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Forecasting with Regional Input-Output Tables

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1 Introduction

In the early developments of regional input-output 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

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traditional CGE models (see Kraybill, 1991; Harrigan et al. 1991). In this paper we focus specifically on the behaviour 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. An appendix provides a description of the Chicago-observed input-output table (CIO). Section 5 concludes the paper.

2 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 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).

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

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

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, and even for CGE systems?

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:

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

where m_i is a multiplier, and m_{ij} are Leontief inverse elements,
$X = [x_i]$ is the output vector, $x = \sum_i x_i$,
$Y = [y_i]$ is the final demand vector, $y = \sum_j y_j$.

Earlier studies would, correctly, argue 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:

$$m_i = 1 + \frac{a_{i.}}{1 - \bar{a}_i}$$

where a_{ij} are regional input-output coefficients, $a_{i.} = \sum_i a_{ij}$ and $\bar{a}_i$ 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]

3 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), 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 play 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:

$$z_i^t = \sum_j a_{ij} x_j^t + \sum_j f_{ij} y_j^t + e_i n_i^t \quad \forall i = 1, \cdots, n \tag{2}$$

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 export,
$Z = [z_i]$ 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. We do this via a set of regression equations where the actual output is a function of expected output, time and, in some cases, autoregressive terms:

$$\hat{X} = A + F(L, Z) \cdot B + \mathcal{E}, \tag{3}$$

where A and B are estimated parameter vectors,
$\hat{X}$ is the estimated output vector,
$F(L, Z)$ is a function of variables L (such as time dummies) and expected output Z,
$\mathcal{E}$ is a matrix of random errors.
We will concentrate only on equation 2 which treats input-output coefficients as a

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

linear operator that predicts output for a given year (equations 2 enters REIM as an identity).

4 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 an exogenous vector, while SAMs endogenize many of the final demand components. Neither modeling system, however, uses information on national variables. 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 which includes (2) and (3) in a time-recursive fashion. This means REIM measures impact in a dynamic sense.

Input-output and final demand coefficients in (2) predict output based on regional and national variables. Due to the different structure of (2) in relation to the traditional Leontief inverse application to the final demand vector, column-sums $a_{i.}$ have no explicit role in the prediction of expected output Z. At the outset, equation (2) is entirely based on the a_{ij} coefficients. Further analysis shows that (2) is normalized, somewhat akin to the column-sum constraints of IM approach. 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 equality does not necessarily hold. This base year identity is achieved by either assuming export as a residual or allowing some adjustment procedure to balance rows and columns of the input-output table. In other words, instead of using a **column constrained** approach as in IM, REIM imposes a **row constraint for the base year**.

IM multipliers can be obtained from input-output tables constructed using different data sources but with a constrained column-sum. Analogously, outputs estimated by REIM can be obtained for any given year with different input-output tables balanced in the same base year. In evaluating the performance of these two modeling systems, we look at how realistic the multiplier estimates are for IM, and how realistic the output estimates are for REIM. The principal difference between these two evaluation methods is that, in the case of REIM, we compare estimated output with observed output. In the case of IM, however, there are no observed multipliers against which to gauge the accuracy of the input-output table.

A second feature 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 section, 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 (2). 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.[3] 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) consisting 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. The export vector is determined as a residual and, therefore, varies for each of the input-output tables.

4.1 Forecast Experiments

In the first experiment we fixed vectors X, Y and N at their 1990 levels. We then generate a vector of expected outputs Z for each of the three tables. We find that none of the above three input-output tables is a consistently superior predictor of the observed output vector X.

We calculate the rate of change between the three expected output vectors for 1990 and the observed output vector for 1990 (expected outputs are generated by three input-output tables: CIO, NIO and RIO). [4] These percent difference series are shown in Graph 1. The line drawn through zero represents no difference between actual and expected values of output. Most values on the graph deviate from zero and none of the three tables produce a clear "winner". For example, prediction errors for sector 1 (agriculture) are 0.91, 0.86 and 1.08 for CIO, NIO and RIO, correspondingly, making NIO the best predictor (0.86 is the value 'closest' to zero). However for sector 23 (miscellaneous mfg.) prediction errors are 0.62, 0.6 and 0.34 for CIO, NIO and RIO, correspondingly, making RIO the best predictor. [5]

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

[4] Thus, we will have three series measured as percent difference, i.e., between CIO and observed, NIO and observed, and RIO and observed.

[5] The relatively large values of these errors may raise questions about using IM for predicting output. In the case of REIM, a non-zero difference between observed and predicted rates of change implies simply a nonzero intercept in equation (3). In other words, these differences are easily

The variations around the zero line in Graph 1.1 are important; the "flattest" line would represent a "winner" and, in this case, NIO appears to emerge as the winner in this category since it provides a better match between actual and predicted output for 1990.

