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Abstract

This paper explores the proposition that SEC Form 10-K backlog information, which is reported annually, can be used to improve extrapolative forecasts of corporate sales. A sample of COMPUSTAT firms was used to compare the predictiveness of ten models derived from the sales order identity. Firms were partitioned on the basis of backlog-to-sales ratios in order to assess subsample differences associated with average delivery period.

The results indicate that 10-K backlog information may be useful in some contexts, but not others. In general, models using only sales data performed quite well, while models using backlogs performed poorly. Firms with the shortest delivery periods showed some promise for exploiting the new order series.

ON THE PREDICTIVE BENEFITS OF FORM 10-K BACKLOG INFORMATION

Forecasts of net sales are important to managers and financial analysts for a variety of reasons. In effect, they are the cornerstone of the budgeting process and the basis upon which financial results are projected. Managers often use expected revenues to formulate marketing and production strategies, whereas financial analysts use expected revenues to project expected results and to plan investment strategies.

The purpose of this paper is to explore the proposition that Form 10-K backlog information, which is reported on an annual basis, can be used to improve extrapolative forecasts of corporate sales. A company registered with the Securities and Exchange Commission (SEC) will disclose order backlogs when considered material to an understanding of its business. Pursuant to SEC Regulation S-K, these disclosures appear within its description of the business (Item 1).

Although unfilled orders have been used to investigate aggregate adjustments to demand changes at the industry level (e.g., Zarnowitz [1962]; Odle, Koshal, and Shukla [1981]), it is surprising that similar research has not been conducted at the firm level. It is also surprising that empirical evidence has not been generated with respect to the predictive benefits of reported unfilled orders, for it can be presumed that one of the main purposes of backlog information is enhanced sales forecasting performance.

In the present study, predictive benefits are viewed in terms of both direct and indirect effects on forecasting performance. Direct benefits result from using the data in models which outperform similar models not using such data. Indirect benefits are less obvious and result mainly from insights gained from having the data. These insights can be helpful in understanding the forecasting environment and in selecting appropriate forecasting strategies.

BACKGROUND

It is generally recognized that firms respond to demand fluctuations in three basic ways.[1] First, the firm can adjust its prices and output to affect sales. Second, the firm can produce to stock and use inventories to cushion the disruptive effects of fluctuating demand on production. Third, the firm can produce to order and use order backlogs to cushion the effects of fluctuating demand on sales and production. While these strategies are not mutually exclusive, they provide a means of characterizing firms and industries. In the limiting case of instantaneous price-output adjustments, both finished goods and unfilled orders would be nil [Zarnowitz, 1962].

Price-Output Adjustments

For the most part, researchers have been concerned with price-output adjustments as they relate to conventional price theory. This option implies that the firm is willing and able to adjust its output to levels of current demand. However, since this reaction may not be feasible in many cases, due to natural lags in the production planning process, firms usually will not adopt this strategy, especially in the short run. Fluctuations in production rates are often considered undesirable by managers because changes in production are associated with reduced efficiency and increased unit costs. Consequently, reduced input flexibility usually indicates a need to stabilize production.[2] Demand and cost factors in an unstable environment thus favor inventory and backlog accumulations rather than price-output adjustments.

Inventory-Backlog Accumulations

Firms which build inventories and accumulate backlogs react to business expansions and contractions in a series of marketing and production decisions. Table 1 depicts over time the relationship between orders received (R), orders shipped (S), and production (P) at selling prices. The sequence of events begins from steady state (t = 1) where the firm is producing as much as it can sell at prevailing prices. Next (t = 2), the firm experiences an increase in demand for its products, but has not yet raised production. It then raises production (t = 3) in response to the perceived increase in demand. As demand continues to rise, the firm again (t = 4) raises production. In the next period (t = 5), however, demand levels out, even though production continues to increase. In the following period (t = 6), demand begins to contract, as evidenced by the relationship between new orders and sales. Excess inventories next (t = 7) dictate reductions in production. In the following period (t = 8), production again equals new orders, but backlogs continue to fall. Production is cut back further (t = 9) in order to reduce inventory levels still more. The process continues until a new steady state is reached (t = 10).

