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Comparing green productivity under convex and nonconvex technologies: Which is a robust approach consistent with energy structure?

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Abstract

Total factor productivity is used to explore the input–output efficiency of the economy and the driving factors behind economic growth. Although scholars have researched the total factor productivity approach, comparisons among different models in empirical research are rare and few scholars have focused on worldwide total factor productivity gains. Using convex and nonconvex technologies, this contribution investigates green productivity gains of 129 worldwide countries during 2000–2019 based on three popular productivity measures, namely, Luenberger–Hicks–Moorsteen indicator, Luenberger productivity indicator, and Malmquist–Luenberger index, respectively. Inspired by a metafrontier approach, we compare their productivity evolutions with the energy structure among 121 economies. A negative relationship is expected between the change in the proportion of fossil fuel energy consumption and green productivity. Our results show that the Luenberger–Hicks–Moorsteen productivity indicator under nonconvex technologies is a more convincing productivity measure when considering undesirable outputs in production technology.

1 | INTRODUCTION

Productivity, a crucial factor in economic growth, is a major concern. There is tremendous income inequality among countries. For instance, based on World Bank statistics, in 2020, Burundi had the lowest gross domestic product (GDP) per capita (237$), while Luxembourg had the highest (135,683$), which was about 573 times higher than the former. The lagging economy and poverty are largely the result of backward production. In turn, they may affect production, creating a vicious cycle whereby low productivity and poverty are exacerbated. Nowadays, many people are still experiencing extreme poverty, and the COVID-19 pandemic further slows productivity growth rates and exacerbates poverty worldwide (Deaton, 2021). With increasing productivity, a country can get more outputs from the same inputs and achieve more efficient use of resources. Additionally, productivity growth can contribute to sustained per capita income growth and poverty reduction (Dieppe, 2021). Productivity growth is a key concern of many countries, and inspires them to strive for greater economic efficiency and higher income. To explore the input–output efficiency of the economy and the driving factor behind economic growth (Bauer, 1990), the total factor productivity (TFP) notion is introduced and used to achieve high-quality and long-term economic development.

Green productivity has become a major concern in research in the last decade. Environmental issues have garnered a lot of attention recently, since climate change, acid rain, the decline in biodiversity, and so forth have become increasingly serious problems (Wang et al., 2020). As reported by the IPCC, global annual average greenhouse gas emissions increased by 12% between 2010 and 2019 (from 52.5 to 59 billion tons). Many international conferences are organized to discuss the climate change issue and to set up plans for reducing global emissions. The public's awareness of environmental issues is promoted. Environmentally friendly and sustainable development models are pursued by a wide range of countries (Yuan et al., 2021).

Traditional economic models focusing exclusively on economic factors when assessing productivity are insufficient. The productivity concept need be enlarged to face the challenges of sustainable development. More and more researchers integrate environmental issues into the framework of productivity by measuring environmental performance under economic growth (Feng & Serletis, 2014). Some undesirable outputs (like carbon dioxide, sulfur dioxide, and nitrous oxide) are used to evaluate the green productivity development of the economy.

While fossil energy is crucial for the economic development of countries, it is also extremely harmful to the environment. Fossil energy has promoted the development of industrial industries, greatly improved productivity levels, and contributed significantly to economic growth (Ivanovski et al., 2021; Sasana & Ghozali, 2017; Shahbaz et al., 2020). It performs an essential function in the production of each country and provides a crucial material foundation for the survival and development of the country (Ellabban et al., 2014). With over 80% of all energy consumption still from fossil fuels, they remain the primary source of energy. Without investment in fossil fuels, many industries are unable to grow, hampering economic growth. However, it also pollutes the environment and consumes large amounts of resources and energy. Higher productivity growth fueled by fossil fuels may be unsustainable in the long run, since they cause climate change and global warming, which have negative environmental effects on humans as well as other creatures (Rath et al., 2019). Therefore, the consumption of fossil energy cannot reconcile economy and ecology, affecting the development of a green economy (Cao et al., 2020; Danish & Ulucak, 2020; Rath et al., 2019; Yan et al., 2020). Clean energy is getting more and more attention as the transformation of the energy structure becomes the current development direction (Xie et al., 2021). However, for many countries, the share of fossil fuels is still growing, dominating energy consumption (Sasana & Ghozali, 2017). The economy is still predominantly powered by fossil fuels due to the rising dependence on fossil fuel usage. Thus, it is difficult to achieve a green economy.

Investigating how energy consumption affects green productivity is critical to the future of the economy. Energy is an important resource endowment. Energy structure evolution and its resource misallocation may lead to unbalanced development among economies. We look for a robust approach to modeling green productivity indices, which is consistent with the energy structure. This study assumes an inverse connection between the share of fossil fuel consumption and green productivity. It believes that fossil fuel energy is a good indicator to test whether the economy has achieved green growth. Studying the correlation between fossil energy and the green economy can provide empirical evidence for energy transition and economic growth that better supports sustainable development.

Whether different approaches to measure TFP provide an empirically good estimation remains uncertain. There are multiple indicators and indices to estimate TFP that transform the static efficiency problem into a productivity measurement problem. Most existing literature has adopted ratio-based Malmquist (Krüger, 2003; Li & Liu, 2010) or Malmquist–Luenberger (ML) indices (Cao et al., 2020; Oh, 2010). Also, a difference-based Luenberger productivity indicator (LPI) (Fukuyama & Weber, 2017) or extensions of these methods to assess productivity change are commonly used. However, a lot of problems exist in these approaches, making it difficult to give a perfect TFP estimation. The Luenberger–Hicks–Moorsteen (LHM) indicator (Briec & Kerstens, 2004; Shen et al., 2019), a complete additive approach, is not so widely used. Although some studies have compared the difference between some of these approaches (Kerstens et al., 2018), it is still hard to tell which model is the best and more realistic and has more accurate calculation results in empirical analysis.

The main objectives of this contribution are two-fold. First, this contribution evaluates and compares the green TFP (GTFP) of 129 countries under different models. Second, to compare the robustness of different approaches, it constructs a two-way fixed model to test the correlation between the energy consumption share and green TFP growth. There are several ways in which this contribution advances the literature in the field. First, it investigates worldwide green productivity gains, which deepens understanding of green productivity across countries and can contribute to improving green growth in different countries. Second, it adopts a by-production (BP) model under a metafrontier approach, which is consistent with the material balance principles (MBPs) and better solves the problem of heterogeneity. Third, it compares the LHM, Luenberger indicators, and Malmquist–Luenberger index under both convex and nonconvex models and determines which one is more robust. This provides some reference for selecting productivity indicators in future research.

The remainder of this study is structured as shown below. Section 2 summarizes the research on the TFP about its calculation, research scope, and relationship with energy structure. Section 3 discusses the approaches to calculating GTFP, the regression model, the description and selection of variables, and the data sources. Section 4 analyzes the fossil energy consumption in different regions, green productivity under different models, and regression results. Finally, Section 5 draws conclusions and provides further discussions.

2 | LITERATURE REVIEW ON GREEN PRODUCTIVITY AND ENERGY STRUCTURE

TFP can be measured by different approaches, which mainly contain two categories. The first category is ratio-based indices. Caves et al. (1982) propose Malmquist input, output, and productivity indices that do not rely on a continuous time assumption, but that need information on parameters to estimate. By calculating the geometric average of the two Malmquist or Malmquist productivity indices, the Törnqvist or Törnqvist productivity indices can be obtained, which can be calculated if prices and quantities are known. Bjurek (1996) proposes the Hicks–Moorsteen index, as a ratio between Malmquist output and input quantity indices, which can accommodate variable returns to scale technologies. Since the Hicks–Moorsteen index is characterized by input and output efficiency measures and the Malmquist productivity index is expressed by distance functions, both these methods ignore byproducts in production. Thus, these indices are insufficient to measure green productivity. Chung et al. (1997) define the ML index based on the directional distance function (DDF) to better treat pollution that inevitably accompanies the production of good outputs. This index is further discussed and developed at the theoretical and empirical levels (see, e.g., Cao et al., 2020; Färe et al., 2001; Kumar, 2006; Oh, 2010).

The second category is difference-based indicators. The first category of indices has some inevitable defects, like zero observations are hard to deal with, as these indices are independent of change in origin (Chambers, 2002). Chambers (2002) proposes the LPI based on DDF, a translation measure rather than a radial presentation. Many scholars have further discussed and improved this indicator. For instance, Briec and Kerstens (2009) use this indicator to explore the infeasibilities of the DDF and their solution is to report any infeasibility that occurs. Balk et al. (2008) show how to convert the LPI to the Malmquist productivity index by selecting a particular directional vector for the DDF. Additionally, the LPI has been extensively employed in various areas of empirical study, like manufacturing (Cao et al., 2020), banking (Fukuyama & Weber, 2017), healthcare (Boussemart et al., 2020), and so forth. However, it does not consist entirely of the difference between total output and input which is not "additively complete" and it cannot be disaggregated into the parts of output and input growth (Ang & Kerstens, 2017). Briec and Kerstens (2004) define an additively complete LHM indicator. Unlike the ratio-based indices, this difference-based indicator can overcome the problem of uncertainty of indices. Besides, it is an additively complete method that can capture the changes in inputs and outputs, better than those incomplete measures as these may cause biased results (Shen et al., 2019).

Compared to other indicators and indices, there is less literature studying the LHM productivity indicator and employing it to measure efficiency changes. Additionally, the majority of these LHM articles are all of recent date. Shen et al. (2019) employ a decomposable LHM productivity indicator to explore the productivity change in China's agriculture. These authors find that the rise in agricultural productivity in China is mostly the result of technological progress. Furthermore, these authors come to the conclusion that both productivity growth rates and the relative significance of their constituent parts vary over time and across provinces. Ang and Kerstens (2017) explore productivity growth in U.S. agriculture by adopting the LHM indicator. The findings indicate that productivity has significantly increased over time, and this growth is attributable to a rise in output rather than a drop in input, with technical change serving as the primary motivating factor. Abad and Ravelojaona (2022) define the environmental disaggregated Hicks–Moorsteen index and LHM productivity indicator. Note that the application of these TFP indices does not require maintaining the traditional convexity assumption.

Although there are many ways to calculate TFP, few studies are comparing LHM indicators with other productivity indicators and indices, which deserves further exploration. Briec and Kerstens (2004) analyze the relationship between the Hicks–Moorsteen productivity index and the LHM indicator and discover that the logarithm of the former one is approximately equal to the latter. Kerstens et al. (2018) discuss the difference between the LHM and LPIs. These authors suggest that these two indicators can be used to study TFP and measure local technical change, respectively.