Graph 1.2 depicts variations in percent errors of Graph 1.1 around the mean for the CIO, RIO and NIO series. From this graph, it is clear that the two methods of input-output table construction –CIO and NIO– produce very similar results, differing on average by only 1.7 percent. The variations for RIO are larger and average 11 percent. To illustrate the similarity between CIO and NIO, we present just those two series in Graph 1.3. A point to note, considering how little information about the economy was incorporated into the randomly generated table RIO, its variation is remarkably close to the variation in the Chicago generated table. Thus, not one of the above three tables provides a clearly better (more accurate) forecast for REIM.[6] 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.[7]

To quantify the differences observed in these three graphs 1.1 – 1.3, we present regression analysis of the forecasting errors, centered around the means (Graph 1.2), generated by CIO, NIO and RIO tables.[8] Table 1 records the results, showing that 99 percent of variations (R-squared = .99) in the CIO table can be explained by the NIO table. The RIO table explains 56 percent of variations (R-squared = .56) generated by the CIO table, an extremely high percentage for a randomly generated table. Based upon both the graphical illustration as well as our regression analysis, we conclude that as far as forecasting output is concerned, there is no advantage in choosing one method of input-output construction versus another.

4.2 Impact Analysis

The second set of experiments is devoted to an impact analysis performed by REIM. Here we fix selected elements of X, Y or N at their 1990 levels. Our choice of variable and sectors is arbitrary; we do not aim to represent any specific economic scenario. We run three experiments, choosing a different sector for each experiment. We chose sector 8 (Lumber and Wood Products), sector 17 (Primary Metals) and the

corrected in REIM.

[6]Our analysis is conducted in a static scenario; it is not clear how the small variations generated by these input-output tables would translate in a cumulative sense, which would be appropriate for judging REIM forecast. We are currently testing the three tables in a dynamic simulation scenario.

[7]Similar experiments for other time periods lead to the same qualitative conclusion.

[8]We use pairwise regressions. Obviously , centering around the mean affects only the intercept and not any other results. Therefore, we would get the same results (except intercept) using the original data of Graph 1.1.

exogenous vector N for our three experiments. As explained, our goal is to illustrate the sensitivity of impact analysis to our choice of tables.

First, we consider the case where the change is introduced in the exogenous vector N. For this experiment, values of all variables (except N) are fixed at their base year (1982) values; the vector N is fixed at its 1990 value. We then compute the three vectors of expected output (one each for CIO, NIO and RIO). Our experiment thus generates an expected output vector, which shows the impact on the 1982 economy when a given variable (in this case N) was changed (from its 1982 value) to its 1990 value. The expected output vector Z is then compared with the actual base year output vector X.[9]

If the CIO, NIO and RIO tables were to have no significantly different effect on expected output Z, then the three expected output vectors Z would be very similar. We calculate the percent difference between the Zs generated by CIO and NIO (centered around their means) and X. If both lines were parallel to each other then the impact estimated by both tables would be identical. Figure 2.1 graphs those percent differences for this experiment, and we see fairly strong variations across the two input-output tables, particularly when compared to Graph 1.3. We view this as an indication that although the CIO and NIO tables generate similar forecasts (Graph 1.3), they produce noticeably different sectorally-distributed impacts (Graph 2.1). In Graph 2.2, we include the RIO table which produces an even more different impact. The maximum percent difference rose to 250 percent (sector 15) in Graph 2.2 relative to 35 percent (sector 19) in Graph 2.1. This is strikingly different than in the forecast case (Graph 1.2) where the three input-output tables produced very similar results. On average, variations between CIO and NIO for this impact case are around 6 per cent, while those between CIO and RIO are 37 percent. Corresponding figures for the forecasting experiment were 1.7 and 11 percent respectively. This clearly underscores the fact that differences in input-output tables play a far more significant role in impact analyses than in forecasting exercises.

In regressions of (mean) centered percent errors of NIO on CIO, we see that variations in the independent variable can only explain 36 percent of variations in the dependent variable. Similar regressions of RIO on CIO indicate that only 1.7 percent of variations could be explained. (See Table 2). We conducted two more such impact analyses, using sectors 8 and 17. Results of regressions run on those two cases are presented in Tables 3 and 4. In both cases, the R-squared is below 80 percent for the NIO and CIO pair, and below 2 percent for the RIO and CIO pair, reinforcing 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, a finding similar to an earlier result by Hewings (1977), and reinforced by Harrigan

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

(1982).

5 Conclusion

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, 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 specification.

