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Abstract

In this paper, we investigate the role of input-output data sources in regional econometric input-output models. While there has been a great deal of experimentation focused on the accuracy of alternative methods for estimating regional input-output coefficients, little attention has been directed to the role of accuracy when the input-output system is nested within a broader accounting framework. The issues of accuracy were considered in two contexts, forecasting and impact analysis focusing on a model developed for the Chicago region. We experimented with three input-output data sources: observed regional data, national input-output, and randomly generated input-output coefficients. The effects of different sources of input-output data on regional econometric input-output models revealed that there are significant differences in results obtained in both forecast and impact analyses. The adjustment processes inherent in the econometric input-output system did not mask the differences imbedded in input-output tables derived from different data sources. Since applications of these types of models involve both impact and forecasting exercises, there should be strong motivation for basing the system on the most accurate set of input-output accounts.

Introduction

In the early development of regional input-output tables, discussion centered on the costs of survey versus nonsurvey data collection (see Hewings and Jensen 1986; Round 1983 for a thorough discussion). These debates, enjoined in earnest in the 1960s, continued for almost two decades without any apparent resolution; Jensen's (1980) distinction between holistic and partitive accuracy seems to have produced a sense of agreement about the ways in which input-output tables produced under a variety of different procedures could be compared.

However, this discussion did not address the issue of survey versus nonsurvey methods (or any combination) in the context of the development of models in which the input-output tables were nested within a broader framework. In this context, one could consider the imbedding of input-output tables in social accounting systems (a modest extension of the simple input-output model) or within general equilibrium models. These possibilities raise a fundamental question: does the source of the input-output data matter when the modeling system is more extensive? The purpose of this paper is to contribute to this new perspective by examining the implications on model output when three different input-output tables are embedded in a regional econometric input-output model (REIM). This study can be considered as one of few studies investigating the role of input-output embedded in the system of simultaneous equations. This system of simultaneous equations is comprised of different blocks such as input-output, demographic, consumption and so forth. In this paper, attention will be directed to only one block -- input-output. The purpose of this analysis is to determine if differently constructed input-output tables would have a significant effect on the input-output block as determined in the Chicago Regional Econometric Input-Output Model (CREIM). It is important to distinguish that the input-output block in CREIM is not a traditional input-output system; it has a stochastic and dynamic nature that facilitates the adjustment of the observed input-output table to time-series variations in the output vector and the final demand matrix. While future research can explore the impact of including additional blocks (generating a more extensive closure of the simultaneous system), it was considered important to determine whether differently constructed input-output tables have a significant impact on the input-output block, prior to the inclusion of other blocks into the analysis.

Hence, we focus specifically on the behavior of the input-output block, which we detach from the rest of the model.[2] Empirical results are drawn from the Chicago input-output table constructed for 1982. The paper is organized as follows. In section 2 we discuss the effect of the choice of data sources for input-output tables on regional static input-output models. Section 3 is devoted to measuring the effect of incorporating these different input-output tables on the results obtained with regional econometric input-output models. Section 4 describes experiments conducted for three input-output tables constructed using different techniques and data sources. [An appendix provides a description of the Chicago-observed input-output table (CIO)]. Section 5 concludes the paper.

Effect of the choice of input-output tables on regional static input-output models

Input-output tables can be constructed by using a variety of methods and data sources; with limited funds available for survey-based table construction, general attention has been focused on appropriate hybrid methods. In this context, the analyst is faced with the problem of allocating scarce resources to those components of the table that are deemed analytically important. Now assume that the input-output table is but one part of a broader modeling system; would the decision-rules adopted in the allocation of survey resources for the construction of an input-output table alone also apply for the case of a more complete modeling system? With the exception of some work by Harrigan *et al.* (1991) in comparing simple input-output and CGE systems, these issues have not been addressed formally. Even in the Harrigan *et al.* (1991) paper, the explicit focus was not on the accuracy of the input-output tables (since the same tables were used for the comparison). Coomes, *et. al.* (1991) tested regional versus national input-output specification in an effort to determine differences in models of regional employment. Using interindustry linkages (input coefficients) expressed in employment terms, the authors were able to link quarterly employment of one industry to employment in other industries.

Some earlier work by Hewings (1977; 1984) provided the basis for the type of assessment adopted in this paper. In one case, two sets of regional input coefficients obtained from two survey based tables for two states were exchanged under a variety of assumptions; a further set of input coefficients was obtained from a random number generator. The results indicated that no matter what the source of the coefficients, it would be possible to approximate the observed regional column multipliers given appropriate margin information. However, when attention was focused on the separate, partial multipliers (i.e., the individual elements of the Leontief inverse), the exchange procedures produced very unsatisfactory results. Hewings (1984) reviewed research which identified analytically important coefficients (the set of coefficients whose correct estimation is deemed critical in generating accurate results) and the issue of analytical importance in more extensive, social accounting systems. The general conclusions were that (i) as economies evolve, the set of analytically important coefficients changes, and (ii) the importance of interindustry transactions seems to decrease when the input-output tables are embedded in social accounting systems. Can these findings be generalized to modeling systems of the REIM type?