Although every combination of events has not been enumerated here, Table 1 does show that backlog changes will lead changes in sales. While excess inventories might also signal shifts in demand, various corporate policies, including certain accounting policies, could serve to mitigate such indicators.[3] Consequently, in the present study, only the relationship between orders and sales was investigated.

The preceding model highlights the complementary relationship between new orders and production. It does not indicate, however, that the risks of building stocks are often greater than the risks of accumulating orders. Thus, a policy to produce to stock could be inherently more risky than a policy to produce to order. Indeed, in many industries the risk of order cancellations has been minimal [Zarnowitz, 1962], and backlogs are thus considered safer and more appropriate than inventories as a means of smoothing production, especially in manufacturing. Since inventory and backlog accumulations rarely parallel one another, they have been treated here as essentially separate issues and, in order to simplify the analysis, inventories are assumed to be neutral with respect to sales over time.[4]

THE RELATIONSHIP BETWEEN SALES AND ORDERS

The process of receiving and completing sales orders provides a framework for relating sales to orders. This framework, depicted in Figure 1, is used to derive appropriate sales forecasting models. In essense, it shows that beginning backlogs plus net orders received (i.e., new orders) will always equal ending backlogs plus net orders shipped (i.e., net sales). In effect, this identity, familiar to every accountant, is used to account for <u>potential sales</u> which are not reflected in the financial statements.

The sales order identity reveals three general approaches to sales forecasting. First, along path f, it indicates that future sales may be largely a function of past sales. This is perhaps the most conventional approach. Second, along path g-h, it shows that future sales can also be thought of as a function of past orders. In cases where sales parallel orders, the second approach would yield results similar to the first approach. Third, along path k, future sales can be viewed as a function of unfilled orders. These relationships are represented as follows:

$$\hat{S}_t = f(S_{t-i}) \tag{i}$$

$$\hat{S}_t = h[g(R_{t-j})] \tag{ii}$$

$$\hat{S}_t = k(B_t) \tag{iii}$$

where

S_t = orders shipped in period t,

R_t = orders received in period t,

B_t = orders backlogged at the end of period t,

i = appropriate lag between observations,

j = average delivery period.

In addition, combinations of these relationships are possible.

RESEARCH DESIGN

The present study was designed to investigate the potential direct and indirect predictive benefits of 10-K backlog information. A sample of COMPUSTAT firms was used to compare the predictive ability of various sales forecasting models and forecasts of annual sales were evaluated using several metrics.

Sample

A sample of SEC-reporting companies with complete data for twelve consecutive years (1970-81) was selected from the COMPUSTAT annual industrial tape. In all, 224 firms satisfied these criteria, but two firms with outliers were excluded in order to provide a sample exactly divisible by three.

The sample was partitioned on the basis of average delivery period which was computed for each firm by dividing average ending backlog by average sales. The backlog-to-sales ratio was used to assess the potential indirect effects of backlogs on sales forecasting performance. Firms were ranked in ascending order and partitioned into three equal groups of 74 firms each. These groups, then, represented short, medium, and relatively long average delivery periods (i.e., backlog-to-sales ratios).[5]

Sales Forecasting Models

Ten separate models were selected to evaluate the predictive benefits of 10-K backlog disclosures. These models, based on available annual data, were selected for the most part for their correspondence to the sales order identity depicted in Figure 1. As such, they have intuitive appeal and theoretical support, since the fundamental relationship between sales and orders is implicit in each model. In order to simplify the discussion, models have been grouped into three basic categories: (1) models using only sales data; (2) models using orders data; (3) models using only backlog data. New orders were derived from the backlogs and the sales that were disclosed.

