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A STUDY OF THE ROLE OF REGIONALIZATION IN THE GENERATION OF AGGREGATION ERROR IN REGIONAL INPUT-OUTPUT MODELS*

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Benjamin H. Stevens died December 9, 1997. For more information, see Miller (1998).

ABSTRACT. Although the need for aggregation in input-output modeling has diminished with the increases in computing power, an alarming number of regional studies continue to use the procedure. The rationales for doing so typically are grounded in data problems at the regional level. As a result many regional analysts use aggregated national input-output models and trade-adjust them at this aggregated level. In this paper, we point out why this approach can be inappropriate. We do so by noting that it creates a possible source of model misapplication (i.e., a direct effect could appear for a sector where one does not exist) and also by finding that a large amount of error (on the order of 100 percent) can be induced into the impact results as a result of improper aggregation. In simulations, we find that average aggregation error tends to peak at 81 sectors after rising from 492 to 365 sectors. Perversely, error then diminishes somewhat as the model size decreases further to 11 and 6 sectors. We also find that while region- and sector-specific attributes influence aggregation error in a statistically significantly manner, their influence on the amount of error generally does not appear to be large.

1. THE GENERAL AGGREGATION QUESTION

Economic researchers have always had the problem of aggregating data to a "reasonable" level so that economic interactions could be analyzed effectively. As Leontief states, "the practical choice is not between aggregation and non-aggregation but rather between a higher and lower degree of aggregation" (1949,

*Some of the discussions in this paper have been presented in more primitive form as early as May 29, 1987, in Binghamton, New York. The first thoughts on the subject first appeared in 1990 as *RSRI Discussion Paper* No. 130. We gratefully acknowledge the comments of Rodney C. Jensen and Ronald E. Miller on that rendition. In 1993, equipped with a full set of simulation results, it was republished as *RSRI Discussion Paper No. 134* with the author order reversed. We gratefully acknowledge the comments of an anonymous referee and Erik Dietzenbacher, in particular, on that paper and its revision. In incorporating the two latest sets of comments to form the present paper, Lahr worked without the benefit of his senior author's wisdom, charity, or approval, and yet all the while recalled his different points of view on some of the paper's aspects, even though they were echoes of conversations over three years old.

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p. 216). An early debate on the objectives and methods of aggregation for economic sectors, summarized by May (1947), led Leontief (1951) to consider acceptable means of aggregating input-output (I-O) models. This fed an extremely lively line of work, which has been reviewed by Chipman (1976), Chakraborty and ten Raa (1981), and Kymn (1990). In addition, Guccione and Gillen (1985) have provided a theoretical critique of some of the more accepted aggregation techniques. In essence, this research led to the inescapable conclusion that the necessary conditions for perfect aggregation are highly restrictive: for any two sectors to be aggregated together, they should be substitutes or complements and also have the same production functions (although much of the literature focuses on the latter). Of course, in practice these conditions are rarely met even for lines of businesses within individual firms, much less for firms within entire industries.

As Balderston and Whitin note, it became clear early on that "the process of aggregation may obscure important relationships between the components of aggregates. It is even possible that the particular information lost may be more important than the more general information available in the solution made possible by aggregation" (1954, p. 79). Yet, the need to obtain numerical solutions to complex economic models using limited computational power made high levels of aggregation a practical necessity, at least through the 1950s. As Morgenstern (1954) reported, it took 48 hours in 1947 to calculate the inverse of a modest-sized 38-sector matrix. He then goes on to let us know that it took only 45 minutes on the fastest computer available at Princeton University in 1952. But rapid progress was continued: by the next year, the computer at the Institute of Advanced Study was able to invert the same matrix in 5 minutes.

Despite the fact that the accelerating speed and growing capacity of computers soon obviated the practical computational rationale for aggregation, the aggregation question has remained an important subject of discussion in the research literature. Beyond the works that have been reviewed elsewhere, methods for minimizing bias when aggregating and the means for determining the size and types of error generated in the use of highly aggregated macroeconomic models in general, and I-O models in particular, also have been explored by Aroche-Reyes (2001), Cabrer, Contreras, and Miravete (1991), Crown (1987), de Mesnard and Dietzenbacher (1995), Dietzenbacher (1992, 1994), Dietzenbacher and Hoen (2000), Harrison and Manning (1987), Howe and Johnson (1989, 1990), Howe and Stabler (1989, 1992), Kimura (1985), Miller and Shao (1991), Murray (1998), ÓhUllacháin (1985), Olsen (1985, 1990, 1993, 2000a, 2000b, 2001), and Oksanen and Williams (1992).

Such continued interest is justified by available socioeconomic data that were rarely as disaggregated as one might like for particular research purposes. In fact, this likely will always be the situation. In any case, studies of aggregation error provide useful information on the reliability of empirical work based on industries. Thus, the question of aggregation error and bias is and will be an important conceptual and empirical issue, especially where the level of aggregation is not under the analyst's control. Nonetheless, for national I-O studies it is no longer a dominant empirical issue

However, aggregation error continues to be an important consideration in regional I-O analysis. Here the analyst is typically forced to use the technology of the nation and to trade-adjust this technology to produce a reasonable facsimile of the region's direct requirements matrix (Jackson, 1998; Lahr, 2001b). Due largely to the problems with the availability of spatially disaggregate data (Polenske, 1989) to trade-adjust the national technology, some researchers use a more aggregate I-O model than that typically employed at the national level. The possible effects of such aggregation on the accuracy and relevance of the results obtained from such models are the subject of the present paper.

In the next section of the paper, we discuss the reasons why higher levels of aggregation are more typical in regional than in national I-O models. This is followed by an analysis of some of the errors that can be caused by the interaction of regionalization and aggregation of national I-O data. We then describe an error simulation experiment and analyze its results. An appraisal of these results and their implications for regional modeling, together with suggestions for further research, complete the paper.

2. THE AGGREGATION ISSUE IN REGIONAL I-O MODELS

The tendency for regional I-O models to be more aggregated than national models is partly a reflection of the difficult conditions under which regional analysts usually have to work. For certain, the days have come and gone when "dollar an hour undergraduates sitting across the table from high-level officers of major companies" (Stevens, 1995, p. 212) can be used to produce detailed survey-based regional I-O tables like the Philadelphia Input-Output Study (Isard, Langford, and Romanoff, 1966–1968; Isard and Langford 1971). Requisite funding, even for modest efforts to produce survey-based models, has simply dried up. The reputed cost effectiveness of "ready-made" and hybrid regional I-O models surely has played a major role in this. Perhaps most important is that "our capacity to develop highly sophisticated regional models has far outrun our ability to implement them, given the nature of available data and data-gathering techniques" (Miernyk, 1976, p. 54).

How "Regional" is Regional Technology

Typically, regional I-O models, survey-based or otherwise, are structured around borrowed technology, such as that of the nation. This is because, as mentioned above, it is rarely possible for the analyst to collect data on regional technology.[1] Nevertheless, this problem eventually may be mitigated or even

[1]Very few survey-based regional I-O models have been constructed. The most ambitious remains the Philadelphia Input-Output Study (Isard, Langford, and Romanoff, 1966–1968; Isard and Langford 1971). Other studies of note in the U.S. have been the Boulder, Colorado, study (Miernyk et al., 1967), the 1965 West Virginia Study (Miernyk et al., 1970), and the series of studies by Bourque and his associates for the State of Washington (1967, 1972, 1977, 1987). By the admission of their

eliminated, if establishment-based I-O Census data, such as those used by Jackson (2001) become available generally.

For the time being, however, borrowed technology, even in its most disaggregate form, may still be too aggregated, especially if the region under study has a complex of closely linked, but distinct, economic activities that are not fully reflected in existing national I-O data. This is aside from the unanswered question of whether national production functions are really "close enough" to be safely borrowed for regional sectors that have the same official classification. (See Jackson, 2001, for some evidence, albeit for aggregated sectors, that shows that national sectors may not be good surrogates for regional ones.)

The question of differences among regional production functions, at least at the detailed four-digit SIC level in the U.S., is relatively less important than the issues that arise in the regionalization of the borrowed technology (Stevens and Trainer, 1976). Survey-based regionalization, which is generally preferable to any nonsurvey method yet devised, requires the collection of data on at least the regional sources of major inputs (including labor) and the destinations of major sales to see if they are within the region.

When survey work is undertaken, the need to have an adequate sample of firms in each of the region's important economic sectors, not to mention by size class of the firms in the sector (Bulmer-Thomas, 1982), causes many analysts to use pre-aggregated models of 50-100 sectors or less as a basis for their survey work.[2] The implications for error generation of aggregating before regionalizing will be explored later.

