

Reconsidering the regional manufacturing indexes

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Regional manufacturing indexes have been gaining popularity in recent years, as more and more Federal Reserve Banks have made them available to the public. Currently, five of the twelve Banks (Chicago, Cleveland, Philadelphia, Richmond, and Dallas) regularly publish manufacturing indexes.¹ As a more comprehensive measure of manufacturing activity than employment data, these indexes can be a valuable tool for monitoring current economic conditions in a region. Moreover, as estimates of regional industry output, these indexes can be incorporated in a variety of research models to test theories of regional growth and structural change. For whatever purpose the indexes may be used, the Federal Reserve Banks are committed to providing the highest quality indexes possible and research on improving the indexes is continuing.

In this paper, previously developed methods for constructing indexes of regional manufacturing activity are reviewed and new methods tested, using the database of the Midwest Manufacturing Index (MMI). In the first part of this study, three nonparametric methods for constructing indexes are presented. In simplest terms, nonparametric indexes are essentially weighted averages of two inputs—labor and capital services, the major components of output. (All indexes currently in use are nonparametric models, in that the weights, or parameters, do not require empirical estimation.) In the second part of this study, five

Refinements in modeling industrial inputs and output can produce big gains in the accuracy of a regional index

parametric models are tested, using standard econometric techniques, to estimate empirically the relationship between output and its inputs. The objective of each part is to determine which method can most accurately forecast output two years ahead. In the conclusion, an overall comparison of the eight methods is made.

The most commonly used method for constructing manufacturing indexes was developed in 1970 by the Federal Reserve Bank of Atlanta.² The Atlanta method, which is a nonparametric method, has become the standard approach, largely because of a study by Fomby.³ His study, which reviewed various methods for constructing indexes, found that the Atlanta method outperformed both parametric and other nonparametric methods. In taking a fresh look at both parametric and nonparametric methods, however, this study concludes that alternatives do exist that are easy to use and more accurate than the Atlanta method.

Fomby's experiment on the accuracy of manufacturing indexes is reproduced here with several modifications. First, tests of forecasting accuracy are limited to two years ahead, rather than the five-year forecast in the Fomby study. Since data used in constructing the indexes are rarely more than two years out of date, the ability to forecast beyond two years is seldom required to extrapolate existing data to

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the present date. With only thirteen annual observations to build the indexes, a two-year forecast will be more accurate than a five-year forecast.

A second fundamental change is the selection of individual manufacturing industries for modeling, as opposed to the aggregated manufacturing sector.⁴ Industries at the two-digit level of Standard Industrial Classification (SIC), e.g., primary metals or transportation equipment, could have growth patterns substantially different from the manufacturing sector on average, and the accuracy over the forecast period can be improved by capturing those diverse patterns over the estimation period.

The third and major innovation of this study is the introduction of a new variable—payroll earnings. Payroll earnings are an important component in constructing regional indexes. However, the variable has typically been approximated, despite the fact that payroll data are available monthly in the Bureau of Labor Statistics' (BLS) *Employment and Earnings* publications. Incorporating the payroll variable into the analysis requires some modification of the traditional neoclassical production function, but increases the explanatory power of the model by introducing more variables into the analysis.

The eight models (five parametric and three nonparametric) developed in this study are tested over the period 1972–85. For the in-sample period (from 1972 through 1983), models are estimated, using data from the Annual Survey of Manufacturing (ASM) data. For forecasts of the out-of-sample period (1984 and 1985), only data reported by the BLS are used. The object of the test is to determine which model generates the lowest mean absolute error for the estimates of total manufacturing output (i.e., value added) in 1984 and 1985, when compared to the known out-of-sample values. For this study, only annual projections are made. However, in reality the data allow one to make monthly interpolations between annual projections of the estimated model. The monthly estimates are the ultimate objective of regional manufacturing indexes.

Nonparametric models

The nonparametric methods of forecasting regional manufacturing output can be con-

trasted by two approaches: the Atlanta method and the Chicago method (nonparametric version). Because of underlying similarities of the two models, the Atlanta method will be described in detail, while the Chicago method will be discussed only where it differs from the Atlanta method.

