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The sign reversal problem in structural decomposition analysis

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ABSTRACT

A structural decomposition analysis (SDA) based on the input-output model disaggregates fluctuations in the total factor budget into shifts in its determinants. The essence of SDA is its ability to quantify the critical factors that contribute to changes in phenomena. However, it is well-known that various uncertainties are manifest in input-output datasets and SDA results may be vulnerable to substantive biases including erroneous sign reversals. This study employs Monte Carlo simulations and investigates this sign reversal problem. The simulations reveal instability in the decomposition results, particularly the effects of the intensity term and the economic structure term. In contrast, the decomposition effect of the final demand term is relatively insusceptible in this regard.

1. Introduction

Structural decomposition analysis (SDA) based on the input-output framework aims to distinguish the critical driving forces of change in many kinds of variables over time (Rose and Casler, 1996; Miller and Blair, 2009; Su and Ang, 2012). This technique has been used extensively with respect to economic, employment, and other socio-economic indicators (Feldman et al., 1987; Skolka, 1989; Martin and Holland, 1992; Dietzenbacher and Hoekstra, 2002; Yang and Lahr, 2010). In the last few decades there has been increasing attention to applications of decomposition analysis within environmental studies, for example, energy issues (Jacobsen, 2000; Kagawa and Inamura, 2001, 2004; Liao et al., 2007; Weber, 2009; Zhang and Lahr, 2014), water use (Zhang et al., 2012; Roson and Sartori, 2015; Feng et al., 2017), material flows (Wood et al., 2009; Weinzettel and Kovanda, 2011) and greenhouse gas emissions (Casler and Rose, 1998; de Haan, 2001; Peters et al., 2007; Guan et al., 2009; Wood, 2009; Lenzen et al., 2013a; Arto and Dietzenbacher, 2014; Xu and Dietzenbacher, 2014; Feng et al., 2015; Hoekstra et al., 2016; Lan et al., 2016; Mi et al., 2017).

In terms of the latter, SDA has been applied not only to emissions dynamics in a single region but also to decomposing changes in global emissions using a multi-region input-output (MRIO) framework (Kagawa and Inamura, 2004; Arto and Dietzenbacher, 2014; Xu and Dietzenbacher, 2014; Hoekstra et al., 2016; Lan et al., 2016; Malik and Lan, 2016; Malik et al., 2016; Fujii et al., 2017). Kagawa and Inamura (2004) introduced the inter-region input-output SDA method using empirical data from China and Japan, and estimated the effects of changes in intra- and inter-region energy demand linkages. Recently, Arto and Dietzenbacher (2014) and Xu and Dietzenbacher (2014) analyzed key drivers of changes in global CO_2 emissions induced by international trade using the World Input-Output Database (WIOD) constructed by Dietzenbacher et al. (2013). Lan et al. (2016) applied a more detailed MRIO SDA to global energy footprints using Eora time series data (Lenzen et al., 2012, 2013b), and revealed that affluence and population growth are the main drivers of increasing footprints in both developed and developing countries.

The essence of decomposition analysis is its ability to quantify the critical factors that contribute to changes in phenomena; results thereof have been used for policy evaluation and formulation. However, it is well known that various uncertainties are manifest in input-output datasets. These uncertainties are associated with survey data, the estimation of transactions, allocations, proportionally assumptions,

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changes in technology, aggregation (Lenzen, 2000; Nansai et al., 2001; Yoshida et al., 2002; Weber, 2008; Wiedmann, 2009), and many kinds of inventory data for environmentally-extended input-output analysis (e.g., Nansai et al., 2012).

If there is a *large* change in technical coefficients during the time period between year 0 and t, errors included in the technical coefficients at year 0 and t does not affect the sign and magnitude of technical change effects that is important to policy implications. The sign reversal problem discussed in this paper is that if there is a *small* change in technical coefficients between year 0 and t, the sign of the technical change effects is sensitive to the errors. Thus, depending on the nature and extent of these uncertainties, SDA results may be vulnerable to substantive biases including erroneous sign reversals. Therefore, care needs to be taken vis-à-vis the selection and utilization of appropriate data in SDA and the subsequent interpretation of results from such analyses.

This study aims to investigate this sign reversal problem in SDA. As a case study, a single region input-output table was focused upon and a Monte Carlo-type simulation was applied to evaluate the reliability of the decomposition results. The remainder of the paper is organized as follows: Section 2 explains the methodology; Section 3 presents results and a discussion; and, finally, Section 4 offers conclusions.