References

Conway R.S. (1990), "The Washington Projection and Simulation Model: ten years of experience with a regional interindustry econometric model" *International Regional Science Review* **13**, 141-165.

Drake R.L. (1976), "A Short-Cut to Estimates of Regional Input-Output Multipliers: Methodology and Evaluation" *International Regional Science Review* **1**, 1-17.

Harrigan F.J. (1982), "The Estimation of Input-Output Type Output Multipliers When no Input-Output Model Exists: A Comment" *Journal of Regional Science* **22**, 375-381.

Harrigan,F., McGregor,P., Dourmashkin, N., Swales, K. and Yin, Y.P (1991), "The sensitivity of output multipliers to alternative technology and factor market assumptions: a computable general equilibrium analysis" in J.H.Ll. Dewhurst, G.J.D. Hewings, R.C. Jensen, (ed.), *Regional Input-Output Modeling: New Developments and Interpretations.* Avebury, 210-228.

Hewings, G.J.D. (1977), "Evaluating the possibilities for exchanging regional input-output coefficients" *Environment and Planning A* **9**, 927-944.

Hewings, G.J.D. (1984), "The role of prior information in updating regional input-output models" *Socio-Economic Planning Sciences* **18**, 319-336.

Hewings, G.J.D., Jensen, R.C. (1986), "Regional, interregional and multiregional input-output analysis" in P.Nijkamp, (ed.), *Handbook of Regional and Urban Economics.* 1, Amsterdam, North-Holland.

Israilevich P.R. and Mahidhara R. (1991), "Hog butchers no longer: 20 years of employment change in metropolitan Chicago" *Economic Perspectives* **15**, Federal Reserve Bank of Chicago, 2-13.

Jensen, R.C. (1980), "The concept of accuracy in input-output" *International Regional Science Review* **5**, 139-154.

Katz J.L. and Burford R.L. (1985), "Shortcut Formulas for Output, Income and Employment Multipliers" *The Annals of Regional Science* **19**, 61-76.

Kraybill, D.S. (1991), "Multiregional computable general equilibrium models: an introduction and survey" *unpublished paper* , Department of Agricultural and Applied Economics, University of Georgia.

Phibbs P.J. and Holsman A.J. (1981), "An Evaluation of the Burford Katz Short Cut Technique for Deriving Input-Output Multipliers" *The Annals of Regional Science* **15**, 11-19.

Round, J.I. (1983), "Nonsurvey techniques: a critical review of the theory and the evidence" *International Regional Science Review* **8**, 189-212.

Sonis, M., Hewings, G.J.D. (1989), "Error and sensitivity input-output analysis: a new approach" in R.E. Miller, K.R. Polenske, A.Z. Rose, (ed.), *Frontiers of Input-Output Analysis.* New York, Oxford University Press, 232-244.

Sonis, M., and Hewings, G.J.D. (1992), "Coefficient change in input-output models: theory and applications" *Economic Systems Research* **4**, 110-121.

Stevens, B.H., and Trainer G.A. (1976), "The Generation of Errors in Regional Input-Output Impact Models" *Working Paper. Regional Science Research Institute, Peace Dale, Rhode Island* , 1-76.

Treyz, G.I., and Stevens, B.H. (1985), "The TFS Modeling Methodology" *Regional Studies* **19**, 547-562.

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).[10] 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 noncompetitive imports information we construct a new type of RPC. Denote this matrix of RPC as A^r_R which is constructed as follows:

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

In this setting A^r_R — REAL RPC — assumes noncompetitive import coefficients as a substitute for LQ coefficients if LQ coefficient (l_{ij}) 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:

$$ne = e - m = [x - \sum_{ij}(X^r_{ij} + Y^r_{ij})] - \sum_{ij}(M^I_{ij} + M^F_{ij}), \tag{5}$$

where ne, e and m are net export, export and import respective scalar,
X^r_{ij} and Y^r_{ij} are intermediate and final regional transaction flows,
M^I_{ij} and M^F_{ij} are intermediate and final import flows.

