THE CHOICE OF INPUT-OUT TABLE EMBEDDED IN REGIONAL ECONOMETRIC INPUT-OUT MODELS*

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Abstract

In this paper we investigate the role of input-out data source in the 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 issued 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 model revealed that there are significant differences in results obtained in impact analyses. However, the adjustment processes inherent in the econometric input-output system seem to mute the initial differences in input-output data when the model is used for forecasting. Since applications of these types of models involve both impact and forecasting exercises, there would still seem to be a strong motivation for basing the system on the most accurate set of input-output accounts.

Keywords: Input-output Analysis, Regional Economics, Regional Econometric Models

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I. INTRODUCTION

In the early developments of regional input-out tables, discussion centered on the costs of survey versus nonsurvey data collection (see Hewings and Jensen, 1986 and 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; 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]. The REIM may be considered as a general equilibrium model, although not as fully specified as more traditional CGE models (se Kraybill, 1991; Harrigan *et al.* 1991). In this paper we focus specifically on the behavior of the input-output block, which we detach from the rest of the model.[1] Empirical results are drawn from the Chicago input-output table constructed for 1982.

The rest of the paper is organized as follows. In Section 2 we discuss the effect of input-output tables on regional static input-output models. Section 3 is devoted to measuring the effect of input-output tables on 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.

II. EFFECT OF INPUT-OUTPUT TABLES ON REGIONAL STATIC INPUT-OUTPUT MODELS

Input-output tables can be constructed by using a variety of different methods and data sources; with limited funds available for survey-based table construction, 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

[1] This input-output block differs from conventional input-output and CGE models, as explained later in Section 4.

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 issued 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).

Some earlier work by Hewings (1977; 1984) provided the basis for the type of assessment adopted in this present paper. Essentially, 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 Are these findings likely to be generalizable to modeling systems of the REIM type?

Regional input-output tables have even wider potential for variation in 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:

$$m_i = \frac{dx}{dy_j} = \sum_i \frac{\partial x_i}{\partial y_j} = \sum_i m_{ij} \tag{2.1}$$

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

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

$Y = [y_i]$ is the final demand vector, $y = \Sigma_j y_j$,

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:

$$m_i = 1 + \frac{a_i}{1-\bar{a}}$$

where a_{ij} are regional input-output coefficients, $a_i = \Sigma_i a_{ij}$ *and* $\bar{a}$ is a mean value of a_i.

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[2]. In the next section we show that REIM-type models require information from a full input-

[2] Intermediate product consumption is determined by the row-sum of the Leontief inverse.

output table, and thus the column sums of a table (a_i) are not sufficient.

III. EFFECT OF INPUT-OUTPUT TABLES ON REGIONAL ECONOMETRIC INPUT-OUTPUT MODELS

In the recent literature on CGE (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 twofold role that input-output tables lay in such models, namely, that of a forecasting tool and a policy impact analysis tool. To illustrate, we concentrate on regional econometric input-output models - REIM (see for example, Conway, 1990, Israilevich and Mahidhara, 1991).

Input-output tables enter REIM twice. First, as a deterministic linear predictor of output:

$$z_i^t = \sum_j a_{ij} x_j^t + \sum_j f_{ij} y_j^t + e_i n_i^t \qquad \forall i = 1,\dots,n \tag{3.1}$$

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,

$N = n_j$ 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 exports,

$Z = z_i$ are predicted output values,

t indicates year. For brevity we omit this superscript in the rest of this paper.

To turn this model into an econometric forecasting model vector, Z has to be stochastically related to the observed vector X, that is, input-output coefficients enter for a second time the set of equations in REIM. The corresponding set of regression equations where the actual output is a function of expected output, time and, in some cases, autoregressive terms, is as follows:

$$X = \alpha + F(L, Z) \cdot \beta + \varepsilon \tag{3.2}$$

where " and $ are estimated parameter vectors,

X is the observed output vector,

F (L; Z) is a function of variables *L* (such as time dummies) and expected output *Z*,

, is a matrix of random errors.

