 ©1994 MCRSA. All rights reserved.

TESTING DYNAMIC SHIFT-SHARE

Anne C. Selting and Scott Loveridge*

Introduction

All economies change over time. Tracking a community's economic life cycle and pinpointing the factors that affect its growth can be done with a variety of tools. One of the most popular is shift-share analysis. Shift-share decomposes total regional growth, ascribing changes in a local economy to three distinct factors. The national growth effect estimates the regional expansion due to growth in the nation. The industry mix effect measures the degree that an area gains jobs or income[1] because it is home to industries that are doing better than the national average. The third factor, the competitive effect, indicates how much a region's own strengths contribute to economic success.[2]

Shift-share has been used heavily since its formal inception in the 1960s (Fuchs 1962; Ashby 1964). The technique generally is applied to describe historical growth trends, forecast regional growth, analyze the effects of policy initiatives, or develop strategic planning for communities. A number of alternative models have appeared in the literature, such as the Esteban-Marquillas (1972) and Arcelus (1984) specifications.[3] The classic formulation remains the most dominant model in empirical work, however, and is cited widely. This article compares static and dynamic versions of the classic shift-share model.

The Choice-of-Weights Problems in Static Shift-Share

The classic shift-share model is:

$$(1)\ E_{ij}^{t} - E_{ij}^{t-1} \equiv \Delta E_{ij} \equiv NE_{ij} + IM_{ij} + CE_{ij}.$$

E_{ij}^{t} = Employment (income) in industry i, region j, at time t;
NE_{ij} = National growth effect;

---

* Anne C. Selting is a Ph.D. candidate in the Department of Agricultural Economics at the University of California, Davis. Scott Loveridge is an assistant professor in the Department of Agricultural and Applied Economics at the University of Minnesota.

1 Growth generally is proxied using either employment or income data.

2 The causes of a positive competitive effect are not isolated (Harris *et al.*, 1987; Buck, 1970; MacKay 1968) but may be influenced beneficially by factors such as a highly trained labor force, strong infrastructure, agglomeration economies, and aggressive policy initiatives designed to attract business.

3 See Selting and Loveridge (1992) for a review of alternative shift-share models.

IM_{ij} = Industry mix effect; and
CE_{ij} = Competitive effect.

The three effects are computed as follows:

$$(2) \quad NE_{ij} = E_{ij} \times (g_{oo})$$

$$(3) \quad IM_{ij} = E_{ij} \times (g_{io} - g_{oo})$$

$$(4) \quad CE_{ij} = E_{ij} \times (g_{ij} - g_{io})$$

where:

g = Employment (income) growth rates;
g_{ij} = The percentage of change in employment (income) in industry i, region j relative to a base year;
g_{io} = The percentage change in nationwide employment (income) for industry i;
g_{oo} = The percentage change in nationwide employment (income).

Between any two time periods, the observed change in growth is the sum of the national growth effect, industry mix, and competitive effects.[4] The national growth effect and the industry mix are determined exogenously. Together, they compose the region's share of growth—the economic expansion the region would enjoy if it grew like the nation. Shift-share analysis assumes that regional industries will grow in the same way that their national counterparts expand. If a region experiences growth that diverges from these expected levels, a shift is said to exist. This shift is embodied in the competitive effect, which is the only endogenous component in the model.

Depending on the analyst's objectives, each of the three components can be estimated for an individual firm, for an industry, or, if summed over all industries, for a whole city, county, region or state. Dunn (1980) and others have argued that shift-share analysis should not be used to examine the performance of individual industries due to the difficulty in interpreting the industry mix effect for a particular sector in a region. In the analysis that follows, an industry by industry approach is sometimes used to better isolate the differences between static and dynamic shift-share. In empirical work, the focus on shift-share results should be on the aggregated values of the national growth

[4] If a local economy is in decline, the magnitudes of the components provide an indication of the relative role each has in dampening growth.

and industry mix effects. Industry level competitive effects are not generally problematic to interpret.