2. Methodology

2.1. Input-output analysis

The output vector $\mathbf{x} = (x_i)$ $(i = 1, \ldots, n)$ in a fundamental input–output analysis with n industries can be expressed as a linear equation: $\mathbf{x} = \mathbf{Ax} + \mathbf{f}$, where $\mathbf{f} = (f_i)$ is the final demand vector, representing the final global demand for the products of industry i, and $\mathbf{A} = \mathbf{Z}\hat{\mathbf{x}}^{-1} = (a_{ij})$ $(j = 1, \ldots, n)$ is an input coefficient matrix, expressing the intermediate inputs for industry i that are necessary per unit of production of the product of industry j, for which $\mathbf{Z} = (Z_{ij})$ represents the intermediate inputs into industry j from industry i and $\hat{\mathbf{x}}$ denotes the diagonalization of $\mathbf{x}$. Solving the above linear equation for output vector $\mathbf{x}$, we obtain:

$$\mathbf{x} = (\mathbf{I}-\mathbf{A})^{-1}\mathbf{f} = \mathbf{Lf} \tag{1}$$

where $\mathbf{I}$ is the identity matrix and $\mathbf{L} = (\mathbf{I} - \mathbf{A})^{-1} = (L_{ij})$ is the Leontief inverse matrix with elements L_{ij} expressing the output of industry i that is directly and indirectly required to satisfy one unit of final demand from industry j.

If the intensity vector is $\mathbf{e} = \mathbf{E}\hat{\mathbf{x}}^{-1} = (e_j)$, the total factor budget Q, e.g., energy uses, environmental burdens or any social accounts can be estimated as

$$Q = \mathbf{e}(\mathbf{I}-\mathbf{A})^{-1}\mathbf{f} = \mathbf{eLf} \tag{2}$$

where $\mathbf{E} = (E_j)$ represents the direct factor budget of industry j.

2.2. Structural decomposition analysis

A structural decomposition analysis (SDA) based on the input-output model is a comparative static method designed to disaggregate fluctuations in the total factor budget into shifts in its determinants such as $\mathbf{e}$, $\mathbf{L}$, and $\mathbf{f}$, herein. Broadly speaking, decomposition analysis methods can be divided into two decomposition forms (additive and multiplicative forms) and two indicator forms (Laspeyres and Divisia families, see Lenzen, 2006 for a detailed discussion). The additive form is more commonly applied than its multiplicative counterpart in the energy and emissions domain because it yields results that are easier to interpret (Lenzen, 2006, 2016; Su and Ang, 2012). In terms of indicator forms and families, in Laspeyres-based approaches Su and Ang (2012) suggest opting for the "SSA method" (Sun, 1998; Albrecht et al., 2002) or the "D&L method" (Dietzenbacher and Los, 1998), both of which are also denoted as the "DSA method" in Lenzen (2006).[1] Those same authors also suggest that the logarithmic mean Divisia index (LMDI) method (Ang and Choi, 1997; Ang and Zhang, 2000; Choi and Ang, 2003) should be preferred in the context of Divisia-based approaches. Both indicator forms have desirable properties such as exactness (Sun and Ang, 2000), time reversal (Hoekstra and van den Bergh, 2003), and zero-robustness (Wood and Lenzen, 2006; Ang and Liu, 2007). These two decomposition methods were implemented following the guidelines in Su and Ang (2012).

In additive decomposition, the change ΔQ in total factor budget from time 0 to time t is decomposed as.

$$\Delta Q = Q(t) - Q(0) = \mathbf{e}(t)\mathbf{L}(t)\mathbf{f}(t) - \mathbf{e}(0)\mathbf{L}(0)\mathbf{f}(0) = \Delta C_{\mathbf{e}} + \Delta C_{\mathbf{L}} + \Delta C_{\mathbf{f}} \tag{3}$$

where the numbers in parentheses represent time, and the ΔCs on the right-hand side denote the effects associated with changes in each determinant. The D&L method (hereinafter referred to as the DSA method) uses the average of $n!$ different but exact forms, and, accordingly, Eq. (3) can be expressed as Eq. (4).

