A DYNAMIC SIMULATION MODEL OF AN OHIO METROPOLITAN ECONOMY

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I. INTRODUCTION

Development and application of regional econometric models for simulations of scenario analysis and forecasting have burgeoned since the late 1950's. Surveys by Bolton, Chen, and Knapp, et al show that the spectrum of regional econometric models varies from small country models to very large multiregional models.[2] Some of these models were constructed to generate forecasts, others were designed specifically for public policy simulation uses, and then there were models built for multiple purposes.

Our paper is concerned with the development of a short-term, multi-equation econometric model designed to generate quarterly forecasts of labor market activities on an ongoing basis and to conduct special situation scenarios such as the impact of changes in public policy or a local plant closing on area employment. There are two reasons why this labor oriented modeling approach was employed. First, timely data related to real output, consumption and investment are either not available or are available but not on a continuous basis. Thus, the typical macroeconomic models constructed at the national level are impossible to replicate as an ongoing project at the metropolitan level. Second, the Canton area economy, being a part of the Great Lakes regional economy, has experienced significant structural changes due to the decline in the production of steel and steel-related products. For example, between 1972 first quarter and 1982 first quarter, Canton area manufacturing jobs declined from 56,000 to 52,000 while the area's total employment increased from 138,000 to 151,000.[3] Employment in manufacturing as a percent of the area's total employment dropped by about six percentage points, from 40.6 percent in the first quarter 1972 down to 34.7 percent in the first quarter of 1982. The decline in the proportion of manufacturing jobs has a significant impact on the local economy because this sector typically generates far more income per manhour worked than nonmanufacturing jobs. In Canton, the average weekly wage in nonmanufacturing was two-thirds of that in manufacturing in 1972, and that proportion declined to 58 percent in 1982. Faced with a slowdown in the job growth rate and a change in the composition of employment, local public agencies have been keenly interested in labor market dynamics. A labor oriented econometric model can be a very useful tool to analyze the impact of any new business entrant or expansion of a local firm on total area employment and wage income. More specifically, alternative development scenarios could be produced and the aggregate employment and wage income consequences estimated by use of our model.

II. THE MODEL AND THE SPECIFICATION OF THE STRUCTURAL EQUATIONS

The Canton model is a quarterly econometric model that contains a total of eighty equations, forty-five of which are stochastic equations and the rest identities. These equations are designed to explain variation in manhours of work, employment, weekly wages and the wage bill for manufacturing and nonmanufacturing sectors. Table 1 gives a list of all two-digit sectors contained in the Canton model. It shows that there is a total of fifteen of them, eight in manufacturing and seven in nonmanufacturing activities. Among the manufacturing group, food and kindred products sector (SIC 20) and the rubber and miscellaneous plastic products sector (SIC 30) make up the manufacturing nondurable activities, and the remaining six sectors constitute the manufacturing durable activities.

Local manufacturing activities are linked to the relevant sectoral activities at the national level. This linkage is unidirectional in the sense that national economic activities impact on the Canton area, not vice versa. This methodology makes the Canton model a member of a group of models referred to as "top-down" models where national variables "drive" regional sectors, a procedure in building regional econometric models which has been advocated by Klein.[4] In his 1985 article, Bolton argues that the feedback from regional models to national models only makes sense in cases where:

> "(a) a region's labor market is large enough to affect national labor costs, e.g., California, or Southeast England, or the Paris Basin, or Stockholm; (b) a region is a dominant producer of one or more products, the exports or imports of which affect the national balance of payments and thus affect financial markets and endogenous policy reactions; (c) a region's governmental policies affect national product markets. Some regions' position in energy production raises possibilities under (b) and (c)."[5]

The Canton metropolitan area, with a population of 380,000 in 1984, does not have a dominant producer of any product nor does its metropolitan public policies impact importantly on national markets. It is appropriate, then, to link the Canton economy to the national economy undirectionally.

To facilitate explanation, all eighty equations are grouped into four blocks: A manhour block, employment block, weekly wage block, and wage bill block. Specifications of equations for individual sectors are discussed next for each block.

(A) Manhour Equations

The model has a total of twenty manhour equations. Fifteen of them are behavioral equations designed to describe manhour activities among the two digit SIC sectors. The five remaining equations are identities defining the manhour activities at the aggregate level, i.e., manufacturing durables, manufacturing nondurables, total manufacturing, total nonmanufacturing, and the metropolitan total.

The specification of behavioral equations within the manhour block is derived from combining a labor requirement model with a labor adjustment model as presented by Intrilligator; Hickman, Coen and Hurd; and McCarthy, Riordan and Storey.[6] The labor requirement model and the labor adjustment model are given, respectively, by equations (1) and (2):

$$(1)\quad Y = a\,L^{b}K^{c} \qquad a>0,\ 0<b,\ c<1$$

$$(2)\quad L/L(-1) = (L^{*}/L(-1))^{d} \qquad 0<d<1$$

where Y denotes real output, L manhour, K capital stock, L(-1) manhour lagged by one quarter, L^* an equilibrium level of manhour to which the short-run manhour will adjust, and d an adjustment factor. The speed of adjustment depends upon the availability of qualified workers and the cost of overtime within a given sector.

