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Abstract: The so-called by-production approach, introduced by Murty and Russell (2002) and Murty et al. (2012), has provided researchers with an improved methodology for approximating polluting production technologies. However, since the original by-production model does not impose any relationship between its economic and environmental sub-technologies, it is not capable of addressing the potential tradeoff between the economic and environmental performance. Although this link has been recently proposed in the extensions to the original by-production approach, the tradeoff framework remains ambiguous with respect to the weights to be assigned to the economic and environmental sub-objectives. This paper proposes a novel approach for estimating the green productivity growth in the Chinese manufacturing sector based on the scenario analysis simulating policy preferences. Our model allows us to measure the tradeoff between faster economic growth and better environmental protection, providing policy-makers with insights on how to steer the Chinese industry towards a more environmentally friendly development path in the future.

Keywords: Tradeoff analysis; By-production technology; Carbon emissions; Green productivity; Chinese manufacturing.

JEL: O47, Q5, O2.

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Highlights:

1. Tradeoff of performance is analyzed using the by-production model and its extensions;

2. The weights associated with efficiency scores have an impact on productivity growth;

3. The scenario analysis simulating policy preferences is illustrated using manufacturing data;

4. Widespread technological progress drove productivity growth in Chinese manufacturing.

Analyzing the Tradeoff between the Economic and Environmental Performance: the Case of Chinese Manufacturing Sector

1. Introduction

Combining the measurement of economic and environmental performance is important in order to assess the negative externalities imposed by the economic growth on the environment. Evaluating the tradeoff between economic revenue and environmental cost has attracted plenty of attention from scholars and policy makers alike. The relationship between economic growth and its impact on the natural environment has been hypothesized using the environmental Kuznets curve (Grossman and Krueger 1991), which posits that growth imposes costs on the environment at its initial phases before reaching a certain threshold, beyond which any further improvements in living standards can be achieved at progressively lower cost to the environment. Although empirical studies of the environmental Kuznets curve have produced mixed results, nearly all underline the existence of a positive relationship between economic performance and environmental impact (e.g. Dasgupta et al. 2002), prompting some scholars to warn about severe consequences for the ecosystems if the costs imposed by growth on the environment continue to be ignored (Antal 2014).

The so-called by-production approach, introduced by Murty and Russell (2002) and Murty et al. (2012), represents a significant step towards the development of an improved framework for modeling a production technology that considers the environmental impact during the measurement of economic performance. The by-production approach is a multi-equation framework based on sub-technologies, whose intersection can be used to specify a pollution-generating technology. However, the original by-production model does not address the potential tradeoff between the economic and environmental performance, since it does not impose the necessary association between the independent sub-technologies. Although this relationship has been addressed in the subsequent studies relying on the by-production approach, the tradeoff framework remains ambiguous with respect to the weights to be assigned to the economic and environmental sub-objectives. This paper proposes a novel approach to estimate the green productivity growth in the Chinese manufacturing sector based on the scenario analysis that simulates alternative policy preferences. Our model allows us to measure the tradeoff between the economic expansion and pollution reduction, offering the decision makers a clear interpretation of this tradeoff.

China has been growing rapidly over the last several decades, becoming the world's largest carbon emitter in 2006. Its industrial sector contributes a significant share of the world's energy consumption, attracting plenty of attention from policy-makers and scholars (National Bureau of Statistics of China, 2008-2018). Energy consumption and environmental efficiency of the Chinese industrial sector have been analyzed in a relatively large number of existing studies. For example, Liu et al. (2012) measured the energy utilization of China's industrial sectors using the environmental input-output analysis and report that the total indirect energy consumption greatly exceeds that of direct energy consumption. Wu and Huo (2014) estimate the energy efficiency in the manufacturing and transportation sectors and rely on the Logarithmic Mean Divisia Index decomposition method to demonstrate that industrial furnace technologies are important for energy saving in China. Watanabe and Tanaka (2007) used the directional output distance function to estimate the efficiency of the Chinese industrial sector under two alternative output definitions. They report that the model assuming only the socially desirable outputs tends to overestimate the productive efficiency compared to the specification incorporating both the desirable and unintended, or socially undesirable, outputs.

Zhang (2009) use Data Envelopment Analysis (DEA) and the Shephard (1970) output distance function to estimate the environmental and technical efficiency of the manufacturing sector using data from China's provinces. Among other results, they demonstrate that the air pollution can be reduced by 60% when the desirable outputs are kept constant. Zhang et al. (2018) use a directional slacks-based model to estimate the green efficiency of China's industry sectors and supply-chains. Their results suggest that sectors representing the light industry had higher sectoral green efficiency and lower supply-chain green efficiency compared to that of heavy industrial sectors in 2012. Wu et al. (2016) use province-level data spanning 2005–2010 to assess the energy and environmental efficiency of the Chinese manufacturing sector. The authors demonstrate that the sector's energy and environmental efficiency was poor especially in the central and eastern parts of the country, and suggest that most provinces need to reduce their carbon dioxide emissions and energy intensity.

In their seminal paper, Ayres and Kneese (1969) proposed the materials balance principle for all transforming processes: the total weight of all material output of the production process must equal the weight of all material inputs. This concept was ignored by the economists until the end of last century (Lauwers 2009), when some environmental economists began considering it in their theoretical and empirical models. For example, Bergh and Nijkamp (1994) developed a macroeconomic model reflecting the relationship between the economy and natural environment. They considered several sectors, including the natural resource extraction, production, and treatment of pollutants, establishing the relationship between the economic processes and the materials balance principle. Ruth (1995) adopted the materials balance perspective to study the U.S. copper mining industry and simulate the optimal resource extraction over time. Krysiak and Krysiak (2003) demonstrated that the conventional applied economic models are not consistent with the physical constraints of mass and energy conservation and demonstrated how the conservation laws can be incorporated into the general equilibrium framework. Finally, Pethig (2006) show how the production-cum-abatement technology can be rendered consistent with the constraints ensuring material balance. While the above studies rely on the dynamic macroeconomic growth models, Coelli et al. (2007) were among the first to add the materials balance-related restrictions to a nonparametric DEA specification for measuring the environmental efficiency.