Equation 3.2 assigns a set of regression coefficients to each row of the input-output table, weighted by annually observed outputs, in the nonlinear fashion. This means that input-output column-sums would not provide enough information for system 3.2. Therefore

Drake's short-cut cannot be used in REIM. We will concentrate only on Equation 3.1 which treats input-output coefficients as a linear operator that predicts output for a given year (Equations 3.1 enter REIM as an identity). Equations 3.1 represent the first step of input-output implementation into the REIM system. Further analysis of other parts of REIM is necessary for the full understanding of input-output effect on the entire system.[3]

The crucial difference between traditional input-output (IM) approach and Equation 3.1 are the weights assigned by 3.1 to each of input-output coefficients. These weights are expressed as outputs, X, for each time period. In order to formalize the difference between IM approach and Equation 3.1, we rewrite Equation 3.1 in matrix form:

$$Z_{REIM} = AX + Y \tag{3.3}$$

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. The estimated output, Z, should be as close as possible to the observed output X; denote the difference between the observed and estimated outputs as $) = Z - X$. Then equation 3.1 can be presented as:

$$Z_{REIM} =) + X = AX + Y \tag{3.4}$$

If the IM approach is used then:

$$Z_{IM} = (I - A)^{-1}Y \tag{3.5}$$

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[3] The authors are currently working on the analysis of the remaining components of REIM related to input-output.

Since, *(I A)* is not an identity matrix Z_{IM} is different from Z_{REIM}. Expressing this in terms of), one can identify the difference beween Equation 3.1 and the IM approach[4]

$$Z_{IM} = (I - A)^{-1}\ ) + X = (I - A)^{-1}\ Y \qquad (3.6)$$

Another distinction between 3.1 and IM approach is in the treatment of impact. In the IM approach impact is entered through vector *Y*, while in 3.1 this impact can be entered through X as well. An impact that is entered through *Y* in system 3.1 is different from the IM impact. We will illustrate this as follows: identify a diagonal matrix $\ulcorner$ that relates predicted and estimated vectors as $Z = \ulcorner X$, then 3.1 can be expressed as:

$$Z_{REIM} = \ulcorner X = AX + Y \qquad (3.7)$$

and

$$X = (\ulcorner - A)^{-1}\ Y \qquad (3.8)$$

This is the simplified REIM multiplier, where ' varies over time. This simplification essentially involves the closure of the system 3.1, while in the full REIM system 3.2, several other relationships are incorporated into the multiplier effect. If the observed *Y* is inserted into 3.8, then estimated output will be equal to the

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[4] If) elements are positive (negative) then IM approach would consistently over (under) predict estimated output Z relative to equation 3.1, as it is determined in 3.6. For example if the value added vector is increasing in time, then the *A* coefficients would be overestimated, making) positive and increasin with time, then $Z_{IM} - X > Z_{REIM} - X$, *i.e. 3.1* estimates are better than IM
estimates. This is true because input-ouput multipliers are greater than unity. However, empirical investigation of IM performance vs. 3.1 prediction is beyond the scope of this paper.

observed output.[5] To conclude, the initial effect of the input-output table on REIM forecast is derived with system 3.1; similarly, the impact of changing elements in *X* can be traved with system 3.1. The impact of final demand on the system is determined with Equation 3.8.

IV. 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. IMs treat final demand as a exogenous vector, while SAMs endogenize many of the final demand components. Neither modeling system, however, uses information on national variable.s REIMs, on the other hand, utilize all the information present in the detailed final demand matrix, including national variables. 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.

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[5] In the IM approach one can not expect to derive the observed output for an observed final demand.

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:

$$Z / X$$

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. In other words, instead of using a **column constrained** approach as in IM or SAM, REIM imposes a **row constraint for the base year**.