Expressing equations (1) and (2) in log form and solving for ln(L) yields the equation

$$(3)\quad \ln(L) = -d*\ln(a/b) + (d/b)*\ln(Y^{*}) - (cd/b)*\ln(K^{*}) + (1-d)*\ln(L(-1))$$

Since the desirable or equilibrium level of capital stock (K^*) is unobservable and since the Canton model is a quarterly model, it is assumed that K^* remains constant in the short-run. The equilibrium level of sectoral real output Y^* is also unobservable; thus, the local real wage bill or a national industrial production index has been used as a proxy variable for Y^* in each sector. Adding trend (TREND), seasonal dummy variables (SD1, SD2, SD3) and a dummy variable for the 1973-75 recession (RD) to equation (3) results in the specification of the behavioral equations in the manhour block as

$$(4)\quad \ln(L) = A_0 + A_1*\ln(PROXY) + A_2*\ln(L-1)) + A_3*SD1$$

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$+ A_4*SD2 + A_5*SD3 + A_6*RD + A_7*TREND + e$

where $A_1 = (d/b)$ and $A_2 = (1-d)$ whose values are expected to be positive, and and A_6 is the coefficient of the recession dummy variable (RD) which should have a negative sign, and e is a stochastic disturbance term having the typical assumptions. The dummy variables are defined as

SD1 = 1 if first quarter, 0 otherwise,
SD2 = 1 if second quarter, 0 otherwise,
SD3 = 1 if third quarter, 0 otherwise,
RD = 1 if 1973-75, 0 otherwise.

(B) Employment Equations

Among the twenty employment equations in the model, fifteen of them are behavioral equations and the other five are identities. Sectoral employment fluctuations are assumed to follow a similar adjustment mechanism as in the case of manhour equations, where actual employment (E) adjusts itself toward an equilibrium level of employment (E^*).[7] The adjustment process is described by:

(5) $E/E(-1) = (E^*/E(-1))^e \quad 0<e<1$

where e is an adjustment factor. The speed of adjustment is a function of cost of hiring, training, firing, and the efficiency of the local labor market.

Since quarterly manhour and quarterly employment are linked by definition as

(6) L = E * Average Weekly Hours * 13,

combining this relation with equations (3) and (4) produces the general specification for sectoral employment equations as follows:

(7) $\ln(E) = B_0 + B_1*\ln(L) + B_2*\ln(1-1)$

$+ B_3*\ln(E(-1)) + B_4*SD1 + B_5*SD2$

$+ B_6*SD3 + B_7*TREND + u$

where $B_0 = e*\ln(g)$, $B_1 = e/d$, $B_2 = e(d-1)/d$, and $B_3 = (1-e)$, and where the values of B_1 and B_3 are expected to be positive and B_2 to be negative, and u denotes the standard stochastic disturbance term.

(C) Weekly Wage Equations

Since some local manufacturing wage rates have been set by national wage agreements, such as in steel and electric machinery, local manufacturing wages (WW^{MF}) are assumed to be a function of the national wages (WW^{US}) of the same sector. Local nonmanufacturing wages (WW^{NM}) are assumed to follow the wage patterns set by local manufacturing sectors and are thus functions of local manufacturing wages. For example, wage rate negotiated in the fabricated metal sector at the national level will also prevail at the local level, and when transportation, communications, and public utilities workers and management negotiate for their wage contracts, the final settlements are generally affected by the pattern set by the local fabricated metal sector. In addition, a one-quarter lagged wage variable of the same sector is also included as an explanatory variable in order to capture the dynamics of sectoral wage agreements.

The specification of the local manufacturing sectors weekly wage equations is thus given in the following general form:

(8) $\ln(WW^{MF}) = C_0 + C_1*\ln(WW^{MF}(-1)) +$

$C_2*\ln(WW^{US}) + C_3*SD1 + C_4*SD2 +$

$C_5*SD3 + C_6*TREND + v$

where C_1 and C_2 are expected to be positive, and v is a stochastic disturbance term.

Local nonmanufacturing weekly wage equations take the form:

(9) $\ln(WW^{NM}) = D_0 + D_1*\ln(WW^{NM}(-1)) +$

$D_2*\ln(WW^{MF}) + D_3*SD1 + D_4*SD2 +$

$D_5*SD3 + D_6*TREND + w$

where D_1 and D_2 are expected to be positive, and w is a stochastic disturbance term.