The relation between production inputs and outputs can be calculated using production technology. In recent years, there have been several pollution-generating technologies, including the weak G-disposability, the by-production model, and the natural and managerial disposability concepts (Dakpo et al., 2016). The first technology cannot describe how pollution is generated, so it is hard to make trade-offs between different types of outputs. Dakpo et al. (2016) point out that natural and managerial disposability cannot present pollution-generating technologies properly. Compared to other methods, the by-production model is consistent with the MBPs (Førsund, 2018; Shen et al., 2021), which can better model the pollution-generating technologies and capture the relation between various types of inputs and outputs. It is superior to other approaches from this perspective.

Distance functions are widely used to obtain production technologies. Shephard (1970) distinguishes between input- and output-oriented distance functions. Bad outputs are considered by Färe et al. (1993) within the context of the Shepherdian distance function. This kind of distance function has been further deepened and developed in subsequent studies (Coggins & Swinton, 1996; Hailu & Veeman, 2000). It posits that outputs change in the same ratio for both good and bad outputs, inconsistent with the purpose of green growth, which is to improve good outputs and decrease bad ones. Directional distance functions allow good outputs to expand while reducing bad outputs and inputs: this is getting more attention gradually (Chambers et al., 1996). For example, Watanabe and Tanaka (2007) adopt DDF to explore and compare the efficiency of Chinese industry. They assert that the research will produce biased conclusions if the bad outputs are not taken into account. Therefore, the efficiency analysis should take into account both good outputs and their byproducts. Zhang and Wei (2015) use non-radial DDF to gauge the environmental performance of China's transportation industry. They discover that the total factor carbon emissions grew by 6.2% between 2000 and 2012, primarily due to technological innovation. Feng and Serletis (2014) develop a primal Divisia-type productivity index based on DDF to estimate the efficiency change in some OECD countries. They assert that if bad outputs are not taken into account, the efficiency assessment may be skewed, which is consistent with the viewpoint of Watanabe and Tanaka (2007).

Two kinds of methods, parametric and nonparametric ones, are often employed to calculate the distance functions. The parametric method uses translog, quadratic, and other pre-defined functional forms. The specific functional form depends on the selection of distance functions. For instance, the Shepard distance function is frequently expressed using the translog functional form, whereas the DDF can be described using the quadratic. Then, the distance functions can be calculated using stochastic frontier analysis (SFA) (Zhou et al., 2014). For example, Safiullah (2021) examines the financial stability efficiency of Islamic and conventional banks using the stochastic meta-frontier stability function. Wu et al. (2022) use SFA to calculate each region's TFP levels in China. The nonparametric method is more flexible than the parametric method since it does not require predefined functional forms. Charnes et al. (1978) develop a typical nonparametric method, which is referred to as data envelopment analysis (DEA). In comparison to some methods, it makes fewer assumptions and can handle the relationship between multiple inputs and outputs better. This approach has been widely employed in subsequent studies measuring TFP (see, e.g., Wang et al., 2013; Baležentis et al., 2021; Shen et al., 2019). The literature using nonconvex production technology, also known as the free disposal hull (FDH) model, to study productivity is much less widespread than DEA.

Nonconvex technologies can occur for a wide variety of reasons (see Mas-Colell (1987) for an overview). First, inputs and outputs can be indivisible and cannot be varied continuously. Second, setup times and setup costs due to indivisibilities in initiating production may be substantial depending on the nature of technologies. Third, increasing returns to scale, due to indivisibilities, learning, or organizational advantages in the internal structure of production, lead to nonconvexities in production. Fourth, negative externalities can also induce nonconvexities. Fifth, economies of specialization (e.g., Romer, 1990, on nonrival inputs in the new growth theory) are another source of nonconvexity. Other sources for nonconvexities exist.

Convexity is maintained in economics and part of operations research because of the assumption of perfect time divisibility. For instance, Shephard (1970, p. 15) states clearly that convexity is "valid for time divisibly-operable technologies". But, if time is only imperfectly divisible, then nonconvexities may well substantially matter for the analysis of production and, for example, cost functions alike. Yuan et al. (2021) analyze the environmental and economic efficiency of the Belt and Road countries using DEA and FDH models, discovering the outliers have a more significant effect on the former than the latter. Balezentis et al. (2023) implement an additive LHM productivity indicator and report even opposite signs between convex and nonconvex technologies for a substantial part of the sample in each of the years in their panel. Thus, nonconvexity may matter substantially for empirical analysis, and therefore, we explicitly test between convex and nonconvex technologies.

Much literature discusses TFP growth in different countries or regions. The research range in the literature includes Europe (Baležentis et al., 2021), OECD (Cui et al., 2022), the Belt and Road (Yuan et al., 2021), and some individual countries, like China (Shen et al., 2019), United States (Ang & Kerstens, 2017), and Australia (Li & Liu, 2010). The research estimating TFP globally is more limited than the regional and national studies. Krüger (2003) adopts the Malmquist index to explore the TFP of 87 countries from 1960 to 1990 and discovers that the pace of capital accumulation influences productivity significantly in different regions worldwide. Espoir and Ngepah (2021) investigate the correlation between income inequality and TFP in 88 countries, concluding that compared to developed nations, income disparity presents a higher and more significant influence on the TFP in developing nations.

Some literature explores the correlation between the energy structure and TFP, and the results present differences. Rath et al. (2019) reveal that renewable energy consumption and fossil fuel have an opposite impact on TFP growth. The effect of the former one is positive, while the latter one is negative. Xie et al. (2021) claim that the percentage of renewable energy consumption, which represents the energy transition, exhibits an inverse "N" nonlinear relationship with green TFP. The connection between the energy transition and TFP has been discussed in some literature, but the relationship between the consumption of fossil fuels and green growth has received less attention. Since the green economy is the key direction of future development, greater focus should be given to the impact of the energy revolution.

To sum up, a lot of literature discusses the measurement of TFP theoretically. Besides, there are some empirical studies corresponding to each method. However, comparisons among different models in empirical research are rare and few scholars have considered the worldwide TFP gains. The correlation between the transformation of energy structure and green TFP deserves further consideration. Given that the green economy is gaining more and more attention, this contribution measures and compares the GTFP using the Malmquist–Luenberger index, LHM, and Malmquist indicators under convex and nonconvex by-production technologies based on a metafrontier approach. Then, it tests the correlation between the share of fossil fuel energy consumption and GTFP and determines which model is the most robust.

3 | MATERIALS AND METHODS

3.1 | The calculation of GTFP growth

3.1.1 | Production technology and DDF

Production technology, also referred to as benchmark performance, is often expressed by a production function, which specifies the highest output that a certain vector of inputs can achieve. The by-production model, proposed by Murty and Russell (2002) and Murty et al. (2012), can introduce the set of production possibilities constraints by economic axioms. In this model, there are two different types of inputs, nonpolluting inputs x^c and polluting inputs x^d, and two kinds of outputs, desirable outputs y and undesirable outputs z. Polluting inputs result in externalities during production while nonpolluting inputs do not contaminate the environment. As a result, undesirable outputs, also known as by-products, are always produced alongside desirable outputs during the production process. Among different inputs and outputs, there is a relationship that polluting inputs and nonpolluting inputs that can contribute to desirable outputs, while only polluting inputs produce undesirable outputs. Two sub-technologies T_1 and T_2 simulate the above relationship as T_1 describes the process in that all inputs are transformed into desirable outputs and T_2 reflects how polluting inputs produce undesirable outputs. The BP model, which combines these two sub-technologies, solves the limitation of traditional efficiency analysis in which only the desirable output is taken into account by including externalities in the production. The specific form of the BP technology is as follows:

$$\begin{aligned} T_{BP} &= T_1 \cap T_2 \\ &= \left\{ (x^c, x^d, y, z) \in \mathbb{R}_+^{C+D+M+J} : (x^c, x^d) \text{ can produce } y; x^d \text{ can generate } z \right\} \\ T_1 &= \left\{ (x^c, x^d, y) \in \mathbb{R}_+^{C+D+M} | f(x^c, x^d, y) \leq 0 \right\} \\ T_2 &= \left\{ (x^d, z) \in \mathbb{R}_+^{D+J} | g(z, x^d) \leq 0 \right\} \end{aligned} \tag{1}$$

where $f(\cdot)$ and $g(\cdot)$ are two continuously differentiable functions of inputs and outputs. The dimensions C, D, M, and J represent the quantity of nonpolluting inputs, polluting inputs, desirable outputs, and undesirable outputs, which equal 2, 1, 1, and 1 in the empirical part of this contribution, respectively. T_1 set satisfies the free-disposability properties, while the costly disposability property is imposed on T_2 (Murty et al., 2012), which needs the substitution of inputs from the production of desirable outputs to reduce the amount of already-produced byproducts (Ray et al., 2018). There is joint disposability between polluting inputs and bad outputs (Baležentis et al., 2021). Without reducing polluting inputs, undesirable outputs cannot be reduced (Shen et al., 2021).

Conventional literature asserts that good and bad outputs are positively correlated. To model this positive relationship, these studies treat by-products as inputs on a free disposability basis or outputs based on the weak disposability and null-jointness properties (Murty et al., 2012). According to the weak disposability assumption, bad outputs can only be decreased by raising inputs or lowering good outputs (Ray et al., 2018). Besides, under the null-jointness condition, two kinds of outputs must be decreased proportionally. Thus, good output is inseparable from the generation of by-products. Desirable outputs are also 0 if the undesirable outputs are, reflecting that by-products are difficult to dispose off completely (Baležentis et al., 2021). Under the methodologies mentioned above, some errors in the trade-offs of inputs and outputs could happen that are inconsistent with the MBPs. BP technology assumes costly disposability in polluting inputs and pollution, allowing inefficiencies in the production process, which is congruent with the MBP. Based on the above discussion, the BP method is selected to introduce bad outputs into our study.

Besides, convex and nonconvex production technologies are adopted in this contribution. The point in the production frontier must be a real country for the FDH technology, a nonconvex technology introduced by Deprins et al. (1984), whereas it is not necessarily real under the convex DEA approach. Due to the additivity and divisibility of the DEA method, the FDH method is a more general model dropping the convexity assumption with estimators consistent with convex and nonconvex production sets. In some cases, some decision-making units (DMUs) are in the frontier under nonconvex technology, but there is still some room for improvement in the convex technology. Thus, the inefficiency scores in the FDH are usually lower than those in the DEA method.