To begin with, the Atlanta method breaks down the value of output (represented by value added) for each industry in the region into two basic components—total cost of labor and total cost of capital services. The capital services component includes other factors, such as business services and overhead costs, as part of value added. Other factors, such as cost of energy and materials, are already excluded from shipments to derive value added. All nominal values are deflated by industry-specific price deflators in order to create “real” values.⁵

As the first model to be tested for its accuracy, the basic equation of “real” output for each regional industry takes the form of the Atlanta method:

$$1) \quad VA = (S_L * Q_L * L) + (S_K * Q_K * K)$$

where:

VA = regional output (measured by value added in constant dollars)

S_L = payroll earnings per value added in constant dollars (or share of labor)

L = total hours worked (amount of physical labor input)

Q_L = value added per L in constant dollars (productivity of labor)

$S_K = 1 - S_L$ (share of capital services)

K = kilowatt hours (proxy for amount of capital services)

Q_K = value added per K in constant dollars (productivity of capital services).

Since deflated ASM values for value added and payroll were used for the in-sample period (1972–1983), Equation 1 leads to an identity, i.e., value of output must equal the value of all inputs. However, projections of the out-of-sample years (i.e., 1984–1985) required some assumptions about the trends in labor and capital shares (S_L and S_K) and the trends in labor and capital productivity (Q_L and Q_K). Following the Atlanta convention, factor shares were held constant at their 1983 levels. The productivity adjustments were allowed to grow at their average annualized rate of growth between 1972 and 1983. That is:

$$\begin{aligned}
S_{1984} &= S_{1985} = S_{1983} \\
S_{K84} &= S_{K85} = S_{K83} \\
Q_{L84} &= Q_{L83} + \{(Q_{L83}/Q_{L72}) - 1\} \\
Q_{L85} &= Q_{L83} + 2*\{(Q_{L83}/Q_{L72}) - 1\} \\
Q_{K84} &= Q_{K83} + \{(Q_{K83}/Q_{K72}) - 1\} \\
Q_{K85} &= Q_{K83} + 2*\{(Q_{K83}/Q_{K72}) - 1\}
\end{aligned}$$

The Chicago method introduces monthly BLS payroll earnings data to approximate ASM payroll earnings. Interestingly enough, the product of S_L and Q_L is simply the price of labor, or the average wage rate for the industry (remembering that payroll earnings is simply the price of labor times hours worked). The product of S_K and Q_K is the price of capital services. Since L and K are known, the model is essentially trying to predict input prices on an *ad hoc* basis. While the price of capital services remains unknown, the price of labor, i.e., wage rates or average hourly earnings, has long been known and is even available on a monthly basis. Furthermore, the cost of labor, or wage rate times hours worked, is readily available as payroll earnings, generated by BLS along with its collection of employment and hours data. In other words, one key variable over the forecast period does not have to be predicted, which theoretically should reduce forecasting errors.

For the calculation of capital services costs in the Chicago method, two different approaches can be used. The first approach strictly parallels the Atlanta method. As such, the second model to be tested simply takes the form:

$$2) \quad VA = PAY + (S_K * Q_K * K)$$

where: PAY = payroll earnings.⁶

The second approach is a 'substitution' approach that can assume a linear relationship between the year-to-year change in the relative price of capital to labor and the capital-labor ratio. That is, one can start with the following regression:

$$3) \quad [(P_{Kt}/P_{Lt})/(P_{Kt-1}/P_{Lt-1})] = b * [(K_t/L_t)/(K_{t-1}/L_{t-1})]$$

where:

- P_{Kt} = price of capital in period t
- P_{Kt-1} = price of capital in period t-1
- P_{Lt} = price of labor in period t
- P_{Lt-1} = price of labor in period t-1
- K_t = amount of capital in period t
- K_{t-1} = amount of capital in period t-1

- L_t = amount of labor in period t
- L_{t-1} = amount of labor in period t-1
- b = regression coefficient.