Aside from meeting survey needs, aggregation may be justified if the region specializes in just a few types of industrial production. Often many minor (and even, perhaps, fairly dissimilar) industries can be aggregated on the basis that individually or combined they are not likely to be used as major sources of change in regional final demand in future applications of the model. Such selective aggregation has apparently been used judiciously in some of the better survey-based studies, such as those for the State of Washington by Bourque and his associates (1967, 1971, 1977, 1987) and for West Virginia by Miernyk et al. (1970).[3] Thus, although throughout this paper we warn against aggregation of regional I-O models, it is clear that appropriate application of

authors, all of these studies are based on various mixtures of survey and nonsurvey data. Hence, it is likely that the issue of aggregation discussed here applies to models such as these as well.

[2]Note that, even at high levels of aggregation, realizable sample sizes for important sectors may fall short. The surveyed establishments often fail to understand what is really wanted or refuse to answer on the basis that the information is proprietary. Many simply do not know the ultimate geographical source of their inputs and answer, quite honestly, "from the wholesaler down the street." For further discussion of this problem, see Isard and Langford (1971).

[3]In addition to the needs of survey research (i.e., the production of national and regional accounts) or for strictly pedagogical purposes (e.g., Miller and Blair, 1985), two other reasons to aggregate regional I-O tables are: (1) for linking to econometric-type models for which only aggregate regional final demands can be forecast (Olsen, 1993, 2000a) and (2) for comparative studies over time or between regions for which the tables might otherwise be incommensurate.

such judiciously aggregated models can overcome many of the perils against which we caution.[4]

Industry Mix and Borrowed Technology

Unfortunately, it is not always made clear in those regional I-O studies that use aggregate I-O tables how the aggregation is actually performed. Ralston, Hastings, and Brucker (1986) do report that they use detailed employment estimates to aggregate the national technology to the desired sectors for Delaware. But Bourque, whose succession of I-O models for the state of Washington are generally considered among the best available, does not always report which of his aggregate production functions were based on the results of his sample survey, which may have been aggregated from the national technology, or even which weights were used in the aggregations.

In many cases, it turns out that the regional analyst simply adopts a "standard" aggregation of the national I-O table.[5] For example, in the U.S. there is now available, on a regularly updated basis, an 86-sector (approximately two-digit SIC) version of the 500-plus-sector U.S. I-O Table (U.S. Bureau of Economic Analysis, 2001) upon which many regional analysts rely.[6] As its name implies, this standard national aggregation is obtained by simply weighting the columns and rows in the national I-O table by their national outputs. Such a model will fail to reflect those technological differences between national and regional aggregate sectors that are caused by regional variations in industrial mix. Differences in the percentage distributions of detailed sectoral outputs between a region and its nation should cause commensurate differences between the regional and national aggregate technologies that are calculated by using regional or national outputs as weights.

Most regional I-O analysts have glossed over the aggregation problem because they have perceived that regional data realities force the use of aggregate technology. Shen (1960) recognized the importance of variations in industrial

[4]By "appropriate application," we mean that analysts should only use aggregated models in applications for which they were designed. For example, although the survey-based Washington State models are excellent for analyzing industries for which they maintain detail—fishing, forestry, logging, sawmills, related paper manufacturing, aluminum, aerospace, and shipbuilding; it would be foolhardy to use them to analyze the effects of the industries that were aggregated during the model's construction—that is, services, construction, mining, chemicals, and fabricated metals.

[5]Hirsch (1959) compared national technology (with the national industrial mix) to survey-based regional technology (with the regional industrial mix) and deduced that nonsurvey regionalization techniques do not provide sufficient accuracy for many sectors. Hence, he improperly concluded that only survey-based analysis will suffice at the regional level.

[6]See, for example, Jackson (1998), although Lahr (2001b) points out that problems obtain from such applications in a regional setting. In the development of a regional model structure akin to a computable general equilibrium model, Treyz, Friedlaender, and Stevens (1980) and Treyz (1993) assume uniform technology across regions of a nation. This assumption is probably unexceptional, at least at the 500-sector level. However, it is arguable whether this uniformity should extend to the 53-sector level as implied by Treyz and Stevens (1985). Again, for more on this, see for example Jackson (2001) who finds that technology across regions is not the same at the two-digit level.

mix when he used regional weights in aggregating the 450-sector 1947 U.S. technology to construct a New England model.[7] But, the conceptual difficulties involved and the small number of available survey-based I-O tables have limited the contributions to theoretical analyses of the aggregation problem in the regional I-O literature.[8] Roy, Batten, and Lesse (1982) provide one notable exception: following the lead of Theil (1957), they analyzed the problem of minimizing information loss (and hence error) in the aggregation process.

Smaller Models Are Better?: The Role of Nonzero Cells in Error Transmission

There have been a few empirical efforts to measure the effects of aggregation on error in regional model applications. Using simulation methods, Doeksen and Little (1968), Williamson (1970), and Hewings (1972) conclude that aggregation, even to very small I-O matrices, has surprisingly little effect on multiplier size. However, Hewings does find an extremely modest increase in error of reported sector outputs for model aggregations with less than 12 sectors.[9]

Note that these simulation studies start with I-O tables that are already highly aggregated: they start out with tables of 27, 12, and 51 sectors, respectively. Stevens and Trainer's (1976) simulations suggest that both multiplier and output errors strongly increase with the reduction in matrix size (from the 100-sector level), at least until very small sizes are achieved. It seems clear that the Stevens and Trainer results differ from those in the earlier studies (e.g., Doeksen and Little, 1968; Williamson, 1970; Hewings, 1972). We hypothesize that this is due partly to the nature of the "pre-aggregation" I-O tables used in the analyses. The earlier studies use small tables already fitted to specific regions through selective aggregation. Thus, each detailed sector is generally an important producer and already quite strongly linked to other regional sectors even before further aggregation.

On the other hand, the pre-aggregation 100-sector I-O models used by Stevens and Trainer were formed from randomly generated coefficients whose values are nonzero for only about 30 percent of the cells.[10] This was done intentionally to reflect a density more like that of the 500-sector national I-O

[7]Later Morimoto (1971) developed a general analytical piece on weighting sectors in aggregation. More recently Conway (1975, 1980) and Afrasiabi and Casler (1991) have shown that industry-mix changes are a main cause of instability in national coefficients, thereby highlighting the importance of industry mix as a critical factor in determining regional direct requirements.

[8]Indeed, most of the aspatial literature on aggregation in I-O has been theoretical in nature. A notable recent exception is Olsen (2000a), who compares aggregation bias in 6 "branches" of the Danish model ADAM (Dam, 1986) before and after disaggregation into 19 new ones. "Branches" are sectors of an econometric model produced in a Tinbergen-Klein tradition and are also simple aggregates of 64 detailed national I-O industries.

[9]Hewings (1972) shows error for three sectors as induced by a final demand change that is uniformly distributed across all sectors in the detailed model. This simulation approach goes against the principles of the "single purpose" model that he aggregates.

[10]The distribution of coefficients in each column followed Zipf rank-size rule, based on some findings reported in a working paper by Eliahu Romanoff—see Romanoff (2001) for a recent summary.

table than of typical 100-sector aggregations of that table; the latter average about 65 percent nonzero entries. The rationale for simulating such nonzero densities was the obvious conceptual link between the proportion of nonzero cells and the error that can be expected due to aggregation. In highly disaggregated I-O models, which are largely composed of zero entries, some sectors will have only very indirect effects on others through second- (or third- or fourth- etc.) generation linkages or no indirect effects at all if the matrix is reducible (decomposable).

Aggregation almost inevitably combines sectors that have different input patterns, thereby inducing bias in any results from a model consolidated in such a fashion. Resulting aggregate sectors will then tend to have a higher proportion of nonzero coefficients than their pre-aggregation counterparts and, analogously, a higher proportion of sectors with which they are now directly connected. Further, sector technology differences will be averaged together, forcing the intensities of interindustry connections to become more similar across remaining aggregated sectors. Even further aggregation causes these averages to be averaged together. Hence, because remaining sectors become similar through aggregation, the change in technology between successive aggregations is likely to be concomitantly reduced.

Thus, by enhancing the proportion of connections as well as by using an amorphous technology set, aggregation transmits error through the Leontief inverse more freely, thereby leading to spurious multiplier effects. Nonetheless, after a point the matrix becomes entirely composed of nonzero entries and the differences in technology among aggregated sectors does not change much. As a result, further aggregation of small pre-aggregated I-O tables tends to generate relatively little additional error. Conversely, much more error should be generated when aggregating from larger tables that start with a relatively low density of nonzero cells and wide differences in technology among their sectors. Stevens and Trainer (1976) and Miller and Shao (1991) support this argument. The latter pair of authors finds that an initial 10-sector I-O model suffers much less added error as it is progressively aggregated than does a 124-sector model.