Shift-share traditionally is computed using a beginning and end year to estimate changes in growth over multiple year time periods. For example, an analysis of growth in some region from 1980 to 1985 typically uses 1980 employment levels as the beginning year (E_{ij}^{t-1} in equation (1)) and 1985 employment figures as the end year (E_{ij}^{t} in equation (1)). Each shift-share component is weighted by some employment level (E_{ij} in equations (2) through (4)). A question arises over which year to use as a weight, the base year (1980 in this example), the terminal year (1985), or some average. Most studies select the beginning year. Using base and terminal years to compute growth rates and weight shift-share results over several years is referred to as *the static approach.*

The weights in the shift-share equation introduce bias that has provoked long-standing questions about the integrity of shift-share results. The most persistent criticism leveled against shift-share is that, *a priori*, selecting a weight introduces the type of bias seen in economic indices (Dunn, 1960).

Shift-share results are sensitive to weights in two ways. First, the calculations do not account for changes in industrial structure over time. For example, if initial employment levels are chosen as weights, the industry mix in the first year is assumed to be constant throughout the years of the analysis. Because the static approach cannot incorporate changes in the type and number of firms locating in a region after the base year, the industry mix can be a stale indicator of the growth that accrues to an area if shifts in the composition of its industry are occurring (Herzog and Olsen, 1977). This is particularly true for rapidly expanding regions. The longer the span of years in a shift-share study, the more likely the magnitude of bias.

Recognizing the problems in base weighting, the use of terminal weights or an average of base and terminal weights has been suggested (Fuchs, 1959; Stilwell, 1969; Klaassen and Paelinck, 1972). Depending on the nature of change in growth, either alternative at best minimizes, and can aggravate, bias (Ashby, 1970).[5]

The second source of error in shift-share calculations caused by this choice-of-weights problem is the *compounding effect* (Barff and

---

[5] For example, Selting (1993) finds that the use of terminal weights can cause gross distortions in the competitive effect in both dynamic and static shift-share. This tends to occur in small sectors experiencing rapid growth. In one Minnesota county, growth in medical instruments was 168 percent, while national growth in the same industry averaged 10 percent. The resulting competitive effect is grossly exaggerated. Because of this problem, terminal weighting should be used with caution, if at all. This study uses base weights.

Knight, 1988, p. 3). Because the static approach does not account for continuous fluctuations in the size of a region's total employment, the allocation of growth among the three effects is skewed. If a subnational economy grows faster than the nation during the study period, then using base or terminal year weights will attribute too little of the total change in employment (income) to the national growth effect. This underestimation occurs because regional growth each year exceeds what would be expected if the region grew at the same pace as the nation each year, which is assumed in computing the national growth effect using the static approach.[6]

Dynamic Shift-Share

Formalizing the well-established view that shortening the time frame of a shift-share analysis dampens the choice-of-weights problem, Barff and Knight (1988) present a new approach dubbed *dynamic shift-share*. Rather than calculating components over multiple year periods, the authors suggest that annual computations be performed and summed across the number of years of interest.[7] Dynamic results are theoretically more accurate because there is less change in industrial structure from year to year. Relying on nonstatistical approaches, the authors analyze New England employment changes from 1939 to 1984 and determine that job loss ascribed to the industry mix in the static approach is overestimated. Although both the dynamic and static effects compute negative values for the industry mix, the static value is ten times larger than the dynamic industry mix component. Barff and Knight conclude that the dynamic approach provides superior results by more accurately allocating growth between the components. In addition, the authors emphasize the additional information offered by dynamic shift-share, namely that a region's economic transitions can be followed on an annual basis. A disadvantage not addressed is that annual computations are more complicated and require extra time and better computer capacity.

---

[6] Conversely, in periods of regional contraction, the national growth effect is overestimated.

