FINANCIAL FORECASTING
USING ECONOMIC INDICATORS

by

Joseph D. Vinso

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Joseph D. Vinso
Assistant Professor of Finance
The Wharton School/CC
University of Pennsylvania
Philadelphia, PA 19104

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I. INTRODUCTION

Forecasting sales, cash flows, profits and other financial flows continues to be one of the primary functions in the financial mangement of any organization in that such planning activities as production planning, budgeting, and financing require accurate forecasts of these quantities. While standard forecasting techniques are adequate under many circumstances, they usually are not very useful in predicting turning points. Those times when changes in the direction and levels of sales occur are the very places where forecasting is most needed. Changes in economic activity can lead to changes in sales which result in over (under) production, high (inadequate) inventory, and finally over (under) capacity for the firm. Similarly, errors in forecasting can lead to excessive (insufficient) financing and investment activities by the organization all of which lead to depressed profits.

It is certainly most desirable to be able to make these forecasts.[1] Recently, however, technology has been developed which allows much more accurate forecasting by formally considering the role of various economic indicators which are pertinent to a particular organization. This technology has been tested on various organizations and found to be far more effective than other methods currently available.

II. CURRENT FORECASTING METHODS

Current forecasting practices in most organizations involve various degrees of sophistication. Some of the more common methods are now reviewed.

Ad Hoc Forecasting

For many, an overall forecast merely involves a compilation of forecasts made by subunits. Take, for example, the process for generating sales forecasts. Many firms obtain sales estimates by product from each of the various sales offices. These estimates are generally obtained from the sales representatives in a given area. Overall product forecasts then consist of a summary of these individual forecasts.

Several problems exist with such methods in that sales representatives generally are not able to detect subtle changes in demand which may be occurring until an actual change in sales is experienced. Furthermore, since forecasting is not a primary activity of the sales representative, the forecasts obtained are only intuitive expressions of the immediate concerns of the sales rep or merely just extrapolations of past experience.

Combining such forecasts often results in nonsensical estimates of overall product demand--either excessive or deficient. As a result most managers adjust overall forecasts so as to obtain a more representative estimate of future sales for a product. Forecasts made at this level tend to utilize quantitative methods in addition to qualitative factors.

Quantitative Methodology in Forecasting

An example of quantitative methods used in forecasting is the practice of generating sales forecasts by extrapolating trends in past sales history using some weighted average of past sales levels giving more or less weight to various lags. This process is referred to as exponential smoothing. In its simplest form:

$$\bar{S}_t = \sum_{i=0}^{n-1} (W_e(1-W_e)^i S_{t-1}) + (1-W_e)^n S_a \qquad (1)$$

and

$$\hat{S}_{t,T} = \bar{S}_t \qquad (2)$$

where: S_{t-1} = the sales at time t-1

$\bar{S}_t$ = the exponentially weighted average of past sales at time t

$\hat{S}_{t,T}$ = the estimate of sales made at time t for period t + T

W_e = the weight placed on current versus past sales; $0<W<1$

M = the number of periods of data available

S_a = the initial estimate.

Equations (1) and (2) are easy to interpret: they state that the estimate of the permanent component of sales is corrected by some fraction (W_e) of the previous period's forecast. The size of W_e determines how much emphasis is placed on current versus past data. For example, if $W_e = 0.5$, the weight on the most current four years' observations is 0.9375. If $W_e = 0.1$, the weight on the most current four years' observations is 0.350.

Most companies exhibit some trend in sales data, and hence, equation (2) usually is too naive. However, one may specifically account for perceived trends by making the sales prediction a function of both $\bar{S}_t$ and the perceived trend:

$$\hat{S}_{t,T} = f(\bar{S}_t, \text{ sales growth term}).$$

The trend effect can be introduced as either an additive or multiplicative term. To present the more complete models here is unnecessarily time-consuming and the reader is referred to Elton and Gruber (1972) and Winters (1960) if more information is desired.

In sum, then, the general approach of exponential smoothing is to identify a pattern representing a combination of trend, seasonal, and cyclical factors based on historical data for that variable. The pattern is then smoothed to eliminate the effects of random fluctuations (in other words, the variable is "normalized" to the exclusion of unexpected change) and extrapolated into the future to provide a forecast.

