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Estimation errors in input–output tables and prediction errors in computable general equilibrium analysis

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ABSTRACT

We used 1995–2000–2005 linked input–output (IO) tables for Japan to examine estimation errors of updated IO tables and the resulting prediction errors in computable general equilibrium (CGE) analysis developed with updated IO tables. As we usually have no true IO tables for the target year and therefore need to estimate them, we cannot evaluate estimation errors of updated IO tables without comparing the updated ones with the true ones. However, using the linked IO tables covering three different years enables us to make this comparison. Our experiments showed that IO tables estimated with more detailed and recent data contained smaller estimation errors and led to smaller quantitative prediction errors in CGE analysis. Despite the quantitative prediction errors, prediction was found to be qualitatively correct. As for the performance of updating techniques of IO tables, a cross-entropy method often outperformed a least-squares method in IO estimation with only aggregate data for the target year but did not necessarily outperform the least-squares method in CGE prediction.

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1. Introduction

Input–output (IO) tables are one type of data essential for constructing the social accounting matrices (SAM) used in computable general equilibrium (CGE) modeling. They also give CGE models attractive features as a multi-sectoral model describing details of industrial activities useful for empirical policy analysis, such as trade, environment, and tax policies. However, the availability of IO tables is often limited, because IO tables with such details are costly to construct. IO tables for Japan are constructed regularly every five years after intensive works with the target year data for several years. Many countries with poorer statistical organizational capacity cannot afford to construct IO tables on a regular basis.

Such low availability of IO tables forces CGE modelers to use IO tables that are several years old. When data and models are too old to use for their analysis, CGE modelers have to update IO tables themselves with simpler methods and fewer data than those employed by professional statisticians. CGE modelers employ a so-called non-survey method to update new IO tables by replacing a part of old IO tables with the target-year data, which are often incomplete and sometimes inconsistent with each other. The updated IO tables inevitably suffer some estimation errors compared with true tables.

There are two main problems that CGE modelers face. One is that the updated IO tables may suffer estimation errors. (In connection with this issue, they might also be interested in finding methods of updating that can reduce estimation errors.) The other problem is prediction errors in CGE analysis caused by the estimation errors in IO tables.[2] Usually, we cannot examine the estimation errors in IO tables because we have no true IO tables for a target year and, thus, have to estimate them permitting some estimation errors. Without true IO tables or true CGE models, we cannot measure prediction errors of CGE analysis, either.

In the literature, Robinson et al. (2001) estimated stylized SAMs for Mozambique with two different matrix balancing methods: RAS and cross-entropy (CE) methods. They found that these estimated SAMs were similar in flow data but that the CE method was likely to estimate a SAM closer to prior values in input coefficients. Cardenete and Sancho (2004) did experiments estimating a regional SAM for Andalusia, Spain and found results similar to the ones by Robinson et al. (2001). Then, they simulated tax reforms with CGE models calibrated to their updated SAMs to compare their simulation results with each other. However, these two studies compared a table estimated with one method to a table estimated with another method, or a CGE simulation result based on an estimated SAM to another, not to a true SAM or a CGE simulation result based on a true IO table/SAM. They could not conclude anything about the accuracy of the estimated SAM or the performance of the matrix balancing methods.

As true IO tables were not available, Bonfiglio and Chelli (2008) randomly created "true" IO tables by a Monte Carlo method for their numerical experiments to examine the performance of various estimation methods. Real true tables have been used very rarely. Jalili (2000) did

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[2] Although CGE models are not used only for prediction, we refer to errors of simulation results in CGE analysis as prediction errors to avoid confusion with estimation errors in updated IO tables.

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experiments by updating an IO table for the Former Soviet Union from 1966 to 1972 with various methods such as RAS and least-squares (LS) methods and compared them to the true table for 1972. Jackson and Murray (2004) did similar experiments by updating the US tables from 1966 to 1972 and from 1972 to 1977 with 10 different matrix balancing methods and found no better methods than the RAS method overall. These studies focused on estimation errors of updated IO tables, but did not examine prediction errors in CGE analysis calibrated to these updated tables.

In this study, we used linked IO tables for 1995, 2000, and 2005 from the Ministry of Internal Affairs and Communications (2011) and measured (1) estimation errors of updated IO tables from 1995 or 2000 to 2005 by comparing them with the true IO table for 2005 and (2) prediction errors in CGE analysis caused by the estimation errors in the updated IO tables (Fig. 1.1). We considered a LS method and a CE method among many matrix balancing methods and two cases of rich and poor data availability for the target year in updating IO tables. Finally, we developed CGE models calibrated to these estimated and the true IO tables and made two numerical policy experiments to measure their prediction errors attributable to richness and age of information as well as matrix balancing methods. We found that the effect of richness and age of information used in updating IO tables was clear and straightforward but that the effect of matrix balancing methods was not.

Our paper proceeds as follows. Section 2 discusses estimation methods and estimation errors of IO tables. Section 3 shows simulation results of CGE analysis to measure prediction errors. Section 4 concludes the paper, followed by an Appendix A demonstrating the robustness of CGE simulation results with respect to key trade elasticity.