Equation 5 can be written as

$$\begin{aligned} ne = e - m \quad &= \quad x - \sum_{ij}[(X^r_{ij} + M^I_{ij}) + (Y^r_{ij}) + M^F_{ij})] = \\ & \quad\quad x - \sum_{ij}(X_{ij} + Y_{ij}). \end{aligned} \tag{6}$$

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

Therefore,

$$ne = x - \sum_{ij}(X_{ij} + Y_{ij}). \tag{7}$$

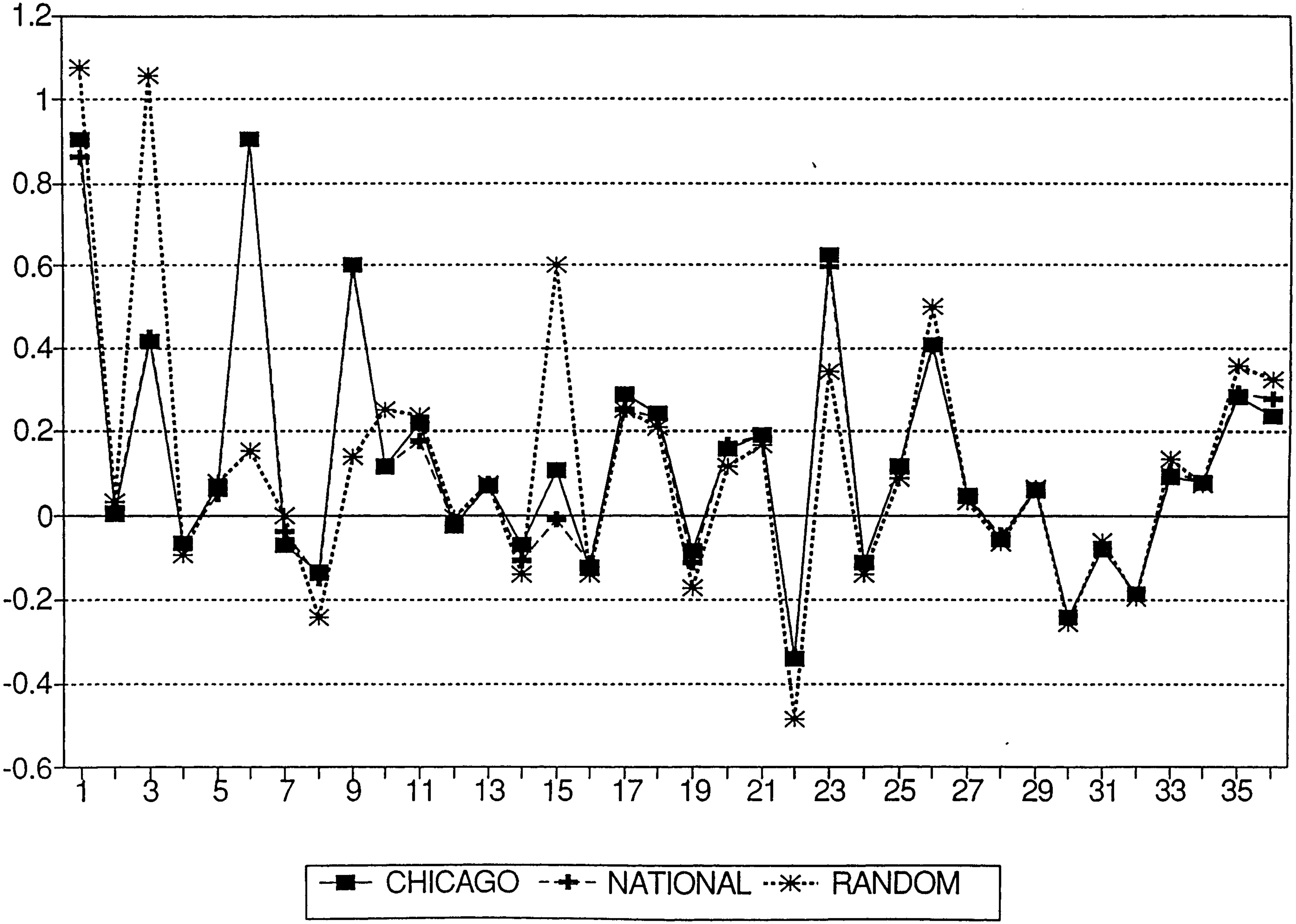
As a result, the adjustment for the ne are made before regionalizing transaction flows. This means that the matrix of intermediate and final transaction flows is multiplied by a scalar:

$$[\tilde{X}_{ij}|\tilde{Y}_{ij}] = [X_{ij}|Y_{ij}] \cdot \frac{x - ne}{\sum_{ij}(X_{ij} + Y_{ij})}$$