Several problems exist with exponential smoothing, though. First, exponential smoothing looks only for patterns in the original time series but fails to utilize information contained in errors experienced between previous forecasts and subsequent realizations. Second, it assumes that the sales in any time t are a function of the average of all previous sales values as well as the identified patterns. In general this is not true. Finally, exponential smoothing predictions do not reflect the causal relationships that may exist between sales and other exogenous variables such as economic activity.

Regression and Econometric Methods

Most managers are cognizant of the role that changes in economic factors will have on a firm's sales, profits, cash flow and the like, but generally have no systematic way of introducing such extraneous influences as changes in money supply, personal income, unemployment and a myriad of other indicators of economic activity. Usually, a manager will peruse many such indicators without any notion of which indicators are important and how they effect financial flows of the firm. In most cases a manager will look at twenty, thirty or more such indicators so as to not miss one which might be important. Much managerial time and effort is wasted in such endeavors by looking at those economic series which have no relationship to demand and by trying to determine how changes in other indicator's which may be significant, are related to sales, cash flow, etc.

To aid the manager organize this effort, some firms utilize regression or econometric models for forecasting of the form:

$$\text{Sales}_t = a+bX_{t-1} + cX_{t-2}+\ldots+mY_{t-1}+nY_{t-2}+\ldots+u_t$$

where: X,Y represent past values of sales data and combinations of various economic indicators.

a,b,c,m,n,etc. are constants established by applying the ordinary least squares method to past data

t = time

u_t = an error term accounting for unexplained deviations of actual data from the computed regression line.

As with exponential smoothing, such regression methods also have problems. Sales at time t may be related to lagged values of sales or economic indicators but how far back does one go in trying to establish this relationship? Which lags are to be included? Are all lags weighted the same? Generally these questions are answered by trial and error. Furthermore, multicollinearity, heteroscedasticity, and more likely autocorrelation plague the attempts to develop appropriate econometric methods.[2] A more important limitation arises when trying to estimate the role of these indicators. If a large number of indicators are to be used there may not be sufficient data for all of the necessary estimations.

The ability to forecast financial flows can therefore present some problems. It would be useful to search for a methodology which reduces the impact of the problems presented here. The purpose of this paper is to review a method which attempts to avoid these problems by introducing economic indicators directly into forecasting process.

III. FORECASTING WITH EXPANDED INFORMATION

The process of Time Series Cross Correlation Analysis (TSA) overcomes some of the drawbacks inherent in the exponential smoothing and regression analyses. In particular, more than just establishing that the series to be forecast is merely correlated with various economic indicators, TSA demonstrates the role played by each economic variable. Hence, TSA incorporates a great wealth of information ignored by exponential smoothing and generally underutilized by regression analysis. Moreover, instead of ignoring unexpected changes in the environment or past forecast errors, TSA specifically identifies such disturbances and uses them to predict future changes in the series to be forecast.

Choosing Relevant Series

Before beginning the process, one must first decide which series are to be forecast. Sales, profits, and cash flows are typical choices. The question is not unambiguous, however. For example, if we are interested in forecasting sales, which sales series do we choose? Top management may be interested in forecasting total sales or sales by divisions. Division or general managers on the other hand may prefer to forecast sales of groups of products or even single products. This step is not a trivial matter in that the process generating sales for one product will not in general be the same as for another product. Likewise, combining several products, each following different sales patterns, will often result in a sales generating series different from any of the underlying series. So it is important to specify exactly which series are to be forecast.

After the series to be forecast have been determined, it is also necessary to determine which economic variables are most likely to influence demand. General economic indicators such as disposable income, unemployment, trade deficits, employment, prime lending rate, stock market indicators or other similar indices might prove to be useful. Besides these general indices, industry specific indicators may be useful. For example, steel manufacturers may find such series as Sales of Passenger Cars, Private Housing Starts, or Appliance Sales as useful indicators of future sales of steel. In general, whatever series have been reviewed by managers in preparing previous forecasts should be included here. It is immaterial how many data series are used in that the methodology outlined here does not suffer from the same data limitation problems as regression analysis. Furthermore, TSA determines which indicators are useful and which ones can be ignored. As a result, one should not limit possible candidates at this stage.

