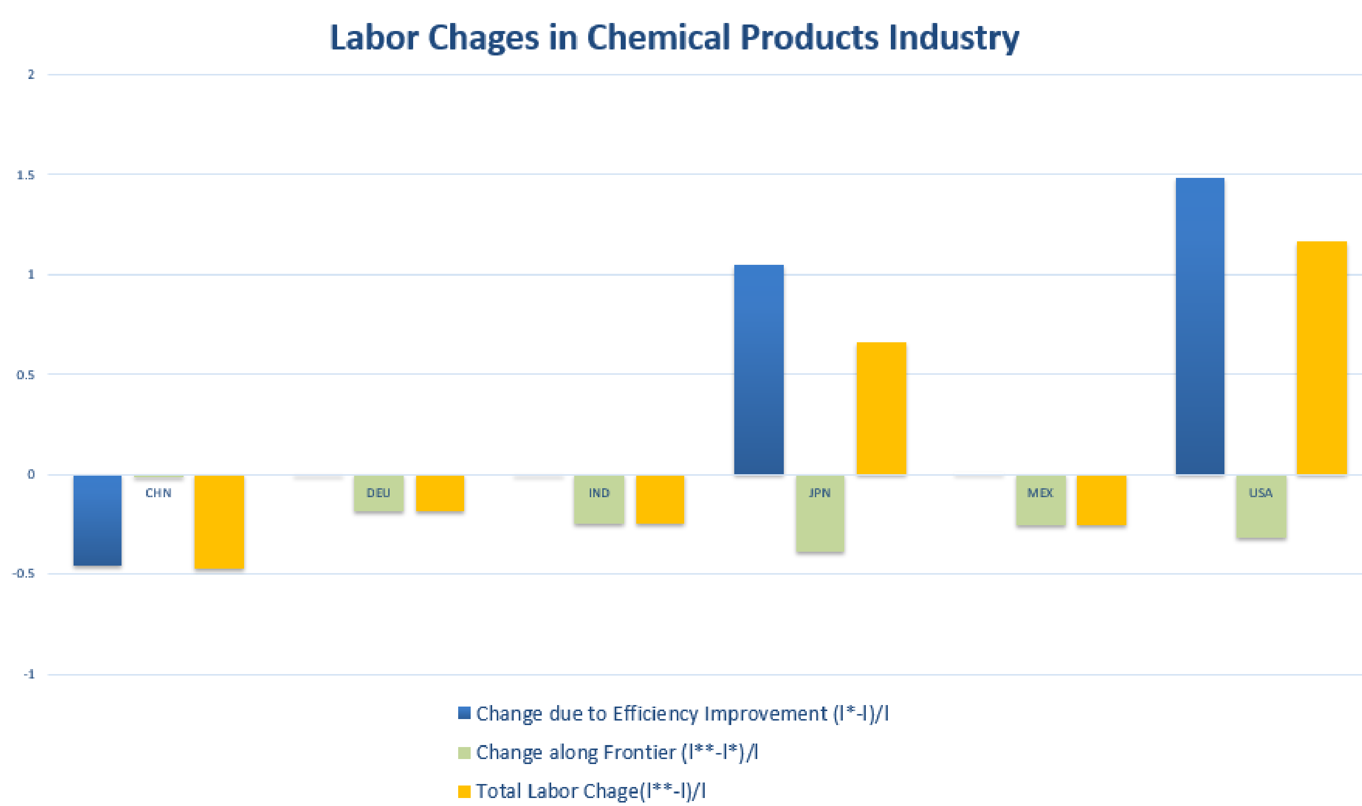

Figure 2c. Comparison of Labor Changes in Chemical Products Industry (in proportion)