The production technology can be expressed by the DDF and this DDF can also be understood as an inefficiency score (Chambers et al., 1996), which can quantify the discrepancy between observed values and the production frontier. The points on the production frontier can be regarded as a "model" for other DMUs. Therefore, the calculated distance can indicate a particular path for improvement for the points that are not on the production frontier. The DDF is flexible and it contains several types, like input-oriented, output-oriented, and input/output-oriented DDFs. These generalized DDFs, which are in the period $p \in \{t, t+1\}$ while the production technology exists in the period $q \in \{t, t+1\}$, are defined as follows, respectively:

$$D^q(x^p, y^p, z^p; g_x^p, 0, 0) = \max\{\delta \in \mathbb{R} : (x - \delta g_x^p, y^p, z^p) \in T(q)\}, \tag{2}$$

$$D^q\left(x^p, y^p, z^p; 0, g_y^p, g_z^p\right) = \max\left\{\theta \in \mathbb{R} : \left(x^p, y + \theta g_y^p, z - \theta g_z^p\right) \in T(q)\right\}, \tag{3}$$

$$D^q\left(x^p, y^p, z^p; g_x^p, g_y^p, g_z^p\right) = \max\left\{\theta, \delta \in \mathbb{R} : \left(x^p - \delta g_x^p, y^p + \theta g_y^p, z^p - \theta g_z^p\right) \in T(q)\right\}, \tag{4}$$

where g_x, g_y, and g_z describe the directional vectors of inputs, good, and bad outputs, respectively. δ and θ measure the maximum optimization of inputs and outputs. $(p,q) \in \{t, t+1\} \times \{t, t+1\}$ allows the estimation of productivity change in mixed periods. In practice, we choose the evaluated observations as the directional vectors. This not only guarantees a proportional interpretation of the DDF: see Briec (1997). Furthermore, this proportional distance function (PDF) also guarantees that productivity measurement satisfies a generalized commensurability property, which is not the case under a DDF with some general direction vector: see Briec et al. (2022) for details.

3.1.2 | Luenberger–Hicks–Moorsteen, LPIs, and Malmquist–Luenberger index

While the above distance functions can calculate the inefficiency scores, some productivity indicators or indices can help us change efficiency problems into productivity analysis. This contribution adopts the LHM, LPI, and ML index to study productivity growth. We explore the difference between the three ways to express productivity to have a better understanding of productivity measurement.

The LHM productivity indicator is considered firstly, described as the difference between the input and output indicators. To prevent picking a base period at random, t and $t+1$ periods are selected. There are S DMUs. The following expression is an LHM indicator for the base period t:

$$LHM^t = \begin{pmatrix} \left[D^t\left(\mathbf{x}_s^t, \mathbf{y}_s^t, \mathbf{z}_s^t; \mathbf{0}, \mathbf{g}_y^t, \mathbf{g}_z^t\right) - D^t\left(\mathbf{x}_s^t, \mathbf{y}_s^{t+1}, \mathbf{z}_s^{t+1}; \mathbf{0}, \mathbf{g}_y^{t+1}, \mathbf{g}_z^{t+1}\right) \right] \\ - \left[D^t\left(\mathbf{x}_s^{t+1}, \mathbf{y}_s^t, \mathbf{z}_s^t; \mathbf{g}_x^{t+1}, \mathbf{0}, \mathbf{0}\right) - D^t\left(\mathbf{x}_s^t, \mathbf{y}_s^t, \mathbf{z}_s^t; \mathbf{g}_x^t, \mathbf{0}, \mathbf{0}\right) \right] \end{pmatrix}, \tag{5}$$

where the first and second production technologies in the brackets indicate the distance along the output direction to the frontier, while the third and fourth terms denote the distances from the production frontier along the input direction. Similarly, for the base period $t+1$, the LHM indicator is expressed as follows:

$$LHM^{t+1} = \begin{pmatrix} \left[D^{t+1}\left(\mathbf{x}_s^{t+1},\mathbf{y}_s^t,\mathbf{z}_s^t;\mathbf{0},\mathbf{g}_y^t,\mathbf{g}_z^t\right) - D^{t+1}\left(\mathbf{x}_s^{t+1},\mathbf{y}_s^{t+1},\mathbf{z}_s^{t+1};\mathbf{0},\mathbf{g}_y^{t+1},\mathbf{g}_z^{t+1}\right)\right] \\ -\left[D^{t+1}\left(\mathbf{x}_s^{t+1},\mathbf{y}_s^{t+1},\mathbf{z}_s^{t+1};\mathbf{g}_x^{t+1},\mathbf{0},\mathbf{0}\right) - D^{t+1}\left(\mathbf{x}_s^t,\mathbf{y}_s^{t+1},\mathbf{z}_s^{t+1};\mathbf{g}_x^t,\mathbf{0},\mathbf{0}\right)\right] \end{pmatrix}. \tag{6}$$

To avoid an arbitrary base period, it is custom to take the arithmetic average value of LHM indicators for periods t and $t+1$:

$$LHM^{t,t+1} = \frac{1}{2}\left(LHM^t + LHM^{t+1}\right) = \frac{1}{2}\begin{pmatrix} \left[D^t\left(\mathbf{x}_s^t,\mathbf{y}_s^t,\mathbf{z}_s^t;\mathbf{0},\mathbf{g}_y^t,\mathbf{g}_z^t\right) - D^t\left(\mathbf{x}_s^t,\mathbf{y}_s^{t+1},\mathbf{z}_s^{t+1};\mathbf{0},\mathbf{g}_y^{t+1},\mathbf{g}_z^{t+1}\right)\right] \\ -\left[D^t\left(\mathbf{x}_s^{t+1},\mathbf{y}_s^t,\mathbf{z}_s^t;\mathbf{g}_x^{t+1},\mathbf{0},\mathbf{0}\right) - D^t\left(\mathbf{x}_s^t,\mathbf{y}_s^t,\mathbf{z}_s^t;\mathbf{g}_x^t,\mathbf{0},\mathbf{0}\right)\right] \\ +\left[D^{t+1}\left(\mathbf{x}_s^{t+1},\mathbf{y}_s^t,\mathbf{z}_s^t;\mathbf{0},\mathbf{g}_y^t,\mathbf{g}_z^t\right) - D^{t+1}\left(\mathbf{x}_s^{t+1},\mathbf{y}_s^{t+1},\mathbf{z}_s^{t+1};\mathbf{0},\mathbf{g}_y^{t+1},\mathbf{g}_z^{t+1}\right)\right] \\ -\left[D^{t+1}\left(\mathbf{x}_s^{t+1},\mathbf{y}_s^{t+1},\mathbf{z}_s^{t+1};\mathbf{g}_x^{t+1},\mathbf{0},\mathbf{0}\right) - D^{t+1}\left(\mathbf{x}_s^t,\mathbf{y}_s^{t+1},\mathbf{z}_s^{t+1};\mathbf{g}_x^t,\mathbf{0},\mathbf{0}\right)\right] \end{pmatrix}. \tag{7}$$

The change in productivity from the previous year can be shown in the rise or fall of TFP. Productivity increases when the TFP growth rate exceeds 0; it decreases when it is less than 0. For the LPI based on differences, this interpretation likewise holds. The LPI allows inputs and outputs to be optimized simultaneously and it is widely used. It is defined as follows:

$$LPI^{t,t+1} = \frac{1}{2}\begin{pmatrix} D^t\left(\mathbf{x}_s^t,\mathbf{y}_s^t,\mathbf{z}_s^t;\mathbf{g}_x^t,\mathbf{g}_y^t,\mathbf{g}_z^t\right) - D^t\left(\mathbf{x}_s^{t+1},\mathbf{y}_s^{t+1},\mathbf{z}_s^{t+1};\mathbf{g}_x^{t+1},\mathbf{g}_y^{t+1},\mathbf{g}_z^{t+1}\right) \\ +D^{t+1}\left(\mathbf{x}_s^t,\mathbf{y}_s^t,\mathbf{z}_s^t;\mathbf{g}_x^t,\mathbf{g}_y^t,\mathbf{g}_z^t\right) - D^{t+1}\left(\mathbf{x}_s^{t+1},\mathbf{y}_s^{t+1},\mathbf{z}_s^{t+1};\mathbf{g}_x^{t+1},\mathbf{g}_y^{t+1},\mathbf{g}_z^{t+1}\right) \end{pmatrix}. \tag{8}$$

Chung et al. (1997) propose an ML productivity index that asymmetrically treats good and bad outputs (Kumar, 2006). However, it is noncircular and may have infeasible issues with linear programming when calculating the cross-period DDF (Färe et al., 2001; Oh, 2010). Different from LHM and LPIs, for this index, if the value is larger than 1, then there are gains in productivity. If it is less than 1, then productivity declines. The ML productivity index has the following form:

$$ML^{t,t+1} = \left[\frac{1+D^t\left(x_s^t,y_s^t,z_s^t;g_x^t,g_y^t,g_z^t\right)}{1+D^t\left(x_s^{t+1},y_s^{t+1},z_s^{t+1};g_x^{t+1},g_y^{t+1},g_z^{t+1}\right)} \times \frac{1+D^{t+1}\left(x_s^t,y_s^t,z_s^t;g_x^t,g_y^t,g_z^t\right)}{1+D^{t+1}\left(x_s^{t+1},y_s^{t+1},z_s^{t+1};g_x^{t+1},g_y^{t+1},g_z^{t+1}\right)}\right]^{1/2} \tag{9}$$

The details on the calculation of the PDFs are presented in Appendix A.

3.1.3 | Estimation strategy: Inspired by the metafrontier method

Productivity varies significantly between 129 nations due to variations in the economies, environments, institutional settings, and other factors. If only one production technology is used, some deviations may occur. For instance, it is difficult to gauge efficiency in some nations because they are too far from the production frontier. Thus, this contribution adopts the metafrontier method which is an unrestricted technology set following O'Donnell et al., 2008. The samples are divided into three groups, each containing 43 countries, based on average GDP levels during 2000–2019. The production technologies are estimated using three group frontiers. The contemporaneous production frontier of the group h in the period t is described as $T_h^t = \{(x^c,x^d,y^t,z^t) : (x^c,x^d) \text{ can produce } y^t; x^d \text{ can generate } z^t\}$, where $t = 1,\ldots,T$. The intertemporal production technology of the group h is expressed as $T_h^I = T_h^1 \cup T_h^2 \cup \ldots \cup T_h^T$. The global production technology set is described as $T^G = T_1^I \cup T_2^I \cup \ldots \cup T_H^I$, which is an envelope curve of group frontiers and consists of all observations made across all groups and periods (O'Donnell et al. (2008)). The union operator does not preserve convexity results (Kerstens et al., 2019). Thus, the metafrontier of convex group technologies is nonconvex, and also the metafrontier of nonconvex group technologies is nonconvex (in a different way from the preceding one).