Approaches for modeling technologies characterized by the production of socially undesirable outputs can be divided into three main categories. The first group includes the studies that either treat the undesirable outputs as inputs or focus on detrimental inputs only. For example, Reinhard et al. (2000) did not consider any unintended outputs and defined environmental efficiency as the ratio of minimum feasible to observed quantity of environmentally harmful inputs, such as nitrogen, phosphate and energy use. Hailu and Veeman (2001) measured the productivity in the Canadian pulp and paper industry by treating the undesirable outputs as inputs in the context of the Chavas-Cox approach. They report higher productivity improvements when pollutants are taken into account during measurement compared to the estimates that do not take undesirable outputs into account. Considine & Larson (2006) consider sulfur dioxide emissions as an environmental resource and include them among the variable factors of production in their study of the U.S. utilities. They argue that emissions are similar to production inputs in that they must be tied to tradeable allowances to comply with the environmental regulations and are therefore costly. Similarly, in their study of productivity of the OECD countries Mahlberg and Sahoo (2011) treat greenhouse gas emissions as an input because they argue countries seek to decrease their level to minimize abatement costs.[1] Regardless of its intuitive appeal, this approach has been criticized in the literature due to its underlying assumption that, similar to inputs, unintended outputs can be increased indefinitely (Färe and Grosskopf, 2004).

The second approach considers the production of the different types of output as a joint process, following the ideas of weak disposability and null-jointness proposed by Shephard (1970) and Shephard and Färe (1974), respectively. For example, Färe et al. (1986) and Färe et al. (1989) relied on the assumption of weak disposability of outputs in their nonparametric studies of the utility companies and paper mills, respectively. Intuitively, the weak disposability axiom stipulates that since the undesirable and desirable outputs are closely interrelated, the former cannot be decreased at the frontier of technology without incurring cost in terms of the foregone output. In other words, if undesirable outputs are to be reduced then the desirable outputs must be reduced as well. The null-jointness assumption implies that if no undesirable outputs are produced then no desirable outputs can be produced, either. Despite suggestions that the weak disposability of outputs disregards the materials-balance considerations thereby violating the first law of thermodynamics (Coelli et al. 2007, Hoang and Coelli 2011), the approach based on this assumption has remained relatively popular in the literature.[2]

Finally, the third group includes the studies using the "by-production" model, introduced by Murty and Russell (2002) and generalized by Murty et al. (2012), Murty (2015) and Murty and Russell (2018), who argue that socially undesirable by-products need not always be produced jointly with desirable outputs and are instead caused by pollution-generating inputs. Under by-production, the technology is formed by combining two separate sub-technologies, i.e. a conventional sub-technology invented by humans and a pollution-generating sub-technology consistent with the notion of materials balance.[3] As we explain below, our specification extends this approach by introducing an exact relationship between the underlying sub-technologies.

The remainder of the paper is organized as follows. We introduce our methodology in Section 2, describe the data and results in Section 3 and discuss possible directions for future research along with our conclusions in the final section.

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[1] See, for example, Lee et al. (2002), Korhonen and Luptacik (2004), and Yang and Pollitt (2009) for additional studies based on this approach.

[2] Recent papers using the weak disposability model include, among others, Dakpo et al. (2016), Färe et al. (2017), Ray et al. (2018) and Pham and Zelenyuk (2019).

[3] Førsund (2009, 2018) emphasized a similar idea using the term "multi-equation model."

2. The by-production approach and its derivative models

The reduced form of the by-production technology was introduced by Murty and Russell (2002) and Murty et al. (2012). However, their original model lacks the explicit connection between the sub-technologies, which may lead to biased results (Dakpo et al., 2016; Baležentis et al., 2019). The tradeoff between the economic and environmental performance is naturally based on this connection and can be imposed in terms of the weights associated with efficiency scores from sub-technologies. However, as we demonstrate below, the original by-production model or some of its extensions cannot be used to model this tradeoff. We examine the existing models and propose a new specification allowing us to address this issue.

2.1. By-production technology

To define the by-production technology, we assume there are K decision-making units (DMUs) which in our case correspond to provinces in China. Each DMU consumes inputs and produces outputs. Two groups of inputs can be defined when defining the production set, namely, the 'clean' inputs (x^n) and polluting, or 'dirty,' inputs (x^p). Both inputs can produce the desirable outputs (y) while only the 'dirty' inputs generate the undesirable outputs (z). Accordingly, the production technology is separated into two sub-technologies: the production process that focuses on intended outputs is regarded as the economic sub-technology (T_1), whereas the pollution-generating process is modelled in the environmental sub-technology (T_2). The by-production technology (T_{BP}), proposed by Murty et al. (2012), can be defined as follows:

$$
\begin{aligned}
T_{BP} &= T_1 \cap T_2 \\
&= \left\{ (x^n, x^p, y, z) \in R_+^{N+P+M+J} : (x^n, x^p) \text{ can produce } y \text{ ; } x^p \text{ can generate } z \right\} \\
T_1 &= \left\{ (x^n, x^p, y) \in R_+^{N+P+M} \mid f(x^n, x^p, y) \leq 0 \right\} \\
T_2 &= \left\{ (x^p, z) \in R_+^{P+J} \mid g(x^p) \leq z \right\}
\end{aligned}
\quad (1)
$$

where f and g are continuously differentiable functions, with derivatives with respect to inputs and outputs, respectively. The production technology also satisfies the standard economic assumptions, such as convexity, closedness, disposability of inputs and outputs, and returns to scale. In order to distinguish desirable and undesirable outputs, the free disposability (A_1) is imposed on T_1 for all inputs and desirable outputs, which implies that the given outputs can be produced by more inputs than is absolutely necessary or given inputs can produce less outputs. The cost disposability (A_2) is imposed on T_2 for pollution-generating inputs and undesirable outputs, which indicates that the undesirable outputs cannot be abandoned as freely as the desirable ones. The free disposability and cost disposability are given below:

$$\begin{aligned}&A_1: \textit{if } (x^n, x^p, y, z) \in T_1, \textit{ then } (\tilde{x}^n, \tilde{x}^p, \tilde{y}, \tilde{z}) \in T_1 \textit{ for all } (-\tilde{x}^n, -\tilde{x}^p, \tilde{y}) \leq (-x^n, -x^p, y).\\ &A_2: \textit{if } (x^p, z) \in T_2, \textit{ then } (\tilde{x}^p, \tilde{z}) \in T_2 \textit{ for all } (\tilde{x}^p, -\tilde{z}) \leq (x^p, z).\end{aligned} \quad (2)$$

In our empirical application, we assume the manufacturing output is produced using labor force, capital stock and energy, while the province-level carbon emissions caused by the energy consumption are used to measure the environmental performance.