(10) Wage Bill Equations

All twenty wage bill equations are identities. At the sectoral level (i.e., two-digit SIC level), the wage bill is defined as:

(10) wage bill = employment * weekly wage * 13.

At the aggregated level, wage bills are defined as the sum of the wage bills of their respective components. For example, Canton's total wage bill is given by the identity:

(11) Total wage = MWB + NMWB,

where MWB and NMWB are, respectively, manufacturing and nonmanufacturing wage bills, and MWB is computed as:

(12) MWB = MFDWB + MFNWB,

where MFDWB and MFNWB are the durables and nondurables wage bills.

III. ESTIMATION OF THE MODEL

The sample period used to estimate the parameters of all behavioral equations, except those equations describing the local government sector, typically covers 60 quarters, from 1965 first quarter through 1979 fourth quarter.[8] Complete labor market data pertaining to government sectors are only available after 1971. Thus, only 30 quarters of observations, between the first quarter 1972 and the fourth quarter 1979, were used to estimate equations related to government activities.

All forty-five behavioral equations were estimated by the ordinary least squares (OLS) procedure. Using OLS estimation procedure in a simultaneous equation system results in biased and inconsistent estimators. However, other single equation estimation procedures as well as system estimation procedures also have their respective problems.[9] Since there are occasions where OLS may yield "good" estimators in terms of a certain set of criterion, OLS has continuously been used as an estimation method in building multi-equation regional models. Examples of regional models using OLS as the estimation procedure include the Mississippi model by Adams, Brookings and Glickman, the Ohio model by Baird, and the Philadelphia model by McCarthy, Riordan and Storey.[10] Furthermore, our experience in estimating the equations for a similar model indicates no pronounced differences in results between using OLS and the two stage least squares (TSLS) procedures.[11]

The decision rules used to evaluate and select the explanatory variables for inclusion in each stochastic equation follow those adopted by Liu and Hwa in their monthly econometric model of the U.S. economy.[12] That is, after each behavior equation is specified and estimated, the variables with incorrect signs, in terms of a priori theoretical or institutional reasoning, attached to their respective coefficients are either dropped from the equation or the equation is reestimated using a different sample period, and/or the equation is reestimated in non-log form. Further, all variables with correct signs attached to their estimated coefficients are included in the final equations regardless of whether the values of these estimates are statistically significant or not. For example, contract construction manhours typically reach their peak during the third quarter of a year, hence the coefficient for the third quarter seasonal dummy variable should be positive in value. If the estimated coefficient value of this dummy variable is positive but not statistically significant, we still would include this third quarter dummy variable. Other things being the same, the forecasts of construction manhours associated with the third quarter would be higher than that of the fourth quarter of the same year because of the presence of the third quarter dummy varible. On the other hand, if the estimated coefficient value of the third quarter dummy variable turns up to be negative in an equation describing contract construction manhours, then regardless of whether the estimate is statistically

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significant or not, the third quarter dummy variable would be dropped from this particular equation.

Results from the estimated equations are summarized in Tables 2 and 3.[13] Table 2 shows that in terms of R^2 values there are more successes in fitting individual employment and average weekly wage series than manhour series. Out of a total of 15 manhour series there are only 3 of them having R^2 values of .95 or higher. On the other hand, there are 13 employment equations and 12 weekly wage equations having R^2 values in this range. One reason for this discrepancy seems to be the greater volatility of manhours during cyclical episodes than in the case of employment and wages. Employers, confronted with high costs of firing, hiring, training and paying fringe benefits, generally vary manhours worked in terms of more or less work hours, instead of changing employment level to meet changing market demand for product.

In addition, within the manhour, employment and weekly wage sectors there are large variations in R^2 values. In general, since nonmanufacturing activities are more stable in nature than those in manufacturing, the estimated R^2 values are generally higher in the nonmanufacturing than in the manufacturing sectors. As shown in Table 3, whereas there are 16 out of a total of 21 non-manufacturing sectors having R^2 values of .95 or better, there are only 12 of the 24 manufacturing sectors with comparable R^2's.

IV. SIMULATION AND EX POST FORECASTING

To assess the performance of the Canton model as a whole system of equations, the model was simulated historically and dynamically using the Gauss-Seidel iterative procedure. The simulations cover the sample period of 1972 second quarter through 1979 fourth quarter. In the historical simulation, the actual values of the right hand side lagged endogenous variables are used to simulate all endogenous variables of the current quarter, thus forcing the simulation back on track. In contrast, the dynamic simulation employs only simulated values for the right hand side lagged endogenous variables, leading to cumulative errors over time in simulating the current endogenous variable.

Simulation errors as measured by the root-mean-square percent error (%RMSE) were computed by the following expression:

$$(13)\quad \%RMSE = ((1/T)\Sigma((S_t - Y_t)/Y_t)^2)^{1/2},$$

where S_t is the simulated value of an endogenous variable, Y_t is the actual value of the same variable at time t, and T is the number of time periods in the simulation. Results are summarized in Tables 4 and 5.

