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Assessing drivers of economy-wide energy use and emissions: IDA versus SDA

H. Wang[a,*], B.W. Ang[a], Bin Su[b]

[a] *Department of Industrial and Systems Engineering, National University of Singapore, Singapore*
[b] *Energy Studies Institute, National University of Singapore, Singapore*

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ABSTRACT

Index decomposition analysis (IDA) and structural decomposition analysis (SDA) are analytical techniques that have been extensively used by researchers to study drivers of changes in energy consumption and energy-related emissions for energy and climate policy assessment and development. We compare the two techniques from the methodological and application viewpoints and with specific reference to economy-wide analysis where the overlap between the two is the greatest. Our study brings up to date several previous studies and provides a detailed assessment of the post-2010 developments. In addition, a framework for additive and multiplicative decomposition methods is presented, specific application in policy analysis is discussed with representative examples given, and the selection between the two techniques is described. Despite the differences between the two techniques in terms of origin, there has been some convergence in their application in some specific areas. However, even if the same dataset is used, application of the two techniques will lead to different numerical results due to underlying differences in some core concepts and the meanings of the drivers of change defined. A good understanding of these similarities and differences will help researchers in making sound judgment in their adoption and implementation in policy studies.

1. Introduction

Climate change has had widespread impacts on human and natural systems (IPCC et al., 2014). To mitigate the impacts, efforts have been made at the global, regional, national and sub-national levels to reduce anthropogenic CO_2 emissions. The 1992 Kyoto Protocol and the 2015 Paris Climate Agreement are examples of such efforts at the global level. Arising from these efforts and since the energy sector contributes to the bulk of the CO_2 emissions, countries have developed programmes and taken actions to reduce growth in energy use and energy-related CO_2 emissions. In developing such programmes, an area that is often looked into is the driving forces behind changes in energy consumption or CO_2 emissions. A good understanding of these driving forces is essential to develop realistic reduction targets as well as to track and evaluate performance. Over the years, researchers have used several different analytical tools for such purposes. They include econometric techniques, systems dynamics, computable general equilibrium (CGE)[1] models, and decomposition analysis. This study focuses on decomposition analysis.

Decomposition analysis is an accounting or descriptive technique that has been widely used to analyse and have a better understanding of energy or emission systems. It essentially distributes a change in an aggregate indicator for a system of interest into components related to several predefined factors. These predefined factors are known as drivers since they drive changes in the aggregate indicator. The decomposition results, also known as effects, are used to explain the observed change of the aggregate indicator. The sign and magnitude of the effects are related to policy measures. In energy studies, Myers and Nakamura (1978) and Bossanyi (1979) are two of the earliest that use basic decomposition concepts to study changes in energy consumption. Since then, several different decomposition techniques have been proposed and adopted. The two most widely used ones are the index decomposition analysis (IDA) and the structural decomposition analysis (SDA).

IDA, the simpler of the two, was first applied to decompose changes in industrial energy consumption into effects associated with a number of factors using sub-aggregate data in the late 1970s and 1980s.[2] The simplest IDA model deals with the decomposition of a change in total

* Corresponding author.
E-mail address: hwang@u.nus.edu (H. Wang).

[1] All symbols and acronyms used are summarized in Table 1.
[2] Sub-aggregates are entities that make up an aggregate. For example, they are individual commodities in measuring price and quantity indexes based on a basket of goods. In industrial energy studies they are industrial sectors, sub-sectors or products that industry comprises.

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energy consumption into three effects, i.e. effects associated with activity energy intensity, activity output share, and overall activity level. A change in total energy consumption, i.e. the aggregate indicator of interest, over a specific time period can be explained by the three effects whose sign and magnitude are often of interest to policy makers. A survey of IDA studies reported in the literature prior to 2000 is given in Ang and Zhang (2000). Boyd et al. (1988) point out that IDA is similar to index number problems in economics, where the impact of commodity price or quantity on the change in aggregate commodity expenditure over time is studied. Since then, a number of concepts in index number theory have been adopted, with customization where necessary, in the IDA literature. Due to its simplicity and flexibility, IDA has been widely used to study energy consumption or emissions changes and to track efficiency trends at economy-wide and sectoral levels. A recent overview can be found in Ang (2015).

SDA seeks to distribute a change in an aggregate indicator into a number of components with each associated with a predefined factor based on input-output (I-O) models. Using the I-O model proposed by Leontief (1941), the relationship between an economy's production and consumption is modelled. The economic I-O model was extended to environmental studies in 1970s (Leontief, 1970). SDA was first applied in the 1970s to quantify sources of changes in some dependent variables of the I-O model of interest, e.g. total output, value added, labour, trade, etc. The impacts of demand and production technology are estimated, generally at the economy-wide level. Since the 1980s, SDA has been adopted in energy studies. For example, Gowdy and Miller (1987) and Rose and Chen (1991) investigate change in energy use in the United States, and Chen and Rose (1990) deal with the case of Taiwan. Since around 2000, SDA has increasingly been applied to study growth in CO_2 emissions (Su and Ang, 2012b). More recently, studies involving the consumption-based emissions and emissions embedded in trade (EET) have been reported. For example, Baiocchi and Minx (2010) apply SDA to understand changes in the CO_2 emissions from consumption in the UK, European Environment Agency (2014a) investigates EU's consumption-based CO_2 emissions change using SDA, and Feng et al. (2015) study the drivers of the U.S. emissions change.