From an economic point of view, the social wellbeing can be improved if the desirable outputs increase to satisfy the domestic demand. At the same time, the undesirable outputs lead to negative externalities but are unavoidable in order to achieve the expansion of desirable outputs. In order to evaluate the tradeoff between the economic and environmental development of the Chinese industrial sector, we can formulate performance measures defined with respect to the environmental production technology and apply them to the Chinese provinces. Distance functions, which fully represent a production technology, can be used as a tool for measuring the improvement potential of these provinces when evaluated against the associated production frontier. For example, using a non-radial directional distance function (DDF), introduced by Chambers et al. (1996a), one can expand the desirable outputs and reduce the undesirable outputs simultaneously, i.e.:

$$D(x, y, z; g_x, g_y, g_z) = \max\left\{\delta, \theta \in R_+ : (x, y + \delta g_y, z - \theta g_z) \in T\right\}, \quad (3)$$

where δ and θ can be interpreted as the inefficiency scores that denote, respectively, the maximum possible increase in the desirable outputs and decrease in undesirable outputs in the direction given by the mapping vector (g_y, g_z). If $\delta = 0$ or $\theta = 0$, the evaluated province serves as a benchmark in a certain sub-technology.

2.2. Model specification

The original by-production model with non-radial DDF (Model 1) can be described as:

$$
\begin{aligned}
D(x,y,z;0,g_y,g_z) \;=\; & \max_{\delta,\theta,\lambda,\sigma}\left(w_{Eco}\sum_{m=1}^{M}\delta^m / M + w_{Env}\sum_{j=1}^{J}\theta^j / J \right) \\
s.t.\quad & \sum_{k=1}^{K}\lambda_k y_k^m \geq y_{k'}^m + \delta^m g_y^m,\ m=1,\dots,M \\
& \sum_{k=1}^{K}\lambda_k x_k^n \leq x_{k'}^n,\ n=1,\dots,N \\
& \sum_{k=1}^{K}\lambda_k x_k^p \leq x_{k'}^p,\ p=1,\dots,P \\
& \sum_{k=1}^{K}\lambda_k = 1,\ \lambda_k \geq 0,\ k=1,\dots,K \\
& \sum_{k=1}^{K}\sigma_k z_k^j \leq z_{k'}^j - \theta^j g_z^j,\ j=1,\dots,J \\
& \sum_{k=1}^{K}\sigma_k x_k^p \geq x_{k'}^p,\ p=1,\dots,P \\
& \sum_{k=1}^{K}\sigma_k = 1,\ \sigma_k \geq 0,\ k=1,\dots,K \qquad \text{(Model 1)}
\end{aligned}
$$

where $(g_{y,}g_z)$ is a nonzero vector maximizing the desirable outputs and minimizing the undesirable ones, defined by the value of outputs of the evaluated production plan. We use w_{Eco} and w_{Env} as the objective function weights, associated with the economic and environmental sub-technologies, respectively, and denote by λ_k and σ_k the activity variables for T_1 and T_2, suggesting the two production frontiers may correspond to different benchmarks values of x^p at the optimum.[4] The assumption of variable returns to scale (VRS) is imposed on T_1 and T_2 via $\sum_{k=1}^{K}\lambda_k = 1$ and $\sum_{k=1}^{K}\sigma_k = 1$, respectively.

The two sub-technologies in the by-production model formulated above are not linked explicitly, possibly yielding different benchmarks. Assuming such a link exists is also necessary

[4] Murty et al. (2012) assume $w_{Eco} = w_{Env}$ =50%.

in order to analyze the tradeoff between the economic and environmental performance. Indeed, as we demonstrate in Section 3, the inefficiency scores δ and θ remain constant unless either w_{Eco} or w_{Env} is assumed to be zero when no explicit relationship is imposed between the two sub-technologies. Hence, following Lozano (2015), Dakpo et al. (2016) and Baležentis et al. (2019), we impose this relationship by adding an additional constraint with respect to the optimal quantities of the polluting inputs to Model 1, or

$$\sum_{k=1}^{K} \sigma_k x_k^p = \sum_{k=1}^{K} \lambda_k x_k^p, \; p = 1, ..., P, \tag{4}$$

yielding the modified by-production model (e.g., Dakpo et al., 2016), i.e.:

$$\begin{aligned}
D(x, y, z; 0, g_y, g_z) \; = \; & \max_{\delta,\theta,\lambda,\sigma} \left(w_{Eco} \sum_{m=1}^{M} \delta^m / M + w_{Env} \sum_{j=1}^{J} \theta^j / J \right) \\
s.t. \; & \sum_{k=1}^{K} \lambda_k y_k^m \geq y_{k'}^m + \delta^m g_y^m, \; m = 1, ..., M \\
& \sum_{k=1}^{K} \lambda_k x_k^n \leq x_{k'}^n, \; n = 1, ..., N \\
& \sum_{k=1}^{K} \lambda_k x_k^p \leq x_{k'}^p, \; p = 1, ..., P \\
& \sum_{k=1}^{K} \lambda_k = 1, \; \lambda_k \geq 0, \; k = 1, ..., K \\
& \sum_{k=1}^{K} \sigma_k x_k^p = \sum_{k=1}^{K} \lambda_k x_k^p, \; p = 1, ..., P \\
& \sum_{k=1}^{K} \sigma_k z_k^j \leq z_{k'}^j - \theta^j g_z^j, \; j = 1, ..., J \\
& \sum_{k=1}^{K} \sigma_k x_k^p \geq x_{k'}^p, \; p = 1, ..., P \\
& \sum_{k=1}^{K} \sigma_k = 1, \; \sigma_k \geq 0, \; k = 1, ..., K
\end{aligned} \tag{Model 2}$$