Table 4 presents a frequency distribution of root-mean-square percent simulation errors by variable which reveal the following issues worthy of note:
(1) As would be expected, the errors associated with the historical simulation are typically smaller in value than the errors associated with the dynamic simulation for reasons discussed above. For example, among a total of 80 endogenous variables contained in the model, the historical simulation resulted in 22 %RMSE's having values smaller than 2 percent, whereas the dynamic simulation yielded only 12 %RMSE's with values smaller than 2 percent. While there are 31 %RMSE's having values greater than 5 percent in the dynamic simulation, the number of %RMSE's with values larger than 5 percent drops to 22 in the historical simulation.
(2) The model simulates better, as measured by smaller %RMSE, sectors in employment and average weekly wage than sectors in manhours and the wage bill. For instance, among a total of 20 variables in each one of the four categories (i.e., manhours, employment, weekly wage and wage bill), 12 of the manhour series and 8 of the wage bill series have %RMSE's less than 5 percent, while the number increases to 14 for the employment series and 15 for the weekly wage series.

Table 5 presents errors of both the dynamic and historical simulations in terms of activity, whether a sector is in manufacturing or non-manufacturing, in manufacturing durables or manufacturing nondurables. As shown in Table 5, the model simulates better in nonmanufacturing activities and activities at the aggregated levels (i.e., total manufacturing activities, total non-manufacturing activities at the Canton metropolitan level) than in manufacturing activities. For instance, under dynamic simulation, there is not a single %RMSE with a value of less than 2 percent among the 20 sectoral manufacturing activities (including manufacturing durable and manufacturing non-durable sectors). However, the same dymanic simulation yielded 12 %RMSE's with values less than 2 percent for non-manufacturing activities and activities at the aggregated levels. Simulation errors resulting from historical simulation show even greater disparity between manufacturing and other activities. For example, while there is only one %RMSE less than 2 percent among sectoral manufacturing activities, there are 21 %RMSE's having values smaller than 2 percent among sectoral non-manufacturing activities and activities at the aggregated levels.

Comparing the distributions of R^2 values given in Table 2 and 3 with the distribution of simulation errors presented in Tables 4 and 5, it seems safe to conclude that, as far as this study is concerned, variables and activities which have closer regression fits at the estimation stage tend to have smaller model simulation errors. Variables and activities with poor regression fits and hence low R^2 values are usually the same variables and activities which have poor simulation results and thus high %RMSE's.

Dynamic simulation results for Canton area manhours, employment, average weekly wage and wage bill are plotted in Figures 1 through 4. The vertical lines located at the fourth quarter of 1979 partition these time series to the within sample period and beyond sample period series. Within the sample period, the actual series are represented by the solid lines, and the simulated series by the dashed lines. These figures provide further evidences that the model tracks closely activities at the metropolitan level. In addition, these figures shows that the model not only simulates well the seasonal fluctuations, but also the turning points associated with the cyclical movements of these series. Considering the large swings in both the manhour and employment series during the middle of the 1970's, these dynamic simulation results are gratifying.

Figures 1 through 4 also show the series of ex post forecasts generated by the model. These forecasts are represented by the dotted lines beyond the fourth quarter of 1979. In generating the series of ex post forecasts, actual values of the exogenous variables are used, but values of all the lagged endogenous variables are generated by the model, a process similar to that of within sample dynamic simulation. Figures 1 through 4 show that the model performs well in generating ex post forecasts of metropolitan area average weekly wages and the wage bill within a time horizon of two years; however, the accuracy of these ex post forecasts deteriorate rapidly beyond the two year time horizon. The ex post forecasts of Canton metropolitan area manhour and employment activities do not perform as well. The ex post forecasts start to deviate sharply from the actual series beyond the two quarters, and the deviations become larger rapidly as the forecasting horizon increases.

Summary error statistics associated the ex post forecasting for the entire model are presented in Tables 6 and 7. Table 6 shows the root-mean-square percent ex-post forecasting error (%RMSFE) by variable, and Table 7 reveals these forecasting error statistics in terms of activity. The %RMSFE is computed as:

$$(14)\ \%RMSFE = ((1/T)\Sigma(F_t = Y_t)/Y_t)^2)^{1/2}$$

where F_t and Y_t denote the forecasted and actual values of an endogenous variable, respectively, and T is the number of time periods used in the

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FIGURE 1. CANTON METROPOLITAN QUARTERLY MANHOURS: ACTUAL SERIES SIMULATED SERIES, AND EX POST FORECASTS, 1972.2 THROUGH 1983.4