The above equation is then estimated over the in-sample period. The price of labor is calculated by dividing payroll by the amount of labor. The price of capital, likewise, is equal to the total cost of capital divided by the amount of capital. Using the estimate of b (b') and the known variables in the above equation, an estimate for P_{Kt} (P_{Kt}') can be calculated:

$$3') \quad P_{Kt}' = b' * [(K_t/L_t)/(K_{t-1}/L_{t-1})] * [(P_{Lt}/P_{Lt-1}) * P_{Kt-1}]$$

The estimate for total cost of capital services would be $P_{Kt}' * K_t$. The third model to be tested, therefore, take the form:

$$4) \quad VA = PAY + (P_{Kt}' * K_t)$$

The potential advantages of the Chicago method (either Equation 2 or 4) become apparent in a comparison with the Atlanta method (Equation 1). To begin with, the Atlanta method makes *ad hoc* assumptions about the growth rates of the factor shares and the productivity adjustments. In particular, the use of 1972 as the base year in the calculations of rates of change in factor shares and productivity adjustments over the projected period (1984-85) has no basis in theory. Calculating a rate of change over the longest period allowable by the data would seem intuitively to give the best estimate by avoiding short-term disruptions to the trends. But, in fact, not only does changing the base year result in different predictions of regional output, for some industries the prediction is more accurate if only the most current years are used and for others the best results are provided by using only years in the latter half of the sample period. Table 1 presents the results of the mean absolute errors using each of the years in the sample period as a base. Simply put, there is no single "best" year that can be chosen that will serve as the appropriate base year for *all* industries.

The Chicago method does not take the arbitrary approach of handling share and productivity factors contained in the Atlanta method, at least for its calculation of the labor component. Using the BLS hours and earnings data, a current figure for payroll earnings can be calculated. Unfortunately, that payroll number has gone through several adjustments

TABLE 1

Mean absolute errors of 1984–85 projections for various base years:
Atlanta method (Equation 1)
(percent)

Industries by SIC	Base year										
	1972	1973	1974	1975	1976	1977	1978	1979	1980	1981	1982
20	7.78	5.42	5.36	5.50	6.86	5.82	5.39	4.61	4.05	3.26	4.04
24	8.36	10.28	10.10	8.10	9.48	8.53	10.21	17.81	15.66	17.86	12.57
25	7.84	8.45	7.02	6.37	5.34	7.68	7.48	7.62	7.64	2.28	7.38
26	3.71	4.31	4.16	2.16	1.92	3.48	4.70	2.88	3.58	1.26	10.90
27	4.00	4.66	2.64	1.21	1.00	1.39	1.35	4.12	7.50	10.00	12.44
28	1.48	1.24	2.80	5.88	6.62	7.22	6.70	9.35	12.27	19.78	20.88
29	29.36	34.24	27.21	23.14	31.10	33.80	41.97	7.60	40.16	10.75	12.93
30	7.26	7.84	7.58	4.86	1.55	7.19	5.38	1.32	5.31	5.58	1.08
31	7.00	6.88	7.29	7.56	7.96	7.94	7.18	14.97	16.42	20.91	17.48
32	8.64	9.48	7.75	6.28	5.82	6.34	7.42	5.97	2.29	5.02	4.02
33	16.67	17.00	16.82	13.60	14.65	14.66	16.98	12.72	12.62	12.56	6.69
34	1.40	1.46	2.16	3.14	2.58	2.62	3.62	6.99	11.66	13.86	10.00
35	6.76	7.76	7.74	5.48	5.81	7.02	7.86	8.62	4.72	6.72	4.31
36	6.74	7.21	6.96	5.08	6.82	8.60	9.44	10.00	7.12	4.61	2.26
37	16.70	16.20	17.46	18.12	16.40	17.00	17.03	15.58	25.18	28.50	35.66
38	8.20	9.94	10.44	7.86	7.94	7.57	7.96	8.08	4.56	4.96	12.95
39	1.56	1.21	1.65	2.60	1.40	2.48	1.86	2.62	15.84	14.46	2.87
Total	8.06	8.06	8.20	7.52	7.76	8.34	8.68	9.00	10.33	11.89	11.96

SOURCE: Federal Reserve Bank of Chicago.