Finally, it is necessary to specify the time span. Pan et al (1977) determined that the most frequent "shortest length" period as well as the most common revision period for forecasting sales is monthly. Furthermore, the vast majority of firms compare sales and profit forecasts with realizations on a monthly basis. As a result, monthly forecasts are usually suggested; however, nothing in the methodology precludes shorter or longer periods subject to data availability.[3] Likewise, using a monthly time span will generally not violate the stationarity requirement over the sample period.

One problem often arises with economic series. Many of the data are provided in "preliminary" form and later are "revised". Which series should be used? In general, one should forecast with whatever series is available at the time the forecast is to be made. Since most revisions are not available without a considerable delay, it is the usual practice to use the preliminary figures in forecasting. In building the forecasting and planning models, it may be useful to use each series, though, as if they were separate data series keeping in mind the publication lag.

Methodology for Model Building

The methodology used for constructing forecasting models is based on the existence and direction of causality between unexplained variations in two time series. The method of examing this causality is now reviewed.

A generally accepted definition of causality, as formulated by Granger (1969), is based upon the time series notion of predictability. That is, given a universe consisting of at least the two variables, x and y, x is said to cause y (without feedback) if y is (in a mean-square error sense) more accurately predicted by taking into account both lagged y's and lagged x's than it is by taking into account only lagged y's. Granger's definition is not necessarily the only accepted definition of causality but is widely used because it is especially appealing for model development.

The method for a model building is based on technology developed by Haugh (1976) who suggests that series x and y be initially filtered into white noise series.[4] The white noise series resulting from this transformation procedure are then cross-correlated. If the cross-correlation coefficients at particular lags are found to be significantly different from zero, a relationship exists between x and y and the direction of the relationship can be examined by using a chi-square test of significance. In particular, given an estimate of the cross-correlation function, r_k, (for lag k) between two prewhitened series, Haugh (1976) has shown that the statistic S*:

$$S^* = N^2 \sum_{k=L_1}^{L2} r_k^2 (N- k)^{-1}$$

is chi-square distributed with ($L_1 + L_2$ +1) degrees of freedom where N is the number of sample observations, L_1 represents the number of future lags, and L_2 the number of past lags. Once L_1 and L_2 are chosen, the statistics S* can be computed and compared to a χ^2 value with ($L_1 + L_2$ +1) degrees of freedom for a given confidence level.

We therefore have a practical test for causality. After prefiltering the x and y series to a white noise series using Box and Jenkins (1970) univariate analysis, the cross correlation function is estimated.[5] Then the chi-square test is applied to determine whether the series are independent by setting L_1 and L_2 equal to lags appropriate for the series under consideration. Directions of causality between two series, x and y, can be examined using the same chi-square test. For example, if causality runs from x to y, future values of x should have coefficients insignificantly different from zero as a group. This relationship can be examined by choosing both L_1 and L_2 to be negative numbers when computing S*.[6]

Once dependence is established between the series to be forecast and various economic indicator series under consideration, a least squares line is fit between the white noise residuals of the dependent series and the white noise residuals of the economic indicator series at the lags indicated by the cross-correlation analysis. In this way, the explanatory power of the model is increased, without the data problems previously outlined in that the appropriate lags are specified prior to the regression. Likewise, the forecaster can tell <u>which</u> economic indicators are important and <u>how</u> they should systematically enter the forecast. Exhibit I outlines the steps in the procedure described here.