Regional input-output tables have even wider potential for variation with respect to sources and methods of construction. Analysts often compare input-output multipliers as a measure of differences between methods and data sources. In general, input-output tables generated by different methods with column sums being constrained to the same vector will produce very similar multipliers (Katz and Burford 1985; Phibbs and Holsman 1981). However, coefficients for both the input-output tables and the Leontief inverse will vary with each method of construction. This distinction can be expressed as follows, by noting that the input-output multiplier is a total derivative composed of a sum of the Leontief inverse elements:

$$m_j = \frac{dx}{dy_j} = \sum_i \frac{\partial x_i}{\partial y_j} = \sum_i m_{ij}, \tag{1}$$

where m_j is a multiplier, and m_{ij} are Leontief inverse elements,

$X = [x_i]$ is the output vector, $x = \sum_i x_i$,

$Y = [y_j]$ is the final demand vector, $y = \sum_j y_j$.

Earlier studies would argue, correctly, that m_i are largely independent of the input-output table components and determined mostly by the column-sum of input-output coefficients. For example, Drake (1976) proposed an approximation for the multiplier based entirely on the column-sum of the input-output table:

$$m_j = 1 + \frac{a_{\bullet j}}{1 - \bar{a}}, \tag{2}$$

where a_{ij} are regional input-output coefficients, $a_{\bullet j} = \sum_i a_{ij}$ and $\bar{a}$ is a mean value of a_j.

Therefore, if the purpose of a study is to determine multipliers only, then it makes little difference how regional input-output tables are constructed, as long as the coefficient column-sum is determined correctly. In other words, in order to predict output for a given vector Y, methods of regional input-output table construction play no significant role. However, in order to answer questions related to the decomposition of multipliers, we have to look at the detailed input-output table. For example, if a single component of the final demand vector (say, food consumption) increases, then the multiplier for the food industry will provide the change in overall economic output. In order to determine the change in demand for intermediate products, we would need a full input-output table.[3] In the next section we show that REIM-type models require information from a full input-output table, and thus, the column sums of a table $(a_{i.})$ are not sufficient.

Effect of choice of input-output tables on regional econometric input-output models

In the recent literature on CGE models (see Kraybill 1991) and regional econometric input-output models (see Conway, 1990; Treyz and Stevens, 1985; Treyz, 1993), there has been limited discussion about how differently constructed input-output tables affect model outcomes. In this paper, we address this issue by analyzing the two roles that input-output tables play in such models, namely, when these models are used for (1) forecasting and (2) for policy impact analysis. To illustrate, we concentrate on regional econometric input-output models, REIM (see for example, Conway, 1990; Israilevich and Mahidhara 1991).

Input-output tables are used in REIM as a deterministic linear predictor of output:

$$z_i^t = \sum_j a_{ij} x_j^t + \sum_j f_{ij} y_j^t + e_i n_i^t \qquad \forall i = 1,\dots,n \,, \tag{3}$$

where f_{ij} is a normalized regional purchase coefficient in the final demand matrix,

$Y = [y_j]$ is the final demand vector consisting of the following components: personal consumption elements, investment, government expenditures, and net exports,

$N = [n_i]$ is a vector of variables exogenous to the regional economy (such as GNP, national industrial production indices and other national data),

$E = [e_i]$ is a vector of normalized regional gross export coefficients,

$Z = [z_i]$ are predicted output values (as opposed to x_i which are observed values of output) and

t indicates year. For brevity we omit this superscript in the rest of this paper. Exports, derived as a residual in the base year, are assumed to be proportional to the corresponding national variable (equation 3); however, this relationship is modified through the process described in equation (17), generating a nonlinear relationship between regional and national exports.

The crucial difference between traditional input-output approaches and equation (3) are the weights assigned by (3) to each of the input coefficients. These weights are expressed as *observed* outputs, X, for each time period. In order to formalize the difference between the traditional input-output approach and equation (3), we can rewrite (3) in matrix form:

$$Z_{REIM} = AX + Y \quad , \tag{4}$$

where A is the input-output matrix and Y is a vector of aggregated final demand; all variables change in time, but we omit the time parameter to simplify exposition. However, the adjustment process takes place in (17) and it is an adjustment of the base year values of the input coefficients and the exports coefficients from (3). Denote the difference between the observed and estimated outputs as $\Delta = Z_{REIM} - X$. Then equation (3) can be presented as:

$$Z_{REIM} = \Delta + X = AX + Y \quad . \tag{5}$$

If the usual input-output (IM) approach is used then:

$$Z_{IM} = (I - A)^{-1} Y \quad . \tag{6}$$

From (5), we have:

$$\Delta + X - AX = \Delta + (I - A)X = Y \quad . \tag{7}$$

Expression (6) then can be rewritten as:

$$Z_{IM} = (I - A)^{-1} Y = (I - A)^{-1} \Delta + X \quad . \tag{8}$$

Now, we can determine the difference between the IM and REIM estimation of outputs as:

$$Z_{IM} - Z_{REIM} = \left[(I-A)^{-1}\Delta + X\right] - (\Delta + X) =$$
$$= \left[(I-A)^{-1} - I\right]\Delta, \tag{9}$$

and, by using the power series decomposition of the Leontief inverse, we have:

$$Z_{IM} - Z_{REIM} = \left(A + A^2 + \ldots + A^\infty\right)\Delta \tag{10}$$

From this expression, it is clear that the difference between the traditional input-output estimates (IM) and those generated by equation (3) (these being the output estimates from REIM), will be amplified by the structure of the A matrix. Hence, the differences between the two estimates will be directly related to the nature of the linkages between industries, measured by the indirect multiplier effects. It is not unreasonable to expect that the use of the input-output system in (3) as opposed to the traditional input-output formulation may amplify the effect of differently constructed input-output tables on the prediction of total output, Z.