(described in footnote 6) and these adjustments may not yield a close enough correlation to ASM payroll earnings to generate a better prediction than the Atlanta method.

Another option offered by the Chicago method is the choice between an *ad hoc* projection of the total cost of capital services and a projection with a theoretical foundation. Utilizing basic economic theory, one would expect a decrease in the capital–labor ratio, if there is an increase in the relative price between capital and labor. In other words, the substitution approach (Equation 4) can treat capital and labor as substitutes.

The results of the tests to determine mean absolute error in the projection of value added with a nonparametric approach are not encouraging. Indeed, as shown in Table 2, the Atlanta method did better than either of the models using the Chicago method. However, it was equally clear that the results were again not consistent across all industries. Some industries did much better using the Chicago method than the Atlanta method, and some

industries did better using the Atlanta approach for projecting total capital costs within the Chicago method, even though the Atlanta method still provided the best overall model for constructing the manufacturing index.

Parametric models

Five parametric models are derived from a microeconomic foundation. As opposed to *ad hoc* methods, a microfoundation makes the results theoretically consistent, offers straightforward interpretation of the parameters, and presents additional material for microeconomic analysis. A traditional Cobb–Douglas (C–D) production function is initially applied to the sample data set, in order to repeat Fomby's experiment. However, unsatisfactory results necessitated some changes that resulted in a C–D-type model and a nonlinear model, both of which use L , K , and time as the only exogenous variables. For the first model, the restriction of linear homogeneity is removed from the traditional C–D model to derive a generalized C–D model. For the second

model, even greater nonlinearity is introduced through a functional form that allows for variable returns to scale and variable elasticities of substitution, based on the model introduced by Vinod.⁷ Finally, a set of three models using the Chicago method (parametric version) are devised to incorporate payroll data, by utilizing a translog production function, based on the model developed by Christensen, Jorgenson, and Lau with all the traditional restrictions on the translog coefficients.⁸

To begin with, the most basic parametric model in this analysis is a generalized C-D model, where no restrictions on the sum of the coefficients, a_l and a_k , are imposed. As the fourth model in the series to be tested, then, the generalized C-D model takes the form:

$$5) \ln VA = a_0 + a_l \ln L + a_k \ln K + a_t T$$

where \ln = logarithmic values of variables
 t = time trend

(The time subscripts on variables are dropped for convenience.)

Another parametric model is a nonlinear model that includes the product of logs of labor and capital in addition to the traditional C-D variables. As the fifth model to be tested, the nonlinear model takes the form:

$$6) \ln VA = a_0 + a_l \ln L + a_k \ln K + a_{lk} \ln L \ln K + a_t T$$

Both this model (Equation 6) and the earlier model (Equation 5) present capital and labor as the only observed regressors (besides the time trend).

As mentioned above, the purpose of this analysis is to introduce payroll data into the forecast of the out-of-sample period. This purpose can be achieved by manipulating a translog production function of the general form:

$$7) \ln VA = a_0 + a_l \ln L + a_k \ln K + a_{lk} \ln L \ln K + .5 a_{ll} (\ln L)^2 + .5 a_{kk} (\ln K)^2 + a_t T$$

The first half of the right-hand side of the equation is identical to Equation 6. The quadratic terms in the second half of the equation add flexibility to the model, but do not yet introduce payroll data into the analysis.