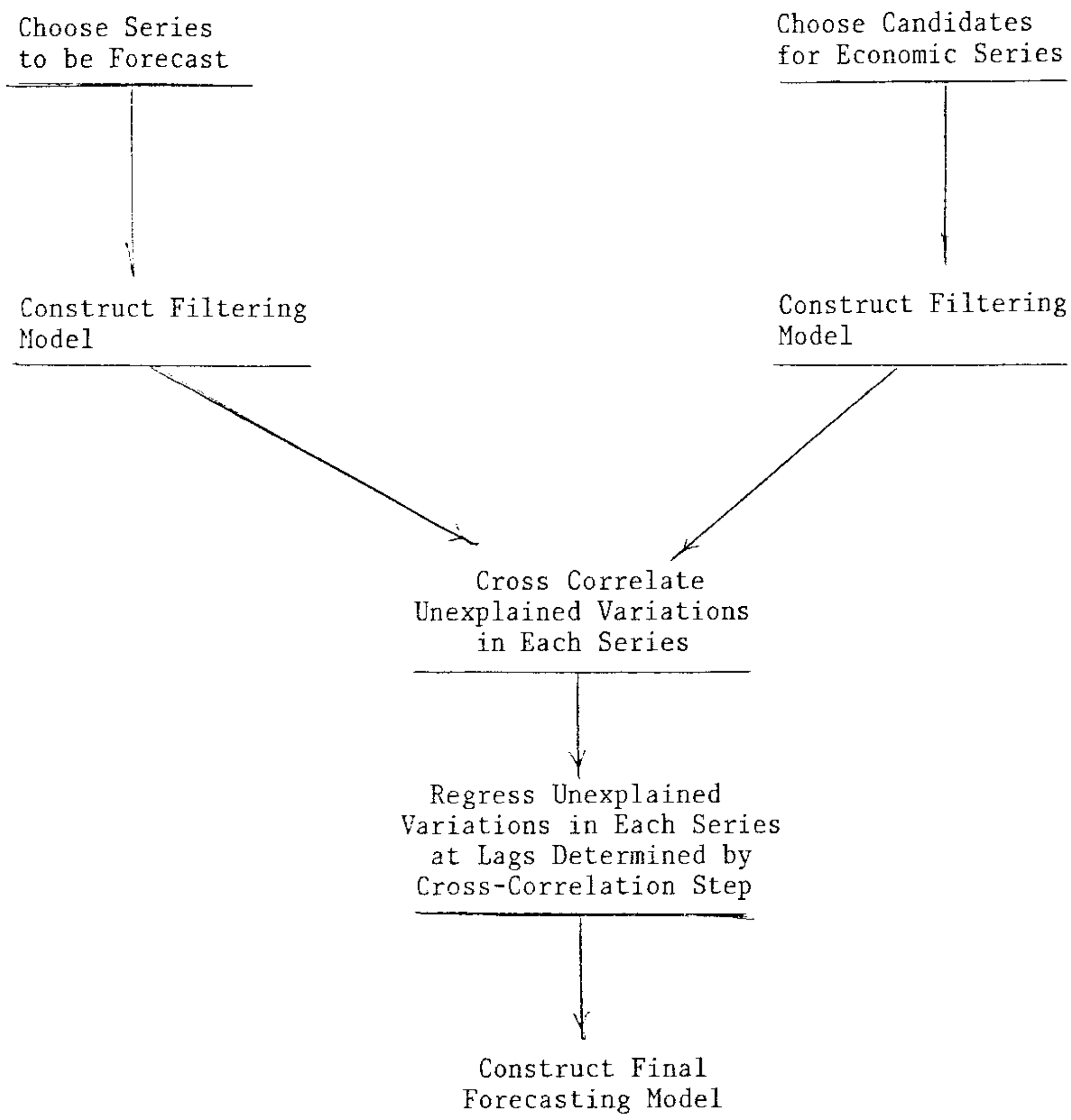

Exhibit I. Process for Developing Forecasting Model Using TSA

IV. FORECASTING WITH TSA

An example of a manager's use of this technique will clarify the process. A medium-size Eastern chemical company was encountering difficulty in determining future sales of a highly competitive product line. In particular, the lines of communication between ultimate user and producer were so poor that when retail sales changed it took many months for the company to become sufficiently aware of the changes so as to adjust production levels. As a result, large inventories or severe stockouts frequently occurred leading to increased costs and lost profits.