3. INTERDEPENDENCE OF AGGREGATION AND REGIONALIZATION

The regional I-O model builder is always faced with the difficult problem of regionalization, no matter what the level of aggregation or whether the model is survey-based or not. Recall that the prime task of regionalization is to estimate the geographic pattern of input purchases by a region's industries (Miernyk, 1970; Stevens and Trainer, 1976). In particular, the hybrid and nonsurvey model builder needs to know the proportion of the region's demands for each good or service that is fulfilled by local production as opposed to being fulfilled by imports. These proportions are commonly called RPCs (regional purchase coefficients) or regional supply percentages (Miller and Blair, 1985).

Ceteris paribus, the higher the RPC for a good or service in a region, the greater the regional economic effects of increased input demands for that good or service by other economic sectors. Conversely, lower RPCs imply greater leakage of purchases out of the region and smaller intraregional multiplier effects. In the extensive literature on this subject, Stevens, Treyz, and Lahr (1989) compare the accuracy of various nonsurvey RPC estimating techniques, and Lahr (1992, 1993, 2001a) explores the issue of the best use of survey data for developing a full matrix of RPCs.

Of course, the topic of this section of this paper is not the accuracy of the regionalization method—although this generally is a critical issue—but rather the interplay of regionalization and aggregation in the potential generation of error. The detailed sectors within an aggregate may vary in the proportions of inputs purchased from within the region. The aggregate regional direct coefficients should reflect such variations if the model is expected to provide accurate measures of indirect and induced within-region effects; aggregation before regionalization precludes this, even when weights reflecting regional industry mix are applied in the aggregation process. Thus, even if the disaggregate regional technology and industrial mix were identical to the national, the aggregate regional direct requirements matrix will still differ from the national to the extent that the region provides itself with smaller (or larger) percentages of any of its inputs. Czamanski and Malizia (1969) were probably the first to emphasize the potential importance of regionalizing the national technology before aggregating it; nevertheless, like Schaffer and Chu (1969) and others of that time, they found it much more practical to aggregate first and regionalize afterward.

Aggregation and the Call for Cell-specific RPCs

Other authors have faced some of the same practical problems as did the pioneers of regional I-O table construction but have begun to explore the nature and magnitude of error that derives when a typical aggregated technology is regionalized. Ralston, Hastings, and Brucker (1986) find, through limited survey data collection, that aggregate (two-digit SIC) industries in Delaware vary widely in the proportions of particular inputs they buy from other firms in the State. Therefore, they naturally question the typical assumption of a single uniform RPC for any supplying sector across all purchasing sectors (hereinafter rows-only, as opposed to cell-specific, RPCs). Garhart and Giarratani (1987) raise similar questions about rows-only RPCs, demonstrating the errors generated by this assumption through simulations using the Washington I-O model.

It is true that Ralston, Hastings, and Brucker (1986) needed aggregated technology for their survey work, and Garhart and Giarratani (1987) had only a pre-aggregated model for use in their simulations. Still, both teams of authors should have noted that some of the problems they uncover with rows-only RPCs are caused as much by the aggregation procedures they employed as by the limitations of the typical RPC estimation methods. These methods all tend to produce a single RPC for each supplying sector at the aggregation level for which the RPC estimation is performed.

Suppose regionalization is performed first. This will generally mean in the case of a nonsurvey regional I-O model that a diagonal matrix of rows-only RPCs will be multiplied by a matrix of disaggregate technology to obtain a matrix of disaggregate "regional" direct coefficients (Jackson, 1998; Lahr 2001a). Aggregation of this new technology, if regional weights are used, produces an I-O model in which each resulting regional coefficient reflects industrial mix in both technology and input purchase patterns. Even though the original rows-only RPCs are uniform across the disaggregated purchasing sectors, the implicit RPCs for the aggregated regional technology are cell-specific.

The above point will be expanded in Section 4. For the moment, note that there is likely to be significant variation with regard to the proportions of each input purchased within the region among sub-industries (five-digit SIC sectors) and certainly among establishments within industries. Ultimately, rows-only RPCs will cause some error even at the most disaggregated level of available data, as noted by Lahr (2001a). Nevertheless the error levels that will be achieved are not likely to be anywhere near as high as those reported by Garhart and Giarratani (1987) who used rather highly aggregated tables for their simulations.

Aggregation, Regionalization, and Error through Naïve Application

Failure to recognize regional industrial mix in both outputs and purchase patterns can lead to much larger errors than those that can be attributed to aggregation alone. Nonetheless, the resulting errors will vary depending on whether the effects are direct or indirect. For example, a nonregionalized, aggregated model for greater Gary, Indiana, (presently a region in the U.S. with operating integrated steel works) might combine all primary metals production into a single sector. An increase in final demand for aluminum, naïvely applied directly to this sector, would then give completely erroneous results because primary metals production in this region consists (by assumption, for the purposes of this discussion) entirely of iron and steel. Hence, such an I-O calculation would generate entirely fictitious intraregional multiplier effects.

A less extreme, but much more likely, error in using this same regional I-O model might occur if one were analyzing the indirect effects of a final demand change for fabricated metals. Assume that, within the nation as a whole, this (aggregated) sector typically buys 50 percent of its primary metal inputs from the steel industry and the other 50 percent from the primary aluminum industry. Now the RPC for the primary metals sector (an aggregation of both the primary aluminum industry and the iron and steel industry, among other detailed sectors) in Gary, if estimated at the aggregate level, would probably be close to unity. This is because the supply-demand ratio for undifferentiated primary metals in Gary is very high due to its heavy concentration of iron and steel, much of which is intended for export to other regions. In this case, the failure to regionalize before aggregation will result in almost all, rather than half, the primary metal inputs being (apparently) supplied by the region's primary metal sector; the resulting multipliers and outputs will be commensurately inflated.

Aggregation, Diversification, and Self-Sufficiency

As an extension of the arguments in the previous subsection, aggregation error tends to be smaller for highly diversified economies like that of Philadelphia, as suggested by the work of Karaska (1968). A corollary to this is that models of regional economies that are more self-sufficient will also yield smaller errors. In both cases, this is because the economies should display at least some representation in most industrial sectors, thereby obviating part of the spurious or exaggerated effects that may be generated when using an aggregate model for a place like Gary. Small, specialized economies like Gary call, perhaps paradoxically, for large detailed I-O models, especially if they are to be constructed by nonsurvey methods.[11]

Evidence on the Interplay of Aggregation and Regionalization

Prediction of the error caused by the interplay of aggregation and regionalization poses an even more intractable analytical problem than that posed by aggregation alone. Hence, there have been few simulations on this subject. Sawyer and Miller (1983) start with a 255-sector national I-O table and show that regionalizing and then aggregating generates, on the whole, less error than vice versa. They measure differences in the direct coefficients themselves as well as in Type II value-added multipliers, when compared with the survey-based 1972 Washington I-O model.

Paralleling Sawyer and Miller, but starting with a more-detailed 492-sector national matrix, Lahr (1987) demonstrated that regionalizing technology using nonsurvey RPCs before aggregation approximates the 1972 Washington model better than does aggregating the national technology first and then applying the known, survey-based, aggregate RPCs for Washington state. Our intention in the current paper is to extend this work, as well as that by Stevens and Trainer (1976), through simulations using several nonsurvey regional input-output models.[12]

[11]A referee points out that, technically speaking, it is not the size of the table that matters per se but rather the amount of detail that is provided for region-specific characteristic industries. He illustrates further by stating “all of the ‘empty’ industries in the Gary example can be combined easily into a single sector, without affecting the results.” The authors agree with this in principle and have observed that some constructors of regional accounts apply this approach well (see, e.g., Robison, et al., 1994, who pared back the number of sectors to facilitate calculations in a multiregional setting). Nevertheless, an issue arises in the case of so-called “ready-made” models that are produced by one organization for another organization. In such cases, model users may not know which sectors have been omitted in the fashion suggested by the referee and, therefore, may in certain situations find themselves employing a “second best” sector to meet their modeling need. Therefore, as a general rule for constructing nonsurvey regional input-output tables, we support the retention of national sectors that do not exist in a region. Hence, we put forward—for economic models not derived from survey work—that “bigger is better” especially in the case of open, nondiverse economies.

[12]Jackson and West (1989) and Giarratani and Garhart (1991) provide useful reviews of a wide range of simulation studies that have been performed to measure error. They also evaluate other aspects of regional I-O models.

4. HYPOTHESES AND VARIABLES IN THE SIMULATION

Hypotheses

Summarizing the arguments made in Sections 2 and 3, we expect higher levels of error in the results of regional I-O calculations to be associated with:

(1) Higher levels of aggregation of a given I-O matrix, with error diminishing with the size of the aggregated matrix;

(2) Aggregation using national rather than regional weights;

(3) Aggregation before, rather than after, regionalization.