Stochastic equation for the input-output components

To turn this model into an econometric forecasting model, vector Z has to be stochastically related to the observed vector, X. In REIM, this is accomplished through a set of regression equations:[4]

$$\log\left(\frac{x_{it}}{z_{it}}\right) = \alpha_0 + \alpha_z\left(\frac{z_{i,t-1}}{x_{i,t-1}}\right) + \alpha_g g_{it} + \varepsilon_{it} \qquad \forall i = 1,\ldots,N; \quad \forall t = 1,\ldots,T \tag{11}$$

where $z_{i,t-1}$ is a lagged input-output-generated predicted output, and g_i is the set of exogenous variables selected by the modeler [there are $(T \times N)$ equations in (11)]. The lag structure shown in (11) varies by sector; in some cases, the lag will be zero, while in other cases a first-order or even second-order nonlinear difference equation will be appropriate. Equation (11) is estimated separately for each industry i with the vector of random errors, ε_i. Equations are estimated using EGLS, assuming autocorrelation, otherwise an OLS procedure is adopted.

Equation (11) assigns a set of regression coefficients to each row of the input-output table, weighted by annually observed outputs, in a nonlinear fashion. This means that the input-output column sums would not provide enough information for the system (11) and, hence, Drake's (1976) short-cut method could not be employed in REIM.

In a fully specified REIM system, the final demand matrix is itself endogenous within the whole model. However, for the presentation in this section, we break the link with the rest of the REIM by assuming that vector Y is exogenously determined. As a result, system (11) can be represented in the following fashion to illustrate the relationship to traditional input-output computations. First, denote the right-hand side of (11) as:[5]

$$\beta_{it} = \exp\left(\alpha_0 + \alpha_z \log\left(\frac{z_{i,t-1}}{x_{i,t-1}}\right) + \alpha_g g_{it}\right) \qquad \begin{array}{l} \forall i = 1,\ldots,N; \\ \forall t = 1,\ldots,T \end{array} \quad . \tag{12}$$

Then (11) can be rewritten (dropping the time subscript) as:

$$x_i = \beta_i z_i \quad \forall i = 1,\ldots N;\ \forall t = 1,\ldots,T \quad . \tag{13}$$

By diagonalizing β_i as a diagonal matrix, $\hat{\beta}_i$, and utilizing (3), the system (11) can be presented as:

$$X = \hat{\beta}AX + \hat{\beta}Y \quad \forall t = 1,\ldots,T \quad , \tag{14}$$

or, finally, as:

$$X = \left[\left(I - \hat{\beta}A\right)^{-1}\hat{\beta}\right]Y \quad \forall t = 1,\ldots,T \quad . \tag{15}$$

It is important to stress that the matrix, $\hat{\beta}$ is a nonlinear first-difference operator that modifies the static Leontief inverse into a dynamic one. This modified inverse, $L = \left[\left(I - \hat{\beta}A\right)^{-1}\hat{\beta}\right]$ changes with the choice of the input-output table in two respects. First, if A is modified, then the estimates in (11) will change (i.e., β is a function of A) and secondly, the matrix A itself will be different.

The system of equations (15) provides a forecasting or impact capability, assuming that Y is determined exogenously. However, in REIM only the vector of exports within final demand Y is a function of exogenous variables (such as national indices of industrial production, GDP etc.). All other components of final demand are linked to other submodules within REIM. Hence, (15) does not represent a full REIM-based solution but provides insight into how the input-output component plays a different role from standard input-output analysis.

Shock specification in REIM

In the standard IM system, a shock is usually introduced through a change in an element of the final demand vector. Similarly, the system (15) can be shocked exogenously by adding a vector of change to the output, X. Therefore, the impact on all outputs, X, is measured as:

$$X = \hat{\beta}AX + \hat{\beta}Y + s \qquad \forall t = 1,\ldots,T \tag{16}$$

where s is a vector with positive (negative) shock, s_i, and zeroes elsewhere, and thus represents a positive (negative) shock to sector i.[6] The closed form solution for the impact analysis is:

$$X = \left(I - \hat{\beta}A\right)^{-1}\left(\hat{\beta}Y + s\right) \qquad \forall t = 1,\ldots,T \tag{17}$$

However, recall that Y is part of a larger system within REIM and therefore the closed form solution would involve interactions with other equations from other modules within REIM. In both forecasting and impact analysis (equations 15 and 17), the differences in A can be compensated by the estimated $\hat{\beta}$. In other words, $\hat{\beta}$ compensates for differences in input-output tables so that the final fit to the observed output is achieved by minimizing random error. As a result, one may argue that survey-based input-output tables within REIM would yield the same results for impact analyses and forecasts as those generated with nonsurvey tables. If this is the case, then the efforts expended on estimating the input-output coefficients should be minimized. The implications from this assertion are that the debates initiated by Drake (1976) may have applicability in REIM systems. In the next section, we attempt to test this assertion with empirical analysis.