REIM is used for two purposes: forecast and impact analysis. 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. In other words, Equation 3.2 transforms input-output into a forecasting tool, but, in order to understand the role of the construction method of input-output in the forecasting system, we start our analysis with Equation 3.1 and ignore Equation 3.2 in this paper. A second aspect of REIM is in its role in impact analysis; in a 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 (3.1). 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.[6] 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.

4.1 Forecast Experiments

In order to estimate the Z variables of Equation 3.1, we allow vectors *X, Y* and *N* to vary over time using three different sets of

[6] A brief description of the CIO construction is provided in the appendix.

input-output coefficients: CIO, NIO and RIO. We find that none of the above three input-output tables is a consistently superior predictor for the observed output vector *X*. We measure differences between three predictions using two sets of measures.

- First, we measure forecasting error as mean absolute percent errors (MAPE), weighted by each sector's share of total output. This measure represents variations over time. Weighted MAPEs for the years 1969-1990 are presented in Graph 1.7. All three forecasts derived from the three tables are very similar, as observed in Graph 1[7]. For example, forecasts errors derived with CIO are only 0.9 percent higher than that of NIO and 5.4 percent lower than RIO for 1990. This is an average measure of forecasting error and it does not reflect variations in forecasting errors across time.
- Secondly, we measure variations across time for each sector weighted by the sector's share in total output. This is done by regressing the vector *Z* derived from CIO, NIO and RIO for each sector on the observed vector *x*. The resultant R^2 are multiplied by a time varying weight matrix, where the elements are each sectors' share of total output in a given year. The

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[7] Weighted MAPE is defined as following:

$$m^t = \sum_i \frac{|z_i^t - x_i^t|}{x_i^t} w_i^t$$

where t is time, w^t_i share of output i in total output.

results are presented in Table 1; indeed, all three tables can explain variations in X fairly well. CIO fits the observed data the best but the difference between results from CIO and NIO are negligible; even RIO yields a very good fit.[8]

These results suggest that while there may be other reasons for choosing one input-output table over another, there is no clear choice as far as forecasting accuracy is concerned.

4.2 Impact Analysis

The second set of experiments is devoted to impact analyses. There are two types of impact analysis that can be performed within the framework of REIM. First, we consider changes in the exogenous variables, which represent changes in one vector of final demand; this impact effect is similar to the traditional Leontief multiplier. The second type of impact is the effect of changes in the *X* vector on the *Z* vector; this type of impact is not considered in the traditional input-output approach. However, this effect is important for REIM because the *Z* vector represents forecasted output which enters Equation 3.2, and, in turn, determines all other forecasting variables. In this part of 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

[8] The R^2 in Table 1 is a weighted average of 36 sectors. Components of this measure related to an individual sector - R^2 for each sector - are similar for all three tables. Results are available upon request.

comparison, we form two sets of pairs: the first pair NIO and CIO, and the second pair is RIO and CIO.

First, we consider the case where a change is introduced in the exogenous vector N. For this experiment, values of all variables in the final demand were allowed to vary in time with only vector N fixed at its 1982 value. We then compute the three vectors of expected output (for CIO, NIO and RIO) based on Equation 3.8 Thus, our experiment generates an expected output vector, assuming that elements of vector N (exogenous variable such as GNP, FRB index or other national variables) are fixed at their 1982 level. The expected output vector Z is then compared with the actual base year output vector X_B[9]. In other words, each of the three tables estimates the effect of assuming the national economy remaining at the 1982 level for all observed periods.

To describe the results of experiments, we present two types of comparisons for each of the three tables (CIO, NIO and RIO). First, the derived Z was compared with the base output of 1982. For that purpose, we defined the percentage change (call it v) of expected output Z relative to the base output X_B as $\left(v_i = \frac{|Z_i - X_{iB}|}{X_{iB}} \right)$. These percent changes (v_i) are computed for each of the three tables. Then we construct weighted MAPEs using these three variables. Therefore, for each year we have three weighted MAPE

[9] Remember that in the base year, actual output X equals expected output Z.

measures presented in Graph 2. Here, we observe substantial differences between results derived with each of the three tables. For example, the difference between output changes estimated with CIO is 20 percent higher than the same results estimated with NIO and 30 percent lower than that estimated with RIO.