$$\begin{aligned}\Delta Q^{\mathrm{DSA}} = & \frac{1}{6}\Delta\mathbf{e}\{2\mathbf{L}(0)\mathbf{f}(0) + \mathbf{L}(t)\mathbf{f}(0) + \mathbf{L}(0)\mathbf{f}(t) + 2\mathbf{L}(t)\mathbf{f}(t)\} \\ & + \frac{1}{6}\{2\mathbf{e}(0)\Delta\mathbf{L}\mathbf{f}(0) + \mathbf{e}(t)\Delta\mathbf{L}\mathbf{f}(0) + \mathbf{e}(0)\Delta\mathbf{L}\mathbf{f}(t) + 2\mathbf{e}(t)\Delta\mathbf{L}\mathbf{f}(t)\} \\ & + \frac{1}{6}\{2\mathbf{e}(0)\mathbf{L}(0) + \mathbf{e}(t)\mathbf{L}(0) + \mathbf{e}(0)\mathbf{L}(t) + 2\mathbf{e}(t)\mathbf{L}(t)\}\Delta\mathbf{f}\end{aligned} \tag{4}$$

Here, $\Delta\mathbf{e} = \mathbf{e}(t) - \mathbf{e}(0)$, $\Delta\mathbf{L} = \mathbf{L}(t) - \mathbf{L}(0)$, and $\Delta\mathbf{f} = \mathbf{f}(t) - \mathbf{f}(0)$.[2] The first, second, and third terms on the right-hand side of Eq. (4) correspond to $\Delta C_{\mathbf{e}}$, $\Delta C_{\mathbf{L}}$, and $\Delta C_{\mathbf{f}}$, respectively.

On the other hand, Eq. (3) can be written using the logarithmic mean Divisia index (LMDI) as.

$$\begin{aligned}\Delta Q^{\mathrm{LMDI}} = & \sum_{ij}^{n} \mathrm{LM}(Q_{ij}(t), Q_{ij}(0)) \ \ln\frac{e_i(t)}{e_i(0)} + \sum_{i,j}^{n} \mathrm{LM}(Q_{ij}(t), Q_{ij}(0)) \ \ln\frac{L_{ij}(t)}{L_{ij}(0)} \\ & + \sum_{ij}^{n} \mathrm{LM}(Q_{ij}(t), Q_{ij}(0)) \ \ln\frac{f_j(t)}{f_j(0)}\end{aligned} \tag{5}$$

where $Q_{ij} = e_i L_{ij} f_j$ and $\mathrm{LM}(Q_{ij}(t), Q_{ij}(0))$ represent the logarithmic mean defined as $\mathrm{LM}(Q_{ij}(t), Q_{ij}(0)) = \frac{\Delta Q_{ij}}{\Delta \ln Q_{ij}}$. Here, it should be noted that if we have $Q_{ij}(t) = Q_{ij}(0)$, $\mathrm{LM}(Q_{ij}(t), Q_{ij}(0)) = Q_{ij}(t) = Q_{ij}(0)$. As with Eq. (4), the first, second, and third terms on the right-hand side of Eq. (5) correspond to $\Delta C_{\mathbf{e}}$, $\Delta C_{\mathbf{L}}$, and $\Delta C_{\mathbf{f}}$, respectively. To handle zero values in the computation of LMDI, the "analytical limits strategy" given in Ang et al. (1998) was employed as recommended by Wood and Lenzen (2006).[3]

[1] The two methods using Shapley values (Shapley, 1953) proposed in Sun (1998) and Albrecht et al. (2002) were shown to be identical by Ang et al. (2003). Later, Lenzen (2006) noted the similarity between D&L and SSA, and referred to them both under the umbrella term "DSA method" after "Dietzenbacher/Los-Sun-Albrecht".

[2] Following Lenzen (2006), the general DSA equation of n variables with function $y = x_1 x_2 \cdots x_n$ is expressed as $\Delta y^{DSA} = \frac{1}{n!}\sum_{\pi[S(j)]}\sum_{i=1}^{n}\left(\prod_{j=1}^{i-1} x_{S(j)}(0)\prod_{j=i+1}^{n} x_{S(j)}(t)\Delta x_{S(i)}\right)$, where $S(j)$ represents any sequence of numbers from 1 to n, and $\pi[S(j)]$ expresses the permutation of the sequence of numbers $S(j)$.

[3] Ang and Liu (2007) compared the analytical limit strategy with the small value strategy which substitutes zeros with a small number, δ, between 10^{-10} to 10^{-20}, and concluded that the small value strategy is preferred in the context of Index Decomposition Analysis (IDA) (Ang and Zhang, 2000). See Hoekstra and van den Bergh (2003) for a comparison between SDA and IDA.