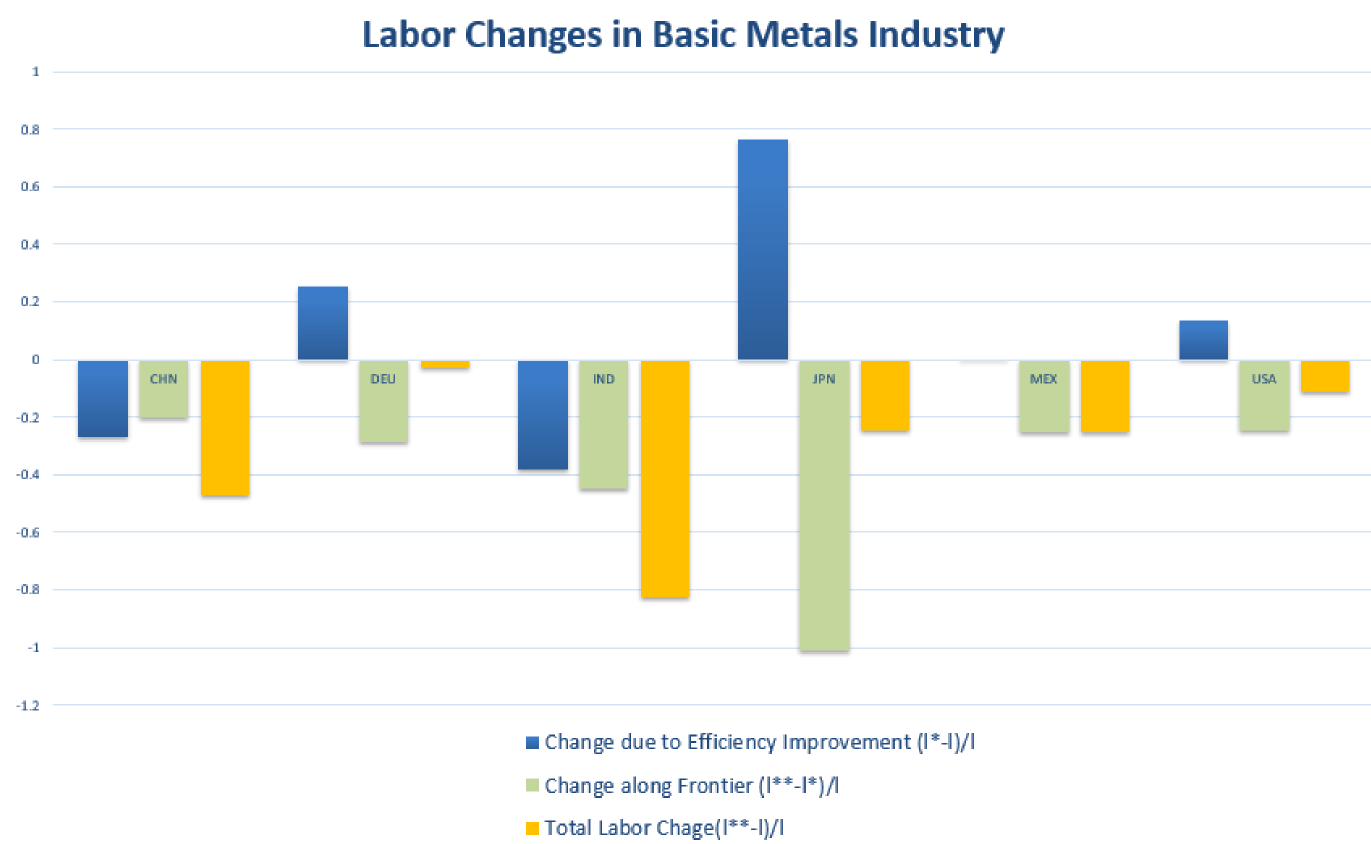

Figure 2d. Comparison of Labor Changes in Basic Metals Industry (in proportion)

	Paper Products	Coke and Refined Petroleum Products	Chemical Products	Basic Metals
country	C17	C19	C20	C24
AUS	0.7495	0.2195	0.3172	0.4182
AUT	0.4614	0.7807	0.9369	0.6151
BEL	0.6048	1.0000	0.4999	0.5766
BRA	1.0000	0.4479	0.8659	1.0000
CAN	1.0000	0.2757	1.0000	1.0000
CHN	0.4443	0.4097	0.5078	0.5246
CZE	0.5523	1.0000	0.4126	0.4683
DEU	0.7122	1.0000	0.6501	0.5975
ESP	0.3888	0.2393	1.0000	0.8555
FIN	0.7238	0.2047	0.7070	0.4338
FRA	0.5878	0.6208	0.7777	1.0000
GBR	1.0000	0.2240	0.6272	0.3898
GRC	1.0000	1.0000	1.0000	1.0000
HUN	1.0000	0.4466	0.5187	0.5075
IDN	1.0000	1.0000	1.0000	1.0000
IND	0.3993	0.6658	1.0000	0.4596
ITA	1.0000	0.2838	0.7560	1.0000
JPN	0.6643	0.2683	0.3750	0.4413
KOR	0.7266	0.6002	1.0000	0.4387
MEX	1.0000	1.0000	1.0000	1.0000
NLD	0.5388	0.2493	0.2718	0.4875
NOR	0.6635	0.3326	0.1594	0.2765
POL	1.0000	0.5193	1.0000	1.0000
PRT	0.5965	0.2953	0.9974	1.0000
ROU	0.8411	0.3683	0.2045	0.6795
RUS	1.0000	0.4216	0.1659	1.0000
SVK	1.0000	0.3273	0.4152	0.3335
SWE	1.0000	0.4483	1.0000	0.5525
TUR	1.0000	1.0000	1.0000	0.6096
USA	0.6666	0.3528	0.4696	0.6996

Note: we summarized environmental-oriented efficiency scores for 31 countries which includes the data for all the selected industries.

Table A1. Environmental-Oriented Efficiency Score

	Paper products	Coke and Refined Petroleum products	Chemical Products	Basic Metals
country	C17	C19	C20	C24
AUS	1609	8887	1095	398
AUT	1875	1584	5885	531
BEL	24260	5411	6405	1264
BRA	2530	18159	6709	184
CAN	2816	8903	380	1084
CHN	19416	18193	3975	559
CZE	10287	19047	4033	1310
DEU	1427	3185	5418	1317
ESP	4605	18216	6431	905
FIN	1598	12116	7844	1452
FRA	3425	5219	3739	149
GBR	1689	6406	4530	1638
GRC	11478	3065	2329	2282
HUN	25312	18153	6501	2856
IDN	11547	18113	4408	2904
IND	642	18091	6762	4856
ITA	4526	14975	6255	1174
JPN	1360	18211	7658	1542
KOR	3653	8214	6649	1249
MEX	1362	3911	5062	2385
NLD	9922	9251	7991	1144
NOR	8478	18137	6768	1559
POL	3831	6076	946	362
PRT	1828	18124	4322	21079
ROU	5144	18117	2376	1540
RUS	18674	18372	3421	105
SVK	9871	18282	9389	1084
SWE	17971	8760	4466	1661
TUR	19600	6532	15182	2085
USA	1045	14724	3284	582

Note: we summarized the costs of emission reduction for 31 countries which includes the data for all the selected industries.

Table A2. Cost of Emission Reduction in terms of Foregone Revenue ($/ton)