Figure 1 presents the metafrontier method under both DEA and FDH models. In the nonconvex group technologies, the technologies T_1^t, T_2^t, and T_3^t are represented by the horizontal axis and the polyline $A_1B_1C_1D_1E_1F_1G_1$, $A_2B_2C_2D_2E_2F_2G_2$, and $A_3B_3C_3D_3E_3F_3G_3$, respectively. The metafrontier of three group technologies is the union of three group technologies and consists of all points between the polyline $A_1B_1HB_2IB_3C_3D_3JD_2E_2F_2KF_3G_3$ and the horizontal axis. Convex group frontiers T_1^t, T_2^t, and T_3^t are shown by the horizontal axis and the polyline $A_1B_1C_1D_1E_1$, $A_2B_2C_2D_2E_2$, and $A_3B_3C_3D_3E_3$, respectively. According to Jin et al. (2020), some points can only be reached under the convexification strategy, like the projection point R_1'' of R_1. If we do not assume the convexity of metafrontier, the point R_1'' is infeasible. In general, the convexification method of assuming a convex metaset yields erroneous results (see Jin et al., 2020; Kerstens et al., 2019). Thus, the metafrontier of T_1^t, T_2^t, and T_3^t should be the region between the polyline $A_1B_1FB_2C_2GB_3C_3D_3E_3$ and the horizontal axis.

In line with our research interest, in the remainder, we estimate separate group technologies using convex and nonconvex specifications. But, we are not interested as such in the estimation of the nonconvex metatechnology. This simply serves as a conceptual framework underscoring the importance of testing for convexity and nonconvexity at the group technology level.

3.2 | Regression model

Given that the fixed-effect regression model is more robust because it is always consistent no matter whether invariant omitted estimators are correlated with error terms, this contribution uses a fixed-effect model to explore the correlation between the share of fossil fuel energy consumption and green TFP. To control individual and time heterogeneity, this contribution chooses a two-way fixed effect model. The regression model is specified as follows:

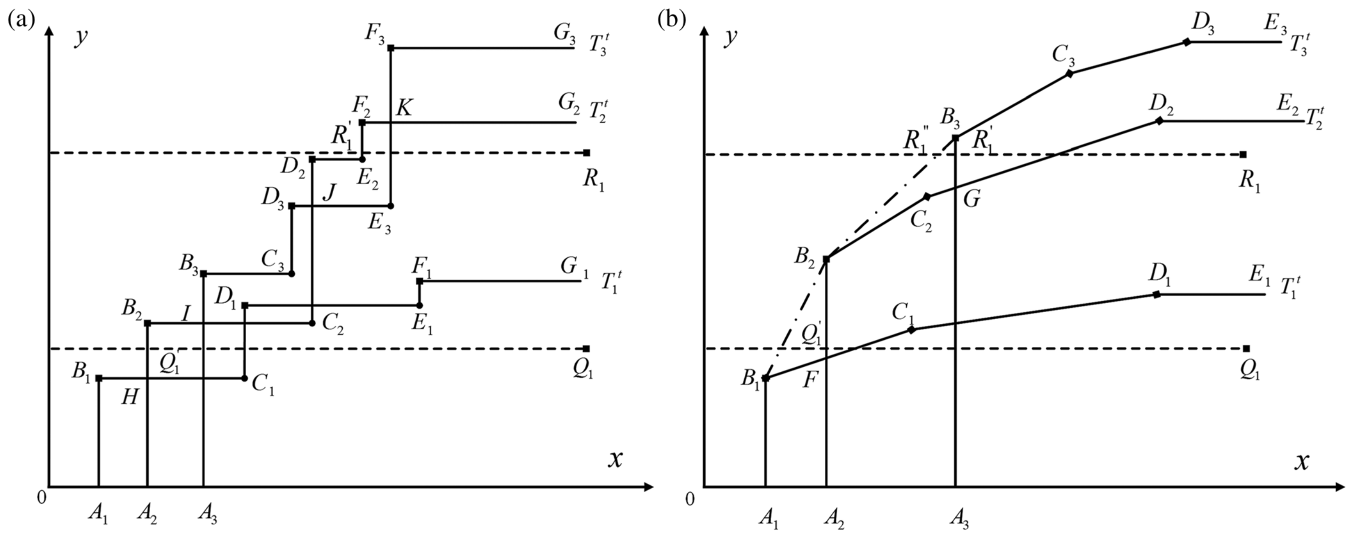

FIGURE 1 (a) Nonconvex and (b) convex group technologies and nonconvex metatechnologies.

$$\ln(CGTFP_{it}) = \alpha \ln(fossil_{it}) + \chi \ln(X_{it}) + \tau_i + \gamma_t + \varepsilon_{it}, \tag{10}$$

where $CGTFP_{it}$ is the cumulative green productivity. The cumulative green TFP has some small values that are sometimes negative. Thus, we add two to each GTFP value and then take the logarithm. The coefficient α represents the impact of the fossil fuel energy consumption share on the cumulative GTFP, and χ is the effect of control variables on the cumulative GTFP. $fossil_{it}$ is the share of fossil fuel energy consumption. X_{it} consists of a set of control variables, containing GDP per capita $pgdp_{it}$, industrial structure $secind_{it}$, trade openness $trade_{it}$, population density den_{it}, foreign direct investment fdi_{it}, and government intervention gov_{it}. τ_i is the country fixed effect, γ_t is the year fixed effect, and εit is a random error term. To avoid problems when taking logarithms, we add two to all variables before taking logarithms.

3.3 | Variables

3.3.1 | Explained variable

The calculation of GTFP consists of four parts—nonpolluting input, polluting input, desirable output, and undesirable output. In this study, the nonpolluting inputs contain capital stock and labor force. Energy consumption is considered a type of polluting input. They all contribute to the creation of GDP, which is a type of good output. The emission of carbon dioxide is regarded as an undesirable output. The detailed definition and descriptive statistics are presented in Table 1.

3.3.2 | The core explanatory variable

The core explanatory variable is the use of fossil fuel energy, measured as the share of fossil fuel energy consumption. Currently, the energy structure is accelerating to diversify, clean, and low-carbon, and developing toward high efficiency and integration. In this transition process, the share of renewable energy will increase progressively, gradually replacing fossil energy in the energy source. However, fossil energy has been the main energy source for many years, and the prospects for achieving the transition are grim. It is essential for us to study the specific effect between the use of fossil energy and green growth.

3.3.3 | Control variables

Following Xie et al. (2021), Yan et al. (2020), and Rath et al. (2019), this contribution selects several control variables. The first control variable is GDP per capita (PGDP), measured as constant 2015 US$. A country can afford to pursue a green transition more when PGDP rises in the area. The second control variable is industrial structure (SECIND), with the definition being as the share of industry value added including construction to GDP. Although the development of the industry can drive economic growth, it also consumes a lot of resources and causes environmental pollution, influencing green growth. The third control variable is trade openness (TRADE), the sum of imports and exports of goods and services divided by the GDP. On the one hand, the "Pollution haven" argument claims that trade openness and pollution are positively correlated because enterprises with major pollution problems frequently invest in regions with lax environmental regulations. This lowers costs but worsens pollution levels. On the other hand, the development of green trade will also promote green growth, reducing environmental pollution and improving economic efficiency. The fourth factor is population density (DEN), measured as the number of people per square kilometer of land area. More human capital can help the economy thrive; however, when population density increases, resource waste and environmental deterioration problems worsen. The fifth control variable is foreign direct investment (FDI), defined as the total foreign investment inflows as a percentage of GDP. The country's opening to the outside can improve economic efficiency and facilitate financial inflows, but it also inexorably results in pollution issues (Cao et al., 2020). The final control variable is government intervention (GOV), which is expressed as the ratio of government fiscal expenditure to GDP. Government intervention can compensate for the market failure that exists in the area of green development. Government investment can not only promote the transformation of highly polluting and energy-consuming enterprises, but it also provides policy support for the development of environmentally friendly enterprises. Consequently, the government is crucial in advancing green development (Xie et al., 2020, 2021).

3.4 | Data sources

This study uses panel data of global 129 countries from 2000 to 2019. Countries are categorized into high, middle, and low GDP groups based on their average GDP levels during the sample period. There are 43 high-GDP countries, such as Canada, Germany, China, Australia, France, and India. Furthermore, there are 43 middle-income countries like Denmark, Finland, New Zealand, Sudan, Syria, and Ireland. Finally, low GDP countries contain 43 countries, including Mongolia, Nepal, Bolivia, Zambia, and Zimbabwe. Detailed information on these three groups is presented in Table 2.

TABLE 1 Descriptive statistics for inputs and outputs.

Indicator	Variable	Definition	*N*	Mean	SD	Min	Max
Nonpolluting input	K	Capital stock at current PPPs (in mil. 2017US$)	2580	2932.49	8270.45	16.42	101,544.20
	L	Number of persons engaged (in millions)	2580	22.34	80.38	0.14	799.31
Polluting input	E	Energy use (100 tons of oil equivalent)	2580	926.13	3078.84	6.76	33,691.07
Desirable output	GDP	Output-side real GDP at current PPPs (in mil. 2017US$)	2580	714.32	2096.14	7.02	20,566.03
Undesirable output	CO_2	Total CO_2 emissions (thousand metric tons of CO_2 excluding land-use change and forestry)	2580	225.60	864.68	0.66	10,416.59

TABLE 2 High, middle, and low GDP groups of 129 countries.