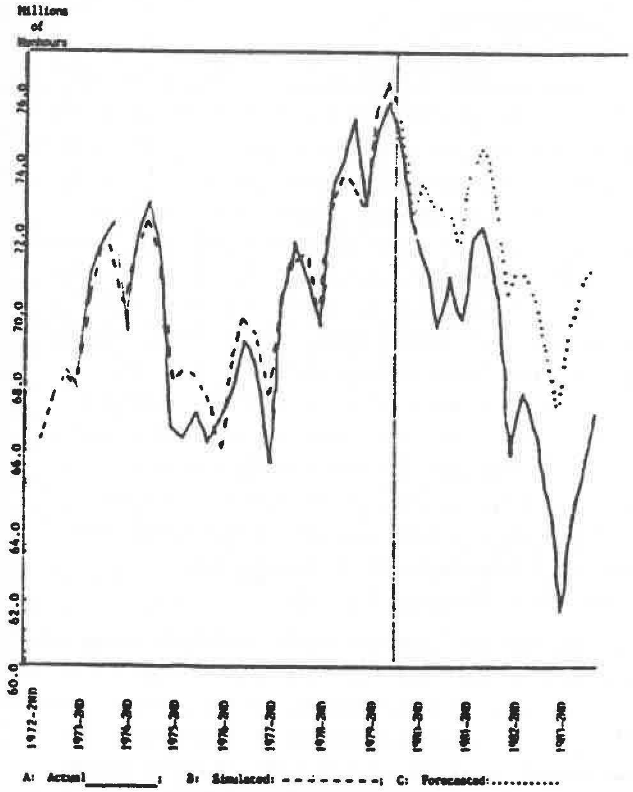


FIGURE 2. CANTON METROPOLITAN QUARTERLY EMPLOYMENT: ACTUAL SERIES SIMULATED SERIES, AND EX POST FORECASTS, 1972.2 THROUGH 1983.4

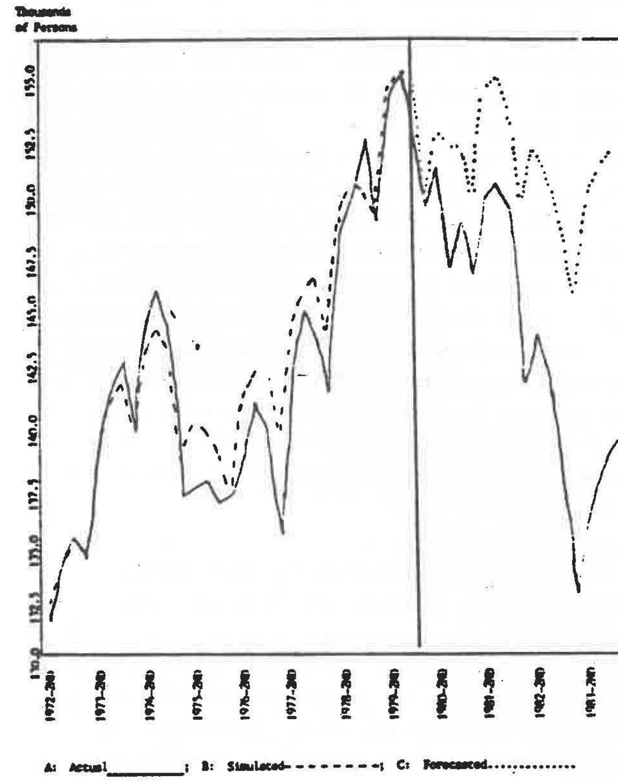


FIGURE 3. CANTON METROPOLITAN AVERAGE WEEKLY WAGE: ACTUAL SERIES SIMULATED SERIES, AND EX POST FORECASTS, 1972.2 THROUGH 1983.4