[7] This advance is not completely novel. Recognizing the advantages of shortening the study period, several authors have split the length of their shift-share analysis into subsections to improve results (Thirlwall, 1967; Brown, 1969; Edwards, 1976; Fothergill and Gudgin, 1979). Hale (1971) advocates the use of monthly data to adequately measure the effects of business cycles on shift-share results. Barff and Knight (1988), however, were the first to explicitly suggest that annual shift-share computations should be adopted as a standard method for calculating results.

Testing Dynamic and Static Shift-Share

The literature asserts that there is sizable bias in the static method, which Barff and Knight suggest the dynamic model removes. In its acceptance and use of the dynamic model, recent work (Kochanowski *et al.*, 1989; McDonough and Sihag, 1991) embraces this conclusion. A side by side comparison of dynamic and static shift-share, however, has not been attempted outside the authors' original work.

The rest of the article is organized as follows. First, six hypothetical industries, each with different growth patterns, are constructed to simulate the magnitude and direction of bias in static shift-share. Second, empirical results are computed to determine if these tendencies for bias are discernible in actual shift-share applications. Dynamic and static components are calculated for Minnesota counties and industries from 1979 to 1988.[8] Descriptive statistics and t-tests are used to analyze differences. Results are generated at the state, industry, and county levels. Third, a case study illuminates reasons for differences between the models and illustrates how the selection of a method may significantly alter the conclusions made about a sector's growth performance over time.

Examining the Bias in Static Shift-Share: A Simple Simulation

Without first developing a gauge of bias, it is difficult to conclude that differences in the way the methods compute shift-share for a region stem from weighting problems in the static model. A simulation is created to determine the nature of bias and thus isolate the differences that develop between the models that can be attributed to weighting problems.

Given the three growth rates in the traditional shift-share model, six distinct patterns can be discerned[9] and are defined below. For ease of identification, each pattern is assigned to an industry that hypothetically is asserted to grow in this fashion. It is assumed that growth is measured in changes in employment.

a. Agriculture
   g_{oo}=3%, g_{io}=2%, g_{ij}=1%

---

[8] Data are two digit REIS income data from the Bureau of Economic Analysis. U.S. data are used as the reference economy in all calculations. *County Business Pattern* data provide a first estimate of nondisclosed values. The RAS procedure was used to adjust these estimates to be consistent with industry and county totals. See Miller and Blair (1985) for a description of the RAS procedure.

[9] Three factorial. For example, $g_{oo} > g_{io} > g_{ij}$ versus $g_{oo} > g_{ij} > g_{io}$. Cases of equality between growth rates are not considered.

b. Mining

   g_{oo}=3%, g_{ij}=2.5%, g_{io}=2%

c. Construction

   g_{io}=4%, g_{oo}=3%, g_{ij}=2.5%

d. Manufacturing

   g_{io}=4% g_{ij}=3.5% g_{oo}=3%

e. Wholesale Trade

   g_{ij}=6% g_{oo}=3% g_{io}=2%

f. Retail Trade

   g_{ij}=5% g_{io}=4% g_{oo}=3%

For each growth pattern above, dynamic and static shift-share models are calculated. All calculations are done for three years, assuming constant annual changes in growth rates. A base employment of 100 persons is used. Table 1 summarizes the results of this simulation.

The specific numerical values are no more than a reflection of the numbers selected and are not significant to the analysis. What is important is the difference between the static and dynamic results. In no cases are the results identical; over the relatively short time period of three years the methods produce varying component values. For three industries (agriculture, mining, and construction), the absolute value of all components is greatest in static shift-share, implying that it tends to overstate each effect relative to the dynamic method. This seems to occur when either national growth or national industry growth exceeds regional growth.

The compounding effect plays a significant role in skewing the value of the national growth effect in all six scenarios. Barff and Knight (1988) note that when regional growth rates surpass national growth rates, the static method underestimates the national growth effect. Manufacturing, wholesale and retail trade all exhibit this pattern, ($g_{ij} > g_{oo}$); consequently, their static national growth effects are smaller than the dynamic method's. Conversely, the compounding effect causes an overestimation of the national growth effect if regional growth rates lag national growth rates. This is true in the agriculture, mining, and construction industries, all of which have static national growth effects that exceed the dynamic method's.