Low GDP		Middle GDP		High GDP	
Costa Rica	Mozambique	Chile	Sudan	United States	Egypt
Cameroon	Nicaragua	Kazakhstan	Slovakia	China	Argentina
Paraguay	Albania	Czech	Dominican	India	Pakistan
Nepal	Armenia	Greece	Kenya	Japan	Nigeria
Slovenia	Gabon	Venezuela	Oman	Germany	South Africa
Bolivia	North Macedonia	Portugal	Ethiopia	Russia	United Arab Emirates
Uruguay	Cyprus	Ireland	Bulgaria	France	Philippines
Democratic Republic of Congo	Mongolia	Peru	Tunisia	Brazil	Malaysia
Latvia	Kyrgyzstan	Denmark	Ghana	United Kingdom	Colombia
Cambodia	Mauritius	Israel	Azerbaijan	Italy	Switzerland
Senegal	Moldova	Uzbekistan	Guatemala	Mexico	Algeria
Zambia	Benin	Finland	Serbia	Indonesia	Belgium
Georgia	Tajikistan	Hungary	Syrian	South Korea	Sweden
Honduras	Jamaica	Qatar	Tanzania	Canada	Ukraine
Luxembourg	Congo	Morocco	Croatia	Spain	Viet Nam
Trinidad and Tobago	Haiti	Kuwait	Lebanon	Turkey	Bangladesh
Bosnia and Herzegovina	Niger	Sri Lanka	Panama	Saudi Arabia	Austria
El Salvador	Namibia	Myanmar	Ivory Coast	Iran	Norway
Zimbabwe	Iceland	Belarus	Jordan	Australia	Romania
Estonia	Malta	New Zealand	Yemen	Thailand	Singapore
Brunei Darussalam	Togo	Angola	Lithuania	Poland	Iraq
Botswana		Ecuador		Netherlands	

Note: Considering the huge differences in national input and output at different levels of GDP, countries in the high, middle, and low GDP groups are ranked according to the average GDP level during 2000–2019 from the highest to the bottom.

The data on labor force, capital stock, and GDP are collected from Penn World Table 10.0. The data relevant to energy use, total CO_2 emissions, the share of fossil fuel energy consumption, industry value added, trade, PGDP, population density, and government intervention are collected from the World Development Indicators of the World Bank. Foreign direct investment is collected from the UNCTAD database. Due to data availability issues, this contribution excludes eight countries from the regression analysis (Ivory Coast, Ethiopia, Kuwait, Myanmar, Trinidad and Tobago, Venezuela, Yemen, and Zambia).

4 | RESULTS

4.1 | Ratio of fossil fuel energy consumption in different regions

Figure 2 represents the ratio of fossil fuel energy consumption in total energy use in different regions from 2000 to 2019. It can be seen that the proportion and trend of fossil energy among different regions are quite different. In terms of proportion, the proportion of fossil energy in the Middle East and North Africa is the highest (exceeding 90%). This is followed by North America, East Asia and Pacific, Europe and Central Asia, and Latin America and the Caribbean. There is little difference in the proportion of fossil energy in these areas, which is all situated in the range of 65%–85%. There is a certain gap between South Asia and Sub-Saharan Africa and other regions in the proportion of fossil energy. Sub-Saharan Africa has the lowest proportion of fossil energy, which is situated below 40%. The share of fossil energy in South Asia increases slowly before 2013 (it is below 54%). After 2013, it increases rapidly, reaching the highest point of 66% in 2019. The proportion of fossil energy in all countries together has not changed much. It has even grown a bit from 67% in 2000 to 71% in 2019.

These results reflect a large gap between the relatively high proportion of fossil energy in economically developed regions or major producers of fossil energy and the relatively low proportion of fossil fuels in economically backward regions. Economically backward countries still urgently need to address the issue of economic development, and the proportion of fossil energy still may have a lot of room for growth. Regarding the trend, the proportion of fossil energy shows a downward trend in the Middle East and North Africa, North America, and Europe and Central Asia, and an upward trend in the other regions, especially in South Asia and Sub-Saharan Africa. The proportion of fossil energy in all countries is on the rise.

This phenomenon supports the conclusions of Zou et al. (2016). These authors discover that while demand from emerging economies in the Asia-Pacific region is growing quickly, it is stable in the United States, Europe, and other developed nations. Fossil energy consumption shows a downward trend in North America and Europe. This reflects that economically developed areas and major fossil energy-producing areas are increasingly pursuing green development and gradually replacing fossil energy with renewable energy. However, economically underdeveloped countries mainly pursue rapid economic development and cannot adjust their industrial structure and develop clean energy in the short term. Fossil energy is still the most important supply for industrial development.

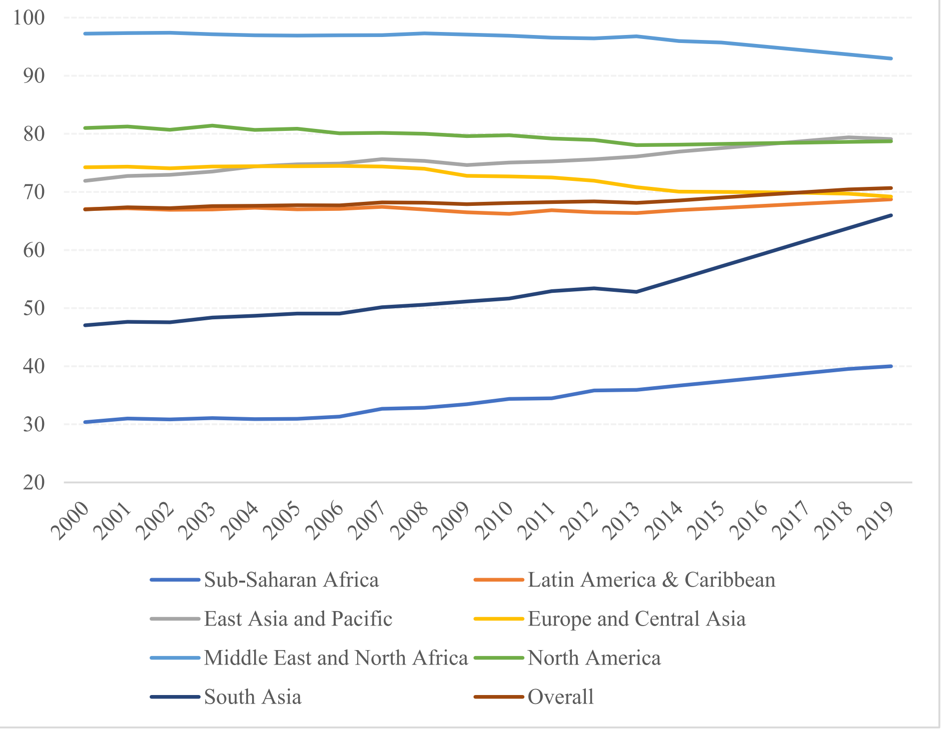

FIGURE 2 Ratio of fossil fuel energy consumption in total energy use in different regions (2000–2019).

4.2 | GTFP growth using the LHM, LPIs, and ML index under different production technologies

Table 3 presents the descriptive statistics of green productivity based on the three group technologies. First, the means of GTFP growth of all indicators and index under convex and nonconvex technologies indicate positive GTFP growth, except for the decline in the LHM indicator under nonconvex technology. Therefore, the LHM productivity indicator under different technologies seems significantly different from the other indicators. The LHM indicator has a higher absolute value than its LPI counterpart, which is in line with Kerstens et al. (2018) and Sala-Garrido et al. (2018). This might be as a result of the incomplete way in which the Luenberger indicator measures TFP. Second, the degree of dispersion of the ML index under FDH technology is the largest, while the DEA model of the ML index shows the slightest fluctuations. The LPI's standard deviation is lower than its LHM indicator counterpart, which confirms the finding of Kerstens et al. (2018). Third, in the difference-based indicator, the LHM TFP indicator has minimum values of −0.794 and −0.620 under the DEA and FDH models, respectively, which are smaller than those in the corresponding models of the LPI. Moreover, the maximum values under the LHM indicator have a larger difference than that of LPI productivity under different technologies. In the ratio-based ML index, the difference in GTFP growth under the FDH model is greater than that of the DEA model, with larger maximum and smaller minimum values. Finally, the minimum and maximum values of the LPI indicator under convex technology and the LHM productivity indicator under both convex and nonconvex technologies all occur in Venezuela in 2015 and 2017, respectively, showing a significant variation in Venezuela's productivity throughout time. Under the LPI indicator with nonconvex technology and ML index with convex and nonconvex technologies, Yemen has the smallest green growth in 2015, while the maximum occurs in Iraq in 2006, Venezuela in 2017, and India in 2013, respectively.

The cumulative GTFP under three group technologies using different productivity models is presented in Figure 3. First, from 2000 to 2019, the cumulative GTFP under nonconvex technology with ML index shows a significant rise and hits a high of roughly 1.5 in 2019, which is much higher than other models. There is a steady increase in the LHM indicator under the DEA model, ML index under DEA technology, and LPI under convex and nonconvex technologies over time. On the contrary, the LHM indicator under the FDH model experiences a downward trend. Thus, the cumulative GTFP of the LHM TFP indicator shows different trends across various technologies. Generally, the trend of green growth in these countries cannot be clearly determined. This result is similar to Kerstens et al. (2018). They discover the only indicator with a downward trend to be the LPI using a nonconvex-VRS technology. Besides, the cumulative GTFP using the LHM indicator under different technologies shows the largest difference, followed by the ML index. The LPI presents a relatively small difference under DEA and FDH models. In addition, a slight drop of cumulative GTFP occurs in 2008 in all models, reflecting that the global economic recession has caused damage to green growth. Wang and Feng (2021) also find a decline in green growth during the financial crisis. The macroeconomic fluctuation is closely related to the green productivity of various countries.

Table 4 displays the average GTFP growth over time for all nations based on different group technologies. First, the average GTFP growth rates for the different methods present some similar results. The years 2004–2005 and 2016–2017 experience positive GTFP growth under all indicators and index, while the years 2000–2001, 2008–2009, and 2013–2014 witness significant negative growth rates of GTFP in all models. All models' estimates of green productivity over these years are consistent. Second, the signs of different indicators and index under convex and nonconvex production technologies also display some differences. For example, in 2002–2003, the LHM indicator under convex technology and the ML index under nonconvex technology are positive, while the results of the remaining four models are negative. Only the GTFP growth in the nonconvex model for the LHM indicator is negative in 2005–2006, while other models show a positive growth trend. This somewhat supports the results of Kerstens et al. (2018), as they find that the results by Luenberger and LHM productivity indicators display considerable differences, although the cumulative growth paths seem quite similar. Third, the green TFP growth of the LHM indicator under the nonconvex technology is negative in most years but positive in only 2 years. There are 14, 10, 9, 10, and 14 years of positive GTFP growth with the LHM indicator under convex technology, LPI under DEA and FDH models, and ML index under both convex and nonconvex technologies, respectively. Compared to the LHM indicator and ML index, the green productivity growth rates determined by the LPI are more similar. Finally, among the LPI under convex and nonconvex models as well as the ML index under nonconvex technology, the average GTFP growth rates in 2004–2005 are the highest, whereas they are the lowest in 2008–2009 in all models except for the LHM indicator under nonconvex production technology.