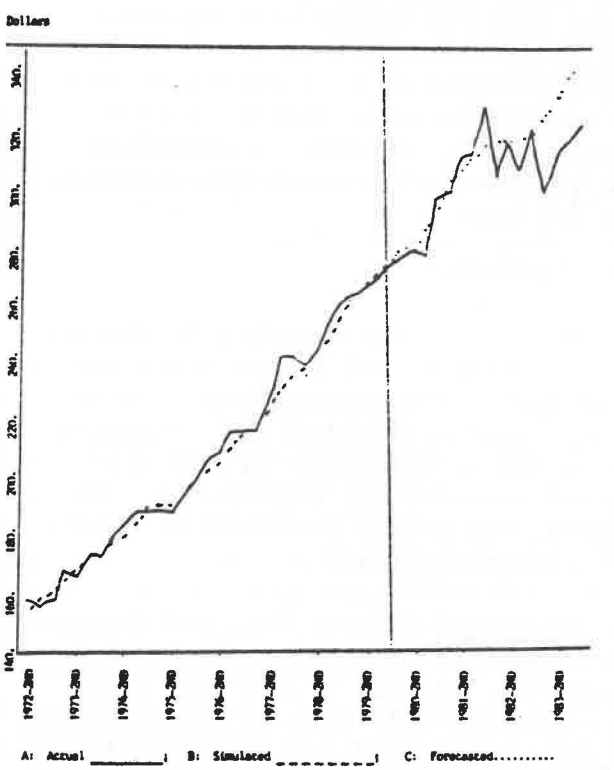
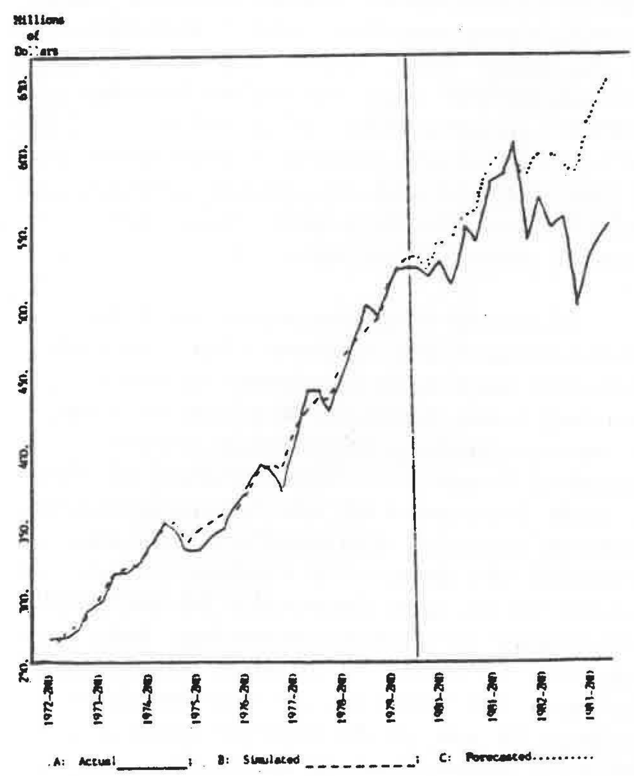


FIGURE 4. CANTON METROPOLITAN QUARTERLY WAGE BILL: ACTUAL SERIES SIMULATED SERIES, AND EX POST FORECASTS, 1972.2 THROUGH 1983.4



simulation.

Magnitudes of these forecasting error statistics should be interpreted with care, because these error statistics are functions of time horizons. As we forecast further into the future, values of these error statistics generally increase quickly. For example, it is meaningless to compare the root-mean-square percent ex post forecasting error generated by this model with those generated by another model if the ex post forecasts produced by the other model cover a time horizon only two or three periods beyond the sample period. Nevertheless, the distributions of these forecasting error statistics are very useful in comparing the model's ability in forecasting different components of the model.

As shown in Table 6, the model performs much better in forecasting average weekly wage variables than for manhour, employment and the wage bill. While there are 11 average weekly wage variables having ex post forecasting errors less than 5 percent, there are only 3 manhour and 5 employment variables having ex post forecasting errors less than 5 percent. None of the 20 wage bill variables has an ex post forecasting error smaller than 5 percent. On the other hand, there are only 3 average weekly wage variables having %RMSFE's greater than 10 percent, while nine of the %RMSFE's from each of the manhour and employment groups and 11 from the wage bill group are greater than 10 percent.

In terms of forecasting sectoral activities, Table 7 shows that the model performs better in forecasting nonmanufacturing sectoral activities than in manufacturing, especially manufacturing durables. The accuracy of the ex post forecasts of total manufacturing, nonmanufacturing and metropolitan activities are generally similar in accuracy to ex post forecasts of sectoral activities in nonmanufacturing, but superior to those in durable manufacturing. For example, in non manufacturing, 16 out of 28 sectors have %RMSFE's lower than 10 percent; whereas in manufacturing, it is 16 out of 32 which have %RMSFE's larger than 20 percent. There is no sector in nonmanufacturing having a %RMSFE over 20 percent.

V. CONCLUSIONS

The model developed in this study is far from perfection, but considering the rapid structural change of the Canton economy, the quality and quantity of data available, the model seems to capture reasonably well the essence of the Canton area labor market activities during the 1970's and the early part of the 1980's. The model not only simulates well these series that are dominated by growth trend, but also closely tracks series subject to wide fluctuations. The better performance in modeling series dominated by trend than series experiencing large fluctuation only confirms similar findings in a study by Haitovsky, Treyz, and Su.[14]

Based on the model's within sample simulation and beyond sample ex post forecasting performance, if a given scenario is simulated or a forecast is generated by the model, we should have confidence in the model's ability to track turning points of the aggregated series. Further, we should have more confidence about the short-term outcomes than the longer term outcomes, and we should expect better results in the simulation or forecasting related to nonmanufacturing sectors than manufacturing sectors, to employment and average weekly wages than manhours and the wage bills.