Notationally, these models are represented as follows:

Category I

$$\hat{S}_t = S_{t-1} + \delta \qquad (1)$$

$$\hat{S}_t = (1+r)S_{t-1} \qquad (2)$$

$$\hat{S}_t = (1+r')S_{t-1} \qquad (3)$$

$$\hat{S}_t = a_0 + a_1S_{t-1} \qquad (4)$$

Category II

$$\hat{S}_t = R_{t-1} \qquad (5)$$

$$\hat{S}_t = (1+r)R_t \qquad (6)$$

$$\hat{S}_t = a_0 + a_1R_{t-1} \qquad (7)$$

$$\hat{S}_t = a_0 + a_1R_{t-1} + a_2S_{t-1} \qquad (8)$$

Category III

$$\hat{S}_t = a_0 + a_1B_{t-1} \qquad (9)$$

$$\hat{S}_t = W^{-1}B_{t-1} \qquad (10)$$

where

S_t = net sales in period t,

R_t = new orders in period t,

B_t = backlogged orders at the end of period t,

r = average growth rate in sales or orders,

r' = predicted growth rate in GNP,

a_i = regression coefficients,

W^{-1} = inverse of average delivery period,

δ = drift term.

<u>Error Metrics</u>

Two error metrics, mean absolute relative error (MARE) and mean squared relative error (MSRE), were used to evaluate the predictive ability of the competing models in a two-year holdout period (1980-81). These metrics represent linear and quadratic loss functions, respectively, and both may be thought of as measures of accuracy. Notationally, they were computed for each set of predictions as follows:

$$\text{MARE} = \frac{1}{N} \sum_{i=1}^{N} \left| \frac{P_i - A_i}{A_i} \right|$$

$$\text{MSRE} = \frac{1}{N} \sum_{i=1}^{N} \left[\frac{P_i - A_i}{A_i} \right]^2$$

where:

P_i = predicted sales for company i,

A_i = actual sales for company i,

N = number of companies indexed by i.

Test Procedures

In order to evaluate the alternative forecasting models, an analysis of variance (ANOVA) model was used. Notationally, it can be represented as follows:

$$X_{ijkm} = \mu + \alpha_i + \beta_j + \gamma_k + \alpha\beta_{ij} + \alpha\gamma_{ik} + \beta\gamma_{jk} + \alpha\beta\gamma_{ijk} + \varepsilon_{0(ijkm)} \quad (11)$$

$i = 1, 2, \ldots, 10$
$j = 1, 2, 3$
$k = 1, 2$
$m = 1, 2, \ldots, 72$

where

μ is the grand mean,

α_i is the forecast model effect,

β_j is the backlog-to-sales ratio effect,

γ_k is the year effect,

$\alpha\beta_{ij}$, $\alpha\gamma_{ik}$, $\beta\gamma_{jk}$, and $\alpha\beta\gamma_{ijk}$ are interactions,

$\varepsilon_{0(ijkm)}$ is experimental error,

m is the number of firms in each backlog-to-sales group.

The above model represents a three factor design with repeated measures on factor A (forecast model). Factor B (backlog-to-sales ratio) is nested under factor C (year). Using this model, the following null hypotheses were examined for both metrics:

H_0^1: There are no differences in forecasting performance among the ten models.

H_0^2: There are no differences in forecasting performance among the three backlog-to-sales groups.

H_0^3: There are no differences in forecasting performance between years 1 and 2.

Hypotheses concerning interactions were also examined.

RESULTS

Tables 2 and 3 provide descriptive evidence in terms of MAREs and MSREs, respectively. Both mean errors and mean ranks are presented for the complete sample and for each delivery period group. The tables reveal nominal differences between certain models, and show that models (1), (2), (3) and (5) appear to perform the best, whereas models (9) and (10) appear to perform the worst. There also appear to be differences in forecast accuracy among the delivery period groups. In order to evalute the statistical significance of these results, the ANOVA tests are presented next.

First, two important assumptions underlying the repeated measures ANOVA design are (1) the population covariances between pairs of treatment levels are constant and (2) the population variances for each of the j treatment levels are homogeneous. In short, a homogeneous variance-covariance matrix is required, and if this condition is violated, the conventional F-test tends to overstate the significance of results.