Three input-output table experiments

Input-output models (IM), social accounting matrices (SAM), and regional econometric input-output models (REIM) differ in the information they use in calculating output. The IMs treat final demand as an exogenous vector, while the SAMs endogenize many of the final demand components. Neither modeling system, however, uses information on national variables in the sense that the multipliers of these two systems would not change with a change in national variables. The REIMs, on the other hand, utilize all the information present in the detailed final demand matrix, including national variables; therefore, the REIM multipliers will change with different values of n_i. All three approaches (IM, SAM, and REIM) incorporate direct and indirect effects. However REIM does not calculate the Leontief inverse explicitly; instead it runs a system of simultaneous equations [including (3.1) and (3.2)] in a time-recursive fashion, thereby measuring impact in a dynamic sense.

In REIM, there is only one input-output table on which all historical estimates and forecasting values are based. For the year (base year) corresponding to the input-output table:

$$Z \equiv X,$$

for all other years, this identity does not hold. This base year identity is achieved by either assuming export as a residual or allowing some adjustment procedure to balance rows only of the input-output table. For all other periods, $\hat{\beta}$ adjusts the rows of the input-output table through equation (17). Since (17) is derived from (11), in which there is a random error term, X on the left-hand side of (11) is estimated, not observed. This balancing procedure is different from the *columns and rows* adjustment approaches used in more traditional input-output and social accounting systems. Although this is a potential limitation, in our experience the procedure did not produce coefficients that violate the Hawkins-Simon conditions. In macro national models, such as the one developed by Hudson and Jorgenson (1974), the input coefficients are estimated through a derivation using Shepard's Lemma. In this type of approach, analysts balance derived input coefficients with column-constrained adjustments. As shown by Israilevich (1991), this procedure may cause imbalances.

In designing experiments to address the issue of the importance of the choice of input-output tables, we noted that REIMs are used for two purposes: forecast and impact analyses. Accordingly, in our investigation we analyze the forecasting ability of the input-output model and its impact analysis features.

While the forecasting ability of input-output is not of great interest in itself, we investigate it as it is a building block in REIM-type models. We thus analyze how differently constructed input-output tables affect its forecasting ability. A second aspect of REIM is in its role in impact analysis; in this respect, REIM is similar to IM. Both models lack an observed figure against which the performance of the model can be judged, since no one knows what the "true" impact is. In the following two subsections, we test both the forecasting performance and the impact performance of input-output.

For the tests, we consider the input-output portion of the Chicago REIM (CREIM). We consider three tables which are balanced for 1982, according to equation (3). The Chicago-observed input-output table (CIO) is constructed from observed (Manufacturing Census) data combined with regionalized data from the national input-output table and other sources.[7] The second table is referred to as the Chicago-national input-output table (NIO) and is constructed directly from the national input-output table using location quotients for the regionalization procedure. Finally, in the spirit of earlier work by Hewings (1977), a third table is constructed; the Chicago-random input-output (RIO) table consists of randomly generated input-output coefficients. All three tables have the same normalized final demand matrix f_{ij}; some variations in this final demand matrix are the result of construction procedures explained in the appendix. All three tables are balanced to the same total outputs. The export vector is determined as a residual and, therefore, varies for each of the input-output tables. Since the purpose of this study is to explore the effects of changes in the input-output table on the output vector specified in (17), all changes due to simulations with different input-output tables will be recorded as changes in X.

Forecast Experiments

In order to estimate the Z variables of equation (3), we allow vectors X, Y, and N to vary over the historical period (1983-92) using three different sets of input-output coefficients: CIO, NIO, and RIO. Afterwards, we reestimate β coefficients for each of the three versions of Z. This completes the estimation of coefficients necessary for the simulation of the system (14). The other REIM modules are unchanged since the estimation of these modules is unaffected by the changes in the input-output table. [The system (14) is endogenized within REIM by making the final demand vector F endogenous. For example, changes in personal income will affect personal consumption (part of F)]. Accordingly, we derive three versions of REIM that we simulate over the historical period.

Table 1
Average Absolute Percent Difference

Number of occasions $\lvert\varepsilon_{NIO}\rvert > \lvert\varepsilon_{CIO}\rvert$	Average Percent Difference [NIO-CIO]	Number of occasions $\lvert\varepsilon_{RIO}\rvert > \lvert\varepsilon_{CIO}\rvert$	Average Percent Difference [RIO-CIO]
Resources		*Resources*	
3 out of 4	2.4	2 out of 4	11.1
Manufacturing		*Manufacturing*	
16 out of 19	42.1	13 out of 19	73
Services		*Services*	
10 out of 13	13.1	9 out of 13	12.4

In order to gauge the differences among the three simulations, we compare estimated outputs with observed outputs in the following manner:

- First, we accumulated absolute percent errors, over the simulation period (1983-92). The results are presented in figure 1. In this figure, errors are averaged over time and accumulated over industries. The best results were obtained with the Chicago input-output model (CIO) while the national table adjusted to Chicago totals produced forecasts that were superior to those obtained from the randomly generated input-output table.
- Second, we accumulated absolute percent errors for each individual industry over the simulated period (see figure 2). In this figure, we compare the results from NIO and CIO.[8] It is clear that, for most industries, CIO provides better estimates. The comparisons are summarized in table 1.