However, this specification is still not capable of assessing the tradeoff between the economic and environmental performance, because its 3rd, 5th and 7th set of constraints, or

$$\begin{aligned}
&\sum_{k=1}^{K}\lambda_k x_k^p \le x_{k'}^p,\ p=1,\dots,P\\
&\sum_{k=1}^{K}\sigma_k x_k^p = \sum_{k=1}^{K}\lambda_k x_k^p,\ p=1,\dots,P\\
&\sum_{k=1}^{K}\sigma_k x_k^p \ge x_{k'}^p,\ p=1,\dots,P
\end{aligned} \tag{5}$$

collapse to a single restriction, given by

$$\sum_{k=1}^{K}\sigma_k x_k^p = \sum_{k=1}^{K}\lambda_k x_k^p = x_{k'}^p,\ p=1,\dots,P. \tag{6}$$

implying the quantity of the polluting inputs, which both help produce the good outputs and generate the socially unintended ones, remains fixed at its observed level at the optimum. As a result, the tradeoff between the roles played by the polluting inputs will not manifest itself properly in the solution to the above model and neither will the tradeoff between the sub-technologies and their associated efficiency scores. In other words, similar to Model 1, the above specification yields mostly identical optimal inefficiency scores δ and θ, suggesting no tradeoff between the economic and environmental performance. Following Baležentis et al. (2019), we solve this problem by dropping the constraint $\sum_{k=1}^{K}\sigma_k x_k^p \ge x_{k'}^p$, implying the attainable quantity of each dirty input is restricted to be less than or equal to its corresponding observed level. Hence, our Model 3 is given by:

$$D(x,y,z;0,g_y,g_z) = \max_{\delta,\theta,\lambda,\sigma}\left(w_{Eco}\sum_{m=1}^{M}\delta^m / M + w_{Env}\sum_{j=1}^{J}\theta^j / J \right)$$

$$\begin{aligned}
s.t.\quad & \sum_{k=1}^{K}\lambda_k y_k^m \geq y_{k'}^m + \delta^m g_y^m,\ m=1,\ldots,M \\
& \sum_{k=1}^{K}\lambda_k x_k^n \leq x_{k'}^n,\ n=1,\ldots,N \\
& \sum_{k=1}^{K}\lambda_k x_k^p \leq x_{k'}^p,\ p=1,\ldots,P \\
& \sum_{k=1}^{K}\lambda_k = 1,\ \lambda_k \geq 0,\ k=1,\ldots,K \\
& \sum_{k=1}^{K}\sigma_k z_k^j \leq z_{k'}^j - \theta^j g_z^j,\ j=1,\ldots,J \\
& \sum_{k=1}^{K}\sigma_k x_k^p = \sum_{k=1}^{K}\lambda_k x_k^p,\ p=1,\ldots,P \\
& \sum_{k=1}^{K}\sigma_k = 1,\ \sigma_k \geq 0,\ k=1,\ldots,K
\end{aligned}$$

(Model 3)

2.3. Scenario setting

Given the choice between faster economic growth and better environmental protection, analyzing environmental performance requires knowledge of the decision-makers' individual preferences. We treat these preferences as exogenous and model them using the weights entering the objective functions associated with Models 1-3. By changing the weights attributed to the corresponding sub-technologies, we can model a variety of scenarios representing the decision makers' different policy choices or preferences, summarized in Table 1. In addition to several relatively balanced weighing schemes, we also include two extreme scenarios corresponding to purely economic and environmental approaches attributing zero weight to the environmental and economic efficiency, respectively.

Table 1 Weights on economic and environmental sub-technologies for scenarios

Scenario	Approach	**Economic Weight** w_{Eco} (%)	**Environmental Weight** w_{Env} (%)
1	Economic	100	0
2		90	10
3	↑	80	20
4		70	30
5		60	40
6	Balanced	50	50
7		40	60
8		30	70
9	↓	20	80
10		10	90
11	Environmental	0	100

2.4. The Luenberger productivity indicator and its decomposition

Since distance functions can be used to define indicators of productivity change, we can use the DDF in (3) to measure productivity growth between time periods t and $t+1$ by relying on the difference-based output-oriented Luenberger productivity indicator (Chambers 1996, 2002) in the presence of undesirable outputs, given by:

$$LPI^{t,t+1} = \frac{1}{2}\begin{bmatrix} D^t\left(x^t, y^t, z^t; 0, g_y^t, g_z^t\right) - D^t\left(x^{t+1}, y^{t+1}, z^{t+1}; 0, g_y^{t+1}, g_z^{t+1}\right) \\ +D^{t+1}\left(x^t, y^t, z^t; 0, g_y^t, g_z^t\right) - D^{t+1}\left(x^{t+1}, y^{t+1}, z^{t+1}; 0, g_y^{t+1}, g_z^{t+1}\right) \end{bmatrix} \quad (7)$$

Following the insights of Chambers et al. (1996b), the Luenberger indicator can be decomposed into the efficiency change (EC) and technological progress (TP) components. The former component, which is often referred to as the catch-up effect, measures the changes in the distance to the production frontier occurring over time and can signal possible improvements attributed to a more efficient use of resources. The latter component indicates the frontier shift between time periods t and $t+1$ and reflects the productivity gains due to technological innovations.