We hypothesize (1), (2), and (3) simply because they represent improper practice as has been discussed earlier in this paper. We also expect that the error deriving from (2) and (3) will cancel each other out somewhat.

We also hypothesize that the following should induce error.

(4) Small proportion of nonzero cells in the pre-aggregation regional I-O matrix;

(5) Low mean RPC levels in the pre-aggregation regional model;

(6) Low levels of regional industrial diversification.

Conceptually, hypotheses (4), (5), and (6) are highly related to each other and deal with the interconnectedness of the input-output table as a whole. The principle behind hypothesis (4) is that error tends to transmit through a more highly connected (in terms of percentage of cells) I-O matrix. Hypotheses (5) and (6) are based upon the principle that models of highly diversified economies will yield fewer spurious errors. Thus, we hypothesize that aggregated models of highly concentrated import-dependent economies will be unable to reflect well their more detailed counterparts, especially when the industries in the detailed model are not well linked.

In each observation of our simulations, we shock a regional economy with demand for the local output of single sector. Hence, we have developed tentative (and less important) hypotheses that relate enhanced error to this sector's following two relationships to the rest of the regional economy:

(7) Low use of the sector's production in meeting the region's demand for the sector's product;

(8) The relative concentration of the region's production in the sector.

Both of these hypotheses are related to issues of spurious error and, therefore, are essentially corollaries to hypotheses (5) and (6) above. Hypothesis (7) deals with the economy's self-sufficiency as it relates specifically to the sector in which the shock occurs. Hypothesis (8) pertains to the region's concentration in the shocked sector. These hypotheses may well be the rationales behind some of the findings on lack of additional error that Hewings (1972) obtained in his aggregation simulations.

Notation for the Aggregation Approaches

Consider the regional I-O model

$$\Delta \mathbf{x} - \hat{\mathbf{r}}\mathbf{A}(\Delta \mathbf{x}) = \hat{\mathbf{r}}_{\mathbf{y}} \Delta \mathbf{y} \tag{1}$$

where $\Delta \mathbf{y}$ is some final demand shock $[y_i]$,
$\Delta \mathbf{x}$ is the resulting vector of regional outputs changes $[x_j]$,
$\mathbf{A}$ is the national technology matrix $[a_{ij}]$,
$\mathbf{r}$ is a vector of rows-only RPCs $[r_i]$, which when converted to a diagonal matrix is denoted $\hat{\mathbf{r}}$. We assume here that intermediate and final demand have separate RPC vectors. Letting $\mathbf{r}$ represent the RPC vector for intermediate demand, $\mathbf{r_y}$ then is a specialized vector of final-demand RPCs.

As was mentioned in the last subsection, in each simulation observation we shock a regional economy with the demand for the regional production from a single sector. Because the shock is the demand for the region's production, the final-demand RPC is unity for each sector shocked. This simplifies Equation (1) to

$$\Delta \mathbf{x} - \hat{\mathbf{r}}\mathbf{A}(\Delta \mathbf{x}) = \Delta \mathbf{y} \tag{2}$$

Thus, we explicitly assume that we can determine, by whatever method, only a single RPC for each supplying sector in the region, r_i. On the other hand, we also assume that such an RPC can be estimated at any realistic level of disaggregation of the (borrowed) national technology.

Clearly if one must present aggregated results, the most accurate estimates of the effects of the shock $\Delta \mathbf{y}$ are obtained after solving Equation (2) for $\Delta \mathbf{x}$ using a direct requirements matrix with full detail and aggregating using $\mathbf{S}^m$, the $m \times n$ matrix of ones and zeros that consolidates from n to m sectors, to obtain the aggregated vector $\Delta \mathbf{x}^m$

$$\Delta \mathbf{x}^m = \mathbf{S}^m \Delta \mathbf{x} = \mathbf{S}^m (\mathbf{I} - \hat{\mathbf{r}}\mathbf{A})^{-1} \Delta \mathbf{y} \tag{3}$$

Unfortunately, as we discussed earlier, for one reason or other many regional I-O model constructors have felt compelled to aggregate prior to obtaining $\Delta \mathbf{x}$ in Equation (3). Traditionally they have aggregated the direct coefficients matrix from n to m sectors to produce an aggregate model using one of three approaches: where (1) technology is regionalized before aggregation and regional weights are applied; (2) technology aggregation using regional weights occurs before regionalization, and (3) technology aggregation using national weights occurs before regionalization. We present each of these formally in turn.

Regionalization Followed by Regionally Weighted Aggregation. The first of the three aggregation approaches presented in this section should yield an aggregate model that will produce the least error. An element from the direct requirements matrix resulting from this approach is represented as

(4a) $$ {}^{xR}a_{kl}^{m} = \sum_{i \in k} \left(\frac{\sum_{j \in l} r_i a_{ij} x_j}{\sum_{j \in l} x_j} \right) $$

where k and l are the indices for the sets of detailed rows and columns, respectively, for a given element in the aggregated matrix; the first left-hand side superscript x denotes that regional output weights were used, the second left-hand side superscript R denotes that the technology was regionalized prior to aggregation, the right-hand side superscript m denotes the rank of the resulting direct matrix, and x_j is the regional output of sector j (where the region's output vector is denoted as $\mathbf{x}$). In producing the denominator of Equation (4a), the corresponding output vectors must be aggregated

(4b) $$ \mathbf{x}^{m} = \left[x_j^{m} \right] = \sum_{j \in l} x_j $$

and the vector of demand shocks must be aggregated, so that it conforms with the matrix that is obtained through Equation (4a) in order to estimate the aggregated equivalent of Equation (3)

(4c) $$ \Delta\mathbf{y}^{m} = \left[\Delta y_j^{m} \right] = \sum_{j \in l} \Delta y_j $$

In matrix notation Equation (4a) becomes

(4d) $$ {}^{xR}\mathbf{A}^{m} = \mathbf{S}^{m}\hat{\mathbf{r}}\mathbf{A}\hat{\mathbf{x}}\left(\mathbf{S}^{m}\right)'\left(\mathbf{S}^{m}\hat{\mathbf{x}}\right)^{-1} $$

where $\mathbf{S}^m$ is an $m - n$ aggregation matrix of ones and zeros, which if postmultiplied by a vector of length n, consolidates it to m sectors, where ^ denotes a matrix with the underlying vector on the diagonal and the rest of the matrix composed of zeros, and ′ denotes the matrix transpose. In this case, model results equivalent to $\Delta\mathbf{x}^m$ in Equation (3) are obtained using the equation

(5) $$ {}^{xR}\Delta\mathbf{x}^{m} = (\mathbf{I}^{m} - {}^{xR}\mathbf{A}^{m})^{-1}(\mathbf{S}^{m}\Delta\mathbf{y}) $$

where $\mathbf{I}^m = \mathbf{S}^m\mathbf{I}(\mathbf{S}^m)'$.

Regionally Weighted Aggregation Followed by Regionalization. In the two remaining aggregation approaches that have been employed in the regional literature, the technology and RPCs are aggregated separately. The first case represents the situation where analysts use regional weights to properly aggregate the matrix so that they can apply aggregate RPCs because they are under the belief that detailed data for producing such RPCs cannot be obtained or derived. That is

(6a)
$$ {}^{x}a_{kl}^{m} = \sum_{i\in k}\left(\frac{\sum_{j\in l} a_{ij}x_j}{\sum_{j\in l} x_j}\right) $$

Alternatively, in matrix notation

(6b)
$$ {}^{x}\mathbf{A}^{m} = \mathbf{S}^{m}\mathbf{A}\hat{\mathbf{x}}\left(\mathbf{S}^{m}\right)'\left(\mathbf{S}^{m}\hat{\mathbf{x}}\right)^{-1} $$

The RPCs pose a special problem, in that they should be aggregated using demand- rather than output-based regional weights

(6c)
$$ \mathbf{r}^{m} = \left[r_k^m\right] = \left[\frac{\sum_{i\in k} r_i\left[\sum_{j=1}^{n}\left(a_{ij}x_j\right) + y_i\right]}{\sum_{i\in k}\sum_{j=1}^{n}\left(a_{ij}x_j\right) + y_i}\right] $$

where $\mathbf{y}$ (= $[y_i]$) is the vector of the region's final demand.[13] Letting $\mathbf{d} = \mathbf{A}\hat{\mathbf{x}}\mathbf{i} + \mathbf{y}$, in matrix notation Equation (6c) becomes

(6d)
$$ \mathbf{r}^{m} = [\mathbf{S}^{m}\hat{\mathbf{d}}]^{-1}[\mathbf{S}^{m}\hat{\mathbf{r}}\mathbf{d}] $$