Greenhouse and Geisser (1959) provide a measure of the extent to which the variance-covariance matrix departs from homogeneity.[6] We performed this test for both the MARE and the MSRE metrics and adjusted the degrees of freedom for the F-test accordingly. The ANOVA results, based on this conservative F-test, are presented in Table 4. For both error metrics, there is a significant model effect, as well as a significant interaction between model and backlog-to-sales group, but the other interactions are not highly significant.

In order to assess further any model effect, pairwise comparisons were performed for all possible model pairs. These results appear in Table 5. These comparisons show that the ten models can be partitioned into two groups based on relative forecast accuracy. Moreover, models (4), (6), (9), and (10) performed significantly worse, on average, than the other six models. Interestingly, both backlog models performed poorly relative to the six most accurate models. Also, it can be noted that there is apparently little basis on which to choose between models that are a function of past sales and those models that are a function of past orders.

The statistically significant interaction between forecast model and backlog-to-sales group was also interesting. First, however, some understanding of the nature of the model-group interaction can be gained by reviewing Tables 2 and 3. Indeed, a pattern emerges if we restrict the analysis to models (1), (2), (3) from the sales category and models (5), (7), and (8) from the orders category. Differences in forecast accuracy among backlog-to-sales groups, seem to depend on the various models. For those models using only sales data, firms with the smallest backlog-to-sales ratio seem to have the largest sales forecast errors and the firms with the largest backlog-to-sales ratio seem to have the smallest forecast errors. In contrast, for the models using orders data, there is a tendency for firms in the middle backlog-to-sales group to have the smallest forecast errors.

The statistical significance of these differences is shown in Table 6. In effect, the statistical test used here was a test of the "simple main effects" of the backlog-to-sales groups.[7]

Considering first the best models that used only past sales, i.e., models (1), (2), (3), there are significant differences between the long and short delivery period groups in five of the six cases, taking the results for the MARE and the MSRE metrics together. When examining the relationship for the forecast models that employed new orders data, i.e., models (5), (7), and (8), the results are less clear. However, there is a tendency for the middle backlog-to-sales ratio group to have the lowest forecast errors. The results are stronger based on the MARE metric than the results based on the MSRE metric.

SUMMARY AND CONCLUSIONS

The purpose of this study was to assess the direct and indirect predictive benefits of Form 10-K backlog information in a sales forecasting context. Accordingly, ten models were used to predict sales and a sample of 222 SEC-reporting companies provided the needed sales and backlog data. New orders for each year were derived from these data.

We examined three basic categories of extrapolative models: (1) Category I models based on sales data, (2) Category II models based on orders data, and (3) Category III models based on backlog data. These models were derived from the sales-order identity which states that beginning backlog plus new orders must equal ending backlog plus orders shipped.

Direct benefits, defined as those benefits directly attributable to the data and the models using the data, were not indicated by the results. Models using only sales data performed as well, if not better, than any of the others. Moreover, the models using backlog data per se performed by far the worst.

Indirect benefits, defined as those benefits attributable to the insights gained from having the data, were assessed by partitioning the sample into three equal groups on the basis of average delivery period. It was hypothesized that firms with longer delivery periods might be different from firms with shorter delivery periods. The results support this hypothesis. Indeed, the firms with the longest delivery periods (i.e., backlog-to-sales ratios) seemed to be the easiest to predict with Category I models (i.e., the models using only sales data). On the other hand, the firms with the shortest delivery periods seemed to be the easiest to predict with the Category II models (i.e., the models using orders data). One possible explanation of this phenomenon is that order backlogs tend to smooth the sales series enough to result in better sales predictions vis-a-vis the new order series. It appears, then, that sales forecasts using new orders are more susceptible to demand fluctuations which, in turn, reduce predictive ability.