Its measurement is rendered possible by estimating four different distance function values using various combinations of the data and reference technology associated with the two time periods. The decomposition of the Luenberger indicator can be summarized as:

$$
\begin{aligned}
&LPI^{t,t+1} = EC^{t,t+1} + TP^{t,t+1}, \\
&EC^{t,t+1} = D^{t}\left(x^{t}, y^{t}, z^{t}; 0, g_{y}^{t}, g_{z}^{t}\right) - D^{t+1}\left(x^{t+1}, y^{t+1}, z^{t+1}; 0, g_{y}^{t+1}, g_{z}^{t+1}\right), \\
&TP^{t,t+1} = \frac{1}{2}\left[\begin{array}{l} D^{t+1}\left(x^{t}, y^{t}, z^{t}; 0, g_{y}^{t}, g_{z}^{t}\right) - D^{t}\left(x^{t}, y^{t}, z^{t}; 0, g_{y}^{t}, g_{z}^{t}\right) \\ + D^{t+1}\left(x^{t+1}, y^{t+1}, z^{t+1}; 0, g_{y}^{t+1}, g_{z}^{t+1}\right) - D^{t}\left(x^{t+1}, y^{t+1}, z^{t+1}; 0, g_{y}^{t+1}, g_{z}^{t+1}\right) \end{array}\right].
\end{aligned}
\tag{8}
$$

3. Data and results

3.1. Data

For our empirical illustration, we use province-level manufacturing data corresponding to 30 Chinese provinces except Tibet. Table 2 presents the summary statistics describing our dataset. We assume capital and labor are the ‘clean’ inputs and energy is the ‘dirty’ input, generating the undesirable output. Due to the lack of the official data on industrial capital stock in China, we approximate it by applying the perpetual inventory method, i.e.

$$k_t = i_t / p_t + (1-\sigma_t)k_{t-1}, \qquad (9)$$

where k, i, p, and σ represent capital stock, fixed asset investment, price index for fixed asset investment, and depreciation rate, at time period *t*, respectively.

We aggregate the fixed asset investment corresponding to the manufacturing sector with production and supply of electricity, as well as the water and gas industries, to obtain the provincial-level volume of fixed asset investment. We subsequently convert this volume into the 2008 values using the fixed asset investment price index in order to account for inflation. We follow Chou (1995) to calculate the initial capital stock and set the depreciation rate at 10%. Similarly, we obtain the labor input by aggregating the number of employees across the same manufacturing sectors. Both the capital and labor data are collected from the China Statistical Yearbook. Our only polluting input – energy – consists of ten different types of fuel, including coal, coke, crude oil, diesel, kerosene, petrol, fuel oil, natural gas, liquefied petroleum gas and refinery dry gas, which we collect using the province-level regional energy balance tables. Considering coal is used as a final input but also for secondary purposes such as the generation of power and heating, we express our coal input as the sum of all coal consumed for various purposes. The other types of fuel are represented using their final consumption values. Finally, we convert the different types of fuel into their associated coal-equivalent values using the corresponding conversion coefficients. The energy use data and the conversion coefficients are taken from the China Energy Statistics Yearbook (National Bureau of Statistics of China, 2008-2018).

Our only desirable output comes from the China Industrial Statistical Yearbook (National Bureau of Statistics of China, 2009-2017) and represents the industrial value added, expressed in 2008 prices using the price index of industrial products. We rely on carbon dioxide emissions as our only undesirable output and calculate it by multiplying the quantities of energy generated by each fuel type by the corresponding carbon emission factor. These factors come from the Provincial GHG Inventory Preparation Guide compiled by the National Development and Reform Commission of China (2011).

Table 2 Dataset summary statistics

	Indicator	Unit	Mean	Std.Dev	Trend
Clean inputs	Capital	10^8 RMB at 2008 price	62484.6	83360.6	3.70%
	Labor	10^4 employees	332.9	362.7	4.32%
Dirty input	Energy	10^4 tons of coal equivalent	11632.7	7275.8	3.94%
Good output	GDP	10^8 RMB at 2008 price	7942.3	6998.5	8.07%
Bad output	CO_2	10^4 tons	22730.2	16116.0	2.29%

Except Tibet, Hong Kong, Macao, and Taiwan, the provinces are grouped into three geographical zones for performance analysis. The eastern region includes 11 provinces, such as Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, and Hainan. The inland region comprises 8 provinces, i.e. Shanxi, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, and Hunan. Finally, the western region’s 11 provinces include Inner Mongolia, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia, and Xinjiang.

3.2 Results

We measure the performance of China's manufacturing sector by applying different specifications of the by-production model and estimating the linear programs given in Models 1-3. Our economic and environmental efficiency scores take into account various preferences with respect to the tradeoff between these two types of performance, which we model using a range of weights, illustrated in Table 1, attached to the efficiency scores in the objective function. In addition, all our models allow for non-radial changes in both the inputs and outputs, implying different variables can be adjusted to a different extent to reach the production frontier.

Model 1 is the basic by-production model that assumes no explicit links between the economic and environmental sub-technologies. Model 2 introduces this relationship by imposing equality between the quantities of the 'dirty' inputs used by the two sub-technologies, but does not allow these quantities to vary. Model 3 is the most general of the three in that it allows the quantity of the 'dirty' input to be contracted while simultaneously restricting it to be the same across the two sub-technologies. In Table 3 we summarize the corresponding economic and environmental efficiency scores, which we obtained by taking the average across all time periods and provinces. To demonstrate the true tradeoff between the sub-technologies, we choose to report the inefficiency estimates δ and θ rather than $w_{Eco}\delta$ and $w_{Env}\theta$, allowing us to disregard the impact the weights may have on the results.

Table 3 The average economic and environmental inefficiency scores for the Chinese manufacturing sector (% p.a., 2008-2017)

Scenario	Approach	Model 1		Model 2		Model 3	
		δ (%)	θ (%)	δ (%)	θ (%)	δ (%)	θ (%)
1	Economic	22.18	-5.81	17.82	-9.46	22.18	-2.15
2		22.18	46.36	17.82	45.56	22.07	56.51
3	↑	22.18	46.36	17.82	45.56	21.47	59.88
4		22.18	46.36	17.82	45.56	20.78	61.96
5		22.18	46.36	17.82	45.56	19.07	65.08
6	Balanced	22.18	46.36	17.82	45.56	16.71	67.93
7		22.18	46.36	17.82	45.56	13.81	70.31
8		22.18	46.36	17.82	45.56	6.56	74.13
9	↓	22.18	46.36	17.82	45.56	-6.52	78.49
10		22.18	46.36	17.82	45.56	-17.28	80.43
11	Environmental	-58.43	46.36	-40.82	45.56	-57.51	80.98

Note: δ and θ are inefficiency scores associated with the good and bad output, respectively.