2. Estimation of IO tables

2.1. Availability of target year data and settings of prior values

Let us update an old IO table ($IO^0_{u,v}$) for 1995 or 2000 to a new one ($IO_{u,v}$) for a target year of 2005 by partly replacing old data with the target year data. The IO table ($IO_{u,v}$) can be subdivided into a few submatrixes,

$$\left(IO_{u,v}\right) = \begin{pmatrix} \left(X_{i,j}\right) & \left(F_{i,f}\right) \\ \left(Y_{y,j}\right) & 0 \end{pmatrix},$$

where

- $(X_{i,j})$ intermediate input from industrial sectors i to j,
- $(Y_{y,j})$ value added of the y-th factor used by the j-th sector, and
- $(F_{i,f})$ final demand by the f-th user purchased from the i-th industrial sector.

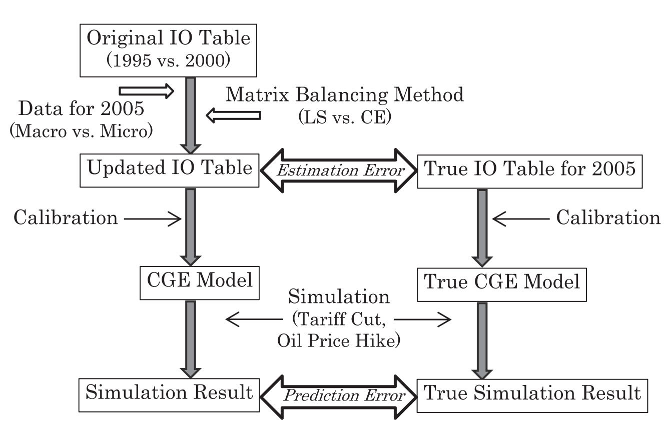

Fig. 1.1. Outline of the study.

The updated tables must satisfy the row-sum and column-sum consistency for each industry i:

$$\sum_j X_{j,i} + \sum_y Y_{y,i} = \sum_u IO_{u,i} = \sum_u IO_{i,u} = \sum_j X_{i,j} + \sum_f F_{i,f} \quad \forall i. \tag{2.1}$$

If additional information is available for some cells in the new IO table, those values are fed into the estimation process by pinning down these cell values with constraints. In this study, the available information was retrieved from the true IO table for 2005 ($IO^{2005}_{u,v}$) for ease of comparison.[3] If the final demand of the i-th good by the f-th user $F^{2005}_{i,f}$ is available for each cell, we can impose a constraint as follows:.

$$F_{i,f} = F^{2005}_{i,f} \qquad \forall i, f\,. \tag{2.2}$$

Similarly, if we know the y-th value-added component of the j-th sector $Y^{2005}_{y,j}$, we can impose a constraint as follows:

$$Y_{y,j} = Y^{2005}_{y,j} \qquad \forall y, j\,. \tag{2.3}$$

In contrast, while these microeconomic data may be less likely to be available, we can more often obtain macroeconomic data. That is, if we know the final demand of the f-th user in total (e.g., total household expenditure) $\sum_i F^{2005}_{i,f}$, we can impose a constraint, which is looser than Eq. (2.2), as follows:

$$\sum_i F_{i,f} = \sum_i F^{2005}_{i,f} \quad \forall f. \tag{2.4}$$

We can consider a similar constraint for the total of the y-th value added component $\sum_i Y^{2005}_{y,i}$, which is looser than Eq. (2.3), as follows:

$$\sum_i Y_{y,i} = \sum_i Y^{2005}_{y,i} \quad \forall y. \tag{2.5}$$

We may well conjecture that the signs of cell values in the old tables are still kept in the target year and impose a sign condition:

$$\mathrm{sign}\left(IO_{u,v}\right) = \mathrm{sign}\left(IO^0_{u,v}\right) \qquad \forall u, v\,. \tag{2.6}$$

We can also conjecture the level of cell values (prior values). For example, if we assume that input patterns are stable over time, we can compute an input coefficient for industries or expenditure share for final demand $a_{u,v}$ as follows:

$$a_{u,v} = \frac{IO^0_{u,v}}{\sum_u IO^0_{u,v}} \quad \forall u, v. \tag{2.7}$$

By combining this coefficient/share $a_{u,v}$ with the IO table margin data $\sum_u IO^{2005}_{u,v}$, we can update the prior values as follows:

$$IO^0_{u,v} = a_{u,v} \sum_u IO^{2005}_{u,v} \quad \forall u, v. \tag{2.8}$$

We can estimate another type of prior value. When we know all the cell values in the value-added matrix ($Y_{y,j}$) and the final demand matrix ($F_{i,f}$) in addition to the column totals for the j-th industrial sector $\sum_u IO^{2005}_{u,j}$ as assumed for Eqs. (2.2) and (2.3), we need to estimate

[3] In reality, there are various factors that can cause deviations of data in the compiled true IO tables from true data, such as measurement errors in the original data and matrix balancing done for row-column consistency. However, we simplified our discussion by assuming the data in the IO table for 2005 to be true.

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