The first column of table 1 records the number of industries for which the forecasting error derived with NIO exceeds the forecasting error with CIO. Similar information is recorded in the third column for the comparison between CIO and the randomly generated coefficients. In the second and fourth columns, the averaged absolute percent differences are recorded for both sets of paired comparisons.

These results suggest that the differences in the construction of input-output tables translates into differences over the forecast period. Within the sectors, the manufacturing sector exhibits the greatest difference; here the survey-based input-output table predicts better by 42 percent over the table constructed using the national coefficients and over 73 percent in comparison to the randomly generated tables. This is not surprising since the manufacturing component of CIO was derived from aggregations of individual establishment-level data. On the other hand, the differences in the nonmanufacturing sectors are smaller than those observed in manufacturing.

Figure 1

Forecasted Output Average Absolute Cumulative Error, 1983-1992

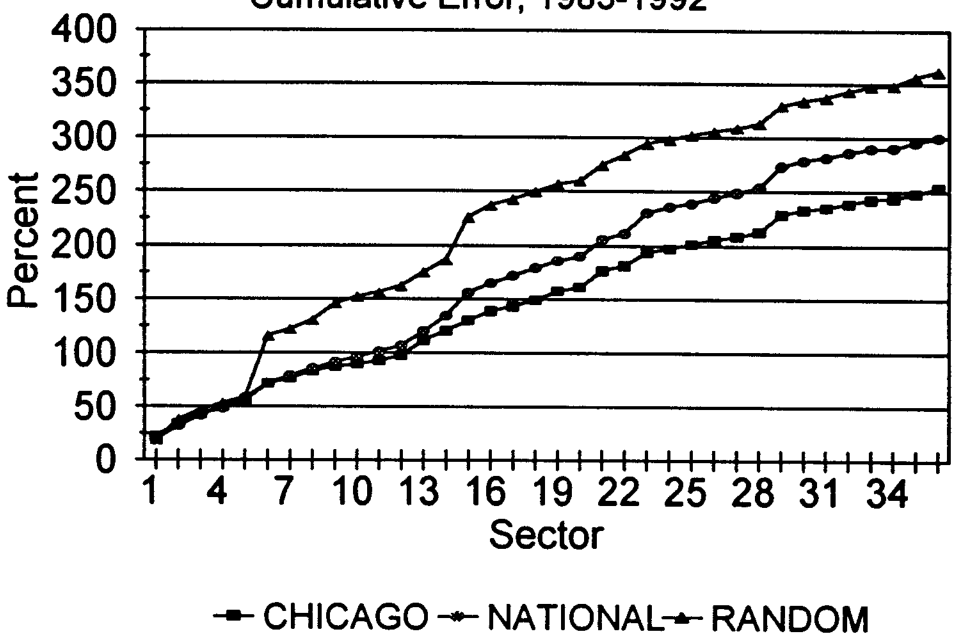
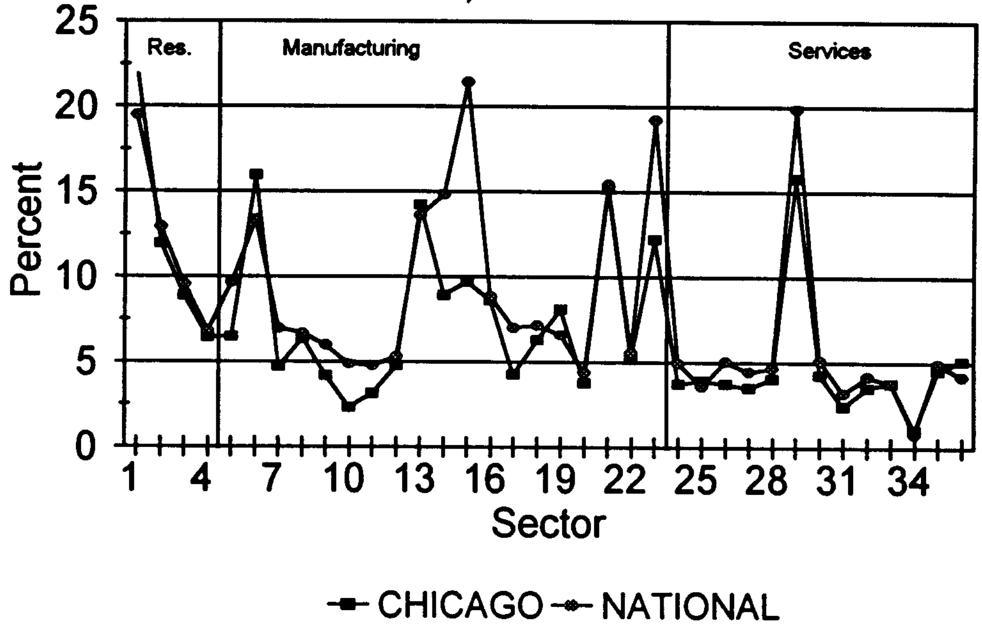


Figure 2
Cumulative Absolute Percent Error by Sector, 1983-1992



Impact Analysis

The second set of experiments is devoted to impact analysis. In the forecast analysis, we allowed the entire set of exogenous variables to vary over time. In the impact analysis, we fix all exogenous variables for the year in which the shock is implemented. Then, we change one exogenous variable, in this case, the export of a given industry, to represent a shock to that sector. Once this shock is entered in the model, changes in the outputs of all other industries are recorded. The information derived from these changes is similar in form to that of a column of the traditional Leontief inverse as specified in equation (1).

