Journal of Cleaner Production 151 (2017) 109–120

Contents lists available at ScienceDirect

Journal of Cleaner Production

journal homepage: www.elsevier.com/locate/jclepro

Comparison of technology efficiency for CO_2 emissions reduction among European countries based on DEA with decomposed factors

Deuk Sin Kwon, Joon Hyung Cho, So Young Sohn*

Department of Information and Industrial Engineering, Yonsei University, 134 Shinchon–dong, Seoul 120–749, Republic of Korea

ARTICLE INFO

Article history:
Received 2 November 2016
Received in revised form
9 March 2017
Accepted 9 March 2017
Available online 10 March 2017

Keywords:
Two-stage DEA
CO_2 reduction
Technical efficiency
Environmental consciousness
Decomposition analysis
LMDI

ABSTRACT

For consistent and effective CO_2 reduction, many countries need to improve not only the technical efficiency of CO_2 mitigation, but also environmental responsibility. In this study, we examine both the technical efficiency and voluntary environmental consciousness (VEC) of 12 European countries using a two-stage data envelopment analysis (DEA). In the first stage, we measured the technical efficiency of green energy technologies (GET) associated with fossil fuels, renewable energy, and storage technologies of each country for energy generation with regard to CO_2 emissions by surveying GET-related patents. Using the logarithmic mean Divisia index (LMDI), we decomposed CO_2 emissions into the following technological factors: energy intensity, fuel mix, and CO_2 emission coefficient. In the second stage, we quantified the VEC in each country by investigating GET patent changes via research and development (R&D) investment at given changes in CO_2 emissions. The results show different aspects for each country in terms of technical efficiency and VEC, suggesting potential levels of both efficient CO_2 reductions and desirable GET development by using reference countries as a benchmark. Our study methodology and results can contribute to establishing effective national technology policy and aid in calls for common responsibility and the active participation of nations in addressing climate change.

1. Introduction

As rising atmospheric CO_2 concentrations become an increasingly important global issue, many countries have prioritized reducing CO_2 emissions as a main policy goal in national growth plans (Kim et al., 2016). In particular, 15 European countries—the EU Bubble—have strived to mitigate CO_2 emissions (Skjærseth et al., 2013), contributing to a 22% reduction in CO_2 emissions by the EU in 2015 compared to 1990 levels (European Commission, 2016).

For CO_2 mitigation, various technologies have been developed so far in the field of energy generation, mainly for electricity (Kim et al., 2017; Sohn et al., 2015). In particular, energy-related technologies related to fossil fuels, renewable energy, and storage technologies have played critical roles in the reduction of CO_2 emissions. Fossil fuel combustion for energy generation accounted for most CO_2 emissions, and fossil fuels used for electricity generation are implicated in more than 40% of global CO_2 emissions (Quadrelli and Peterson, 2007; Zhang et al., 2013a). Certain renewable energies (e.g., biomass and waste mass) account for a portion of CO_2 emissions, and many carbon-free renewable energies have received attention as alternative green energies that can assist in CO_2 reduction (Noailly and Shestalova, 2013). Storage technology also contributes to the mitigation of CO_2 emissions through improving energy efficiency and managing CO_2 (Hadjipaschalis et al., 2009). Therefore, for consistent and effective reduction of CO_2 emissions, it is important to improve technical efficiency of these energy-related technologies, which are collectively referred to as green energy technologies (GET).[1]

CO_2 emissions can be influential in investment decisions surrounding GET. In general, it is expected that nations with high levels of CO_2 emissions may invest more in GET than other technologies. However, nations with low voluntary environmental consciousness (VEC) would be unwilling to invest in GET despite their large volume of CO_2 emissions. On the other hand, nations with high voluntary environmental consciousness (VEC) would

* Corresponding author.
E-mail addresses: kds0281@gmail.com (D.S. Kwon), paul619@naver.com (J.H. Cho), sohns@yonsei.ac.kr (S.Y. Sohn).

[1] **Non standard abbreviations** EC: fossil fuel energy consumption; GET: green energy technologies; VEC: voluntary environmental consciousness.

http://dx.doi.org/10.1016/j.jclepro.2017.03.065
0959-6526/

have a higher propensity to invest in GET, even if they had a smaller volume of CO_2 emissions. For this study, VEC was defined as the amount of effort made by a country to develop GET for CO_2 reduction, given its level of CO_2 emissions, and was measured by the number of GET-related patents. High and low degrees of VEC were estimated via comparison with the GET patenting efforts of other countries given their corresponding CO_2 emissions levels. We quantified the VEC of each nation, since this can have a significant role in encouraging active participation in creating and enforcing cooperative plans to mitigate CO_2 emissions, when common responsibility and international efforts are required to address climate change. Known factors influencing CO_2 emissions include population, industrial structure, and energy intensity. We decomposed CO_2 emissions into these factors using the logarithmic mean Divisia index (LMDI).

The results of our analysis can be utilized for establishing GET policies for CO_2 reduction. In addition, the VEC information can be used as a barometer to pursue common environmental objectives or to enact international treaties related to climate change.

The outline of the paper is as follows. In section 2, we clarify our research purpose by reviewing the previous literature. In section 3, we introduce a research framework, explain the selected methodologies of two-stage data envelopment analysis (DEA) and LMDI, and describe the data used. In section 4, we show the DEA results in terms of technical efficiency and VEC for each country. In section 5, we discuss the results along with various CO_2 reduction polices in the studied European countries. Finally, in section 6, we conclude with the implications and limitations of this research, presenting areas for further study.