It was determined that the appropriate series for forecasting were monthly sales of Product X and total monthly sales for Department Z. After considering many series, data for indicators regularly used by management were gathered such as monthly sales of passenger cars, private housing starts, personal income, composite index of twelve indicators, etc. were gathered for 81 monthly observations.[7]

To apply the methodology as previously outlined, it is necessary that all series for subsequent analyses be filtered to white noise series.[8] Table 1 provides a summary of the models for the sales series using notation developed by Box and Jenkins (1970).[9] Parameter values and standard errors are also shown along with the Q-statistic for the first twenty-four residual autocorrelations. These values of the Q-statistic are especially noteworthy because they support the notion that the individual series have been reduced to white noise series. Reviewing the filtered series shows that the sales series consist of both seasonal autoregressive-moving average terms as well regular moving average terms.

TABLE 1

SUMMARY OF MODELS FITTED TO DEPENDENT SERIES

Dependent Series (81 observations)	Filtering Model	Standard Error of Estimate	Q-Statistic
Product Sales	$(1 - B^6)z_t = \underset{(0.05)}{(1 - 0.45B^6)}(1 - \underset{(0.103)}{0.483B} - \underset{(0.0892)}{0.2501B^6})u_t$	0.1905	23.9 (32.7)
Total Sales for Department	$(1 + \underset{(0.129)}{0.358B^{12}})(1 - B^{12})z_t = (1 - \underset{(0.048)}{0.083B^{12}})(1 - \underset{(0.0839)}{0.413B} + \underset{(0.1214)}{0.401B^2})u_t$	0.1430	17.6 (31.4)

Notes:

Numbers in parenthesis below parameter estimates are standard errors.

Numbers in parenthesis below Q-statistics are taken from the Chi-square table with the appropriate degrees of freedom at the 0.05 significance level.

Table 2 provides a listing and Table 3 provides a summary of the fitted models for the economic indicator series.[10] The data for these series are obtained from U.S. government publications or other public sources. It can be seen that several series which supposedly are "seasonally adjusted" cannot be considered white noise series. For example, Private Housing Starts (SA) shows six month seasonal moving average terms in addition to other regular moving average terms. The appropriate Q-statistics and parameter values are shown. Standard errors are not shown but are available on request.[11]

Once all of the series were filtered, the forecast errors of the sales series were cross-correlated with those of the economic indicators. Causality is investigated by choosing various values of L_1 and L_2. Many combinations of values were examined but are too voluminous to be shown here. Table 4 presents the summary of significant cross correlations. Several interesting factors became apparent. First, only three of the twelve series were shown to be related to sales of product x while only four were found to be related to sales of Department Z. <u>This means that eight series provided no information useful in forecasting thus wasting considerable managerial time and effort in gathering and analyzing data which have no value in forecasting</u>.

Second, of those series which were found to be related to sales not all lagged by the same amounts. For example, Table 4 shows that changes in personal income lag changes in product x by ten months while changes in private housing starts lag changes in product x by seven months. Finally, changes in sales of passenger cars lag changes in product x by two months. Thus, management would get a signal that sales should change ten months prior to the event. It was not necessary to act immediately, however, so

TABLE 2

Independent Series	ID Number
Domestic Retail Trade Sales of Passenger Car Dealers in Dollars (U)	4
Domestic Retail Trade Sales of Passenger Car Dealers in Dollars (SA)	5
Single Family Home Sales (SA)	6
Total Retail Trade Sales of Passenger Car Dealers in Units (U)	7
Private Housing Starts (SA)	8
Composite Index of Twelve Leading Indicators (with Trend Adjustments)	9
Personal Income (SA)	10
New Construction Put in Place-Private Commercial Buildings in Current Dollars (SA)	11
Total Retail Trade Sales of Passenger Car Dealers in Units (SA)	12
Domestic Retail Trade Sales of Passenger Car Dealers in Units (U)	13
Domestic Retail Trade Sales of Passanger Car Dealers in Units (SA)	14
Real New Construction Put in Place-Private Commercial Buildings in 1967 Dollars (SA)	15