The overall effect derived in Graph 2 may mask some of the sectoral differences. With that in mind, we regressed v_i derived with NIO on v_i derived with CIO, and then repeated the regression for RIO and CIO. These regressions indicate how much the variations in output change derived by one table can explain variations derived with another table. Therefore, our main interest is in R_2, which is reported in Table 2. As we can see, variations among sectoral changes derived with CIO and NIO are not significant and similar to variations between CIO and RIO. Therefore, if one would measure the effect of the exogenous variables with the three tables, one would find that derived averages are significantly different. However, variations around the average are not substantially different between outputs derived with the three tables.

In the second set of impact experiments, we consider the effect of the changes in X vector on Z. We introduced shocks to the system 3.1 through sectors 8 (Lumber and Wood Products) and 17 (Primary Metals)[10] The shock was introduced as follows, output for

[10] In the text, we report results from only these two sectors. Similar results for other sectors are available upon

sector 8 (x_8) was fixed at its 1982 level, while all other variables in equations 3.1 were fixed at 1990 levels. Solving equations 3.1 for *Z* values, we determine the effect of the shock from changing output in sector 8 on all other estimated outputs *Z.* This was repeated for all three input-output tables. Then, the derived three sets of *Z* were compared with the base 1982 output vector, X_B. The percent difference between *Z* and X_B derived with NIO on that derived with CIO and then repeated the exercise for RIO on CIO. Results of regressions are presented in Tables 3 and 4 for both sectors 8 and 17.

For both sectors, the R-squared derived for the NIO and CIO pair, is higher than for the case of RIO and CIO pair. In general, the R-squared for all cases are fairly low, thereby suggesting that variations in the expected output as a result of the shock introduced to *X* elements are fairly strong. This reinforces the results obtained in the first impact experiment. Hence, it would appear that impact analysis is fairly sensitive to the methods of construction of input-output tables, within REIM framework, a finding similar to an earlier result for IM by Hewings (1977), and reinforced by Harrigan (1982).

V. CONCLUSION

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request.

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 the 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, there would appear to be only minimal differences; however, a word of caution should be interjected here. In the full version of REIM, the forecasts are derived from a complex set of equations, many of which have lag structures. Hence, it is likely that even small differences in the observed predictive power of the input-output tables might translate into significant cumulative differences over time.

The differences in the partial, static multipliers associated with impact analysis reveal more significant variations. In this regard, the results parallel most strongly the earlier experiments by Hewings (1977). Taken together, the results suggest that the debate in this context remains unresolved. 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. Finally, the analysis needs to be extended to other general equilibrium formulations to ensure that the conclusions derived here are not merely an artifact of the specific model.

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APPENDIX:

Chicago-observed input-output table (CIO)

The data employed in this analysis combine National BEA Input-Output table for 1982 and the Census of Manufacturers. Census of Manufacturers allowed us to construct the manufacturing sub block of the technological matrix of the Chicago input-output table (SIC 20 through 39). In the second part of CIO construction we determine the regional purchase coefficients (RPC)[11]. To determine the observed shares of inflow of goods from the rest of the world, we again use the Census of Manufacturers. The Census collects information on a very disaggregated level. Our data are based on the 6-digit Standard Industrial Codes (SIC). At this disaggregation level, 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 determine a higher bound on the RPC. Using non-competitive imports information we construct a new type of RPC. Denote this matrix of RPC as A^rR which is constructed as follows:

$$\left[\mathbf{A}^r_R\right] = \begin{Bmatrix} a_{ij} - l_{ij} & \text{if } m_{ij} \geq l_{ij} \\ a_{ij} - l_{ij} & \text{if } m_{ij} < l_{ij} \end{Bmatrix} \tag{4A1}$$

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

In this setting A^{rR} - REAL RPC - assumes noncompetitive import coefficients as a substitute for LQ coefficients if LQ coefficient (l_{if}) had failed to exceed the noncompetitive import coefficient (m_{ij}). The nonmanufacturing sub block of CIO is adopted from the national input-output, however, further modification to this sub-block is applied. This and other modifications are due to the treatment of net export.