And thereby model results equivalent to $\Delta\mathbf{x}^m$ in Equation (3) are obtained using the equation

(7)
$$ {}^{x}\Delta\mathbf{x}^{m} = (\mathbf{I}^{m} - \hat{\mathbf{r}}^{m\,x}\mathbf{A}^{m})^{-1}\,\Delta\mathbf{y}^{m} $$

Aggregation Using National Weights Followed by Regionalization. Perhaps the most common means of inducing aggregation error into results is that obtained by regionalizing an aggregated national matrix. The point here is that analysts may not understand or even realize that aggregation bias has been induced since they have not performed the aggregation procedure themselves. Indeed, the only aggregation the analyst might undertake is in the development of the RPCs. That is, rather than Equation (6a), analysts obtain or are given an aggregated national I-O direct coefficients matrix derived in the following manner

(8a)
$$ {}^{N}a_{kl}^{m} = \sum_{i\in k}\left(\frac{\sum_{j\in l} a_{ij}\,{}^{N}x_j}{\sum_{j\in l} {}^{N}x_j}\right) $$

[13]Means of estimating $\mathbf{y}$ and total regional demand $\mathbf{d}$ are discussed in Treyz and Stevens (1985).

where ${}^{N}\mathbf{x} = [{}^{N}x_j]$ is the vector of national output. Alternatively, in matrix notation

$$(8b) \qquad {}^{N}\mathbf{A}^{m} = \mathbf{S}^{m}\mathbf{A}\,{}^{N}\hat{\mathbf{x}}(\mathbf{S}^{m})'\,(\mathbf{S}^{m}\,{}^{N}\hat{\mathbf{x}})^{-1}$$

And, after applying RPCs developed at best as shown in Equation (6d), obtain model results equivalent to $\Delta\mathbf{x}^{m}$ in Equation (3) by using the equation

$$(9) \qquad {}^{N}\Delta\mathbf{x}^{m} = (\mathbf{I}^{m} - \hat{\mathbf{r}}^{m}\,{}^{N}\mathbf{A}^{m})^{-1}\,\Delta\mathbf{y}^{m}$$

Summary of the Means of Aggregation in a Regional I-O Context. The truly best means of obtaining aggregated results in a regional I-O setting is to obtain detailed model results and then aggregate them. This approach is presented in Equation (3). In the context of this paper, we discuss three alternative means of obtaining aggregate results. As discussed above, all of these alternatives employ an aggregate model and are summarized briefly below.

Of the three, the most reasonable means of developing aggregate results, the *xR* approach shown in Equation (5), is rarely used. This is because the data needed to realize aggregate results obtained in this fashion could be applied just as readily to yield the more-accurate results using Equation (3). Interestingly, one can derive a full matrix of RPCs by performing the Hadamard (element-by-element) division of the properly weighted and rows-only regionalized aggregate direct coefficients matrix ${}^{xR}\mathbf{A}^{m}$ in Equation (4d) by otherwise aggregated direct coefficients matrix ${}^{x}\mathbf{A}^{m}$ (or ${}^{N}\mathbf{A}^{m}$). It is these implicit RPCs that properly should be used in comparisons like those made by Ralston, Hastings, and Brucker (1986).

Next, in order of hypothesized accuracy is the *x* approach, which is displayed in Equation (7). Here the direct requirements table is aggregated properly using regional output weights but the RPCs are not applied prior to aggregation as in Equation (5). The typical reason that this approach is applied is that the analyst cannot develop detailed RPCs due to the paucity of detailed regional data. In our representation of this approach, we show that the aggregated vector of RPCs has been developed using estimates of total regional demand. Regional analysts who apply this approach typically do not undertake such RPC aggregation. Indeed, it is due to the lack of regional data needed to produce RPCs that this approach is applied in the first place. Hence, the RPCs are typically produced from aggregate data rather than as we present them here in Equations (6c) and (6d).

Equation (9), the *N* approach, presents what is probably the most common aggregate regional model. It is also hypothesized to be the approach that induces the most bias and, hence, that yields model results with the most error. It is differentiated from the others by the application of national output weights in aggregating direct coefficients but meanwhile maintaining the regionalization problems inherent in the *x* approach, which uses regional weights in aggregating the direct coefficients.

Characteristics of the Region and Sector

In this section, we first lay out the hypotheses for both the variables that control for regional characteristics and those that control for characteristics of the disturbed sector. Following that, we discuss the results of tests of these hypotheses, derived from the ordinary least squares regression models presented later in Section 5.

Hypotheses for Region Characteristics. The main characteristics of a region that might possibly be reflected in technology and yet be a potential cause of aggregation error are discussed below. As discussed early in this section, we characterize them into three major types of measures: interindustry connectedness, economic self-sufficiency, and economic diversity.

Intraregional interconnectedness. As mentioned earlier (Section 2), we believe there is a link between connectedness within an economy and aggregation error. The hypothesis is based on the fact that zero cells in an input-output model, which are evidence of nonconnectedness, deter the continued generation of error in multipliers, using the general reasoning of Jensen and West (1980). Therefore, because error is allowed to compound itself when an input-output matrix is more connected, we would expect base matrices with more nonzero cells to compound other inherent error when they are aggregated.

We opted to examine interconnectedness in two ways—in terms of the total proportion of nonzero cells and in terms of nonzero RPCs. The first of these more directly addresses the issue of interconnectedness. The proportion of nonzero RPCs duplicates this effort somewhat but also addresses the matter of the potential error through naïve application discussed in the second subsection of Section 3. This last variable also slightly overlaps with the diversification measures discussed later. In any case, as the proportion of nonzero cells (both through RPCs and total) increases, we would expect less error.

Economic self-sufficiency. The regional economy's overall RPC is probably the best single measure of its self-sufficiency. Further, we expect that a region with a higher weighted mean RPC will have less error than an economy with lower values for these variables. The rationale is that economies with weighted mean RPCs that are closer to unity are more self-sufficient and, therefore, have direct requirements matrices that approach those of the nation. Thus, economies with higher RPCs should generate less error when improperly aggregated.

Economic diversity. The single most popular inequality measure, and hence diversity measure, is the Gini coefficient. The higher the Gini coefficient for regional industry employment compared to the nation's, the more diverse is the economy. Despite it being perhaps the single best measure of inequality (see Karoly, 1993), general dissatisfaction with the Gini coefficient led us to consider alternatives. We thought something like the z-score for the supply-demand ratio across the detailed I-O industries in the region would be a reasonable alternative. Hence, we used the standardized variance of the supply-demand ratios of all industries in the region to measure regional economic diversity. The standardized variance of the supply-demand ratio is actually a measure of dissimilarity or nondiversification; that is, as its value increases the region is considered less diverse. We suggest that, as its economy becomes more diverse, a region's technology matrix and industrial mix approach that of the nation. One would expect that aggregation error would decrease as the level of economic diversity increased because we "borrowed" national technology to create the regional models. Hence, we would expect aggregation error to be positively related to the variance of the region's supply-demand ratio and negatively related to the region's Gini coefficient.

As was mentioned earlier, even though it is not a direct measure of diversity, the number of nonzero row-average RPCs used to regionalize the national technology indicates a form of diversity (specifically the nonsurvey model's similarly to the borrowed technology). Hence, as the values of this variable increased, we would expect declines in aggregation error. This hypothesis for nonzero RPCs does not conflict in sign with the one we claimed for the same variable with respect to interindustry interconnectedness.

Hypotheses for Sector Characteristics. As discussed in Section 4, the hypotheses for the sector altered in the context of the simulation are merely extensions of those for self-sufficiency and diversification the economy at large. The equivalent variable for nonzero RPCs was not used because we wound up dropping all observations with zero RPCs for the sector that was altered.

Local dependence. Again, a sector's RPC is the single best measure of the rest of the economy's use of that sector's goods or services. The reasoning behind the hypothesis for this variable is that the higher the disturbed sector's RPC, the greater is its multiplier effect. The greater the multiplier effect, the more error is compounded. In summary, the higher the region's dependence on the altered sector's production, the higher the amount of error introduced when that sector is not presented in full detail in the direct requirements matrix.

Concentration. We use a simple measure of the sector's share of the region's total output. The hypotheses is that as the disturbed sector's production increases relative to the rest of the economy (as a proportion of a region's production), we would expect aggregation error to decrease. The thought behind this is that the sector will be well-represented in any aggregations when this concentration ratio is high (Doeksen and Little, 1970; Hewings, 1972).