Table 5 provides an illustration of the regional annual average cumulative GTFP growth rates under three group technologies. First, the overall annual green growth rates range from −2.31% to 2.37%,

TABLE 3 Descriptive statistics of GTFP growth using the Luenberger–Hicks–Moorsteen, Luenberger productivity indicators, and Malmquist–Luenberger index under three group technologies and convexity and nonconvexity.

Variable	Obs	Mean	SD	Min	Max
LHM_DEA	2,451	0.011	0.085	−0.794	0.544
LHM_FDH	2,451	−0.021	0.083	−0.620	0.913
LPI_DEA	2,451	0.002	0.047	−0.507	0.539
LPI_FDH	2,451	0.001	0.065	−0.566	0.578
ML_DEA	2,451	1.002	0.044	0.606	1.501
ML-FDH	2,451	1.006	0.106	0.462	3.567

Note: The GTFP of Iraq in 2005 using ML index under nonconvex has no value because the inefficiency score under the production technology of the t period and the output and output-oriented DDFs in the $t+1$ period is too small. Thus, we take this value to be 1.

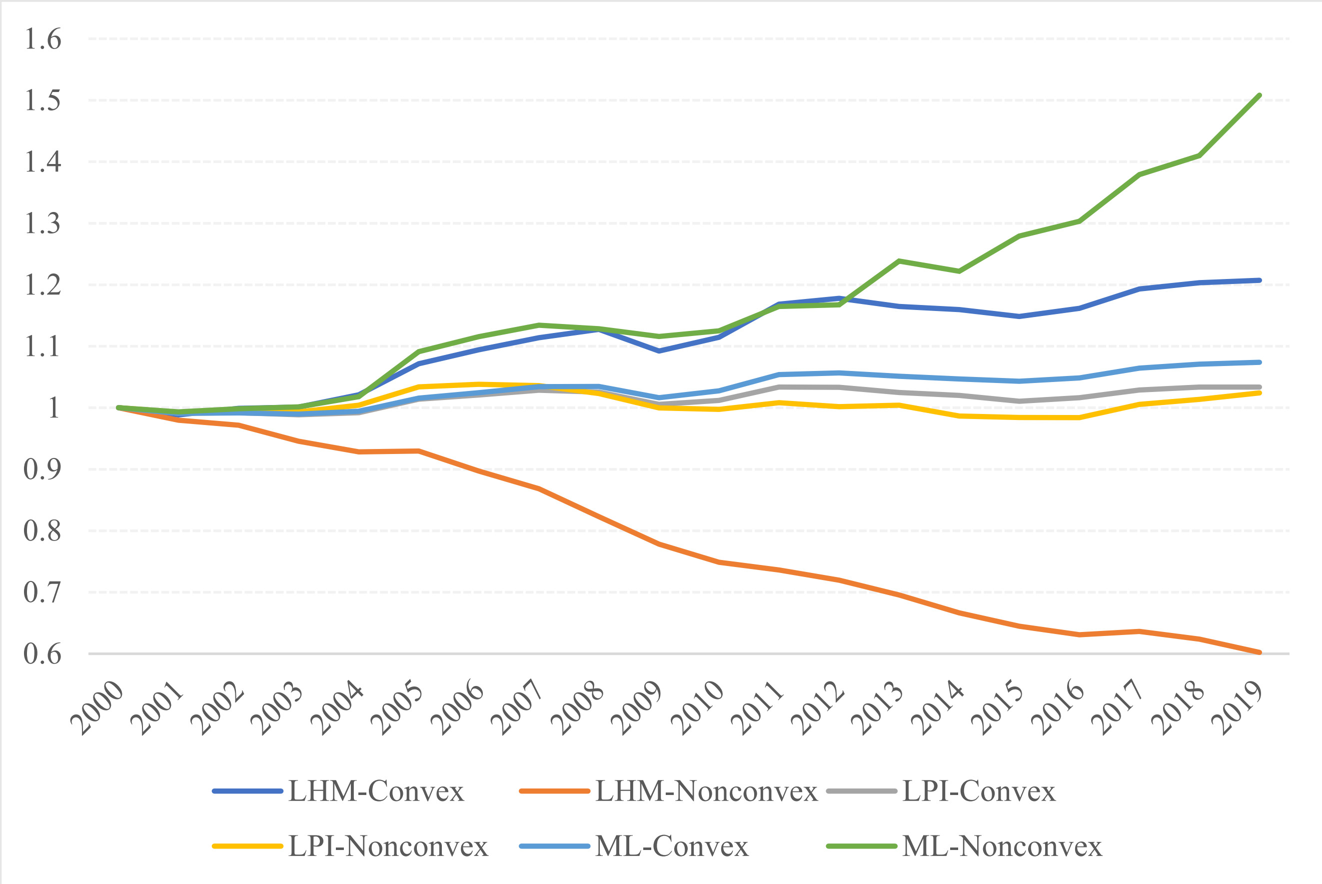

FIGURE 3 Cumulative GTFP with the Luenberger–Hicks–Moorsteen, Luenberger productivity indicators, and Malmquist–Luenberger index under three group technologies and convexity and nonconvexity (2000–2019).

reflecting significant differences between the results of different indicators and index under different technologies. The annual GTFP growth rates also present similarities. Only the annual growth rates of the LHM indicator under nonconvex technology are negative, while other models show positive annual growth. Generally, there is an upward trend in worldwide green productivity. Second, the annual green growth rates in Sub-Saharan Africa are all negative, while other regions experience different degrees of progress in green growth. The sub-Saharan region has always lagged in terms of green productivity, and this gap is getting worse with respect to other regions. The most productive area varies under different approaches. But overall, Europe and Central Asia are the area with the greatest growth momentum, as their annual green growth rates are ranked first under most models. This result partly supports the study of Wang and Feng (2021). These authors discuss green growth of different income level countries and conclude that the green productivity performance in the high-income group and the upper middle-income group is better than that of the lower middle-income group. This result demonstrates that green productivity performs better in economically developed regions than it does in economically underdeveloped regions. Third, the annual green productivity growth rates of the LHM indicator under nonconvex technology are all negative among all regions, while most calculated by other approaches are positive. The green growth of East Asia and Pacific (11.78%) and South Asia (19.2%) calculated by the ML index under the nonconvex approach is far more than those calculated by different approaches in other regions. The annual GTFP growth rates determined by the ML index using nonconvex technology in various regions vary more than those determined by other methods.

4.3 | Regression analysis

Table 6 provides the regression results of the LHM, LPIs, and ML index under FDH and DEA models. The dependent variable is the logarithm of the cumulative productivity. The use of fossil energy can pollute the environment and exacerbate climate change, failing to reconcile the economy and environment well, which inhibits the TFP that considers the undesirable outputs. Interestingly, different models present some insightful results. Strong evidence of a negative correlation between the fossil fuel energy consumption and productivity of the LHM indicator under DEA and FDH models is found in the first and second columns, respectively, which is in line with our assumption. It also supports the findings of Danish and Ulucak (2020), Yan et al. (2020), and Rath et al. (2019). Furthermore, the negative effect of the

TABLE 4 Average GTFP growth for the Luenberger–Hicks–Moorsteen, Luenberger productivity indicators, and Malmquist–Luenberger index under three group technologies and convexity and nonconvexity.

	Luenberger–Hicks–Moorsteen		Luenberger		Malmquist–Luenberger	
Year	Convex	Nonconvex	Convex	Nonconvex	Convex	Nonconvex
2000–2001	−0.0116	−0.0202	−0.0089	−0.0075	0.9909	0.9933
2001–2002	0.0107	−0.0083	0.0010	0.0029	1.0000	1.0051
2002–2003	0.0018	−0.0260	−0.0035	−0.0023	0.9963	1.0012
2003–2004	0.0200	−0.0174	0.0034	0.0110	1.0028	1.0141
2004–2005	0.0505	0.0014	0.0219	0.0299	1.0198	1.0519
2005–2006	0.0228	−0.0323	0.0068	0.0042	1.0058	1.0035
2006–2007	0.0198	−0.0289	0.0081	−0.0021	1.0067	1.0030
2007–2008	0.0135	−0.0455	−0.0033	−0.0128	0.9969	0.9900
2008–2009	−0.0353	−0.0445	−0.0198	−0.0234	0.9815	0.9760
2009–2010	0.0223	−0.0295	0.0062	−0.0025	1.0058	1.0001
2010–2011	0.0538	−0.0128	0.0219	0.0110	1.0219	1.0160
2011–2012	0.0093	−0.0165	−0.0003	−0.0065	1.0000	0.9952
2012–2013	−0.0131	−0.0239	−0.0086	0.0024	0.9928	1.0234
2013–2014	−0.0050	−0.0293	−0.0048	−0.0177	0.9957	0.9813
2014–2015	−0.0112	−0.0216	−0.0092	−0.0023	0.9944	1.0043
2015–2016	0.0133	−0.0139	0.0055	−0.0004	1.0059	1.0037
2016–2017	0.0315	0.0053	0.0128	0.0217	1.0118	1.0313
2017–2018	0.0102	−0.0126	0.0046	0.0080	1.0045	1.0100
2018–2019	0.0039	−0.0214	0.0000	0.0106	1.0001	1.0160

TABLE 5 Annual GTFP growth in different regions for the Luenberger–Hicks–Moorsteen, Luenberger productivity indicators, and Malmquist–Luenberger index three different group technologies and convexity and nonconvexity (%).