Looking at the four middle columns of the table we can see that the results rendered by Models 1 and 2 are virtually invariant to the choice of the weights defining the different scenarios. For example, Model 1 suggests the desirable output could be increased by about 22% and the undesirable output simultaneously decreased by roughly 46% when both the economic and environmental efficiency scores are attributed non-zero weights, on average. Turning to the scenario where economic growth carries all the weight with cost to the environmental playing no role whatsoever we note the carbon dioxide emissions could be increased by an average of about 6% while maintaining the same 22% growth in our desirable output, or value added. Our other extreme scenario is the purely environmental approach, which puts the entire weight on the environmental performance and ignores economic inefficiency completely. Looking at the last row of Table 1 we can see that it would require a roughly 58% decrease in the desirable output while the average environmental inefficiency remains the same as in the case of the relatively balanced scenarios (46%).

Results corresponding to Model 2 are very similar in that they too suggest virtually no tradeoff between the two approaches. For instance, the estimates of average economic and environmental inefficiency equal approximately 18% and 46%, respectively, whenever nonzero weights are assumed during estimation. Similar to Model 1, the purely economic approach calls for a 9% increase in the undesirable output while the economic inefficiency remains the same as when the choice between economic growth and environmental protection is relatively balanced. Also similar to Model 1, the purely environmental approach suggests the desirable output should fall by 41% as the average level of carbon dioxide emissions is reduced by approximately 46%.

Model 3 provides more nuanced results across the scenarios. Indeed, the economic inefficiency increases from about 13% to 22% when the weight attributed to the desirable output grows from 40% to 100%. Unlike with the first two specifications, Model 3 can yield negative economic inefficiency estimates under some nonzero weights attributed to economic performance, suggesting a decrease in the desirable output is necessary to reach the production frontier. As shown at the bottom of the next-to-last column of Table 1, this occurs whenever the weight of the corresponding slack falls below 20%. The average environmental inefficiency gradually increases from 57% to 81% as the corresponding weight grows from 10% to 100%. Compared to the two previous specifications, the estimated increase in the carbon dioxide emissions is slightly smaller under Model 3 at roughly 2% on average when the environmental protection is assumed to be completely unimportant.

Our results have both theoretical and empirical implications. For example, regardless of the type of model, the environmental inefficiency estimates are always higher than their economic performance counterparts, except under one of the extreme scenarios which ignores the environmental impact completely. In addition, Models 1 and 2 are not capable of properly taking into account the trade-off between the two sub-technologies and their associated inefficiency scores. Imposing a relationship between the economic and environmental sub-technologies via a suitable constraint in Model 3 yields solutions that are sensitive to the policy-makers' preferences, modelled via weights included in the algorithm's objective function. In other words, the weighted inefficiency estimates contain little information about the tradeoff between the economic and environmental performance unless this additional restriction is included during estimation.

Since the three geographical areas discussed above have experienced varying degrees of economic development, technical progress and environmental degradation, we next turn our attention to the differences in the performance across China's regions. We focus on the Model 3 results and begin by reporting the mean inefficiency scores for the eastern, inland and western region under each of the various scenarios. Our results are illustrated in Figure 1.

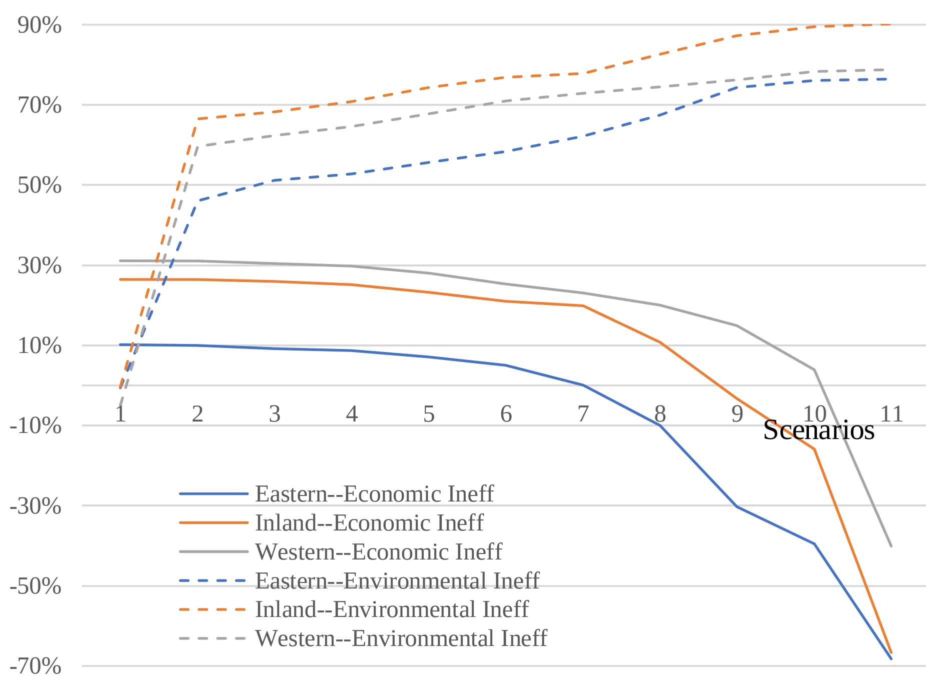


Figure 1 Inefficiency tradeoff across different scenarios under Model 3 (% p.a., 2008-2017)

Note: Scenarios from Table 1 are plotted on the horizontal axis; δ and θ are inefficiency scores for the economic and environmental sub-technology, respectively.