5. SIMULATION METHOD

For the initial national technology matrix **A** we began with the 492-sector RSRI I-O national industry-by-industry direct coefficients matrix, which was adapted from the BEA 1977 U.S. I-O Table. Next we drew a selected sample of nine states, one from each U.S. Census Region, covering a wide range of economic sizes and levels of industrial diversification. Following this we selected a sample of five detailed manufacturing sectors. We chose manufacturing sectors because in our simulations we wanted to employ sectors for which there would be sufficient differences in RPCs and output to make the study interesting. Further, we chose the following because they provided a mixture of sectors by SIC level (two are three-digit SICs and the other three are four-digit SICs):

2052–Cookies and crackers,
2750–Commercial printing,
2830–Drugs,
3411–Metal cans,
3613–Switchgear and switchboard apparatus.

Following that, we applied an arbitrarily selected final-demand change of 10,000,000 dollars for each of the above sectors as the direct effect in an I-O calculation employing, in turn, the model for each of the selected states. We calculated sectoral output (supply) as well as Type II output, employment, and value-added multipliers at the 492-sector level. These results, once aggregated to the appropriate level, formed the basis for later comparisons with results from the aggregated models.

The sectoral totals from these detailed I-O calculations, together with the value added, employment, RPC, supply, demand, and employment for each sector, were aggregated progressively to the three-digit (365-sector), two-digit (81-sector), one-digit (11-sector), and "half-digit" (6-sector) SIC levels.[14] The direct coefficients matrix was then aggregated to the same four levels by each of three different methods described in Section 4. Thus, we compare each aggregated model's results to the most detailed model available (the 492-sector one). Because the aggregations are based on a standard industrial classification system, aggregating from, say, 492 to 6 sectors is the same as aggregating successively from 492 sectors to 365, from 365 to 81, from 81 to 11, and from 11 to 6 sectors. Thus, any error generated by aggregation to any intermediate model should be inherent in the final one.

The first method, represented by Equation (5), weights the 492-sector I-O coefficients by both the RPCs and the predisturbance outputs for the state; this carries the aggregation to the 365-sector level. From there on, only the state output weights enter the calculations for further matrix aggregation because the I-O coefficients already constitute a "regional" technology in that they contain the necessary state purchase pattern information implicitly, as discussed above. This model is designated the xR aggregation (the x denoting correct weighting using regional output and the R denoting the application of RPCs prior to aggregation). The second aggregation method, displayed in Equation (7), weights the technology coefficients by state outputs, thereby reflecting only interstate differences in industrial mix. The third method is shown in Equation (9); here the output weights used are national rather than

[14]The eleven-sector aggregation does not strictly reflect one-digit SIC sectoring. Rather it reflects a "typical" aggregation into what are commonly thought of as the major industries: The U.S. BEA calls this the "division level." Similarly, the six-sector table reflects the set of industries in Miller and Blair (1985), among other sources. Sectoral definitions at all levels of aggregation that are used here are available in Lahr (1992).

state-specific. These two models are designated the x and N aggregations, respectively (the N denoting the application of national outputs as aggregation weights). In both of these last two cases, RPCs were applied after aggregation. Results were obtained for each aggregation type by producing separate models for each aggregation level (365-, 81-, 11-, and 6-sectors) using techniques described in Section 4.

We applied the original disturbances to the appropriate aggregated sectors for each state, and calculated the multiplier and output results for the three types of aggregations. In each case, both the "correct" outputs and multipliers from the original four-digit model and the appropriate aggregations of the fully disaggregated ("correct") sectoral results were compared with the results from the aggregated models. This process normally would have produced 540 observations (9 states × 4 aggregation levels × 3 aggregation types × 5 industries). However, the final sample contained only 516 observations, because one of the "affected" sectors did not exist in two of the states. Changing a nonexistent sector, at the aggregate level, would have produced infinite mean absolute percentage errors because a nonzero result would be divided by the actual zero value. The same would occur when applying primary aluminum demand to an aggregated model of Gary.

The simulation results for the 516 observations include the mean absolute percentage errors (MAPE) for each of three types of multipliers (output, employment, and value added) for the shocked sector, and Theil's U for the errors in sectoral outputs for the economy as a whole. (Note that unity was subtracted from the multipliers prior to measuring the error. Unity is subtracted because it reflects the impact of the direct effects themselves, which in this exercise can contain no error.) Theil's U is calculated as

$$ {}^{g}U = \left[\sum_{i=1}^{m} \frac{\left(x_i^m - {}^{g}x_i^m \right)^2}{{}^{g}x_i^m} \right]^{0.5} $$

where the superscript g denotes the particular aggregation type (xR, x, or N) for which Theil's U is being measured.

General Error Results

Table 1 presents the means and standard deviations for the three types and four levels of aggregation for the six categories of error, averaged over the nine states and five industrial final-demand disturbances. Although the results for standard deviations are interesting in their own right, we focus on the means in this investigation. The results are generally encompassing in the sense that the use of regional output weights in the aggregation process appears to give better results than those obtained using national industrial mix. In addition, and again as expected, error levels for the xR aggregations generally tend to increase with increased levels of aggregation, mirroring the pattern found by Stevens and

TABLE 1: Aggregation Error by Aggregation Type and Level

		Aggregation Level (Number of Sectors)							
		365		81		11		6	
Measure	Method	Mean	Standard Deviation	Mean	Standard Deviation	Mean	Standard Deviation	Mean	Standard Deviation
MAPE of Output Multipliers									
	xR	1.6	0.9	33.3	38.3	32.2	51.6	32.2	51.7
	x	1.5	0.8	95.4	30.4	26.4	41.3	26.5	41.5
	N	95.1	21.0	117.4	25.2	91.8	18.4	92.3	18.5
MAPE of Employment Multipliers									
	xR	3.5	3.0	39.0	44.1	45.7	63.2	47.0	65.4
	x	3.2	3.0	123.9	124.9	39.6	51.6	41.0	53.5
	N	95.3	36.5	147.9	103.7	117.1	35.7	121.9	36.5
MAPE of Value Added Multipliers									
	xR	1.7	0.9	35.4	39.7	43.7	61.4	44.0	61.9
	x	1.5	0.9	115.4	71.1	36.4	48.9	37.0	49.5
	N	94.8	33.0	138.9	65.1	116.1	27.6	117.7	27.8
100 × Theil's U for Output									
	xR	0.9	0.7	14.1	13.1	29.3	38.3	30.2	39.1
	x	1.3	0.9	40.2	12.2	25.1	31.2	26.0	31.8
	N	23.1	8.3	43.6	9.4	74.1	12.5	75.9	12.8

Notes: MAPE (Mean Absolute Percentage Error) is the measure used to calculate aggregation error, except for one case when we used Theil's U. *xR* denotes aggregation with sectors weighted by both state outputs and RPCs. *x* denotes aggregation with sectors weighted by state outputs only. *N* denotes aggregation with sectors weighted by national outputs only.

Trainer (1976). However, it is puzzling that regionalization before aggregation seems to be worthwhile at the 81-sector level only. Nonetheless, this level of aggregation is that at which many analysts regionalize U.S. national tables.

By far the most intriguing anomaly in the results shown in Table 1 is the decline in error for the *x* and *N* aggregations as matrix size falls below the two-digit SIC level (81 sectors). To understand this somewhat unexpected result, we studied the relationship between matrix size and multiplier error in greater depth. What appears to happen is that, as offending sectors are further aggregated, they tend to be combined with, and are often dominated by, sectors whose technologies may be very different. Thus, the unique character of the sectors that transmit the excess initial indirect effects (such as primary and fabricated metals in Gary) gradually become submerged in an amorphous mix of indistinguishable direct input coefficients at higher aggregation levels. Hence, during the aggregation process the variation of technology across sectors decreases as the within-sector variation of technology across firms in the sector increases. Therefore, after a point, we may even expect decreasing error returns to aggregation. This may explain why aggregation error plateaus, and perhaps even declines, when the number of sectors in an I-O matrix depicting a highly diversified economy gets sufficiently small.

Table 1 shows absolute percentage error, and a similar table (Lahr, 1992) with real percentage error (where the absolute value of the error is not calculated) was practically identical, with minor differences appearing only at the 365-sector level of aggregation.[15] Thus, it is clear that the error induced through aggregation is almost always due to over- rather than under-estimation of multiplier effects. Keep in mind that such exaggerated multiplier effects are due solely to errors in indirect and induced effects because we eliminated all cases from the sample for which the disturbed industry did not exist.

In summary, based on Table 1, one might contend that an aggregation of a regional input-output model weighted with national outputs is unacceptable under any circumstances. On the other hand, based on the same results one can also argue that a highly aggregated model constructed using regional aggregation weights may be as good as any other model from the viewpoint of multiplier error. Of course, what it lacks is the detail on sectoral effects.

At the 81-sector level, the x and xR aggregations alone are the best means of producing an aggregated regional input-output model. If one is going to build a model at about the two-digit (81 sectors) SIC level, xR aggregation is by far the best choice although the error results we obtain for this level of aggregation militate heavily against its use, in general, and for use of a regional I-O model with the full dimension of the national model.