	Luenberger–Hicks–Moorsteen		Luenberger		Malmquist–Luenberger	
Region	Convex	Nonconvex	Convex	Nonconvex	Convex	Nonconvex
Sub-Saharan Africa	−0.93	−4.32	−0.94	−0.52	−0.37	−1.29
Latin America & Caribbean	0.88	−2.71	0.43	0.83	0.74	−0.31
East Asia & Pacific	1.12	−3.28	0.17	2.48	0.18	11.78
Europe & Central Asia	2.55	−0.15	1.12	1.98	1.16	1.15
Middle East & North Africa	1.05	−3.26	−1.11	1.47	−0.70	0.72
North America	0.34	−0.56	0.38	3.10	0.47	2.25
South Asia	0.59	−5.65	0.44	3.35	0.78	19.20
Overall	1.18	−2.31	0.20	1.41	0.44	2.37

consumption of fossil fuel on the LHM indicator under the FDH model is greater than that under the DEA model. As for the LPI, the share of fossil fuel energy use and the green growth of the economy under the nonconvex technology are negatively correlated at a 1% significance level. However, the contrary results occur under the DEA model, inconsistent with the assumption. The LPI indicator under different production technologies presents contradictions. To some extent, the accuracy and robustness of this model are questionable. Likewise, the ML index shows similar results with the LPI indicator, with positive and negative influences under DEA and FDH models, respectively. Besides, the correlation between fossil fuel energy consumption and the ML index is not significant. Generally speaking, the LHM productivity indicator is the best with the most consistent results, most in line with the actual situation, while the results calculated by the other two methods under convex and nonconvex models present contradictory results. From the perspective of convex and nonconvex technologies, the nonconvex specification consistently obtains the right negative significant sign for each GTFP. However,

TABLE 6 Regression results using the Luenberger–Hicks–Moorsteen, Luenberger productivity indicators, and Malmquist–Luenberger index under three group technologies and convexity and nonconvexity.

	Regression models					
	LHM_DEA	LHM_FDH	LPI_DEA	LPI_FDH	ML_DEA	ML_FDH
lnfossil	−0.033***	−0.052***	0.003	−0.044***	0.007	−0.026
	(0.010)	(0.011)	(0.006)	(0.008)	(0.005)	(0.018)
lnpgdp	0.112***	−0.045***	0.053***	0.029***	0.059***	0.014
	(0.013)	(0.014)	(0.008)	(0.010)	(0.006)	(0.023)
lnsecind	−0.108***	−0.031*	−0.025***	−0.047***	−0.021***	−0.006
	(0.015)	(0.016)	(0.009)	(0.012)	(0.007)	(0.026)
lntrade	−0.048***	−0.069***	−0.034***	0.010	−0.028***	0.031**
	(0.008)	(0.009)	(0.005)	(0.007)	(0.004)	(0.014)
lnden	−0.180***	−0.591***	−0.224***	−0.072***	−0.142***	−0.076**
	(0.018)	(0.021)	(0.011)	(0.015)	(0.009)	(0.033)
lnfdi	−0.091***	−0.132***	−0.050***	−0.088***	−0.047***	−0.093*
	(0.030)	(0.033)	(0.018)	(0.025)	(0.015)	(0.053)
lngov	0.004	−0.095***	0.007	−0.012	−0.005	0.012
	(0.012)	(0.014)	(0.007)	(0.010)	(0.006)	(0.022)
Constant	1.677***	4.919***	1.832***	1.544***	1.401***	1.355***
	(0.164)	(0.185)	(0.100)	(0.137)	(0.083)	(0.295)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,420	2,420	2,420	2,420	2,420	2,420
R-squared	0.732	0.820	0.775	0.717	0.771	0.667

Note: Robust standard errors are in parentheses.
*$p < .1$, **$p < .05$, and ***$p < .01$.

also the right effect can be observed from the LHM productivity indicator under a convex technology. The effect of LPI and ML index under a convex model both show opposite and insignificant effects.

Regarding the other control variables, productivity is found to positively correlate with per capita GDP under most models. However, the LHM indicator under the FDH production technology shows the opposite correlation. This is consistent with Yan et al. (2020), as they state that low-income regions would have a larger development potential for green growth. The percentage of value added by industries to GDP and the economy's green growth are negatively associated. Moreover, the negative effect of the LHM productivity indicator under convex technology is larger than that of the LPI and ML index. This negative effect differs from Yan et al. (2020): the latter find a positive but insignificant relationship between industrial structure and green productivity in China. This result illustrates the fact that modernizing and transforming industrial structures is a common trend that might support sustainable growth.

The ratio of trade to GDP has a negative impact on productivity under LHM-DEA, LHM-FDH, LPI-DEA, and ML-DEA methods, while a positive impact is observed from LPI-FDH and ML-FDH models. This effect is uncertain as the trade may bring pollution or promote the transformation of economic structure and increase the region's competitiveness. According to Cui et al. (2022), international trade is positively correlated with green growth in OECD countries, as it can contribute more effectively to the flow of goods and the division of labor. Yan et al. (2020) find that trade has a positive but insignificant impact on the growth rate of green productivity. Rath et al. (2019) conclude that trade openness contributes positively to TFP growth as it can stimulate innovation.

There is an apparent negative relationship between population density and green growth, with negative coefficients presented in all models. Among the results, the population density contributes most to the productivity measured by the LHM-FDH model. An increasing population can bring adverse effects on the resources and environment, influencing green growth. This negative effect is supported by the discovery of Xie et al. (2021).

Green growth and FDI are found to be inversely correlated. Therefore, even while foreign investment will help the economies of these countries grow, it is particularly detrimental to the environment and inhibits overall green development. This finding somewhat confirms the study of Cao et al. (2020), which finds that FDI inhibits green growth in low-pollution industries. However, according to Rath et al. (2019), FDI is observed to contribute positively to the growth of TFP with more technology being introduced.

Government intervention has a negative effect only on the GTFP calculated by the LHM indicator under FDH technology. This may be due to the fact that if the government gets too involved, it will exacerbate the mismatch of resources in the green industry and prevent the rational flow of resources, thus inhibiting the development of the green industry. This effect differs from Xie et al. (2020) and Xie et al.

(2021) as these authors find government plays an active role in green economic development among 27 EU member countries. Government intervention has no significant effect on the ones calculated by other models.

Note that the standard errors of the estimated regression coefficients are robust. In particular, we have been using the procedure available in Stata to robustify the regression results.

5 | CONCLUSIONS

If an insufficient energy supply appears in an economy, it has to rely on external energy imports. The stable development of the economy will be impacted by energy prices. For example, the recent Russo-Ukraine war has led to volatility in energy prices in Europe. Furthermore, whether productivity indicators are consistent with the country's energy structure can affect the measurement of green growth. Inspired by the metafrontier approach, this contribution measures the green productivity gains of 129 countries using the LHM, LPIs, and ML index under both convex and nonconvex by-production models. Then, it tests the robustness of different indicators and indices through a two-way fixed effect regression model between the GTFP and the share of fossil fuel energy consumption for 121 countries. The findings have provided a deeper insight into the selection of models for measuring GTFP in empirical analysis. The results gained from this study may assist in facilitating energy transition and sustainable development. We are now in a position to summarize the main findings.

First, the results indicate that there are large differences in the share and trend of fossil energy in different regions. Generally speaking, the share of fossil energy in economically developed areas, such as North America, Europe and Central Asia, and major energy-producing countries, such as the Middle East and North Africa, is high and is declining. Economically disadvantaged regions, such as South Asia and Sub-Saharan Africa, have a smaller and rapidly increasing share of fossil energy compared to other regions. This reflects that economically developed regions and major fossil energy-producing regions are increasingly seeking green development. However, economically less developed countries are mainly focusing on rapid economic development and fossil energy is apparently the most important energy source for industrial development.

Second, GTFP calculated from various indicators and index presents significant differences, which is consistent with Kerstens et al. (2018) and Sala-Garrido et al. (2018). The green productivity using the LHM indicator under nonconvex group technologies presents opposite results to other models. The annual growth rates of GTFP vary between regions. There is an upward trend in worldwide green productivity, except under LHM-FDH. The annual green growth rates in Sub-Saharan Africa are all negative. Europe and Central Asia are the most productive regions according to most models. Productivity decline is closely related to poverty. Therefore, it is urgent for lagging countries to increase productivity and escape poverty.

Third, fossil fuel energy inhibits green economic growth. Thus, there is a need to strengthen and innovate energy regulation and promote clean energy development. The regression model illustrates that the LHM indicator is the most robust and consistent in the empirical analysis since the LPI and ML indices results are contradictory under convexity and nonconvexity. This result confirms the research of Kerstens et al. (2018) that the LHM indicator is an optimal method for measuring TFP, while the LPI does not maintain a TFP interpretation by approximation. Theoretically, the LHM indicator can solve the problem that the ML index cannot handle values at or near 0 and the problem that the LPI cannot be separated into output and input growth (Ang & Kerstens, 2017; Balk et al., 2008; Shen et al., 2019). Therefore, in theory, the LHM indicator is also the best measure of TFP among the three methods. The empirical results present consistent results with the theory. Given our framework that explicitly tests for convexity, our contribution shows that the LHM productivity indicator under a nonconvex technology is slightly more convincing when considering undesirable outputs compared to the convex alternative.

Despite the great advantages mentioned above, there are some pitfalls. The first is the selection of methods for measuring TFP. We just consider a few popular methods containing LHM indicator, LPI, and ML index, but do not include additional indicators and indices. There are numerous ways to calculate the TFP. Future researchers should consider more approaches to gain a more comprehensive understanding and comparison of TFP measurement. Second, only the share of fossil fuel energy consumption is selected as the core explanatory variable and then regression analysis is performed with GTFP to explore the robustness of the model. More variables could be incorporated to test the robustness of different approaches under convexity and nonconvexity. Choosing the proper methods to measure TFP can better capture economic growth and drive long-term economic growth. Third, this contribution is unable to include all countries in the regression analysis due to missing data on some of the control variables. Later, if more data become available, then more countries can be included in the regression analysis to present a more complete and convincing conclusion.

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DATA AVAILABILITY STATEMENT

Data will be made available on request.