As expected, the three regions differ in terms of both their mean economic and environmental performance. For instance, the inland regions appear to be the most environmentally inefficient ones, while the western zone is associated with the highest economic inefficiency regardless of which scenario we assume. Both the economic and environmental performance appears to be the best in China's relatively developed east. We also note that the economic inefficiency is more sensitive to the weighting scheme than is the environmental performance. The decrease in the importance attributed to the economic performance triggers a relatively steep fall in the economic inefficiency and, in turn, improvements in the super-efficiency along the economic dimension when the regions are considered simultaneously. However, the environmental super-efficiency can only be established under a single scenario representing a purely economic approach. In other words, achieving economic super-efficiency assuming environmental protection is relatively important appears to have been easier, albeit at a substantial cost in terms of environmental inefficiency, than attaining environmental super-efficiency even if policy-makers chose to adopt scenarios disregarding environmental degradation and focused almost exclusively on economic growth.

We next turn our attention to the analysis of productivity using distance functions, which was outlined in Section 2.4. As we showed in Table 3, the economic and environmental efficiency scores corresponding to Model 3 vary across different scenarios. Therefore, the productivity measures based on these estimates will also vary with the change in policy-makers' preferences for the two types of performance in question. Hence, we rely on the Luenberger productivity indicator in order to analyze the dynamics and sources of the productivity change in China's industrial sector between 2008 and 2017 as a whole. Table 4 summarizes the average year-on-year results corresponding to the change in efficiency, technology and productivity we obtained using Model 3.

Table 4 Efficiency, technical and productivity change under various scenarios

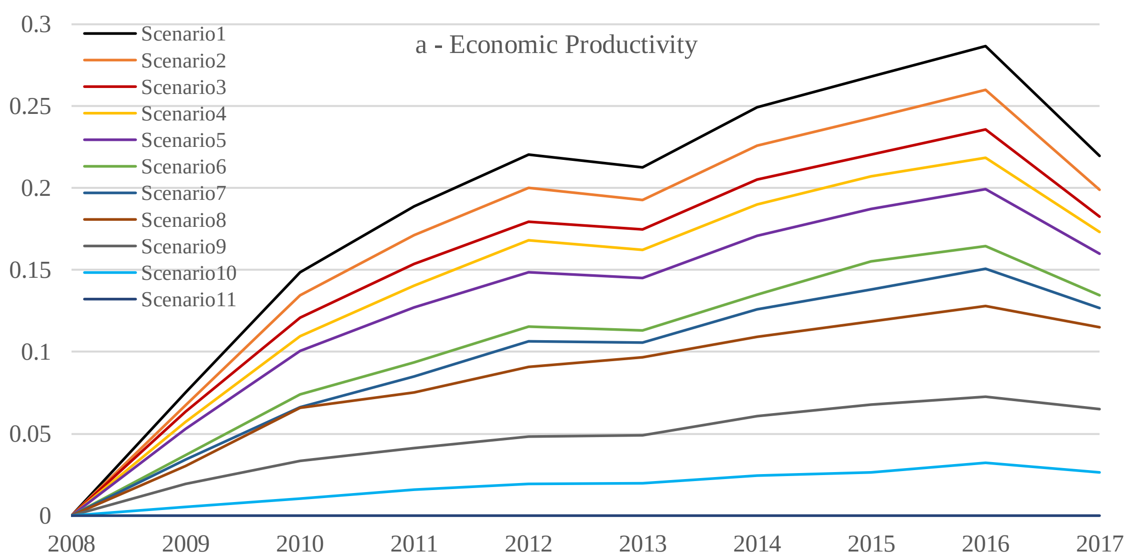
(% p.a., 2008-2017)

Scenario	Approach	Overall			Economic			Environmental		
		TFP	EC	TP	TFP	EC	TP	TFP	EC	TP
1	Economic	2.56	-1.81	4.37	2.56	-1.81	4.37	0.00	0.00	0.00
2		2.49	-1.74	4.23	2.32	-1.63	3.96	0.16	-0.11	0.27
3	↑	2.36	-1.68	4.05	2.12	-1.46	3.58	0.24	-0.22	0.46
4		2.17	-1.60	3.77	2.01	-1.29	3.31	0.16	-0.31	0.47
5		1.93	-1.48	3.41	1.83	-1.29	3.13	0.09	-0.18	0.28
6	Balanced	1.64	-1.28	2.93	1.59	-1.17	2.76	0.05	-0.12	0.17
7		1.27	-1.07	2.34	1.48	-0.98	2.46	-0.20	-0.09	-0.12
8		0.80	-0.84	1.64	1.27	-0.81	2.08	-0.47	-0.03	-0.43
9	↓	0.31	-0.52	0.82	0.72	-0.69	1.41	-0.41	0.18	-0.59
10		-0.08	-0.16	0.08	0.32	-0.26	0.58	-0.40	0.10	-0.51
11	Environmental	-0.43	-0.07	-0.36	0.00	0.00	0.00	-0.43	-0.07	-0.36

The pattern of the change in productivity appears to be consistent with what we reported in Table 3 about the average environmental inefficiency generally exceeding the average economic inefficiency regardless of the policy-makers' preferences. Indeed, looking at the estimates of the change in environmental productivity summarized in Table 4 we can see that its best improvement could have been achieved under the third scenario and would have equaled 0.24% per year on average. We can also see that environmental productivity deteriorates under all scenarios treating environmental performance as relatively important. By contrast, the annual mean economic productivity growth is always positive and its lowest estimate equals 0.32% when the purely environmental approach is not taken into account. In other words, our findings suggest the average change in economic productivity has been positive but also more substantial than the improvements in environmental productivity.