When the national growth effect is underestimated, the static model may over or underestimate the remaining components. In two cases (manufacturing and retail trade), the industry mix and competitive components are higher than the dynamic method. In the case of wholesale trade, it is the dynamic method that produces the largest industry mix and competitive effects. The simulation shows that while it is not possible to predict *a priori* how other components in the model will behave when regional growth outpaces national growth, the overall trend is that the static model will overestimate the magnitude of each shift-share component. This is true in five of six industries.

It is tempting to transfer these conclusions directly to empirical analysis, but the results of the simulation offer only initial insights into the general trends of bias. It is not possible to determine the magnitude or direction of bias in the static model. Not only is bias related closely to the relative growth of national, industry, and regional growth, it is also a function of how large a difference exists between growth rates. Another complication is that it cannot be expected that the inequalities are consistent for every year of an empirical analysis. Particularly for volatile industries, industry growth may lag regional growth in a year but lead in the following year. Unless data indicate all firms grow in patterns consistent with those outlined in the categories above for every year, the simulation cannot be extrapolated. The important information gained by the simulation is that static shift-share likely introduces bias.

Empirical Differences Between Dynamic and Static Shift-Share

State-Level Results

Table 2 summarizes the differences between the dynamic and static models using base weights to calculate statewide shift-share results.[10] The national growth effect in each model is comparable; the dynamic value is approximately 5 percent lower than the static. At the state level the compounding effect is not severe. It is in the remaining components that larger differences emerge. Both models have negative industry mixes, implying that, on the whole, the base industries in Minnesota have not kept pace with the average growth of these industries nationwide. But the dynamic and static industry mix effects are divergent; the dynamic value is 16 percent more negative than the its static counterpart.

The most striking difference between the models is the variation in the magnitude of the competitive effect and the way in which each method allocates income loss between the industry mix and competitive effect. The static competitive effect is nearly double the dynamic value. Thus, the static model ascribes the greatest loss in income to local factors operating in the state. This contrasts with the dynamic model, which points to the industry mix as the chief source of income loss.

It is clear that the choice of the model affects the interpretation given to the pattern of Minnesota's growth over the decade. The dynamic method suggests that the largest drag on income expansion is caused by a tendency for the state to rely on industries that are growing

---

[10] State results are attained by summing across all industries and counties.

more slowly than average national growth. In contrast, the static model traces most of the downward pressure on income to industry's inability to stay competitive with other firms producing the same goods and services outside the state. If the shift-share results were used in isolation, the dynamic model would suggest that income can be bolstered if firms with high growth potential are encouraged to locate in the state to balance its mix of slow and fast growing industries. Alternatively, the static model's overwhelmingly large competitive effect implies that Minnesota firms are not competing well against other firms. The static results lead to an emphasis on aiding existing in-state firms to match the growth performance of their out-state rivals.

Industry-Level Results

Shift-share is frequently used to examine the performance of industries over time. An important line of inquiry is how the dynamic and static results compare at an industry level. At the two digit level, Minnesota has 75 major industries. Shift-share results for the five most important industries[11] in terms of their total contribution to state income are summarized in Table 3.

The static and dynamic results are relatively uniform for the top income earning industries in the state. Bias, while present, does not change the basic profile that emerges for each industry. Both approaches indicate, for example, that the state's business services is a healthy sector, expanding faster than national growth rates and outpacing its out-of-state counterparts.

Although the differences are not significant enough to suggest disparate conclusions, the tendency for the absolute value of the static competitive effect to be larger than the dynamic effect is repeated at the industry level. As with the state case, bias seems to be exhibited most strongly in the competitive component. This is true not only for the top five income-earning sectors, but for most of Minnesota's industries. Fifty-three industries have static competitive effects that exceed their dynamic counterparts.