VII. ENDNOTES

1. We are indebted to Fari Noorbakhsh, Michael Weddle, and Robert Vazzo for development and update of the Canton M.S.A. data bank and to editor Joseph Gallo and an anonymous referee for useful comments and suggestions. Of course, any errors or omissions remain our responsibility.

2. See Roger Bolton, "Regional Econometric Models," Journal of Regional Science, vol. 25, no. 4 (November 1985), pp. 495-520; Dean Chen, A Tabular Survey of Selected Regional Econometric Models.

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Working Papers in Applied Economic Theory and Econometrics, 11. (San Francisco: Federal Reserve Bank of San Francisco. 1972); and F. L. Knapp, T. W. Fields and R. T. Jerome, Jr., A Survey of State and Regional Models. (Charlottesville, Virginia: Tayloe Murphy Institute, 1978).

3. The Canton metropolitan area refers to the Canton Metropolitan Statistical Area (MSA) that includes Carroll and Stark Counties. Hence Canton metropolitan area labor market data are data describing the Canton MSA labor market activities. All local labor market data of quarterly manhours, employment, average weekly wages and wage bill are computed from Ohio Bureau of Employment Services, Ohio Labor Market Information. (Columbus, Ohio: Ohio Bureau of Employment Services), monthly, 1964 through 1984. Mr. Don Curry, OBES, a labor analyst for Mahoning County, has been particularly helpful in supplying data for this and other modeling projects.

4. Lawrence R. Klein, "The Specification of Regional Econometric Models," Papers, Regional Science Associations, vol. 23, no. 23, (May, 1969), pp. 105-115.

5. Roger Bolton, op. cit., p. 498.

6. Michael D. Intrilligator, Econometric Models, Techniques, and Application. (Englewood Cliffs, New Jersey: Prentice-Hall, Inc., 1978); Bert G. Hickman, Robert M. Coen, and Michael Hurd, "The Hickman-Coen Annual Growth Model: Structural Characteristics and Policy Responses," in Lawrence R. Klein and Edwin Burmeister, ed., Econometric Model Performance. (Philadelphia: University of Pennsylvania Press, 1976); and Michael D. McCarthy, Elliot Riordan, and Chompunut Storey, A Regional Econometric Forecasting Model for the Philadelphia Area (Philadelphia: Wharton Econometric Forecasting Associates, 1977).

7. Michael D. McCarthy, Elliot Riordan and Chompunut Storey, op. cit.; Ruby Fichtenbaum, "Trends and Cycles in Ohio's Unemployment Rate," Growth and Change, vol. 15, no. 1, January 1984), pp. 50-55.

8. Canton area quarterly manhour, employment, average weekly wage and wage bill data are computed from Ohio Bureau of Employment Services, op. cit.; Quarterly data of U.S. manhour, employment, average weekly wage are computed from U.S. Department of Commerce, Bureau of Economic Analysis, Survey of Current Business (Washington, D. C.: Bureau of Economic Analysis of the U.S. Department of Commerce), monthly, 1964 through 1984. Quarter data of U.S. industrial indexes and mortgage rates are obtained from the Federal Reserve Bulletin; consumer price index is obtained from the Monthly Labor Review.

9. Discussions of the advantages and disadvantages of various estimation procedures can be found in many econometric articles and texts, such as Michael D. Intrilligator, Econometric Models, Techniques, and Applications. (Englewood Cliffs, New Jersey: Prentice-Hall, Inc., 1978; Robert S. Pindyck and Daniel L. Rubinfeld. Econometric Models and Economic Forecasts. (New York: McGraw-Hill Book Company, 1981); Ta-Chung Liu and Erh-Cheng Hwa, "A Monthly Econometric Models of the U.S. Economy," International Economic Review, vol. 15, no. 15 (June, 1974), pp. 328-365; and Michael D. McCarthy, The Wharton Quarterly Econometric Model, Mark III. (Philadelphia: Wharton Econometric Forecasting Associates, 1972).

10. F. Gerard Adams, Carl G. Brooking, and Norman J. Glickman, "On the Specification of a Regional Econometric Model: A Model of Mississippi," Review of Economics and Statistics, vol. 57, no. 57 (August, 1975), pp. 286-298; Catherine Baird, "A Multiregional Econometric Model of Ohio," Journal of Regional Science, vol. 23, no. 4 (November, 1983), pp. 501-516; Michael D. McCarthy, Elliot Riordan, and Chompunut Storey, op. cit.

11. Yih-Wu Liu and Anthony H. Stocks, "A Labor-Oriented Quarterly Econometric Forecasting Model of the Youngstown-

Warren SMSA," Regional Science and Urban Economics, vol. 13, no. 3 (August, 1983), pp. 317-340.

12. Ta-Chung Liu and Erh-Cheng Hwa, op. cit.

13. Persons wanting to obtain the estimated equations for the Canton Model should write to Professor Stocks at Youngstown State University, Youngstown, Ohio, 44555.