The most important feature of REIM is to link input-output variables to the available time series. GSP series provides net export figures on the annual basis. CREIM adjusts input-output data to this figure. It is done on the proration basis for the base year as follows. First define net export as:

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

where *ne; e* and *m* are net export, export and import respective scalar,

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

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

Equation 5.2 can be written as:

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

$$= x - \sum_{ij} \left(X_{ij} + Y_{ij}\right) \qquad \text{(A3)}$$

Therefore,

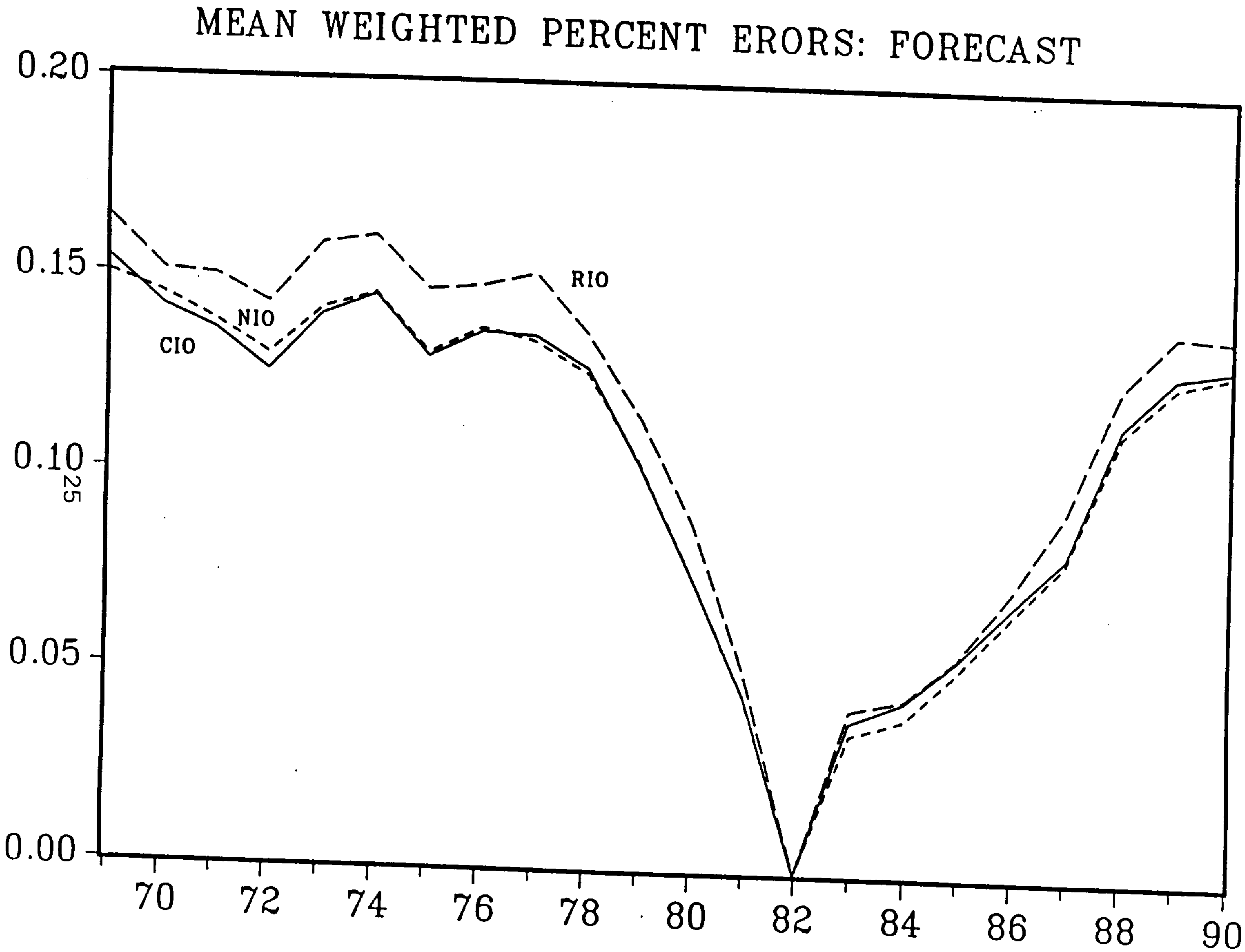
$$ne = x - \sum_{ij} \left(X_{ij} + Y_{ij}\right) \qquad \text{(A4)}$$