Each of the 36 sectors was shocked for 1990, representing a 10 percent change over the base case output (see Israilevich *et al.* 1994 for details), and the average effect on all other sectors was recorded. While the choice of 1990 was arbitrary, other benchmark years would have yielded the same qualitative ordering in the pattern of results. Since REIM has a recursive structure of equations, we had to simulate the model for several years; a shock to the model would eventually lose its effect but there is a minimum number of years that should be considered for tracking the effects. In this case, it was decided to use 6 years, but for any greater number of years, the derived multipliers would be practically the same (see Israilevich *et al.* 1994). In essence, the impact from a shock is largely independent of a chosen number of years beyond some minimum value. Of course, with a REIM, the impact is considered to be more diffused in time in contrast to the comparative static nature of the usual Leontief system in which the time path of the shock through the system is not considered (for modifications, see Romanoff and Levine, 1986; McGregor *et al.* 1995).

In this part of the analysis, there is no observed forecast against which we can compare derived results (as it was the case in the forecasting section). Hence, our analysis compares results derived from each of the three tables. For comparison, we form two pairs: the first pair is NIO and CIO, and the second pair is RIO and CIO.

To enable a concise comparison among the three models, we regress the changes in all sectors induced by a shock in one experiment on the comparable changes found in the other experiments. For example, in comparing the simulation results from NIO and CIO, we form the regression:

$$\Delta X_{NIO} = a + b\Delta X_{RIO} \ . \tag{18}$$

The results are recorded in tables 2 and 3.

Table 2

Pairwise Regressions of Partial Multipliers
National vs. Chicago

Sector	Regression a	Regression b	Standard Errors a	Standard Errors b	R-Squared	F-Stat [0, 1]*
1	0.022	1.031	0.006	0.034	0.964	9.325
2	0.035	1.093	0.012	0.055	0.919	11.543
3	0.012	1.005	0.003	0.020	0.987	7.593
4	0.020	1.034	0.005	0.026	0.979	12.663
5	0.014	1.020	0.003	0.013	0.995	16.702
6	0.008	1.006	0.002	0.010	0.997	11.786
7	0.024	1.018	0.006	0.033	0.966	9.834
8	0.026	0.979	0.005	0.026	0.976	14.603
9	0.026	1.006	0.005	0.031	0.968	13.240
10	0.019	1.094	0.005	0.023	0.986	26.668
11	0.021	1.094	0.006	0.033	0.970	16.290
12	0.023	1.097	0.006	0.026	0.982	24.296
13	0.006	1.053	0.001	0.008	0.998	41.680
14	0.021	1.017	0.005	0.024	0.982	11.495
15	0.019	1.044	0.005	0.028	0.976	10.665
16	0.024	1.021	0.005	0.030	0.972	12.891
17	0.023	1.209	0.005	0.028	0.982	56.023
18	0.034	1.049	0.008	0.048	0.934	11.332
19	0.020	1.081	0.005	0.026	0.980	19.662
20	0.025	1.055	0.006	0.028	0.976	16.646
21	0.014	1.017	0.004	0.019	0.988	11.102
22	0.023	1.021	0.005	0.029	0.974	12.929
23	0.024	1.022	0.006	0.031	0.970	12.112
24	0.020	1.031	0.005	0.023	0.983	10.835
25	0.015	1.009	0.004	0.021	0.986	9.157
26	0.011	1.008	0.003	0.015	0.993	8.706
27	0.020	1.055	0.006	0.028	0.977	11.674
28	0.024	1.031	0.006	0.028	0.975	10.142
29	0.005	1.082	0.001	0.007	0.999	108.387
30	0.025	1.059	0.008	0.035	0.964	11.440
31	0.023	1.062	0.007	0.034	0.966	11.862
32	0.019	1.015	0.005	0.027	0.976	9.785
33	0.025	1.033	0.008	0.040	0.952	9.026
34	0.027	1.048	0.009	0.044	0.943	9.359
35	0.034	1.045	0.009	0.047	0.935	11.517
36	0.023	0.992	0.006	0.028	0.974	9.364
Ave	0.021	1.043	0.005	0.028	0.973	

* F-Stat indicates rejection of null hypothesis at the 95% level in all cases. Note: Nation = *a* + *b**Chicago.