Three steps are required to incorporate the variable, payroll earnings, into the analysis. The first is to substitute $DLK = \ln L - \ln K$

TABLE 2

Mean absolute errors of 1984-85 projections for 1972 base year (percent)

Industries by SIC	Atlanta (Eq. 1)	Chicago w/Atl exten. (Eq. 2)	Chicago w/subst. (Eq. 4)
20	7.83	4.94	10.14
24	8.36	15.74	12.22
25	7.84	5.04	9.03
26	3.70	4.20	7.22
27	4.00	0.62	0.56
28	1.48	2.39	14.03
29	29.36	17.58	14.92
30	7.26	10.54	20.57
31	7.00	7.28	30.84
32	8.64	3.10	1.80
33	16.67	16.76	23.25
34	1.40	2.08	0.28
35	6.76	2.13	2.26
36	6.74	5.44	6.83
37	16.70	25.42	39.18
38	8.20	9.68	19.59
39	1.56	2.76	1.48
Total	8.06	8.20	13.31

SOURCE: Federal Reserve Bank of Chicago.

into Equation 7. Due to the restrictions imposed on the translog function, Equation 7 can now be rewritten as:

$$7') \ln VA - \ln K = a_0 + a_{lk} DLK - .5 a_{ll} DLK^2 + a_t T$$

Note that this modification of the translog form reduces the number of variables in Equation 7 to the same number as in Equation 5, the unrestricted C-D form. This is especially beneficial in the case of a small number of observations (as is the case in this analysis). While a more general functional form than the traditional C-D model, the translog model with its parametric restrictions is not necessarily more general than the unrestricted C-D model (Equation 6).

In the second step for introducing payroll into the model, a derived demand for labor must be obtained. Assuming Shepard's lemma, the labor share (S_L) equation can be derived from the translog Equation 7):

$$8) S_t = a_1 + a_{1L} \ln L + a_{1K} \ln K$$

where the right-hand side of Equation 8 is derived as the logarithmic derivative of VA in Equation 7 in respect to labor (L). Equation 8 can be modified to:

$$8') S_t = a_1 + a_{1L} DLK$$

Substituting 8' into 7', one derives:

$$9) \ln VA - \ln K = a_0 + S_t DLK + .5 a_{1L} DLK^2$$

In addition to the traditional regressors of labor and capital, Equation 9 now includes the payroll variable (as part of S_t). Note that the S_t variable is observed for the in-sample period (1972-83), but is not observed for the forecasting period (1984-85). The problem is to find a way either to estimate a value for S_t , or to get it out of the equation without losing the payroll variable.

For the final step, three variations of Equation 9 are found to solve the problem, while accomplishing the purpose of including the payroll variable. As such, Equation 9 is the fundamental equation for this paper. For the first variation, payroll earnings (PAY) is assumed to have the same variations as the share of labor, so that PAY can be substituted directly into the model as a proxy for S_t . As a result, Equation 9 is modified to become the sixth model to be tested, with the form:⁹

$$10) \ln VA - \ln K = a_0 + a_{pp} PAY * DLK + .5 a_{1L} DLK^2 + a_1 DUM * T$$

where

$$DUM = 0 \text{ if } < 1982 \\ = 1 \text{ if } > 1982$$

Utilizing Equation 10 and payroll earnings data, one can forecast the S_t variable in Equation 9. For the experiment, Equation 9 is estimated and then VA is predicted, using forecasted S_t . For estimation of Equation 9, one has to realize that S_t may deviate from the 'true' share variable, due both to assumptions imposed on the translog coefficients and to measurement errors. Therefore, the share variable is treated as a regressor in Equation 9. Equation 9 now becomes the seventh model to be tested, with the form:

$$11) \ln VA - \ln K = a_0 + a_{sp} S_t DLK + .5 a_{1L} DLK^2$$

For most of the industries, the coefficient, a_{sp} , is significantly different from unity. The nominator for S_t (i.e., PAY) is derived from the BLS data and the denominator (VA) is estimated from Equation 10.

Finally, by substituting $S_t = PAY/VA$ into Equation 9 and rearranging terms, one can derive the eighth and final model to be tested, with the form:

$$12) F = VA \ln VA - (\ln K + a_0 + .5 a_{1L} DLK^2) VA - DUM * PAY = 0$$

All variables in Equation 12 are observed for the out-of-sample period. Therefore, after estimating Equation 9, Equation 12 can be solved with respect to VA , in order to get forecasts for the out-of-sample period. Nonlinearity with respect to VA in this equation does not present a problem, since function F has only two roots. This can be inferred from the first derivative of F with respect to VA :

$$13) F_{VA} = \ln VA + \text{constant}$$

For practical purposes, VA is always greater than one, which insures the choice of one root.