Relationship of Error to Aggregation Level and Type

The influences of aggregation type and level are captured by including interaction variables that are the products of the aggregation level of the matrix and either of the two dummy variables NR (matrix not regionalized before aggregation) and UW (national weights used in the aggregation, i.e., unweighted, hence the acronym). Note both these and the aggregation level are nested dummy variables. Thus, because the x and N aggregation types are not preregionalized, NR equals one for both; an N-aggregation type carries a nonzero UW dummy as well. Similarly, aggregations to 6 sectors take on a nonzero value for the 81- and 11-sector aggregation variables. The 11-sector aggregations have nonzero values for the 81-sector aggregation variable, as well. (We let the 365-sector aggregation be represented in the intercept.) Thus the general simple linear regression model for error that we estimate for the ith observation that we applied is

[15]For clarity's sake, the error values obtained by subtracting the aggregated results of the detailed model from the results of the aggregated models were typically positive and almost never negative. I thank an anonymous referee for pointing out the potential for confusion on this.

$$e_i = \alpha + \left(\sum_{h=1}^{3} \beta_h m_{h,i} \right) + \beta_4 NR_i + \beta_5 UW_i + \left[\sum_{j=6}^{8} \beta_j \left(NR_i m_{j,i} \right) \right] + \left[\sum_{k=9}^{12} \beta_k \left(UW_i m_{k,i} \right) \right] + \left(\sum_{l=1}^{7} \gamma_l c_{l,i} \right) + \varepsilon_i$$

where α, the βs, and the γs are regression parameter estimates; the

- m_i are the nested binary variables for aggregation level;
- NR_i is the binary variable denoting regionalization after aggregation;
- UW_i is the binary variable denoting the use of national weights during aggregation; the
- c_i are the regional and sectoral characteristics; and
- ε_i is the residual, which is assumed to be normal and independent with mean zero across all i.

Descriptive statistics of the variables used to model the above are displayed in Table 2. The results of the modeling process as presented in Table 3 support the discussion in Section 4 on aggregation level and type based on Table 1.[16] That is, the hypothesis that aggregation error tends to increase as the mode of aggregation becomes more improper appears well founded. Nonetheless, it is not quite the strict rule that we hypothesized it to be. To show this, we turn to Table 4, which displays the predicted error. This error is obtained by applying the appropriate coefficients for aggregation type and level while evaluating all sector- and region-based variables at their means.[17] The value under "Marginal" (marginal difference) denotes the error "added" by invoking any new coefficients in the model presented in Table 3. Values in the "Total" columns present the sum of all significant coefficients for the specified aggregation type and level.

In contrast to the results in Table 1, it is clear from Table 4 that a properly produced aggregate model xR induces the least amount of error. In fact, it is only in moving to the 11–sector level (from the 81-sector level) in this aggregation type that we first observed any statistically significant difference in multipliers from the results obtained from a fully detailed model. (A small amount of error was detected at the 81-sector level for output. Aggregating the model to 11 sectors enhanced this error further.) Because it takes as much, if not more, effort

[16]Note by Lahr: In a prior version of this paper (Stevens and Lahr, 1993), we presented the aggregation level as a single continuous variable. Clearly our data, which were aggregated to four levels only, did not support such representation. Nonetheless, my coauthor was fascinated by the results based upon continuous variables. By dropping all terms, in a table quite equivalent to that in Table 3, that do not involve the number of sectors m or aggregation method NR or UW, the equation for output multiplier error reduced to 66.11 NR + 25.36 UW – 1.092 × $10^{-14}m^6$ –2.735 × 10^{-14} ($m^6 \times NR$) + 2.854 10^{-14} ($m^6 \times UW$) – 547.5 ($m^{-1} \times NR$) + 285.7 ($m^{-1} \times UW$) –712212 m^6 When using this functional form for the x and N aggregation, the maximum output multiplier errors occurred at about 145 and 175 sectors, respectively.

[17]All statistically insignificant variables were ignored in producing Table 4.

TABLE 2: General Descriptive Statistics for Model Variables

Variable	Mean	Standard Deviation
Percentage Nonzero RPCs	86.01	7.48
Percentage Nonzero Cells	24.55	1.899
Region's Mean RPC	0.5460	0.06804
Region's Supply/Demand Ratio (S/D)	0.9954	0.03202
Region's $\sigma^2[S/D]/(S/D)$ (Standardized Variance of the S/D)	0.07469	0.01858
Gini of Region's Employment by Sector	0.6195	0.1231
Region's Output (in Bill. $)	85,700.	71,035.
Sector RPC	0.2515	0.2324
Sector Output (in Bill. $)	242.29	498.20
MAPE Output Multiplier*	53.82	51.14
MAPE Value-added Multiplier*	65.21	65.27
MAPE Employment Multiplier*	68.75	77.65
100 × Theil's U for Output	31.98	31.60

*Note that multiplier errors were calculated by first subtracting 1.0 from the multiplier values themselves. This was done since we were interested in measuring error caused by using an improper direct requirements matrix and not an improper specification of the direct effects.

to aggregate a model before using it as compared to simply aggregating the results of a fully detailed model, this option is clearly not very practical, as mentioned earlier.

By applying RPCs after aggregating using regional weights (the x aggregation) we obtained an average of more than 100 percent error on all multiplier measures at the 81-sector level of aggregation (it was 42 percent for Theil's U measure), although no detectable error was obtained in an aggregation to 365 sectors. However, note this type of aggregation experienced a huge drop in error in moving from 81- to 11-sectors for all measures. This follows the rationale in Section 4 with respect to further aggregation of already highly amorphous sectors.

Aggregating by using national weights and regionalizing afterward, à la Jackson (1998) and Treyz and Stevens (1985), generated the most error. This tendency was maintained across all aggregation levels. Again the error peaked at 81 sectors for all but Theil's U measure, which continued to climb dramatically through the 11-sector level. Ignoring Theil's U results, note that the error generated by this N aggregation type is not very different (perhaps not at all from a statistical perspective) at the 365- and 6-sector levels. The reverberation of the error throughout the rest of the aggregated economy did produce more error based on the Theil's U results.

Perhaps the most interesting result is that, regardless of the measure examined, no significant gains in error were experienced in aggregating from the 11- to the 6-sector level. This result follows that discussed at the very end of Section 2 and supported by Stevens and Trainer (1976) and Miller and Shao (1991). That is, once models are already highly aggregated (their technology highly amorphous) and contain few (if any) zero-valued cells, additional

TABLE 3: The Causes of Aggregation Error in Regional Input-Output Models

	Mean Absolute Percentage Error in			
Variable	Output Multiplier	Employment Multiplier	Value-added Multiplier	Theil's U of Output
Intercept	343.3	348.4	340.0	178.2
	(30.48)	(64.04)	(46.63)	(19.84)
Percentage Nonzero RPCs	–198.1	–150.4	–186.1	–115.0
	(27.79)	(58.39)	(42.51)	(18.09)
Percentage Nonzero Cells	–509.6	–687.4	–616.2	–242.2
	(104.1)	(294.3)	(166.5)	(91.17)
Region's Mean RPC	–174.2	–155.9	–151.3	–75.87
	(21.44)	(45.05)	(32.80)	(13.96)
Region's $\frac{\sigma^2[S/D]}{S/D}$	418.5	526.4	477.4	227.7
	(86.64)	(182.0)	(132.5)	(56.40)
Region's Gini	30.21	3.987	39.55	13.61
	(14.48)	(30.43)	(22.16)	(9.430)
Sector's RPC	–8.610	–31.01	–22.15	–12.33
	(6.252)	(13.14)	(9.563)	(4.070)
Sector's Supply Share in Region	–746.5	–881.0	–892.8	38.69
	(334.4)	(702.6)	(511.5)	(217.7)
81-Sector Aggregation (nested)	9.623	15.27	12.59	13.27
	(6.148)	(12.91)	(9.404)	(4.002)
11-Sector Aggregation (nested)	17.69	26.01	27.99	15.14
	(6.148)	(12.92)	(9.404)	(4.002)
Sector Aggregation (nested)	–0.0001	1.236	–0.0881	0.9674
	(6.148)	(12.92)	(9.404)	(4.002)
No RPCs (*NR*)	15.71	20.76	18.70	7.572
	(7.413)	(15.57)	(11.34)	(4.825)
NR and 81 Sectors	86.63	111.0	104.0	25.70
	(8.695)	(18.27)	(13.30)	(5.660)
NR and 11 Sectors	–92.81	–116.9	–112.0	–30.24
	(8.695)	(18.27)	(13.30)	(5.660)
NR and 6 Sectors	0.5944	0.6891	0.9638	–.01442
	(8.695)	(18.27)	(13.30)	(5.660)
National Weights (*UW*)	95.99	97.98	95.97	21.79
	(6.148)	(12.92)	(9.404)	(4.825)
UW and 81 Sectors	–74.01	–73.62	–72.43	–18.42
	(8.695)	(18.27)	(13.30)	(5.660)
UW and 11 Sectors	49.59	60.07	60.24	45.60
	(8.695)	(18.27)	(13.30)	(5.660)
UW and 6 Sectors	–0.1351	2.875	0.7409	0.9558
	(8.695)	(18.27)	(13.30)	(5.660)
$\overline{R}^2$	.7462	.4894	.6152	.6672
F	81.2	26.5	44.1	55.4
N	516	516	516	516

Note: Numbers in parentheses are the standard errors of the coefficients.