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

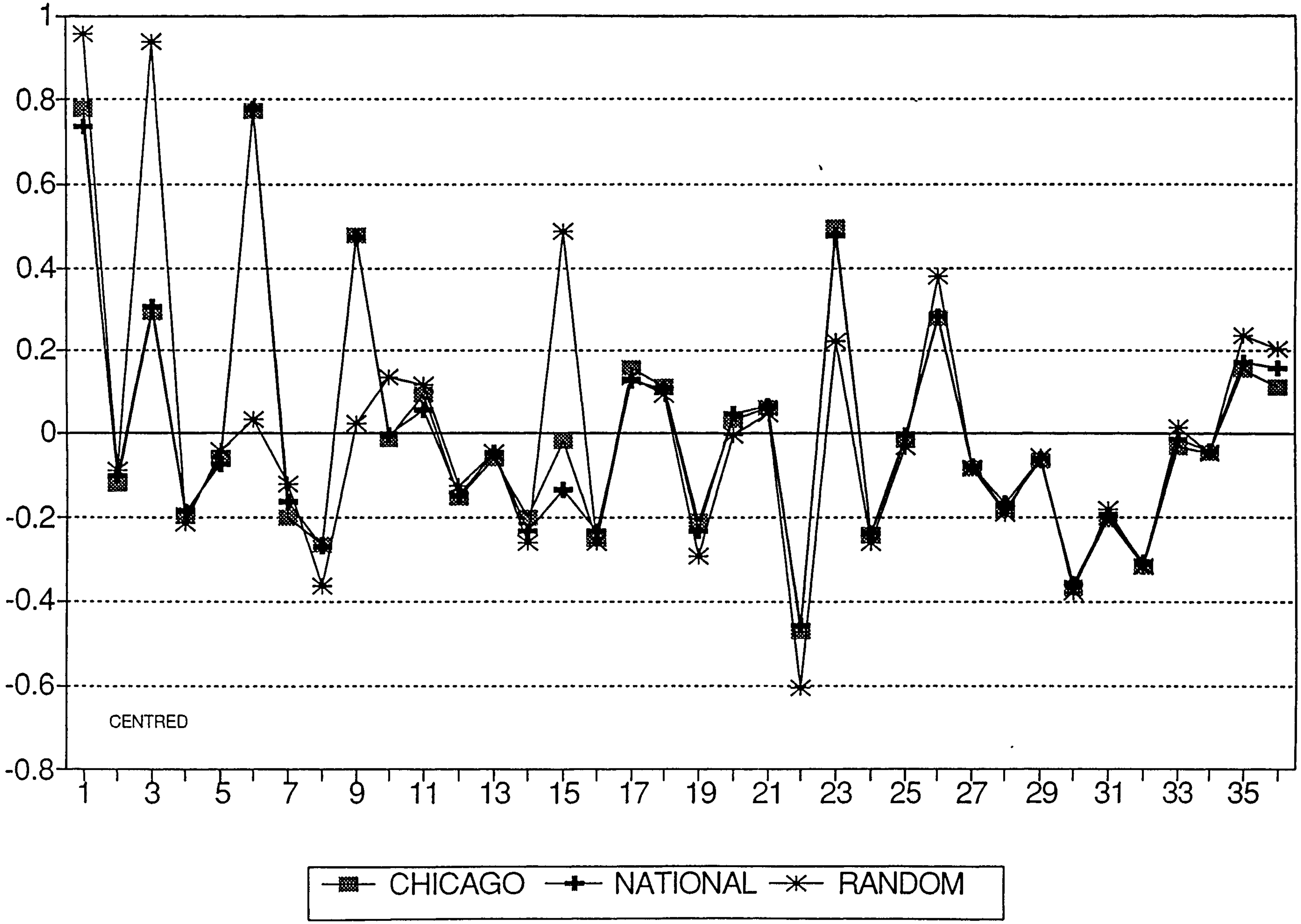
GRAPH 1.1

PERCENT ERROR RELATIVE TO OBSERVED RATE OF CHANGE



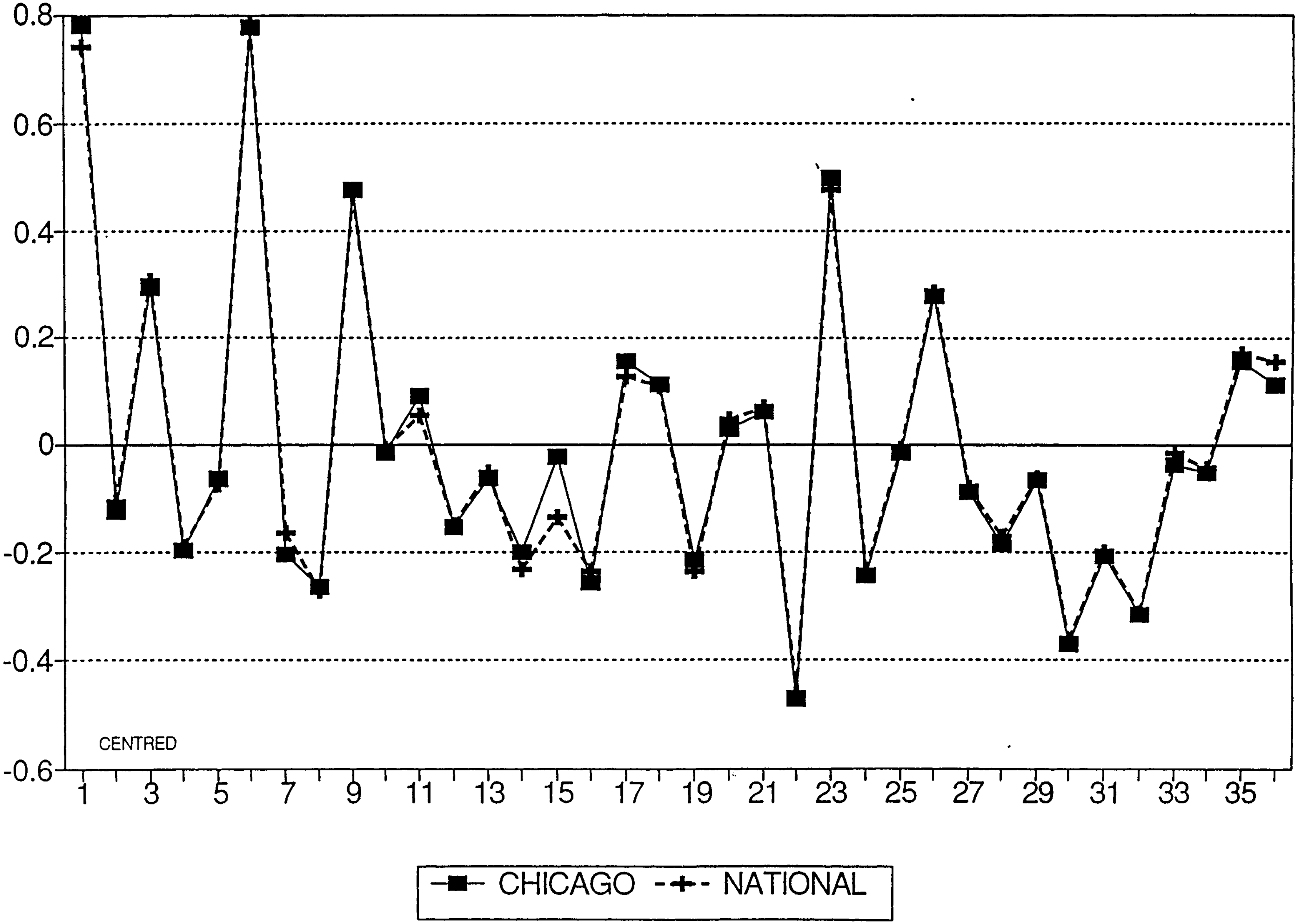
GRAPH 1.2

PERCENT ERROR RELATIVE TO OBSERVED RATE
OF CHANGE



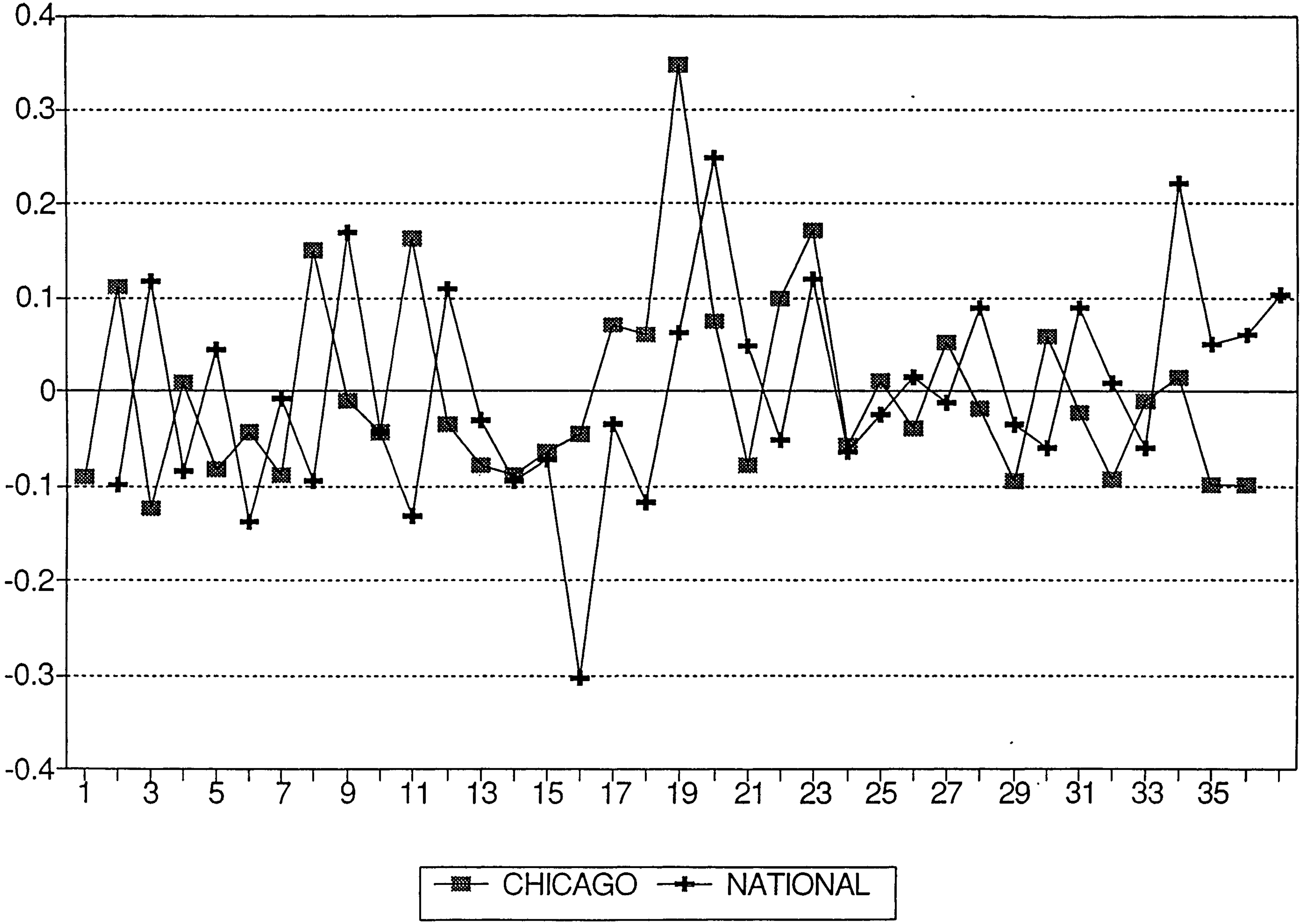
GRAPH 1.3

PERCENT ERROR RELATIVE TO OBSERVED RATE OF CHANGE



GRAPH 2.1

IMPACT ON OUTPUT DUE TO CHANGE IN EXOGENOUS VARIABLES ONLY



GRAPH 2.2

IMPACT ON OUTPUT DUE TO
CHANGE IN EXOGENOUS VARIABLES ONLY

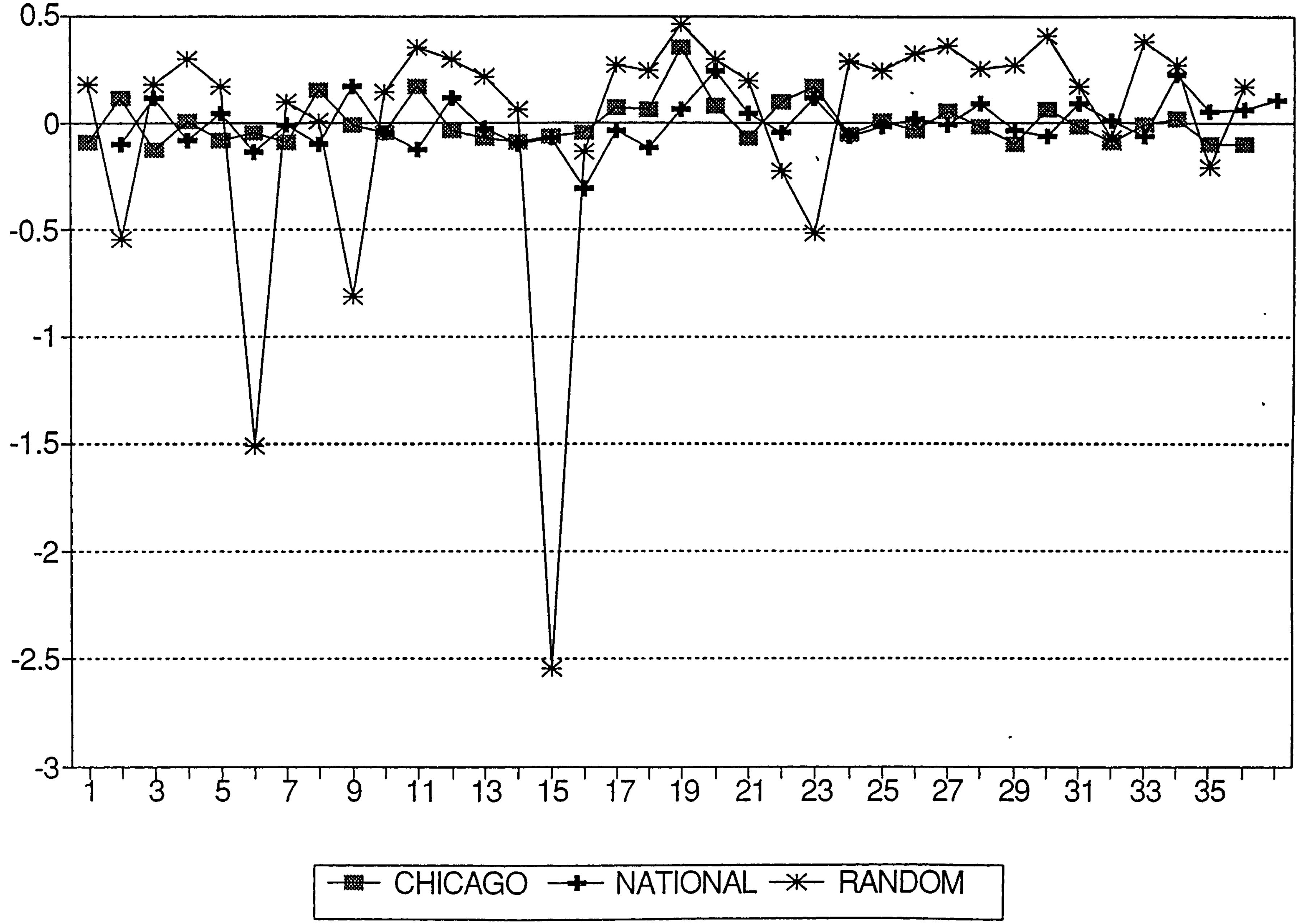


TABLE 1

FORECAST

NIO on CIO (Nation on Chicago)	RIO on CIO (Random on Chicago)
Y1 = -0.0042635 + 0.9809050*X1	**Y2 = 0.0131112 + 0.8351763*X1**