For the average industry, the method chosen will affect results. Only 17 industries (23 percent) had dynamic shift-share components that were within 20 percent of the static component values. Fifty industries had dynamic components whose magnitudes were at least 20 percent higher or lower than static shift-share results. Eight industries not only had sizable differences between methods, but the sign of at least one of the static components was opposite that of the dynamic.[12] This

[11] In 1988.

[12] Four industries had sign changes in the competitive effect (forestry, fisheries, motor vehicles/equipment, and miscellaneous retail). Two industries had sign changes in the industry mix effect (transportation

is the most serious type of discrepancy that can result because the conclusions that emerge from each method are diametrically opposed. Table 4 illustrates this problem for the forestry industry.

Note that the sign of the competitive effect flip-flops between methods. In the dynamic model, the competitive effect is highly positive, while in the static it is slightly negative. Thus, the dynamic method concludes that local factors are influencing the forestry industry positively and that growth in the industry is outpacing growth in forestry products at the national level. The static model suggests the opposite. These cases are relatively rare, but are important because they represent the most drastic differences between the methods.

Flip-flopping is most likely to occur when the industry is small and its growth is erratic. The five smallest industries in the state are among the eight industries that have this problem. Only one industry in the top third of income-earning sectors for the state exhibits sign switching.

While industry size plays a role in the less common cases of flip-flopping, it is not generally a reliable indicator of whether components in the static model will differ greatly from those in the dynamic model. Small and large industries are equally as likely to vary at least 20 percent between models.[13] The greatest differences occur in industries that have high variability in industry and regional growth rates. An analysis of the standard deviations of average industry growth rates (g_{io}) and average growth rates for the industry in the region (g_{ij}) reveals that sectors with the greatest dissimilarities between components have the highest annual standard deviations. Sectors with low variability in these growth rates tend to have few differences in components across the two methods.

Overall, while some sectors are not sensitive to the type of model used to calculate shift-share, this is not true in the majority of industries in the state. An exaggerated competitive effect for the static model also appears in industry analysis.

County-Level Results

Industry and state comparisons focus on how static and dynamic shift-share models perform when data are aggregated over counties and industries. A full examination of differences must also consider how results compare when shift-share is used to track county-level industries. This type of analysis provides the most detailed information about

---

equipment and pipelines). One industry had flip-flopping in the national growth effect (coal mining). For the tobacco manufacturing industry, both the national growth and industry mix effects changed sign.

[13] A small industry is defined as being in the bottom third of income-earning industries in the state.

changes in the subnational economy over time and can be used to answer questions such as how fast local infant industries are expanding, whether large industries that are important to the county are thriving, and if there are significant differences in the competitive effect among counties.

An analysis of 4,690 cases (where each observation is an industry in a county) reveals a familiar pattern. The static competitive effect is roughly a third larger for the average sector than the dynamic competitive effect. For some industries at the county level, the static competitive effects are up to fifty times larger. Paired t-tests of the national growth and industry mix effects across the models suggest that the null hypothesis of equality in the means is not rejected. This is not the case for the competitive effect, which rejects the null. These results are summarized in Table 5.

Categorizing the data by the severity of differences between methods reveals that approximately 5 percent of county-level industries flip-flop in at least one shift-share component. Roughly half of the 4,690 cases vary at least 20 percent in the components.

Case Study: The Cause of an Exaggerated Static Competitive Effect

The simulation implies that there are many ways in which bias can emerge in the static model, but it cannot explain why the differences using Minnesota data are expressed largely in the magnitude of the competitive effect between models. A case study examines this question further.

Farming is the seventh largest income earner in Minnesota.[14] At the state level, the static competitive effect for the farm industry is more than twice as large as its dynamic counterpart. For Blue Earth County, located in south central Minnesota, farming is the fourth largest industry. But as with farming across the U.S., the industry's annual income has been on the decline in the county since the late 1970s. Farm income for the county in 1988 is less than half of its 1979 level (Figure 1).