Table 3

Pairwise Regressions of Partial Multipliers
Random vs. Chicago

Sector	Regression		Standard Errors		R-Squared	F-Stat [0, 1]**
	a	b	a	b		
1	0.004	0.919	0.005	0.030	0.966	3.838*
2	0.002	0.878	0.010	0.045	0.918	4.884
3	0.015	1.252	0.005	0.027	0.984	63.664
4	-0.001	0.950	0.006	0.033	0.960	1.507*
5	0.010	0.841	0.003	0.013	0.992	80.322
6	0.019	0.973	0.003	0.017	0.989	19.746
7	0.013	0.745	0.003	0.017	0.982	108.565
8	0.011	0.910	0.004	0.019	0.985	11.970
9	0.007	1.382	0.006	0.035	0.979	74.008
10	0.009	0.854	0.004	0.022	0.978	22.575
11	-0.001	0.958	0.006	0.033	0.961	1.078*
12	0.006	0.467	0.002	0.010	0.984	1449.599
13	0.016	0.974	0.003	0.017	0.990	14.231
14	0.006	1.483	0.017	0.079	0.911	22.268
15	0.006	0.886	0.006	0.032	0.957	6.375
16	0.007	0.940	0.005	0.028	0.970	2.363*
17	0.016	1.419	0.006	0.031	0.984	124.116
18	0.009	0.988	0.004	0.022	0.983	2.681*
19	0.010	0.957	0.004	0.019	0.986	4.775
20	0.008	0.899	0.004	0.021	0.982	11.770
21	0.010	0.944	0.004	0.020	0.984	5.569
22	0.001	0.991	0.005	0.026	0.977	0.060*
23	0.003	0.991	0.006	0.035	0.960	0.105*
24	0.006	0.806	0.005	0.021	0.978	46.249
25	0.009	0.977	0.004	0.022	0.984	2.700*
26	0.012	0.851	0.004	0.020	0.981	26.926
27	0.010	0.917	0.005	0.024	0.977	6.267
28	0.011	0.796	0.005	0.022	0.975	44.103
29	0.013	0.983	0.004	0.020	0.986	5.684
30	0.013	0.883	0.004	0.019	0.985	19.618
31	0.001	0.878	0.010	0.049	0.905	3.715*
32	0.003	2.106	0.014	0.076	0.957	125.953
33	0.004	0.881	0.006	0.031	0.960	8.389
34	0.007	0.941	0.006	0.029	0.969	2.156*
35	0.008	0.978	0.006	0.031	0.966	0.971*
36	-0.005	0.785	0.014	0.065	0.809	7.540
Ave	0.008	0.983	0.006	0.029	0.967	

* Failed to reject the null hypothesis at the 95% level.

** F-Stat indicates rejection of null hypothesis in 25 of 36 cases.

Note: Random = a + b*Chicago.

The maintained hypothesis, H_0, namely that $a=0$ and $b=1$, implies that there are no differences between the partial multipliers derived from both experiments; a similar hypothesis is formed for the comparisons between RIO and CIO. To test the null hypothesis of $B_0 = [0,1]$, we use an F-statistic, calculated as:

$$F = \frac{\dfrac{\left[(B^{OLS} - B_0)' X' X (B^{OLS} - B_0)\right]}{2}}{\dfrac{SSE_u}{d.f.}},$$

where SSE_u is the sum of squared errors from the pairwise regression and *d.f.* are the degrees of freedom. For both experiments, H_0 was strongly rejected. In essence, the choice of tables provides significantly different results; however, unlike the case of the forecast experiment, no preference ordering can be provided in terms of which set of tables provides the better fit. All we are able to state is that the observed differences are not due to chance.

Finally, we should note that Coomes *et. al.* (1991) show that employment adjusted by input-output coefficients have significant regression coefficients for 10 out of 28 industries. We show, similarly, that input-output coefficients matter for forecasting purposes. Coomes *et al.* (1991) show that the substitution of national coefficients instead of regional coefficients changes regression coefficients for input-output adjusted employment figures in small increments, which, however, "...result in rather large differences in impact multipliers between models." Again, these results are similar to our impact analysis differences. In the present study, the majority of industries have significant intercept but insignificant slope; this result may be due to the deficiencies of the location quotient methodology. The results indicates that the overall level of output prediction by NIO is higher (lower) than the corresponding value predicted by CIO (table 2). Obviously, alternative methodologies, such as the estimation of input coefficients using regional purchase coefficients, could have different results. The sensitivity of the model for impact analysis to changes in input-output coefficients is clearly demonstrated by tables 2 and 3.

Conclusions

In this paper, we have attempted to extend some of the earlier discussions on the role of input-output coefficient estimation in the applications of the underlying model. Our work uses a regional econometric input-output model as the basis for the comparison; in this model, the input-output tables are nested within a larger analytical framework. Three alternative specifications of the input-output tables are used; one contains the most survey-based information, one uses adjusted national coefficients and one uses no local information at all (relying on random numbers).

The results indicate that when the system is used in a forecast mode, the differences appear to be pronounced. Since only the set of coefficients for the manufacturing sectors are fully observed in Chicago, the corresponding input-output coefficients are more independent of those derived from adjustments of the corresponding national coefficients. As a result, the forecast for these sectors were shown to be particularly sensitive to the choice of input-output tables. In essence, the results provide a different perspective to the one advanced by Drake (1976) and Katz and Burford (1985). However, a word of caution should be interjected here.

The differences in the partial, static multipliers associated with impact analysis reveal significant variations as well. In this regard, the results parallel most strongly the earlier experiments by Hewings (1977). The next step would be to promote a similar inquiry in a full forecasting context and to link this work with some of the new developments proposed by Sonis and Hewings (1989, 1992) in the context of the specification of a field of influence of change. Here attention would be focused on the sources of error or change generated by individual coefficients rather than on the source of differences generated by differently constructed tables *in toto*. Finally, the analysis needs to be extended to test the sensitivity to alternative closures and alternative national variable forecasts.