2. Literature review

DEA, proposed by Charnes et al. (1978), is a non-parametric frontier efficiency technique using linear programming for efficiency estimation. DEA has drawn increasing attention in various industries and environmental fields (Han and Sohn, 2011; Sohn, 2006; Sohn and Choi, 2006; Sohn and Kim, 2012). In particular, DEA methods that are appropriate to environmental fields and indices for measuring efficiency have been developed (Shi et al., 2010; Zhou and Ang, 2008b; Chang et al., 2013). Because CO_2 is an undesirable good that causes a problem of biased efficiency measurements in DEA, it was excluded from the analysis until Zhou and Ang (2008b) used CO_2 as an output variable in their DEA model. Subsequently, many studies have used CO_2 emissions as input or output in DEA (Sueyoshi and Goto, 2010, 2011; Wu et al., 2012; Zhou et al., 2014). Sueyoshi and Goto (2010, 2011) measured production efficiency in fossil fuel electricity generation using CO_2 emissions. Wu et al. (2012) gauged the industrial energy efficiency of CO_2 emissions by applying an energy efficiency performance index to a DEA model. Oggioni et al. (2011) measured the eco-efficiency of cement production processes for 21 cement industries in various countries by using DEA with CO_2 emissions as input or undesirable output. Zhou et al. (2014) also used CO_2 emissions as undesirable output in a DEA model to investigate the optimal allocation of CO_2 emissions in several regions of China, the result of which showed that the spatiotemporal allocation strategy could be a good alternative for attaining the optimal control of CO_2 emissions.

Decomposition analysis has also been applied in environmental fields (Baležentis et al., 2016; Miao et al., 2016). In particular, it has been used to quantify the effects of several factors on CO_2 emissions (Sun, 1998; Ang and Zhang, 2000; Wang et al., 2005; Lin et al., 2006). Decomposition analysis investigates the impact of each factor on CO_2 emissions by decomposing the changes in CO_2 into well-defined identities such as emission intensity, energy intensity, and economic activity effects (Ang and Pandiyan, 1997; Ang and Zhang, 2000; Lin et al., 2006; Sun, 1998; Wang et al., 2005). By applying the Divisia index method, Lin et al. (2006) decomposed CO_2 emissions of Taiwan into four factors, including emission coefficient and energy intensity, to identify dominant factors of CO_2 emissions, providing some insights for the CO_2 reduction strategies. In particular, LMDI is preferred over many available decomposition models for CO_2 emissions because it can be applied to small datasets and can measure the exact effects of many factors on CO_2 emissions with zero residual terms (Ang et al., 2003; Liu et al., 2007; Lin and Ouyang, 2014). Lin and Ouyang (2014) applied LMDI to the non-metallic mineral industry of China to investigate five factors causing CO_2 emissions changes. The results suggested that energy intensity and industrial activity are the main drivers of changing CO_2 emissions in the industrial sector.

In recent years, methods combining DEA and decomposition analysis have been utilized in many studies (Chen and Duan, 2016; Wang et al., 2015; Zhou and Ang, 2008a; Zhang et al., 2013b). These studies compute the efficiency between input and output variables through a distance function based on DEA or linear programming similar to the principle of DEA. The produced efficiency is combined with identities in decomposition analysis, creating new identities that reflect technological effects in the environmental sphere and in particular their impacts on changes in CO_2 emissions. Zhou and Ang (2008a) suggested a production-theoretical decomposition analysis (PDA) that decomposes the change in CO_2 emissions into several factors using the Shephard distance function. Chen and Duan (2016) also applied PDA to explore the impact of factors causing CO_2 emissions in a specific region of China during 2001–2010. They evaluated the impact of six driving factors on CO_2 emissions, revealing technical efficiency and technological progress were the main contributors to CO_2 reduction. Zhang et al. (2013b) proposed an alternative decomposition method with a distance function based on DEA to measure the effect of changes in high and low technical efficiencies. They decomposed CO_2 emissions in 25 OECD countries and China into ten factors. Kim and Kim (2012) also combined the Shepard distance function with LMDI to assess energy efficiency. The authors found that the dominant contributing factors to CO_2 reductions in most of the OECD and non OECD countries are potential energy intensity and energy mix among seven components.

However, previous research combining DEA with decomposition analysis considered technological changes and effects to have already been reflected in the decomposed factors. Although the impact of the decomposed factors on CO_2 emissions was elucidated with data on energy sources and energy consumption, the technical efficiency of the relationship between CO_2 emissions and technology was also indirectly investigated. However, to measure exact technical efficiency, the effect of technology on CO_2 emissions changes under the direct relationship between input and output must be investigated. Notably, there have been no studies investigating the effect of technology on CO_2 mitigation thus far that use patent data and CO_2 emissions as input and output variables.

To measure the direct effect of technology on CO_2 emissions, patent data—useful as a proxy of technology development—are used in this study. We used LMDI to more accurately investigate the technological performance of CO_2 reductions by calculating in detail the amount of CO_2 emissions changed by technology. Although patents do not represent all technologies related to CO2 reductions, they can explain many aspects of CO2 reduction when used as input variables for investigating CO2 emissions (Popp,