Because these two values are used to compute the percentage decrease in farming over the nine years of the shift-share analysis, the static model implies a negative growth path and assumes implicitly that farming generates less and less income for the county every year of the analysis. This is represented by the downward linear function in Figure 1, obtained by connecting base (1979) and terminal (1988) farm income. Although the overall trend is downward, Figure 1 shows that there is much fluctuation in farm income through the 1980s. Because the dynamic model weights the differences in growth rates in the competitive effect by current income levels, the dynamic model assigns less of

[14] In terms of 1988 income.

the loss in total farm income to the competitive effect and instead more to the larger, negative industry mix effect.

Can this conclusion be extrapolated to all industries? If industry growth at the regional level tends to be more variable than national industry growth rates, which is frequently the case, then the difference between growth of the industry at the county level and industry growth (g_{ij}-g_{io}) will tend to be large. In the dynamic method this is somewhat tempered because significant booms in local industry growth generally are balanced by downward swings in growth in the following years. These effects tend to be reduced in the dynamic method because results are summed over the study period. Thus, in many instances it is unmitigated variability in growth rather than true shifts in a local economy's competitive edge that is responsible for large static competitive effects.

These large competitive effects will influence the interpretations given to shift-share results. For Blue Earth County, the static model attributes the bulk of loss in farm income to local factors. The dynamic model emphasizes that the county is losing farm income because it is an industry in national decline. This is a more realistic description of the decline in county farming. The difference on average between national growth rates in farming and county-level Minnesota farm growth is not extreme; national farming trends tend to be mirrored at the county level. The more appropriate interpretation of the overall loss in farm income in Blue Earth County seems to stem from the reality that the farm industry is in decline rather than local shortcomings in endowments, technology adoption, productivity, or infrastructure.

Conclusions

That the bias in the static model is contained largely in the competitive effect is a conclusion that is applicable only to Minnesota data. Other states, having different growth profiles, may exhibit different and perhaps less severe patterns of bias. There are several important findings. First, the simulation indicates a tendency for the static model to incorrectly allocate growth over time among components. Static shift-share cannot account for annual changes in the industry mix and under- or overestimates the national growth component (the compounding effect). Second, when both methods are used to analyze total, sectoral, and local growth, differences between the models are persistent, discernible, and may be severe enough to change the interpretation of the results.

Because it minimizes the problem of changing industry structure and eliminates the possibility of the compounding effect, a strong case is made for the use of dynamic shift-share. Dynamic shift-share also produces results that more accurately reflect the causes of growth and decay at the county level. Several other arguments support the use of the dynamic method. Annual shift-share calculations make it possible to develop a time series of the competitive effect, which can be used in forecasting or evaluation of policy initiatives. Yearly shift-share, as Barff and Knight (1988) suggest, is a useful tool for tracking economic performance over time. Finally, dynamic shift-share offers more precision for finely disaggregated data. This study uses two digit SIC codes, a relatively coarse division of industries. As data are disaggregated more finely, the variability of growth rates will increase as the size of the sector dwindles. The dynamic version of classic shift-share has shown itself more able to account for these changes without exaggerating the values of one or more of the shift-share components.

Bibliography

1. Arcelus, Francisco J., "An Extension of Shift-Share Analysis," *Growth and Change*, 15, no. 1 (1984), pp. 3-8.

2. Ashby, Lowell, D., "The Geographical Redistribution of Employment: An Examination of the Elements of Change," *Survey of Current Business* 44, no. 10 (1964), pp. 13-20.

3. Ashby, Lowell, D., "Changes in Regional Industrial Structure: A Comment," *Urban Studies*, 7, no. 3 (1970), pp. 298-304.

4. Barff, Richard A, and Prentice L. Knight III, "Dynamic Shift-Share Analysis," *Growth and Change*, 19, no. 2 (1988), pp. 2-10.