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APPENDIX A

Through linear programming, the PDFs can be estimated for Expressions (7), (8), and (9). As for the LHM productivity indicator, the output-oriented PDFs can be obtained from (LP1) and (LP3), respectively. The input-oriented proportional distance functions are calculated through (LP2) and (LP4).

$$
\begin{aligned}
D(x,y,z;0,g_y,g_z) \;=\; & \max_{\theta,\lambda}\theta \\
s.t.\; & \sum_{s=1}^{S}\lambda_s^1 y_s^m \geq y_{s'}^m + \theta g_y^m, m=1,\ldots,M \\
& \sum_{s=1}^{S}\lambda_s^1 x_s^c \leq x_{s'}^c, c=1,\ldots,C \\
& \sum_{s=1}^{S}\lambda_s^1 x_s^d \leq x_{s'}^d, d=1,\ldots,D \\
& \sum_{s=1}^{S}\lambda_s^2 z_s^j \leq z_{s'}^j - \theta g_z^j, j=1,\ldots,J \\
& \sum_{s=1}^{S}\lambda_s^2 x_s^d = \sum_{s=1}^{S}\lambda_s^1 x_s^d, d=1,\ldots,D \\
& \lambda_s^1 \geq 0, s=1,\ldots,S \\
& \sum_{s=1}^{S}\lambda_s^1 = 1, T_1 \; under \; VRS \\
& \lambda_s^2 \geq 0, s=1,\ldots,S \\
& \sum_{s=1}^{S}\lambda_s^2 = 1, T_2 \; under \; VRS
\end{aligned}
\tag{LP1}
$$

$$
\begin{aligned}
D(x,y,z;g_x,0,0) \;=\; & \max_{\delta,\lambda}\delta \\
s.t.\; & \sum_{s=1}^{S}\lambda_s^1 y_s^m \geq y_{s'}^m, m=1,\ldots,M \\
& \sum_{s=1}^{S}\lambda_s^1 x_s^c \leq x_{s'}^c - \delta g_x^c, c=1,\ldots,C \\
& \sum_{s=1}^{S}\lambda_s^1 x_s^d \leq x_{s'}^d - \delta g_x^d, d=1,\ldots,D \\
& \sum_{s=1}^{S}\lambda_s^2 z_s^j \leq z_{s'}^j, j=1,\ldots,J \\
& \sum_{s=1}^{S}\lambda_s^2 x_s^d = \sum_{s=1}^{S}\lambda_s^1 x_s^d, d=1,\ldots,D \\
& \lambda_s^1 \geq 0, s=1,\ldots,S \\
& \sum_{s=1}^{S}\lambda_s^1 = 1, T_1 \; under \; VRS \\
& \lambda_s^2 \geq 0, s=1,\ldots,S \\
& \sum_{s=1}^{S}\lambda_s^2 = 1, T_2 \; under \; VRS
\end{aligned}
\tag{LP2}
$$

$$
\begin{aligned}
D(x,y,z;0,g_y,g_z) \;=\; & \max_{\theta,\lambda}\theta \\
s.t.\; & \sum_{s=1}^{S}\lambda_s^1 y_s^m \geq y_{s'}^m + \theta g_y^m, m=1,\ldots,M \\
& \sum_{s=1}^{S}\lambda_s^1 x_s^c \leq x_{s'}^c, c=1,\ldots,C \\
& \sum_{s=1}^{S}\lambda_s^1 x_s^d \leq x_{s'}^d, d=1,\ldots,D \\
& \sum_{s=1}^{S}\lambda_s^2 z_s^j \leq z_{s'}^j - \theta g_z^j, j=1,\ldots,J \\
& \sum_{s=1}^{S}\lambda_s^2 x_s^d = \sum_{s=1}^{S}\lambda_s^1 x_s^d, d=1,\ldots,D \\
& \lambda_s^1 = \{0,1\}, s=1,\ldots,S \\
& \sum_{s=1}^{S}\lambda_s^1 = 1, T_1 \; under \; VRS \\
& \lambda_s^2 = \{0,1\}, s=1,\ldots,S \\
& \sum_{s=1}^{S}\lambda_s^2 = 1, T_2 \; under \; VRS
\end{aligned}
\tag{LP3}
$$

$$
\begin{aligned}
D(x,y,z;g_x,0,0) \;=\; & \max_{\delta,\lambda}\delta \\
s.t.\; & \sum_{s=1}^{S}\lambda_s^1 y_s^m \geq y_{s'}^m, m=1,\ldots,M \\
& \sum_{s=1}^{S}\lambda_s^1 x_s^c \leq x_{s'}^c - \delta g_x^c, c=1,\ldots,C \\
& \sum_{s=1}^{S}\lambda_s^1 x_s^d \leq x_{s'}^d - \delta g_x^d, d=1,\ldots,D \\
& \sum_{s=1}^{S}\lambda_s^2 z_s^j \leq z_{s'}^j, j=1,\ldots,J \\
& \sum_{s=1}^{S}\lambda_s^2 x_s^d = \sum_{s=1}^{S}\lambda_s^1 x_s^d, d=1,\ldots,D \\
& \lambda_s^1 = \{0,1\}, s=1,\ldots,S \\
& \sum_{s=1}^{S}\lambda_s^1 = 1, T_1 \; under \; VRS \\
& \lambda_s^2 = \{0,1\}, s=1,\ldots,S \\
& \sum_{s=1}^{S}\lambda_s^2 = 1, T_2 \; under \; VRS
\end{aligned}
\tag{LP4}
$$

The programs (LP1) and (LP2) estimate the convex production technologies, and the nonconvex technologies can be obtained from (LP3) and (LP4). The activity or intensity vector λ_s^1 and λ_s^2 are related to subtechnologies T_1 and T_2, respectively. The scalars θ and δ represent the maximum optimizations of outputs and inputs defined by $\left(0,g_y^p,g_z^p\right)$ and $\left(g_x^p,0,0\right)$ at the period $p \in \{t,t+1\}$.

Similarly, the input/output-oriented DDFs of the LPI can be calculated from the (LP5) and (LP6). From the linear programming of (LP7) and (LP8), the DDFs of the ML productivity index are obtained.

$$
\begin{aligned}
D(x,y,z;g_x,g_y,g_z) &= \max_{\mu,\lambda} \mu \\
s.t.\ \sum_{s=1}^{S} \lambda_s^1 y_s^m &\geq y_{s'}^m + \mu g_y^m, m = 1,\ldots,M \\
\sum_{s=1}^{S} \lambda_s^1 x_s^c &\leq x_{s'}^c - \mu g_x^c, c = 1,\ldots,C \\
\sum_{s=1}^{S} \lambda_s^1 x_s^d &\leq x_{s'}^d - \mu g_x^d, d = 1,\ldots,D \\
\sum_{s=1}^{S} \lambda_s^2 z_s^j &\leq z_{s'}^j - \mu g_z^j, j = 1,\ldots,J \\
\sum_{s=1}^{S} \lambda_s^2 x_s^d &= \sum_{s=1}^{S} \lambda_s^1 x_s^d, d = 1,\ldots,D \\
\lambda_s^1 &\geq 0, s = 1,\ldots,S \\
\sum_{s=1}^{S} \lambda_s^1 &= 1, T_1\ under\ VRS \\
\lambda_s^2 &\geq 0, s = 1,\ldots,S \\
\sum_{s=1}^{S} \lambda_s^2 &= 1, T_2\ under\ VRS
\end{aligned}
\tag{LP5}
$$

$$
\begin{aligned}
D(x,y,z;g_x,g_y,g_z) &= \max_{\mu,\lambda} \mu \\
s.t.\ \sum_{s=1}^{S} \lambda_s^1 y_s^m &\geq y_{s'}^m + \mu g_y^m, m = 1,\ldots,M \\
\sum_{s=1}^{S} \lambda_s^1 x_s^c &\leq x_{s'}^c - \mu g_x^c, c = 1,\ldots,C \\
\sum_{s=1}^{S} \lambda_s^1 x_s^d &\leq x_{s'}^d - \mu g_x^d, d = 1,\ldots,D \\
\sum_{s=1}^{S} \lambda_s^2 z_s^j &\leq z_{s'}^j - \mu g_z^j, j = 1,\ldots,J \\
\sum_{s=1}^{S} \lambda_s^2 x_s^d &= \sum_{s=1}^{S} \lambda_s^1 x_s^d, d = 1,\ldots,D \\
\lambda_s^1 &= \{0,1\}, s = 1,\ldots,S \\
\sum_{s=1}^{S} \lambda_s^1 &= 1, T_1\ under\ VRS \\
\lambda_s^2 &= \{0,1\}, s = 1,\ldots,S \\
\sum_{s=1}^{S} \lambda_s^2 &= 1, T_2\ under\ VRS
\end{aligned}
\tag{LP6}
$$

$$
\begin{aligned}
D(x,y,z;g_x,g_y,g_z) &= \max_{\phi,\lambda} \phi \\
s.t.\ \sum_{s=1}^{S} \lambda_s^1 y_s^m &\geq y_{s'}^m + \phi g_y^m, m = 1,\ldots,M \\
\sum_{s=1}^{S} \lambda_s^1 x_s^c &\leq x_{s'}^c - \phi g_x^c, c = 1,\ldots,C \\
\sum_{s=1}^{S} \lambda_s^1 x_s^d &\leq x_{s'}^d - \phi g_x^d, d = 1,\ldots,D \\
\sum_{s=1}^{S} \lambda_s^2 z_s^j &\leq z_{s'}^j - \phi g_z^j, j = 1,\ldots,J \\
\sum_{s=1}^{S} \lambda_s^2 x_s^d &= \sum_{s=1}^{S} \lambda_s^1 x_s^d, d = 1,\ldots,D \\
\lambda_s^1 &\geq 0, s = 1,\ldots,S \\
\sum_{s=1}^{S} \lambda_s^1 &= 1, T_1\ under\ VRS \\
\lambda_s^2 &\geq 0, s = 1,\ldots,S \\
\sum_{s=1}^{S} \lambda_s^2 &= 1, T_2\ under\ VRS
\end{aligned}
\tag{LP7}
$$

$$
\begin{aligned}
D(x,y,z;g_x,g_y,g_z) &= \max_{\phi,\lambda} \phi \\
s.t.\ \sum_{s=1}^{S} \lambda_s^1 y_s^m &\geq y_{s'}^m + \phi g_y^m, m = 1,\ldots,M \\
\sum_{s=1}^{S} \lambda_s^1 x_s^c &\leq x_{s'}^c - \phi g_x^c, c = 1,\ldots,C \\
\sum_{s=1}^{S} \lambda_s^1 x_s^d &\leq x_{s'}^d - \phi g_x^d, d = 1,\ldots,D \\
\sum_{s=1}^{S} \lambda_s^2 z_s^j &\leq z_{s'}^j - \phi g_z^j, j = 1,\ldots,J \\
\sum_{s=1}^{S} \lambda_s^2 x_s^d &= \sum_{s=1}^{S} \lambda_s^1 x_s^d, d = 1,\ldots,D \\
\lambda_s^1 &= \{0,1\}, s = 1,\ldots,S \\
\sum_{s=1}^{S} \lambda_s^1 &= 1, T_1\ under\ VRS \\
\lambda_s^2 &= \{0,1\}, s = 1,\ldots,S \\
\sum_{s=1}^{S} \lambda_s^2 &= 1, T_2\ under\ VRS
\end{aligned}
\tag{LP8}
$$

The scalars μ and ϕ are the maximum optimizations of inputs and outputs of DDFs under the LPI and ML index, respectively.