Note: U = Unadjusted

SA = Seasonally adjusted

TABLE 3

FILTERING MODELS FOR INDEPENDENT SERIES

Series ID No.	Filtering Model	Q-Statistic
4	$(1-B^{12})z_t = (1-0.08551B^4 - 0.8086B^{12})u_t$	14.0
5	$z_t = (1-0.2501B^3)u_t + 0.008296$	10.8
6	$z_t = (1-0.4265B^5)u_t + 0.00725$	10.9
7	$(1-B^{12})z_t = (1-0.8414B^{12})u_t$	20.7
8	$(1-B^6)z_t = (1-0.8579B^6)(1+0.2333B^7 + 0.4248B^{13})u_t$	20.8
9	$(1-B)z_t = (1-0.3889B^6)(1-0.2827B)u_t$	18.6
10	$z_t = (1-0.3533B^{15})u_t + 0.007257$	17.9
11	$z_t = u_t + 0.004398$	11.6
12	$z_t = (1-0.3514B^3)u_t$	16.6
13	$(1-B^{12})z_t = (1-0.8550B^{12})u_t$	12.7
14	$z_t = (1-0.3837B^3)u_t$	15.4
15	$z_t = u_t + 2.8503$	2.5

they could wait three months to get a confirming signal from the second series at which time production and distribution plans can be altered.

Building the Forecasting Model

While the previously cited benefits are worthwhile, the purpose of the forecasting process is to increase the accuracy of the sales estimates. Once the appropriate lags have been determined, the user can utilize the information obtained so as to forecast product sales.

Table 5 gives the forecasting models for the series investigated here. Depending on the forecast horizon, more or less terms are utilized for forecasting. For example, if a forecast for the next month sales of product x is desired, one would use equation (A). On the other hand, if a six-month forecast is desired, one would use equation (B). Finally if a one-year forecast is needed, current observations of economic variables cannot provide any more information than the original fitted model for Product x sales. Similarly, the forecast horizon will determine which forecasting equation is used for Department Z sales.

It can also be observed that when using all available information, forecasting accuracy is increased significantly. Table 6 shows in this example the standard error of estimate was reduced from 0.1905 to 0.1532 for Product x (a twenty per cent decrease) and from 0.1430 to 0.0934 for Department Z sales (a thirty-five percent decrease). Of course, as the horizon is extended and less information is used the accuracy decreases as expected. Of more importance, however, was the increased ability to correctly forecast turning points in sales with sufficient lead time that adequate measures could be taken to adjust production so as to help prevent inventory accumulation or stockouts.

TABLE 5

FORECASTING MODELS

eries	Standard Error of Estimate	Applicable Forecasting Horizon, Months	
RODUCT x SALES			
$1-B^6)Z_t = (1-0.45B^6)(1-0.483B-.2501B^6)$			
$(0.0342 + 1.84u_{10,10} + 0.034u_{8,7} - 0.24u_{14,2})$	0.1532	1-2	(A)
$(0.0295 + 1.75u_{10,10} + 0.053W_{8,7})$	0.1768	3-7	(B)
$(0.0379 + 1.81u_{10,10})$	0.1885	8-10	(C)
u_t	0.1905	11+	(D)
EPARTMENT Z SALES			
$1+0.358B^{12})(1-B^{12})Z_t = (1-0.683B^{12})(1-0.413B+0.401B^2)$			
$(-0.0142+0.368u_{10,9}-0.593u_{8,6}+0.896u_{9,4}+0.002u_{14,2})$	0.0934	1-2	(E)
$(-0.0251+0.249u_{10,9}-0.631u_{8,6}+0.651u_{9,4})$	0.1224	3-4	(F)
$(-0.0062+0.359u_{10,9}-0.545u_{8,6})$	0.1305	5-6	(G)
$(-0.0149+0.510u_{10,9})$	0.1332	7-9	(H)
u_t	0.1430	9+	(J)

ote: μ_i, j is the residual for fitted series i lagged j periods

TABLE 6

COMPARISON OF STANDARD ERRORS OF ESTIMATE

Dependent Series	Simple Residual	Expression for Residual in Terms of Independent Series Residuals	Percentage Decrease in Standard Error of Estimate
Product x Sales	0.1905	0.1532	19.6%
Total Sales of Department Z	0.1430	0.0934	34.7%

Forecasting Experience and Implementation

After comparing the forecasts produced by TSA for over a year with other means available has demonstrated that TSA has provided more accurate forecasts than obtained by any previously used method. Forecast errors in this example have decreased by approximately twenty percent as compared to those obtained using regression and approximately fifty percent from the ad-hoc methods. While such improvements in forecasts were obtained here, the reduction in forecast errors in general will be a function of the accuracy of current methods. The methodology developed here will improve forecasts most in those instances where current forecasting methods do not provide the desired accuracy. Likewise, it can be observed that the benefits of a TSA analysis are more than improved forecasts. A reduction in managerial time and effort in the forecasting function allows more time for attention to other managerial concerns.