5. Brown, James J., "Shift and Share Projections of Regional Economic Growth: An Empirical Test," *Journal of Regional Science*, 9, no. 1 (1969), pp. 1-18.

6. Buck, T.W., "Shift and Share Analysis—A Guide to Regional Policy?," *Regional Studies*, 4 (1970), pp. 445-450.

7. Dunn, Edgar S., Jr., "A Statistical and Analytical Technique for Regional Analysis, *Papers and Proceedings of the Regional Science Association*, 6 (1960), pp. 98-112.

8. Dunn, Edgar S., Jr., *The Development of the US Urban System*, vol. 1, Chapter 9 (Baltimore, MD: John Hopkins University Press, 1980).

9. Edwards, J. Arwel, "Industrial Structure and Regional Change: A Shift-Share Analysis of the British Columbia Economy, 1961-1970," *Regional Studies*, 10 (1976), pp. 307-317.

10. Esteban-Marquillas, J.M., "A Reinterpretation of Shift-Share Analysis, *Regional and Urban Economics*, 2, no. 3 (1972), pp. 249-255.

11. Fothergill, S., and G. Gudgin, "In Defense of Shift-Share," *Urban Studies*, 16, no. 3 (1979), pp. 309-319.

12. Fuchs, Victor R., "Changes in the Location of U.S. Manufacturing Since 1929," *Journal of Regional Science*, 1, no. 2 (1959), pp. 2-17.

13. Fuchs, Victor R., "Statistical Explanations of the Relative Shift of Manufacturing Among Regions of the United States," *Papers of the Regional Science Association*, 8 (1962), pp. 1-5.

14. Hale, Carl W., "Shift-Share Analysis as a Descriptive Tool in Regional Analysis," *Mississippi Valley Journal of Business and Economics* 6, no. 3 (1971), pp. 65-74.

15. Harris, Anthony, Michael G. Lloyd, Alastair J. McGuire, and David A. Newlands, "Incoming Industry and Structural Change: Oil and the Aberdeen Economy," *Scottish Journal of Political Economy*, 34, no. 1 (1987), pp. 69-90.

16. Herzog, Henry H., and Richard J. Olsen, "Shift-Share Analysis Revisited: The Allocation Effect and the Stability of Regional Structure," *Journal of Regional Science*, 17, no. 3 (1977), pp. 441-454.

17. Klaassen, L.H., and J.H.P. Paelinck, "Asymmetry in Shift and Share Analysis," *Regional and Urban Economics*, 2, no. 3 (1972), pp. 256-261.

18. Kochanowski, *et al.*, "The Shift-Share Methodology: Deficiencies and Proposed Remedies," *Regional Science Perspectives*, 19, no. 1 (1989), pp. 65-88.

19. MacKay, D.I., "Industrial Structure and Regional Growth: A Methodological Problem," *Scottish Political Journal*, 15 (1968), pp. 129-142.

20. McDonough, Carol C., and Balbir S. Sihag, "The Incorporation of Multiple Bases Into Shift-Share Analysis," *Growth and Change*, 221, no. 1 (1991), pp. 1-9.

21. Miller, Ronald E., and Peter D. Blair, *Input-Output Analysis: Foundations and Extensions* (Englewood Cliffs, NJ: Prentice-Hall, Inc., 1985).

22. Selting, Anne C., and Scott Loveridge, "A Summary of the Literature on Shift-Share Analysis," *Staff Paper Series*, Department of Agricultural and Applied Economics, University of Minnesota, St. Paul, June 1992.

23. Selting, Anne C., "An Analysis of Shift-Share Models," M.S. Thesis, Department of Agricultural and Applied Economics, University of Minnesota, St. Paul, July 1993.