TABLE 4: Predicted Marginal and Total Aggregation Error Due to Method and Aggregation Level Only

		Aggregation Level (Number of Sectors)							
		365		81		11		6	
Measure	Method	Marginal	Total	Marginal	Total	Marginal	Total	Marginal	Total
MAPE of Output Multipliers									
	xR	—*	—	—	—	20.2	20.2	—	20.2
	x	—	—	100.8	100.8	–95.1	25.9	—	25.9
	N	100.5	100.5	–78.5	122.8	49.5	97.4	—	97.4
MAPE of Employment Multipliers									
	xR	—*	—	—	—	31.5	31.5	—	31.5
	x	—	—	131.7	131.7	–121.4	41.8	—	41.8
	N	103.4	103.4	–79.1	156.0	61.5	127.6	—	127.6
MAPE of Value Added Multipliers									
	xR	—*	—	—	—	31.7	31.7	—	31.7
	x	—	—	121.7	121.7	–114.3	39.1	—	39.1
	N	101.1	101.1	–77.6	145.2	60.6	123.2	—	123.2
100 × Theil's U for Output									
	xR	—*	—	10.6	10.6	15.6	26.2	—	26.2
	x	—	—	31.0	41.6	–30.3	26.9	—	26.9
	N	24.5	24.5	–21.1	45.0	46.1	76.4	—	76.4

*The marginal effects of the *xR* aggregation at the 365-sector aggregation level could not be distilled from the overall intercepts in Table 3. Given that the error for the *xR* regression shown in Table 2 is close to zero and that the other results shown above are quite similar to those observed for total error in Table 2, it is likely that the actual marginal (and hence total) effect of the *xR* regression at the 365-sector level was not significantly different from zero.

aggregation is unlikely to induce much additional error. Additionally, because we "changed" manufacturing sectors only and because the manufacturing sector was not aggregated further between the 11- and 6-sector levels, this particular finding also corroborates those from the simulations by Hewings (1972) in the sense that little error is obtained when aggregation is performed on sectors that are not included in the direct effects vector.

Discussion of Results on the Characteristics of the Region and Sector

Comparing the "Total" column in Table 4 with the equivalent "Mean" column in Table 2, we see that nearly all of the total aggregation error is explained by the aggregation type and level alone. That is, the influence of regional and sectoral characteristics—the topic of this section—is minimal. Nonetheless, for output multipliers, all but one of the regional and sectoral variables were significant at the 0.05 level or better using a one-tailed test and all had hypothesized signs. The remaining variable, the disturbed sector's RPC, was significant at about the 0.085 level and had the expected sign as well. The full results for this set of variables are reported in Table 3.

The results for the other multipliers and Theil's U for output have similar form. The only variables that are not significant in these measures occasionally are those for the region's Gini coefficient for output and the sector's share of regional output. Only in the case of Theil's U, where the significance level of the sector's share of regional output is about 0.43, does either of these two variables obtain an unhypothesized sign. Comparing Table 1 to Table 4 for x aggregations, it appears that some of the error expected from an x aggregation is mitigated by characteristics of the affected region and sector.

According to Table 3, the two regional-sectoral factors that weighed in most heavily are the region's degree of self sufficiency (the region's overall RPC) and the perturbed sector's share of regional output. High self-sufficiency in nonsurvey models means the regional direct requirements matrix will be similar to its national equivalent. Hence, error is unlikely to transmit itself very differently through the two matrices. When a sector maintains a high share of the regional economy, the results have a tendency to parallel those of Hewings (1972) as discussed earlier in this section. That is, as long as the changed sector(s) is (are) represented well in the model, little error will result despite possible high levels of aggregation in other sectors.

In summary, compared to aggregation type and aggregation level, regional and sectoral characteristics do not much influence the amount of error that results from using aggregated regional I-O models. Nontheless, the diversity of an economy, its connectedness, and its self-sufficiency play significant, albeit small, roles in compounding aggregation error.

6. SUMMARY AND CONCLUSIONS

As hypothesized, both high levels of aggregation and failure to reflect properly regional purchase patterns, industrial mix, or both in the aggregation process increase error in aggregated regional I-O models. These errors are potentially very large: in this study, worst-case output multiplier error is over 95 percent when regional weights are applied during the aggregation procedure and regionalization occurs afterward. Average error is as high as 150 percent when aggregation is performed using national weights and regionalization is undertaken subsequently.[18] These figures compare with a corresponding maximum error of 33 percent for properly undertaken aggregations, and then only at the 11-sector level.

Most importantly, for the level of aggregation at which many regional adaptations of aggregate national technology tend to fall (in the U.S. as well as

[18]The comparable employment multiplier errors here (Table 2) are actually somewhat smaller than those obtained by Isserman (1977, Table 1). Isserman was calculating regional employment multipliers using economic-base models rather than full-scale I-O. Nevertheless, his estimates, based on location quotients, involve many of the same aggregation issues raised here. Therefore, it is worth noting that he reports spurious employment-multiplier increases of 100–250 percent, for various regions, as he progressively aggregates the employment data, on which his location quotients and export base estimates are based, from the four-digit to one-digit SIC level.

elsewhere) around 50 to 80 sectors, average output multiplier error levels of 120 percent can be obtained. Such magnitudes of the various errors contrast with the relatively modest results reported by Hewings (1972), Sawyer and Miller (1983), and the other authors of the simulation studies referred to previously. As already noted, these studies use I-O models that are already partially aggregated and already fitted, usually with only limited survey data, to a particular region and application—which is good practice. Such tailored modeling and aggregation can minimize potential error transmission. On the other hand, if such good practice is not followed, then the errors obtained can outstrip any concerns about data quality.

The results presented here provide a stronger argument than has been made previously against any unnecessary aggregation of I-O models, particularly those for subnational areas. Furthermore, the results make clear that proper methods must be carefully applied to minimize error generation, if aggregation is truly required by the nature of the study. Clearly, the two simple rules to follow, if at all possible, are to regionalize first and to use regional weights in the aggregation process.

One could argue that a lack of sectorally detailed regional data makes the construction of a regional model with full national model detail impossible. We believe that such an argument is misguided.[19] Using approaches such as those discussed in Lahr (2001b), one can use a minimum of sectorally detailed regional data (e.g., nonfarm employment or earnings by four-digit SIC) in combination with detailed national ratios to maximum effect to produce a reasonable set of regional accounts. These same data can be applied to yield a regional I-O model with the same sectoral detail as the nation's I-O tables. Indeed, the fact that any resulting "fabricated" regional data may not be very precise seems, based on the finding in this paper, likely to be outweighed by the application of the more accurate production functions available from the nonaggregated national input-output table. Furthermore, as long as regional model results are not reported for industry aggregations beyond those for which the less-detailed regional data are published, it seems that the integrity of these regional data may not be compromised much.

Our results call for further research. Although we discovered that the diversity of an economy, its connectedness, and its self-sufficiency play significant roles in compounding aggregation error, the indirect explanation of error transmission through nonzero cell ratios is not totally satisfactory. This is partly because a zero RPC creates a full zero row when nonsurvey techniques are used to create a regional direct requirements matrix. Hence, we surmise that zero cells are of two types (and accordingly may transmit error differently): those belonging to nonexistent production and those due to a lack of demand by industry. Thus, a set of simulations that use I-O matrices that are more like survey-based national and regional equivalents as well as many more

[19]Again, we thank an anonymous referee for encouraging us to reiterate how important it is to maintain maximum sectoral detail in a regional setting.

aggregation levels might provide better insight into the ways in which regional aggregation bias is generated.

In addition to further investigation into the impact of zero-valued cells, there should be further analysis (not reported here due to space limitations) of error found in sectoral output itself due to aggregation. It is clear from our preliminary investigations using this measure that such error behaves somewhat differently from the multiplier errors; also, the mean absolute deviation and Theil's U for output error behave somewhat differently from each other. The error characteristics of sectoral outputs can be very important if the analyst is interested in the I-O results for individual industries rather than simply for the regional economy as a whole.

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