The exact reasons for the relatively poor performance of the backlog data per se are unclear at this point. One possibility is that the backlog series are relatively inaccurate predictors of future sales due to order cancellations, rescheduling, and other factors. Another possiblility is that an annual forecast horizon may be too long. Thus, further research is needed to determine the usefulness of backlog data in other contexts, and until such research is completed, the usefulness of backlog data remains at issue. Perhaps SEC backlog data should be published more frequently or the annual data should be used for other purposes.

FOOTNOTES

[1]Since demand fluctuations are unobservable, they are usually estimated by economists in terms of fluctuations in the volume of new orders. On the other hand, in operations research, demand is often approximated in terms of shipments. Conrad [1976] notes that the newsboy problem, for example, makes use of historical sales data as a proxy for the demand distribution.

[2]Since input flexibility is never complete over an entire range of output, there is always some incentive to stabilize production relative to demand [Zarnowitz, 1962, p. 370].

[3]For instance, some changes in inventories could be due simply to discontinuities in LIFO layering, as well as purposeful shifts in inventory policy.

[4]In the economics literature this is a rather common assumption regarding the determinants of sales volume.

[5]The ratios of backlog-to-sales ranged from .012 to .306 (Group 1), from .307 to .633 (Group 2), and from .634 to 2.528 (Group 3).

[6]The measure is $\varepsilon = \dfrac{g^2(\bar{\sigma}_{jj} - \bar{\sigma})^2}{(g - 1)(\Sigma\Sigma\sigma_{jk}^2 - 2g\Sigma\bar{\sigma}_j^2 + g^2\bar{\sigma}^2)}$

where $\bar{\sigma}$ = the mean of all entries in Σ,

$\bar{\sigma}_{jj}$ = the mean of all entries of the main diagonal of Σ,

$\bar{\sigma}_j$ = the mean of all entries in row j of Σ, and

σ_{jk} = the entry in row j, column k of Σ (Winer, p. 523).

The computed ε values were .253 and .121 for the MARE and MSRE metrics, respectively.

[7]See Kirk [1968, pp. 263-267], or Winer [1971, pp. 544-545]. The test takes the following form [Winer, p. 544]:

$$\underline{t} = \frac{\overline{AB}_{2j} - \overline{AB}_{1j}}{\sqrt{2[MS_{error(a)} + (g - 1)MS_{error(b)}]/nrg}}$$

The denominators of the $\underline{t}$-ratios used in the tests were .024 and .029 for the MARE and the MSRE metrics, respectively.