(0.0048) (0.0156)	(0.0393) (0.1266)
(s.e.) (s.e.)	(s.e.) (s.e.)
Adjusted R-squared = 0.9916	Adjusted R-squared = 0.5481

The percent difference between the Chicago I-O series and the observed series in 1990 is denoted as X1.
The percent difference between the National I-O series and the observed series in 1990 is denoted as Y1.
The percent difference between the Random I-O series and the observed series in 1990 is denoted as Y2.

TABLE 2

IMPACT ANALYSIS: EXOGENOUS VARIABLES SHOCKED

NIO on CIO (Nation on Chicago)	RIO on CIO (Random on Chicago)
Y3 = -0.0030842 + 0.6607125*X2	**Y4 = -0.2196862 + 0.6405549*X2**
(0.0207) (0.1487)	(0.1385) (0.9905)
(s.e.) (s.e.)	(s.e.) (s.e.)
Adjusted R-squared = 0.3487	Adjusted R-squared = -0.0169

The percent difference between Chicago I-O 1990 and observed 1982 is denoted as X2.
The percent difference between National I-O 1990 and observed 1982 is denoted as Y3
The percent difference between Random I-O 1990 and observed 1982 is denoted as Y4.

TABLE 3

IMPACT ANALYSIS: LUMBER AND WOOD PRODUCTS (SIC24) SHOCKED

NIO on CIO (Nation on Chicago)	RIO on CIO (Random on Chicago)
Y5 = 0.0013916 + 0.7623109*X3	**Y6 = 0.0021162 + 0.0279960*X3**
(0.0011) (0.0919)	(0.0004) (0.0351)
(s.e.) (s.e.)	(s.e.) (s.e.)
Adjusted R-squared = 0.6594	Adjusted R-squared = -0.0104

The percent difference between Chicago I-O 1990 and observed 1982 is denoted as X3.
The percent difference between National I-O 1990 and observed 1982 is denoted as Y5
The percent difference between Random I-O 1990 and observed 1982 is denoted as Y6.

TABLE 4

IMPACT ANALYSIS: PRIMARY METALS SECTOR (SIC33) SHOCKED

NIO on CIO (Nation on Chicago)	RIO on CIO (Random on Chicago)
Y7 = -0.0001201 + 2.1659577*X4	**Y8 = 0.0005591 - 0.1208372*X4**
(0.0001) (0.2104)	(0.0001) (0.2337)
(s.e.) (s.e.)	(s.e.) (s.e.)
Adjusted R-squared = 0.7499	Adjusted R-squared = -0.0213

The percent difference between Chicago I-O 1990 and observed 1982 is denoted as X4.
The percent difference between National I-O 1990 and observed 1982 is denoted as Y7
The percent difference between Random I-O 1990 and observed 1982 is denoted as Y8.