14. Yoel Haitovsky, George Treyz and Vincent Su, Forecasts with Quarterly Macroeconometric Models. (New York: National Bureau of Economic Research, 1974), pp. 344-345, 352-353.

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TABLE 1: SECTORS INCLUDED IN THE CANTON MODEL

Sectors	SIC Code
Manufacturing activity:	
Food and kindred products	20
Rubber and misc. plastic products	30
Stone, clay, and glass products	32
Primary metal products	33
Fabricated metal products	34
Non-electric machinery	35
Electrical machinery	36
Transportation equipment	37
Nonmanufacturing activity:	
Contract construction	15-17
Transportation, communications, and public utilities	40-49
Wholesale trade	50-51
Retail trade	52-59
Finance, insurance and real estate	60-67
Services	70-89
Government	---

TABLE 2: DISTRIBUTION OF R^2 VALUES BY VARIABLES

R^2	Manhours	Employment	Weekly Wage	Total
.650 to .699	1	0	0	1
.700 to .749	1	0	0	1
.750 to .799	3	0	0	3
.800 to .849	2	0	1	3
.850 to .899	3	0	1	4
.900 to .949	2	2	1	5
.950 to .974	1	4	1	6
.975 to .999	2	9	11	22

TABLE 3: DISTRIBUTION OF R^2 VALUES BY ACTIVITY

R^2	Manufacturing Durables	Manufacturing Non-Durables	Non-Manufacturing	Total
.650 to .699	1	0	0	1
.700 to .749	0	1	0	1
.750 to .799	2	1	0	3
.800 to .849	1	0	2	3
.850 to .999	1	0	3	4
.900 to .950	4	1	0	5
.950 to .974	3	1	2	6
.975 to .999	6	2	14	22

TABLE 4: DISTRIBUTION OF ROOT MEAN SQUARE PERCENT SIMULATION ERROR (%RMSE) BY VARIABLE, 1972.2 THROUGH 1979.4

%RMSE	Manhours	Employment	Weekly Wage	Wage Bill
0.0 to 1.999	3 (5)	4 (9)	4 (6)	1 (2)
2.0 to 4.999	9 (9)	10 (7)	11 (11)	7 (9)
5.0 to 9.999	6 (5)	4 (3)	4 (2)	10 (7)
10.0 to 14.999	2 (1)	2 (1)	0 (0)	1 (1)
15.0 to 19.999	0 (0)	0 (0)	0 (0)	0 (0)
20.0 to 29.999	0 (0)	0 (0)	1 (1)	1 (1)

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TABLE 5: DISTRIBUTION OF ROOT MEAN SQUARE PERCENT SIMULATION ERROR (%RMSE) BY ACTIVITY, 1972.2 THROUGH 1979.4

%RMSE	MD[a]	MN[b]	NM[c]	MFG[d]	NONMFG[e]	MSA[f]
0.0 to 1.999	0 (1)	0 (0)	4 (10)	1 (3)	3 (4)	4 (4)
2.0 to 4.999	7 (8)	1 (5)	17 (14)	11 (9)	1 (0)	0 (0)
5.0 to 9.999	10 (10)	7 (3)	7 (4)	0 (0)	0 (0)	0 (0)
10.0 to 14.999	5 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)
15.0 to 19.999	0 (1)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)
20.0 to 29.999	2 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)

[a] Manufacturing durable sectors.
[b] Manufacturing non-durable sectors.
[c] Non-manufacturing sectors.
[d] Aggregated manufacturing activities.
[e] Aggregated non-manufacturing activities.
[f] Aggregated activities at the Canton metropolitan level.

TABLE 6: DISTRIBUTION OF ROOT MEAN SQUARE PERCENT EX POST FORECASTING ERROR (% RMSFE) BY VARIABLE, 1980.1 THROUGH 1983.4

%RMSFE	Manhours	Employment	Weekly Wage	Wage Bill
0.0 to 1.999	0	1	1	0
2.0 to 4.999	3	4	10	0
5.0 to 9.999	8	6	6	9
10.0 to 14.999	6	7	2	5
15.0 to 19.999	1	0	1	4
20.0 and over	2	2	0	2

TABLE 7: DISTRIBUTION OF ROOT MEAN SQUARE EX POST FORECASTING ERROR (%RMSFE) BY ACTIVITY, 1980.1 THROUGH 1983.4

%RMSFE	MD	MN	NM	MFG	NONMFG	MSA
0.0 to 1.999	0	0	2	0	0	0
2.0 to 2.999	5	1	5	3	2	1
5.0 to 9.999	5	5	9	5	2	3
10.0 to 14.999	4	2	10	4	0	0
15.0 to 19.999	4	0	2	0	0	0
20.0 and over	6	0	0	0	0	0

Note: Same notations as used in Table 5.

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