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Sources of carbon productivity change: A decomposition and disaggregation analysis based on global Luenberger productivity indicator and endogenous directional distance function

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ABSTRACT

The measurement of carbon productivity makes the effort of global climate change mitigation accountable and helps to formulate policies and prioritize actions for economic growth, energy conservation, and carbon emissions control. Previous studies arbitrarily predetermined the directions of directional distance function in calculating the carbon productivity indicator, and the traditional carbon productivity indicator itself is not capable of identifying the contribution of different energy driven carbon emissions in carbon productivity change. Through utilizing an endogenous directional distance function selecting approach and a global productivity index, this paper proposes a global Luenberger carbon productivity indicator for computing carbon productivity change. This carbon productivity indicator can be further decomposed into three components that respectively identify the best practice gap change, pure efficiency change, and scale efficiency change. Moreover, the carbon productivity indicator is shown as a combination of individual carbon emissions productivity indicators that account for the contribution of different fossil fuel driven carbon emissions (i.e. coal driven CO_2, oil driven CO_2, and natural gas driven CO_2) toward the carbon productivity change. Our carbon productivity indicator is employed to measure and decompose the carbon productivity changes of 37 major carbon emitting countries and regions over 1995–2009. The main findings include: (i) endogenous directions identifying the largest improvement potentials are noticeably different from exogenous directions in estimating the inefficiencies of undesirable outputs. (ii) Carbon productivity indicator calculated with the consideration of emission structure provides a more significant estimation on productivity change. (iii) The aggregated carbon productivity and the specific energy driven carbon productivities significantly improve over our study period which are primarily attributed to technical progress. (iv) Empirical results imply that policies focused on researching and developing energy utilization and carbon control technologies might not be enough; it is also essential to encourage technical efficiency catching-up and economic scale management.

1. Introduction

Climate change and global warming caused by rising greenhouse gases (GHG) emissions has recurrently aroused public concern (Shao et al., 2011). Environmental problems have become one of the most challenging issues worldwide; especially some developing countries (e.g., China) are concerned with reducing the increasing speeds of energy consumption and GHG (e.g., CO_2) emissions while promoting the development of industrialization. The objective of some policies is to keep economic growth under the control of CO_2 emissions from the combustion of fossil fuels which is known as the main source of GHG (Liu et al., 2007). Although the community is paying more attention to carbon emissions, most countries will still be dominated by fossil energy consumption in the short term considering their resources endowment and relative low speed of renewable energy research and development (Armaroli and Balzani, 2014; Wang et al., 2013a,b). Therefore, many scholars have stated this dilemma using the evaluation of carbon

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performance, namely, carbon efficiency and productivity instead of traditional evaluation of energy performance so as to provide deeper insights into the climate policy making and prior actions choosing for energy conservation, emission control and economic growth.

The concept of carbon productivity was proposed by Kaya and Yokobori (1999). They defined it as the amount of GDP generated by per ton of CO_2 emissions, denoting the economic benefits of per unit CO_2 emissions. The measure of carbon productivity helps to reveal the level of low carbon economy for a country and the corresponding development stage of it. He et al. (2010) pointed that the speed of carbon productivity growth could be used to assess the effort and effectiveness of responding global climate change of a country. This point of view has also been recognized by some other researchers. For instance, Stem and Jotzo (2010) identified the relationship between carbon productivity and economic performance; Bhattacharyya and Matsiimura (2010) decomposed carbon productivity change into a contribution of climate, a residual technology variable, and an input and output mix; Davidsdottir and Fisher (2011) further extended this concept to GDP intensity of GHG emissions. In order to provide a more comprehensive understanding of global carbon productivity changes, the current study provide an estimation of carbon productivity[1] changes for 37 major emitting countries and regions, and the sources for carbon productivity change are additionally identified and discussed.