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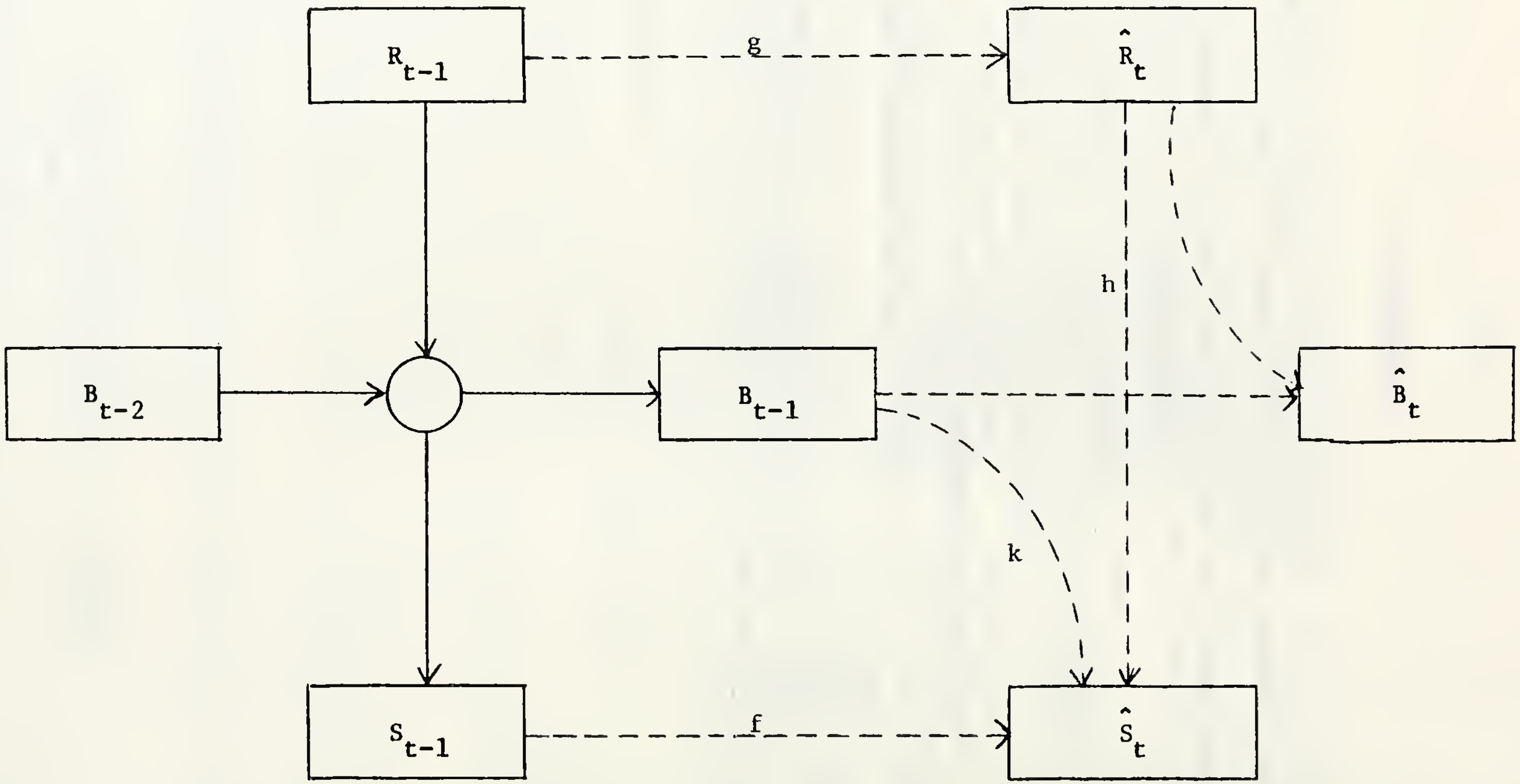
FIGURE 1

APPROACHES TO SALES FORECASTING BASED ON THE SALES ORDER IDENTITY



$B_{t-2} + R_{t-1} = B_{t-1} + S_{t-1}$

$B_{t-1} + \hat{R}_t = \hat{B}_t + \hat{S}_t$

TABLE 1

THE CYCLICAL BEHAVIOR OF BACKLOGS AND INVENTORIES

	Steady State	Expansion				Contraction				Steady State
	t=1	t=2	t=3	t=4	t=5	t=6	t=7	t=8	t=9	t=10
Key Relationships										
R_t versus S_t	$R_1=S_1$	$R_2>S_2$	$R_3>S_3$	$R_4>S_4$	$R_5=S_5$	$R_5<S_6$	$R_7<S_7$	$R_8<S_8$	$R_9=S_9$	$R_{10}=S_{10}$
P_t versus S_t	$P_1=S_1$	$P_2<S_2$	$P_3=S_3$	$P_4>S_4$	$P_5>S_5$	$P_6>S_6$	$P_7=S_7$	$P_8<S_8$	$P_9<S_9$	$P_{10}=S_{10}$
R_t versus P_t	$R_1=P_1$	$R_2>P_2$	$R_3>P_3$	$R_4\geq P_4$	$R_5<P_5$	$R_6<P_6$	$R_7<P_7$	$R_8\leq P_8$	$R_9>P_9$	$R_{10}=P_{10}$
Δ Backlogs	0	+	+	+	0	-	-	-	0	0
Δ Inventories	0	-	0	+	+	+	0	-	-	0
Numerical Example										
R_t versus S_t	10=10	20>15	25>15	25>15	25=25	20<25	15<20	15<20	15=15	15=15
P_t versus S_t	10=10	10<15	15=15	20>15	30>25	30>25	20=20	15<20	10<15	15=15
R_t versus P_t	10=10	20>10	25>15	25>20	25<30	20<35	15<20	15=15	15>10	15=15
Δ Backlogs	0	+5	+10	+10	0	-5	-5	-5	0	0
Δ Inventories	0	-5	0	+5	+5	+10	0	-5	-5	0