As a result, the adjustment 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:

$$\left[\tilde{X}_{y} \middle| \tilde{Y}_{y}\right] = \left[X_{y} \middle| Y_{y}\right] \cdot \frac{x - ne}{\Sigma_{y}\left(X_{y} + Y_{y}\right)} \tag{A5}$$

where $[\tilde{X}_{y} | \tilde{Y}_{y}]$ 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.

GRAPH 1


MEAN WEIGHTED PERCENT ERORS: FORECAST
0.20
0.15
0.10
0.05
0.00
70
72
74
76
78
80
82
84
86
88
90
RIO
NIO
CIO

GRAPH 2

MEAN WEIGHTED PERCENT ERRORS: IMPACT (EXOG)

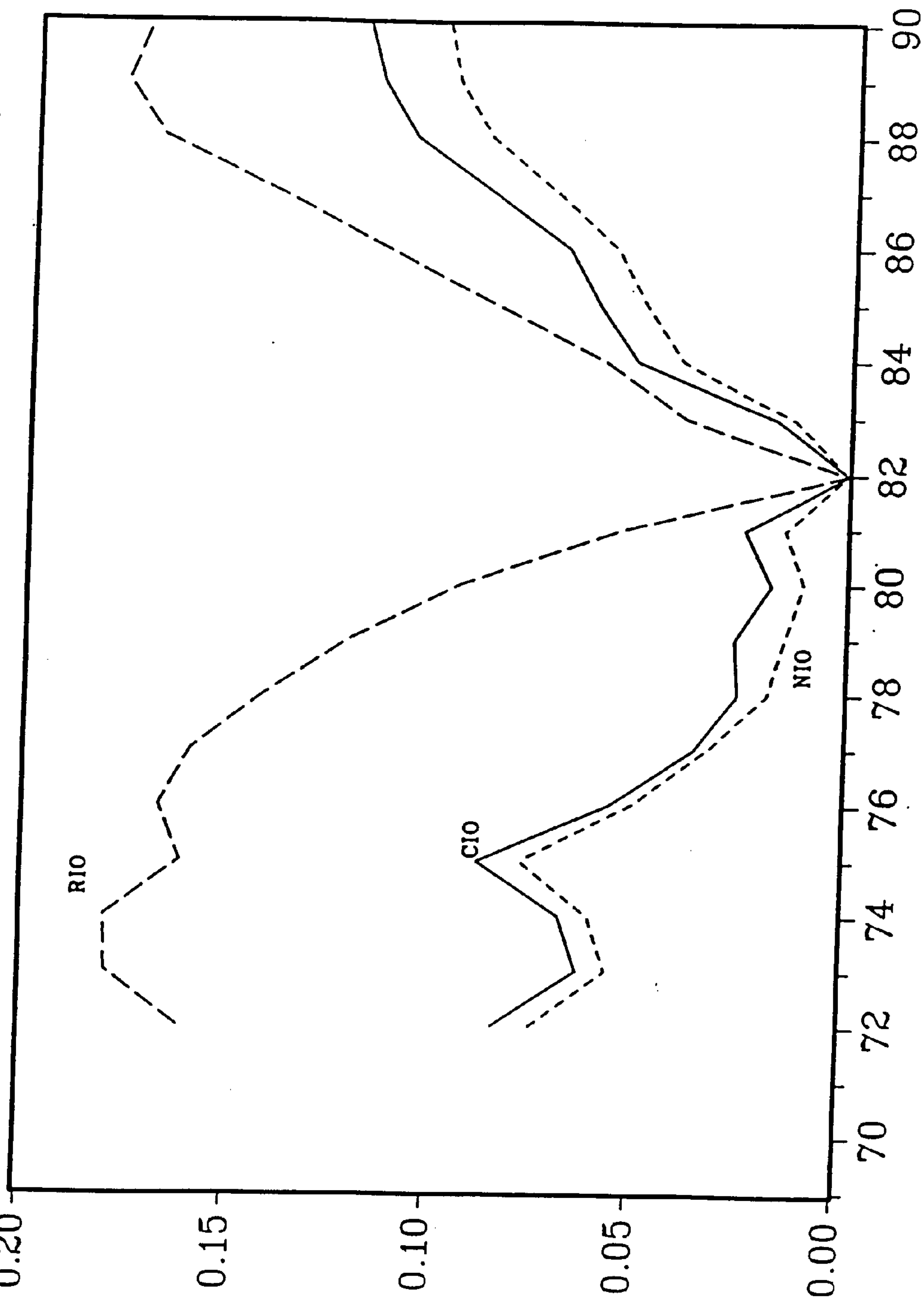


TABLE 1

MEAN WEIGHTED ADJUSTED R-SQUARED

CIO	0.71
NIO	0.7
RIO	0.68

REGRESSION OF FORECAST ON OBSERVED DATA

TABLE 2

ADJUSTED R-SQUARED

YEAR	NIO ON CIO	RIO ON CIO
69	0.906	0.858
70	0.899	0.854
71	0.908	0.873
72	0.904	0.922
73	0.883	0.954
74	0.899	0.95
75	0.911	0.935
76	0.935	0.972
77	0.966	0.984
78	0.933	0.986
79	0.919	0.983
80	0.944	0.986
81	0.822	0.953
82	-	-
83	0.981	0.977
84	0.865	0.83
85	0.899	0.869