24. Stilwell, F.J.B., "Regional Growth and Structural Adaptation," *Urban Studies*, 6 (1969), pp. 162-178.

25. Thirlwall, A.P., "A Measure of the Proper Distribution of Industry," *Oxford Economic Papers* 19 (1967), pp. 46-58.

Table 1—Simulation Results for Dynamic and Static Shift Share Component

	National Growth Effect		Industry Mix Effect		Competitive Effect		Total
	Dynamic	Static	Dynamic	Static	Dynamic	Static	Growth
Agriculture	6.03	6.09	-2.03	-2.05	-2.01	-2.03	2.01
Mining	6.08	6.09	-2.03	-2.05	1.01	1.02	5.06
Construction	6.08	6.09	2.03	2.07	-3.04	-3.09	5.07
Manufacturing	6.11	6.09	2.04	2.07	-1.02	-1.04	7.13
Wholesale Trade	6.18	6.09	-2.06	-2.05	8.24	7.20	12.36
Retail Trade	6.15	6.09	2.05	2.07	2.05	2.09	10.25

*Each value is the change in employment attributed to the shift-share effect

Table 2—Dynamic vs. Static Shift-Share Results for the State of Minnesota (Income Data, 1979-1988)

Shift-Share Component	Dynamic Shift-Share	Static Shift-Share	Absolute Difference Between Components
National Growth Effect	7,747,829	8,137,492	389,663
Industry Mix Effect	-937,286	-786,595	150,691
Competitive Effect	-640,424	-1,180,778	540,354
Total Change in Income	6,170,119	6,170,119	0

Expressed in 1000s of 1988 dollars

Table 3—Dynamic and Static Shift Share Results for the Top Five Minnesota Industries (Income Data 1979-1988)

Industry	Dynamic Method NE	Dynamic Method IM	Dynamic Method CE	Static Method NE	Static Method IM	Static Method CE
Wholesale Trade	560,520	-33,149	-479,218	682,158	-63,364	-570,642
Health Services	591,775	939,874	-236,707	451,444	1,099,594	-256,095
Machinery	484,424	-793,654	658,359	469,814	-792,772	672,087
Business Services	309,834	873,276	54,008	181,340	1,007,028	58,751
Special Trade Contracting	278,537	34,992	-156,674	322,515	39,612	-205,272

Expressed in 1000s of 1988 dollars
Government services is excluded in analysis; machinery does not include electrical machinery

Table 4—Sign Changes in the Competitive Effect: Forestry Industry Income

National Growth Effect		Industry Mix Effect		Competitive Effect	
Dynamic	Static	Dynamic	Static	Dynamic	Static
2,379	1,415	-31,096	-4,645	23,505	-1,982

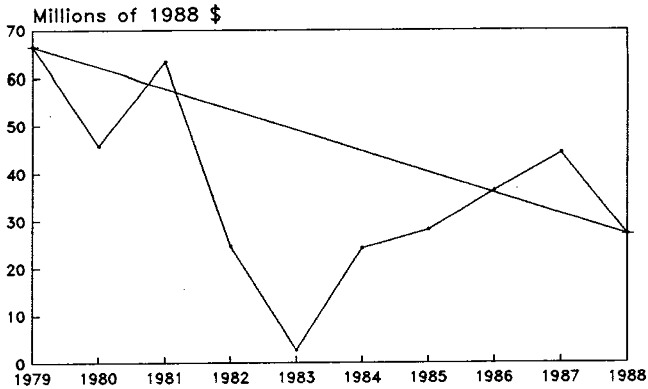
Expressed in 1000s of 1988 dollars. Flip-flopping can be seen in the competitive effect

Table 5—Paired t-tests for Equality Between Means in Components Across Models (Industry-County Level Income Results)

	National Growth Effect		Industry Mix Effect		Competitive Effect	
	Dynamic	Static	Dynamic	Static	Dynamic	Static
Mean	1,651	1,735	-199	-168	-136	-251
t-value	1.91 (Accept)		.75 (Accept)		-4.85 (Reject)	
Correlation	.96		.99		.99	

0.05 significance level, df = 4,689
Means are expressed in 1000s of 1988 dollars

Figure 1—Farm Income in Blue Earth County 1979–1988



Source: REIS