R_t = orders received in period t

S_t = shipments in period t

P_t = production at selling prices in period t

Δ = difference operator

TABLE 2

MEAN ABSOLUTE RELATIVE ERRORS (1980-81)

Model		Mean Errors				Mean Ranks			
		Full Sample	Delivery Period[a]			Full Sample	Delivery Period[a]		
			Short	Medium	Long		Short	Medium	Long
$\hat{S}_t = S_{t-1} + \delta$	(1)	.130	.137	.133	.118	4.51	4.18	4.94	4.41
$\hat{S}_t = (1 + r)S_{t-1}$	(2)	.139	.161	.138	.118	5.14	5.83	5.45	4.14
$\hat{S}_t = (1 + r')S_{t-1}$	(3)	.134	.152	.133	.116	4.85	5.20	5.24	4.11
$\hat{S}_t = a_0 + a_1S_{t-1}$	(4)	.161	.174	.147	.162	6.18	6.36	6.56	5.63
Average	(1-4)	.141	.156	.138	.128	5.17	5.39	5.55	4.58
$\hat{S}_t = R_{t-1}$	(5)	.136	.137	.113	.158	4.51	4.23	4.06	5.25
$\hat{S}_t = (1 + r)R_{t-1}$	(6)	.197	.169	.159	.263	6.70	5.95	6.36	7.80
$\hat{S}_t = a_0 + a_1R_{t-1}$	(7)	.145	.118	.117	.201	4.82	3.31	4.55	6.58
$\hat{S}_t = a_0 + a_1R_{t-1} + a_2S_{t-1}$	(8)	.150	.174	.134	.141	5.26	6.11	5.28	4.40
Average	(5-8)	.156	.150	.131	.191	5.32	4.90	5.06	6.00
$\hat{S}_t = a_0 + a_1B_{t-1}$	(9)	.198	.216	.179	.196	6.39	6.72	6.16	6.28
$\hat{S}_t = W^{-1}B_{t-1}$	(10)	.212	.257	.192	.187	6.63	7.09	6.39	6.41
Average	(9-10)	.210	.236	.185	.192	6.51	6.91	6.28	6.35
Average	(1-10)	.160	.170	.144	.166	5.50	5.50	5.50	5.50

[a] Average backlog divided by average sales (see footnote 5)

TABLE 3

MEAN SQUARED RELATIVE ERRORS (1980-81)

Model		Mean Errors				Mean Ranks			
		Full Sample	Delivery Period[a]			Full Sample	Delivery Period[a]		
			Short	Medium	Long		Short	Medium	Long
$\hat{S}_t = S_{t-1} + \delta$	(1)	.042	.065	.034	.027	4.69	4.34	5.05	4.68
$\hat{S}_t = (1 + r)S_{t-1}$	(2)	.051	.078	.048	.028	5.08	5.86	5.39	3.99
$\hat{S}_t = (1 + r')S_{t-1}$	(3)	.047	.078	.035	.028	4.87	5.17	5.35	4.09
$\hat{S}_t = a_0 + a_1S_{t-1}$	(4)	.061	.086	.044	.053	6.01	6.31	6.42	5.30
Average	(1-4)	.050	.077	.040	.034	5.16	5.42	5.55	4.52
$\hat{S}_t = R_{t-1}$	(5)	.045	.058	.025	.051	4.57	4.32	4.19	5.19
$\hat{S}_t = (1 + r)R_{t-1}$	(6)	.088	.080	.057	.128	6.77	6.04	6.45	7.82
$\hat{S}_t = a_0 + a_1R_{t-1}$	(7)	.052	.063	.029	.065	4.87	3.38	4.57	6.68
$\hat{S}_t = a_0 + a_1R_{t-1} + a_2S_{t-1}$	(8)	.058	.087	.039	.048	5.23	5.97	5.26	4.47
Average	(5-8)	.061	.072	.038	.073	5.36	4.93	5.12	6.04
$\hat{S}_t = a_0 + a_1B_{t-1}$	(9)	.083	.109	.064	.077	6.30	6.53	6.01	6.36
$\hat{S}_t = W^{-1}B_{t-1}$	(10)	.081	.130	.060	.052	6.60	7.07	6.31	6.42
Average	(9-10)	.082	.120	.062	.064	6.45	6.80	6.16	6.39
Average	(1-10)	.061	.083	.043	.056	5.50	5.50	5.50	5.50