Previous studies usually use Malmquist–Luenberger productivity index to evaluate carbon productivity change. The Malmquist–Luenberger productivity index, which was proposed and modified by Caves et al. (1982) and Färe et al. (1992), has three disadvantages: (i) productivity index is not circular; (ii) infeasible situation is existing; and (iii) there are different measures for cross-period observations when computing and decomposing the index (Färe and Grosskopf, 1996). In order to solve these shortages, Berg et al. (1992) proposed an index using a base period technology frontier. It satisfies circularity and has only one measure on cross-period observations, but it still has infeasible situation. Shestalova (2003) introduced a sequential period technology frontier approach. This index produces a single measure of adjacent period data and is immune to infeasibility. But it ignores the technical regress and also fails circularity. Färe et al. (2001) and Zhou et al. (2010) used windows analysis technique to overcome the infeasible situation problem; however this method still pays for the other two shortcomings. Pastor and Lovell (2005) presented a global Malmquist index with all period data. Their index satisfies circularity and generates a single measure for cross-period observations, as well as is immune to infeasible solution. Many studies have been employed global index in empirical analysis. For instance, Oh (2010) utilized global and conventional technology frontier for a comparative analysis of 26 OECD countries. Fan et al. (2015) proposed the global Malmquist–Luenberger index to investigate the performance of CO_2 emissions. Zhang and Choi (2013) and Zhang and Wei (2015) evaluated the total factor carbon emissions performance by combining global frontier and meta-frontier so as to take the group heterogeneity into consideration. In our paper, we extend their index to a global Luenberger carbon productivity indicator for measuring carbon productivity change. It has an addictive structure rather than a ratio form to characterize the carbon productivity change.

When measuring the productivity change with the consideration of both intend or desirable outputs (e.g., product or service) and unintended or undesirable outputs (e.g., pollution), the Luenberger productivity indicator is usually calculated by directional distance function (DDF). Shephard (1970) first proposed the distance function, which proportionally expands desirable and undesirable outputs in the feasible region. Then, Chambers et al. (1996) introduced the directional distance function to simultaneously extend desirable outputs and shrink undesirable outputs or some energy inputs. It can be considered that the directional distance function is a generalized form of the distance function. Since the use of fossil energy will inevitably generate unintended outputs (e.g., CO_2 emissions), DDF approach is considered a powerful tool in modeling energy and environmental efficiency and productivity (Managi and Jena, 2008; Oggioni et al., 2011; Picazo-Tadeo et al., 2014). Moreover, Zhang and Choi (2014) presented a review regarding the recent applications of DDF in energy and environmental efficiency studies.

In most applications of DDF, the directional vectors typically are predetermined by researchers (i.e., exogenous directions). This is considered a sort of arbitrary and unreasonable for capturing the largest improvement potentials on inputs and outputs. Therefore, some recent studies have focused on inquiring a proper direction to the production frontier. Peyrache and Daraio (2012) proposed an approach to investigate how to obtain the most appropriate directional vector of DDF, whereas Färe et al. (2013) and Hampf and Krüger (2014) present a model based on exogenous normalization constraints. These endogenous directions, which can identify the largest improvement under the existing technology, are more reasonable in a sense and considered to be one of the most promising methods in determining the directions. In this analysis, we introduce the endogenous model by Hampf and Krüger (2014) in to our calculation of global Luenberger carbon productivity indicator.

To the best of our knowledge, previous studies on identifying the sources of carbon productivity change mainly focused on the decomposition of carbon productivity change into, for example, efficiency change and technical change (David and Paul, 1996; Mahlberg and Sahoo, 2011; Chang et al., 2012; Mahlberg and Luptacik, 2014; Woo et al., 2015). In this study, including the investigation of carbon productivity indicator from the traditional decomposition perspective mention above, we further investigate the carbon productivity change from a perspective of additionally identifying the contribution of specific desirable and/or undesirable output factors (e.g., CO_2 emissions from the consumption of specific energy). We name this analysis as disaggregation, which is considered a complement of decomposition analysis.

It is important to explore the carbon productivity change from the decomposition perspective, since the carbon productivity change has at least two effects on economic development. First, decomposition could provide some useful information on policy formulation for low carbon economic. Second, it is a guideline for technology improvement. Therefore, in this study, on the one hand, the carbon productivity indicator is decomposed into pure efficiency change (*PEC*), scale efficiency change (*SEC*) and best practice gap change (*BPC*) so as to help identifying the effects of catching-up and technical progress in carbon productivity growth. However, on the other hand, the global Luenberger carbon productivity indicator itself is not capable of reflecting the contribution of individual output sources. Thus, in this study, the outputs are disaggregated in a way that makes us to measure the contribution of individual output sources to productivity change. The output sources include desirable outputs, i.e., gross outputs of industry (GO), and undesirable outputs, i.e., different energy (e.g., coal, oil and natural gas) consumption driven CO_2 emissions.

For discussion convenient, in this study, we name the global Luenberger carbon productivity indicator with the consideration of carbon emissions structure (i.e., total CO_2 emissions are disaggregated into different energy driven CO_2 emissions) as aggregated

[1] In our study, carbon productivity is defined as the total factor carbon emissions productivity which calculates the total factor productivity with the consideration of CO_2 emissions as an undesirable output. For expression convenience, we use the shortened form "carbon productivity" in the following text.