In all, five parametric models are tested and five sets of forecasts are derived. Errors of forecasts are recorded in Table 3. A plus sign indicates the minimum value of the forecasting error for each industry. At the bottom of Table 3, weighted sums of errors are presented. Weights are derived from shares of value added for each industry for 1985. Errors in Table 3 are mean absolute errors, combined for 1984 and 1985. Errors of each procedure correspond to the indicated equation.

Among the parametric models, the use of only capital and labor variables fails to improve upon the accuracy of the Atlanta method (equation 1). This is consistent with Fomby's results. Moreover, only two industries (SIC 26, paper and paper products, and SIC 34, fabricated metals) have the best results using either equation 5 or 6.

The main objective of this analysis, however, is to determine whether the new variable, payroll, is beneficial to the index. Here, two models using the Chicago method (Equations 10 and 11) did better than models using only K and L as exogenous variables. Equation 10 provides the smallest error, only 7.3 percent for the combined two years. Indeed, this error

TABLE 3

Mean absolute errors of 1984–85 projections, parametric models
(percent)

Industries by SIC:	Models w/K & L		Translog model w/K, L & PAY		
	Generalized C–D model (Eq. 5)	Vinod model (Eq. 6)	PAY as proxy for S_L model (Eq. 10)	S_L as regressor model (Eq. 11)	Nonlinear model (Eq. 12)
20	0.134	0.126	0.071+	0.103	0.106
24	0.074	0.085	0.187	0.069+	0.156
25	0.068	0.073	0.009+	0.021	0.168
26	0.033	0.014+	0.023	0.017	0.017
27	0.052	0.126	0.046+	0.084	0.123
28	0.228	0.229	0.154+	0.291	0.256
29	0.364	0.278	0.179+	0.366	0.555
30	0.051	0.034	0.031+	0.158	0.145
31	0.229	0.093	0.159	0.119	0.090+
32	0.115	0.137	0.026	0.016	0.010+
33	0.224	0.226	0.297	0.124	0.026+
34	0.063	0.059+	0.061	0.102	0.087
35	0.061	0.092	0.024+	0.087	0.173
36	0.030	0.031	0.029+	0.064	0.139
37	0.118	0.132	0.084	0.023	0.019+
38	0.077	0.032	0.025+	0.047	0.239
39	0.052	0.063	0.024	0.051	0.023+
Total	0.100	0.107	0.073	0.093	0.115

NOTE: Plus sign (+) denotes lowest error per industry among parametric models.

SOURCE: Federal Reserve Bank of Chicago.

is 0.8 percentage points lower than the Atlanta method, which represents an improvement of 10 percent over the accuracy of the Atlanta method. Thus, if one is looking for a parametric method to construct indexes that is still relatively straightforward, Equation 10 would provide an index with better accuracy than the Atlanta method. Based on the data sample used in this study, therefore, *Fomby's finding that nonparametric models outperform parametric models is rejected.*

Finally, if one would choose the best results for each industry among the five parametric models in Table 3, based on the *a posteriori* results (indicated by pluses), the total error is reduced to only 4.3 percent for the combined two years—roughly half the error generated by the Atlanta method. An error of this small magnitude (averaging about 2 percent per year) is a substantial accomplishment and would strengthen the credibility of regional manufacturing indexes.

Building a better model

The basic findings of this study can be summarized as follows. First, in repeating Fomby's analysis of the accuracy of manufacturing indexes using the same variables but an entirely different set of data, this study derived identical results—the simple Atlanta method provides better results than any other nonparametric method or parametric method. Second, however, when the new variable—payroll earnings—is added to the models, Fomby's results are completely reversed. With the new variable, the parametric models do better than nonparametric models. Finally, and most importantly, the study finds that no single method can be found that produced the lowest mean absolute errors for all industries in the set. In other words, even better results can be obtained by modeling each industry individually to find the lowest predicting error, and then combining all the industry series into an aggregate manufacturing index, based on

weights derived from each industry's share of total value added.