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APPENDIX:

Chicago-observed input-output table (CIO)

The data employed in the construction of the Chicago input-output table (CIO) draw on the US (BEA) Input-Output Tables for 1982 together with data derived from the individual establishment-level files of the *Census of Manufactures*. This latter source was used to construct the manufacturing sub block of the technological matrix of the Chicago input-output table (SIC 20 through 39). The Census collects information on a very disaggregated level and, at this level, we were able to identify the lower bound of inflow of goods from the rest of the world; the details are presented below. In the second part of the CIO construction, we determine the regional purchase coefficients (RPC).[9] By matching observed purchases and observed production at a 6-digit level of disaggregation, we were able to determine that a great number of items that were consumed in Chicago were not produced there. This information enabled us to determine a matrix of *noncompetitive imports*. Clearly, the matrix of noncompetitive imports will enable the specification of an upper bound on the RPC (see Miller 1986; Guccione *et al.* 1988). Using the non competitive imports matrix, we construct a new type of RPC. Denote this matrix of adjusted RPCs as A_R^r which is constructed as follows:

$$\left[A_R^r\right] = \begin{cases} a_{ij} - m_{ij} & \text{if } m_{ij} \geq l_{ij} \\ a_{ij} - l_{ij} & \text{if } m_{ij} < l_{ij} \end{cases} \quad . \tag{A1}$$

In this setting A_R^r assumes noncompetitive import coefficients as a substitute for LQ coefficients if the LQ coefficient $\left(l_{ij}\right)$ had failed to exceed the noncompetitive import coefficient $\left(m_{ij}\right)$. The nonmanufacturing sub block of CIO is adapted from the national input-output tables, but with further modifications related to the treatment of net exports.

The most important feature of REIM is its link of the output variables to the available time series. The annual gross sate product series provides net export figures on the annual basis; this Illinois series is first adapted to represent the six-county Chicago metropolitan region. The Chicago REIM then adjusts input-output data to be consistent with these export data through a proration procedure for the base year as follows. First define net exports as:

$$ne = e - m = \left[x - \sum_{ij} \left(X_{ij}^{r} + Y_{ij}^{r} \right) \right] - \sum_{ij} \left(M_{ij}^{I} + M_{ij}^{F} \right) \quad , \tag{A2}$$

where *ne*, *e*, and *m* are scalars of net exports, exports and imports respectively,

X_{ij}^{r} and Y_{ij}^{r} are intermediate and final regional transaction flows, and

M_{ij}^{I} and M_{ij}^{F} are intermediate and final import flows.

Equation A2 can be re-written as:

$$\begin{aligned} ne = e - m &= x - \sum_{ij} \left[\left(X_{ij}^{r} + Y_{ij}^{r} \right) + \left(Y_{ij}^{r} \right) + \left(M_{ij}^{F} \right) \right] = \\ &= x - \sum_{ij} \left(X_{ij} + Y_{ij} \right) \end{aligned} \quad . \tag{A3}$$

Therefore,

$$ne = x - \sum_{ij} \left(X_{ij} + Y_{ij} \right) \ . \tag{A4}$$

As a result, the adjustments for the *ne* are made before regionalizing transaction flows. This means that the matrix of intermediate and final transaction flows is multiplied by a scalar:

$$\left[\widetilde{X}_{ij} \middle| \widetilde{Y}_{ij} \right] = \left[X_{ij} \middle| Y_{ij} \right] \cdot \frac{x - ne}{\sum_{ij} \left(X_{ij} + Y_{ij} \right)} \ , \tag{A5}$$

where $\left[\widetilde{X}_{ij} \middle| \widetilde{Y}_{ij} \right]$ is a matrix of adjusted transaction flows. This adjustment was applied to all three matrices CIO, NIO, and RIO. After the *ne* adjustment, RPC procedures were applied to the adjusted matrix, and a vector of gross exports was computed as a residual.

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[1] Special thanks to Robert McGuckin and staff of the Center for Economic Studies, US Bureau of the Census, for providing data and advice necessary for the completion of this project.

[2] This input-output block differs from conventional input-output and CGE models, as explained later in Section 3.

[3] Intermediate product consumption is determined by the row-sum of the Leontief inverse. See also the discussion in Harrigan (1982).

[4] This specification was adopted from Conway (1990).

[5] We specify here an equation estimated by OLS; the autoregressive component for the β estimates would serve to modify this equation.

[6] In Conway (1990), the shock was entered through equation (11), which is identical to (15). In Conway, by substituting $X = \hat{\beta}Z + s$ for Z in (4), one may derive (16).

[7] A brief description of the CIO construction is provided in the appendix. The manufacturing output series are constructed using data from various sources. Wages from BEA and output deflators from the BLS are used, value added, cost of materials, and payroll data from the Census of Manufactures and Annual Survey of Manufactures are also included. We then take Census Product, cost of materials plus value added, multiplied by the ratio of BEA wages to Census payroll. This is then deflated using the BLS deflator.

[8] A similar figure for RIO was omitted because it does not convey new information; a summary of the comparisons is provided in table 1.

[9] For the conventional RPC estimation see Stevens and Trainer (1976).