The use of IDA in energy studies was earlier than that of SDA. Although they differ in terms of origin and methodological foundation, the basic underlying concept of decomposing an aggregate indicator into effects associated with several predefined factors are the same. Rose and Casler (1996) point out that IDA and SDA are related. According to Hoekstra and van der Bergh (2003), IDA and SDA are consistent in decomposition methods, i.e. indexes originated from index number theory, but differ in the modelling of an aggregate indicator. They further extend decomposition methods used in one approach to the other. Su and Ang (2012b) compare more recent methodological developments in IDA and SDA. Lenzen (2016) treats SDA as a generalization of IDA in terms of mathematical formulation.

In the past few years, there were some new developments in both IDA and SDA when applied to energy and emissions. A systematic review and comparison between IDA and SDA on both the methodological and application fronts will bring the literature up to date and help to guide policy development and assessment. The purpose of this study is to fill this gap with a focus on economy-wide analysis.[3] We first present a framework for additive/multiplicative decomposition methods. Applications of IDA and SDA decomposition methods are then discussed. We then focus on IDA and SDA literatures on economy-wide analysis and pay special attention to the period 2010–2015. We discuss the main findings and the choice between IDA and SDA from the viewpoint of policymakers. For illustration purposes, a case study comparing IDA and SDA empirically using China's energy consumption data is presented.

[3] The focus on economy-wide analysis is to allow for comparisons that are more meaningful since the scope of SDA studies is generally economy-wide while that of IDA studies is much wider and more varied.

2. A framework for decomposition analysis

As discussed in the foregoing, the objective of decomposition analysis is to isolate the impacts of pre-defined factors on an aggregate of interest, which is in line with the concept of index number problems in economics. In view of the past developments of IDA and SDA, one way of looking at the various reported decomposition methods is that they are theoretically rooted in index number problems. Index numbers are traditionally used to quantify the impacts of price change and quantity change on the aggregate expenditure change. The change in aggregate expenditure is decomposed into two parts, i.e. price and quantity effects. In some index number problems, three or more factors may appear, e.g. decomposing aggregate labour cost into hourly wage, working hours per day and days worked (Balk, 2003). Without loss of generality, we model an aggregate indicator as:

$$V = \sum_{j=1}^{m} V_j = \sum_{j=1}^{m}\left(\prod_{i=1}^{n} x_{j,i}\right) \tag{1}$$

where V is the aggregate indicator of interest that can be divided at m entities (or sub-aggregates, depending on the level of disaggregation) and expressed as the product of n factors. Suppose data for time 0 and T are available. The arithmetic and ratio change in the aggregate indicator during the time period from 0 to T are respectively formulated as:

$$\begin{aligned} V^T - V^0 &= \sum_{j=1}^{m} x_{j,1}^T x_{j,2}^T \dots x_{j,n}^T - \sum_{j=1}^{m} x_{j,1}^0 x_{j,2}^0 \dots x_{j,n}^0 \\ &= \Delta V_1 + \Delta V_2 + \dots + \Delta V_n + \Delta V_{rsd} \end{aligned} \tag{2}$$

$$\frac{V^T}{V^0} = \frac{\sum_{j=1}^{m} x_{j,1}^T x_{j,2}^T \dots x_{j,n}^T}{\sum_{j=1}^{m} x_{j,1}^0 x_{j,2}^0 \dots x_{j,n}^0} = D_1 D_2 \dots D_n D_{rsd} \tag{3}$$

where ΔV_i and D_i are the additive and multiplicative effects for the n factors, respectively. The terms ΔV_{rsd} and D_{rsd} denote potential residual. When a residual does not exist, we have ΔV_{rsd}=0 or D_{rsd} =1. An arithmetic or ratio change in the aggregate indicator can be completely explained by effects associated with the n factors.

2.1. Additive decomposition analysis

To calculate the additive effects in Eq. (2), we first differentiate V with respect to time t as follows:

$$\begin{aligned} \frac{dV}{dt} &= \sum_{j=1}^{m} \frac{dV_j}{dt} = \sum_{j=1}^{m} \left(x_{j,2} \dots x_{j,n} \frac{\partial x_{j,1}}{\partial t} + x_{j,1} x_{j,3} \dots x_{j,n} \frac{\partial x_{j,2}}{\partial t} + \dots \right. \\ &\quad \left. + x_{j,1} \dots x_{j,n-1} \frac{\partial x_{j,n}}{\partial t} \right) \\ &= \sum_{j=1}^{m} \left(\frac{V_j}{x_{j,1}} \frac{\partial x_{j,1}}{\partial t} + \frac{V_j}{x_{j,2}} \frac{\partial x_{j,2}}{\partial t} + \dots + \frac{V_j}{x_{j,n}} \frac{\partial x_{j,n}}{\partial t} \right) \end{aligned} \tag{4}$$

The arithmetic change of the aggregate indicator V between 0 and T can be derived by integrating Eq. (4), which reads

$$\begin{aligned} V^T - V^0 &= \int_0^T \frac{dV}{dt} dt \\ &= \int_0^T \sum_{j=1}^{m} \left(\frac{V_j}{x_{j,1}} \frac{\partial x_{j,1}}{\partial t} + \frac{V_j}{x_{j,2}} \frac{\partial x_{j,2}}{\partial t} + \dots + \frac{V_j}{x_{j,n}} \frac{\partial x_{j,n}}{\partial t} \right) dt \\ &= \int_0^T \sum_{j=1}^{m} V_j \left(\frac{\partial \ln x_{j,1}}{\partial t} + \dots + \frac{\partial \ln x_{j,n}}{\partial t} \right) dt \end{aligned} \tag{5}$$

The second line of Eq. (5) deals with linear changes in factors, i.e.