The results of this study are interesting from a purely academic perspective, but they have a very direct application as well. As regional manufacturing indexes gain wider usage both inside and outside the Federal Reserve System, the accuracy of these indexes will become an increasingly important issue. As more indexes are tested for the best mod-

els, discoveries and innovations can be quickly incorporated into other regional indexes.

Work currently underway to revise the Midwest Manufacturing Index builds on the knowledge gained by this study and is expected to improve significantly the accuracy of the index. The ultimate goal of research in this area should be to develop regional indexes that have as much credibility as the Federal Reserve Board's Index of Industrial Production.

FOOTNOTES

¹See, for example, *Chicago Fed Letter*, Federal Reserve Bank of Chicago; *The Southwest Economy*, Federal Reserve Bank of Dallas; *Mid-Atlantic Manufacturing Index*, Federal Reserve Bank of Philadelphia; *Cross Sections*, Federal Reserve Bank of Richmond; and *Economic Trends*, Federal Reserve Bank of Cleveland, various issues. Indexes also are incorporated into analyses of business conditions of District economies. See, for example, Israilevich and Schnorbus (1988) and Schnorbus and Israilevich (1989).

²See Pym, C.S., 1970.

³See Fomby, 1986.

⁴The total index is then calculated as a weighted average of all the industries (seventeen, in the case of the MMI), using each industry's annual share of total value added in the region.

⁵The amount of physical output produced in a region is approximated by the current dollar value of shipments less cost of materials (i.e., value added) that is adjusted for inflation. This method of approximating "real" output is vulnerable to a variety of problems that are common to deflators, but for which there are few alternatives. For further discussion, see A.S. Giese, (1989).

⁶While BLS employment data cover both the number of production and supervisory workers in the same way as ASM employment, BLS coverage of payroll earnings differs from ASM coverage. BLS earnings data cover only production workers. Therefore, a two-step adjustment needs to be made to the BLS earnings data in order for them to represent earnings of total employees on an ASM basis. First, using ASM data from the in-sample period, a ratio of total earnings to production earnings can be calculated. Then, using this ratio, the following adjustment to BLS production earnings per worker can be made:

$$\text{EARN}' = \text{EARN} * \text{TE83/PE83} * [1 + \{(\text{TE83/PE83}/\text{TE72/PE72}) - 1\}]$$

where:

TE83 = total earnings in 1983 (ASM data)

TE72 = total earnings in 1972 (ASM data)

PE83 = production earnings in 1983 (ASM data)

PE72 = production earnings in 1972 (ASM data)

EARN = production earnings per worker in 1984-85 (BLS data)

Second, payroll earnings on a ASM basis (RP_{ASM}) for total employment is then calculated by multiplying the adjusted earnings (EARN') by total employment (EMP) from BLS, such that:

$$RP_{BLS} = \text{EMP} * \text{EARN}'$$

An additional adjustment is made to account for differences in sampling between ASM and BLS data, which was done in the following manner:

$$RP_{ASM} = \text{DUM} + bRP_{BLS}$$

where:

DUM = 1, if year \leq 1975

0, if year $>$ 1975

RP_{BLS} = real payroll earnings (BLS data)

RP_{ASM} = real payroll earnings (ASM data)

b = regression coefficient on RP_{BLS} .

The estimate of payroll earnings to be used in the model, then, is:

$$\text{PAY} = b' * RP_{BLS}$$

where:

PAY = calculated value of real payroll earnings,

b' = estimate of b

⁷See Vinod, 1977.

⁸See Christensen, et al (1973).

⁹Because payroll data are provided by both ASM and BLS, alternative selections of this variable are created for the in-sample period. (For the out-of-sample, only BLS data are available). The differences between the BLS and ASM sources were greater at the beginning of the period than at the end of the period. The two last years of the in-sample period represent the beginning of a new business cycle. For these two reasons, payroll for the 1982 and 1983 period was adopted from BLS. This, in turn, requires the addition of a dummied time variable, DUM*t.

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