The overall annual productivity growth combines the change in economic and environmental productivity and depends on the chosen scenario as well. Its estimate ranges from -0.43% when the environmental performance is attributed the entire weight to 2.56% under the purely economic approach. Under a relatively balanced approach assuming both economic growth and environmental protection are equally important, the average annual improvement in productivity equals 1.64%, with the economic productivity growth of 1.59% acting as the main driver of this change. As regards the decomposition of the overall productivity growth itself, the annual improvement in technology (2.93%) more than offsets the simultaneous drop in the efficiency level (-1.28%) under the balanced approach, suggesting the productivity growth and the technological progress that powers it would have been driven by a relatively small number of relatively overperforming regions. Looking at the efficiency change estimates, or EC, we note a relatively widespread increase in both economic and environmental inefficiency under almost all scenarios, pointing to lack of any significant spread of the best production and environmental protection practices from the relatively efficient regions to the relatively inefficient ones, as the latter are struggling to catch up.

Finally, we consider cumulative productivity change for 2008-2017 under different scenarios, illustrated in Figure 2. Looking at the trends corresponding to the growth in economic productivity depicted at the top panel, we can see that the magnitude of its overall increase depends on the underlying scenario and equals around 14% under the approach assuming equal weights. As expected, both the overall magnitude of change and the annual rate of growth decline when policy-makers choose to pursue approaches favoring primarily the environmental performance. For example, the cumulative improvement in economic productivity would have equaled just 2.5% under scenario 10, which attributes a 90% weight to the environmental sub-technology. The change in environmental productivity appears to have followed a negative trend between 2008 and 2012 before recovering towards a positive trajectory from 2013 onwards. However, the overall cumulative environmental productivity would have declined under half of our scenarios, lending support to the premise that the improved economic performance of the Chinese industrial sector has likely come at the substantial cost to the environment.



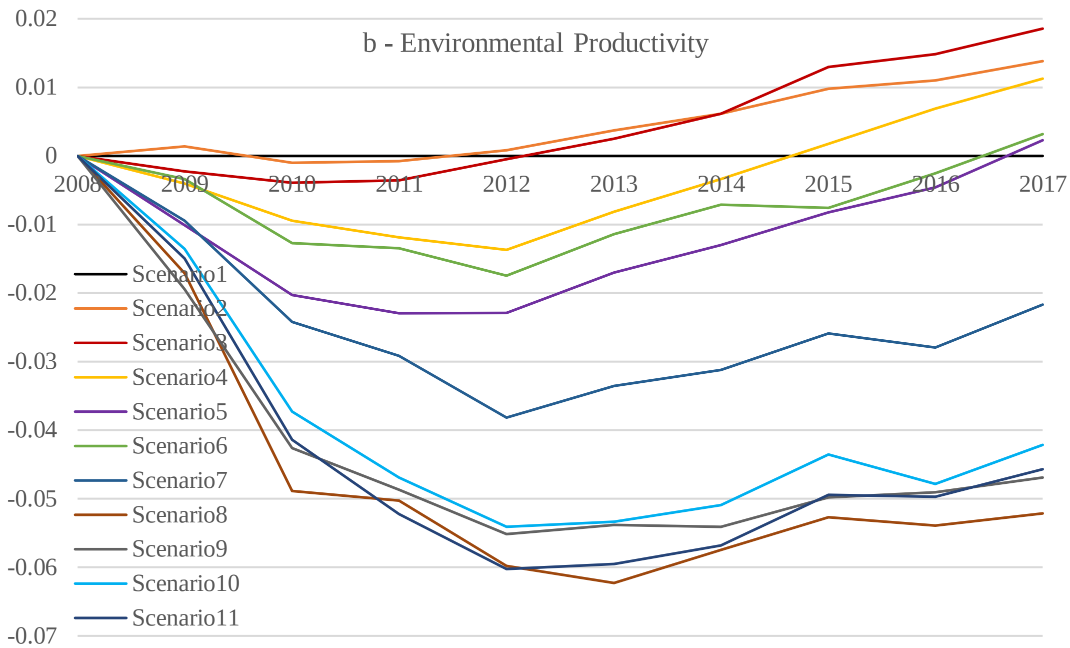


Figure 2 Cumulative change in the economic and environmental productivity across different scenarios (% p.a., 2008-2017)

4. Conclusions

We extend the so-called by-production model for the measurement of environmental efficiency by proposing a modification accounting for the relationship between the model's economic and environmental sub-technologies. In addition to linking the two sub-technologies, our main contribution lies in the proposed specification's flexibility, allowing the quantity of the polluting inputs to vary at the optimum. Extensions to the original by-production model recently proposed in the literature do not account for the tradeoff between the roles these inputs play in the production of good and bad outputs.

We use Chinese province-level manufacturing data to illustrate our approach empirically. Our estimates of the change in efficiency, technology, and productivity between 2008 and 2017 assume a range of scenarios policy-makers may wish to pursue given the tradeoff between the economic and environmental performance. Our results suggest the regions have almost always fared much better in terms of their economic efficiency than the environmental one, implying they may be far more similar to one another with regards to the traditional practices companies use to create value than they are in terms of the procedures aimed at curbing their carbon dioxide emissions. Indeed, environmental efficiency appears to be fairly difficult to achieve, as the only possible scenario under which it would have been feasible is the extreme case of the purely economic approach attributing no importance to the pollution levels whatsoever.

We also demonstrate that the total productivity in China would have increased under all scenarios attributing a meaningful weight to the economic sub-technology. This improvement in the overall performance, which combines the economic and environmental productivity, is driven almost exclusively by its economic component as the environmental productivity stays almost unchanged under the relatively balanced approaches. The improvements in both economic and total productivity are in turn a consequence of widespread technological progress, whose magnitude is as a rule more than sufficient to offset the equally widespread simultaneous increase in both economic and total inefficiency. Looking forward, it would be interesting to see to what extent the relatively inefficient regions manage eventually to catch up with the technically efficient geographical zones driving this progress.

As China is set to continue improving its standard of living in the post COVID-19 era and given the emergence of increasingly finessed approaches for measuring the impact of economic growth on the environment, it is important to assess the choices policy-makers have under their disposal as they try to strike the perfect balance between economic growth and environmental protection. We propose a framework for the measurement of efficiency and productivity allowing policy-makers to choose from a number of alternative scenarios associated with this tradeoff.

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