86	0.923	0.883
87	0.906	0.875
88	0.911	0.885
89	0.913	0.88
90	0.913	0.88

TABLE 3

IMPACT ANALYSIS: LUMBER AND WOOD PRODUCTS (SIC24) PERTURBED

NIO on CIO (Nation on Chicago)	RIO on CIO (Random on Chicago)
Y5 = 0.0013871 + 0.7622312*X3	**Y6 = 0.0026354 + 0.0231538*X3**
(0.0067) (0.0921)	(0.0004) (0.0684)
(s.e.) (s.e.)	(s.e.) (s.e.)
R-squared = 0.6682	R-squared = 0.0033

X3 IS THE PERCENT DIFFERENCE BETWEEN 1990 OUTPUT GENERATED BY CIO AND THE OBSERVED 1982 VA
Y5 AND Y6 ARE CORRESPONDING VALUES FOR NIO AND RIO.

TABLE 4

IMPACT ANALYSIS: PRIMARY METAL PRODUCTS (SIC33) PERTURBED

NIO on CIO (Nation on Chicago)	RIO on CIO (Random on Chicago)
Y7 = 0.00000325 + 0.0054127*X4	**Y6 = 0.0006072 + 0.0643408*X3**
(0.00001) (0.0059)	(0.0008) (0.2859831)
(s.e.) (s.e.)	(s.e.) (s.e.)
R-squared = 0.0239138	R-squared = 0.0014865

X4 IS THE PERCENT DIFFERENCE BETWEEN 1990 OUTPUT GENERATED BY CIO AND THE OBSERVED 1982 VA
Y7 AND Y8 ARE CORRESPONDING VALUES FOR NIO AND RIO.