As for implementation, it must be emphasized that the process described here is not difficult to implement in most firms. Computer programs are widely available or easily obtained to perform the analyses shown here. Once the initial model is developed, a trivial amount of time is spent on its upkeep. As a result, forecasting will not require significant resources in order to produce accurate estimates of financial flows.

V. CONCLUSION

The process described here consititutes one of the first attempts at directly introducing economic indicators systematically into the forecasting problem. It has proved useful in many cases by helping management to forecast financial flows such as sales, cash flows, and the which series can be used as leading indicators to turning points and which series provide confirming signals to expected changes.

As with all such tools, this methodology cannot and should not replace the experienced forecaster. While this process does not remove all forecasting error it can provide more and better information to help management produce the best possible forecasts. This process assures that the relevancy of any available information can be determined and the influences can systematically be taken into account.

This approach has proved effective in reducing costs and lost profits and can be adapted to handle any types of series to be forecast (such as product demand, production, cash flows, etc.) and any types of indicator series. It also removes the bias usually associated with subjective forecasting. Finally, the TSA method provides information with which the user can develop better understanding of the forces acting in the market. Such an increased understanding will increase the effectiveness of the manager besides improving his ability to forecast.

FOOTNOTES

*Assistant Professor of Finance, The Wharton School, University of Pennsylvania. Research support by the Rodney L. White Center for Financial Research, The Wharton School, is gratefully acknowledged.

[1]A recent study by Pan, Nichols, and Joy (1977) provides some insight into some of the current forecasting practices of firms. The level of response and willingness to provide such information is an indication of the intensity of interest and concern in most firms.

[2]The problem of autocorrelation is even more acute than perceived in that most forecasting models contained lagged dependent variable terms yet the Durbin-Watson test is used for an analysis of the presence of serial correlation. It has been shown that such a test is inappropriate under these conditions (see, for example, Dutta (1975, pp. 112-114) for a description of the test and the problems encountered in the presence of lagged dependent variables).

[3]Many of the economic indicators are only published on a monthly basis. For shorter time periods, data will not be available. For longer periods, the stationarity requirement for the data series may be violated in trying to get sufficient observations.

[4]A white noise series is a random sequence which is independent, normally distributed with zero mean and constant variance.

[5]Because no discussion of the theory and methods of this particular filtering procedure is probably better than a necessarily brief one, the reader is referred to Box and Jenkins (1970) or Nelson (1972) for a complete discussion.

[6]For a more comprehensive discussion of the methodology used for determining dependence and direction of causality, see Rogalski and Vinso (1977).

[7]Haugh (1976) demonstrates that consistent results can be obtained using samples as small as 50 observations.

[8]All series are estimated in terms of percentage changes of the form:

$$Z_t = \frac{X_t - X_{t-1}}{X_{t-1}}$$

Nothing in the methodology precludes using the raw series directly as the forecast for Z_t is easily converted to X_t.

[9]The criterion of model selection followed here has been the representation of each series in the most parsimonious form that is consistent with its stochastic structure. Parameters included in the models are those for which estimates are significant or which are required to eliminate serial correlation in residuals. Thus, the procedure has not been to minimize the variance of prediction errors but to obtain the simplest adequate representation.

[10]The economic indicator series shown here are those which are general indicators of economic activity. Several other series specific to an industry under investigation can also be utilized. These were not used in the example discussed here to preserve the anonomity of the specific firm and product line discussed here. It is appropriate, however, to include such series in the analysis.

[11]The estimated autocorrelation functions for the economic indicators are too voluminous to include. They are available on request.

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