[a] Average backlog divided by average sales (see footnote 5)

TABLE 4

ANOVA RESULTS

MARE				MSRE			
Source of Variation	Degrees of Freedom Unadj.	Degrees of Freedom Adj.	F Statistic	Source of Variation	Degrees of Freedom Unadj.	Degrees of Freedom Adj.	F Statistic
Main Effects				Main Effects			
A	9, 1971	4, 1005	23.728**	A	9, 1971	2, 473	7.518**
B	2, 219	1, 112	1.093	B	2, 219	1 53	1.376
C	1, 219	1, 112	.187	C	1, 219	1, 53	.966
Interactions				Interactions			
A X B	18, 1971	9, 1005	7.115**	A X B	18, 1971	7, 473	3.059**
A X C	9, 1971	4, 1005	1.581	A X C	9, 1971	2, 473	1.403
B X C	2, 219	1, 112	3.553	B X C	2, 219	1, 53	2.527
A X B X C	18, 1971	9, 1005	1.693	A X B X C	18, 1971	7, 473	.885

A = forecast model effect
B = backlog-to-sales group effect
C = year effect

** Significant at $\alpha \leq .01$

TABLE 5

PAIRWISE COMPARISONS OF FORECASTING RESULTS

MARE				MSRE			
Model Pairs	F Stat.	Model Pairs	F Stat.	Model Pairs	F Stat.	Model Pairs	F Stat.
(1) (2)	-.561	(3) (9)	-8.155*	(1) (2)	-.651	(3) (9)	-4.112*
(1) (3)	-1.349	(3) (10)	-10.252*	(1) (3)	-1.168	(3) (10)	-3.810*
(1) (4)	-4.449*	(4) (5)	3.583*	(1) (4)	-2.415	(4) (5)	2.090
(1) (5)	-.866	(4) (6)	-5.033*	(1) (5)	-.325	(4) (6)	-3.500*
(1) (6)	-9.483*	(4) (7)	2.225	(1) (6)	-5.915	(4) (7)	1.131
(1) (7)	-2.224	(4) (8)	1.621	(1) (7)	-1.284	(4) (8)	.398
(1) (8)	-2.829	(4) (9)	-5.055*	(1) (8)	-2.017	(4) (9)	-2.865*
(1) (9)	-9.504*	(4) (10)	-7.152*	(1) (9)	-5.280*	(4) (10)	-2.563*
(1) (10)	-11.601*	(5) (6)	-8.616*	(1) (10)	-4.978*	(5) (6)	-5.590*
(2) (3)	-.788	(5) (7)	-1.358	(2) (3)	-.517	(5) (7)	-.959
(2) (4)	-3.888*	(5) (8)	-1.962	(2) (4)	-1.764	(5) (8)	-1.692
(2) (5)	-.305	(5) (9)	-8.638*	(2) (5)	.327	(5) (9)	-4.955*
(2) (6)	-8.921*	(5) (10)	-10.735*	(2) (6)	-5.264*	(5) (10)	-4.653*
(2) (7)	-1.663	(6) (7)	7.258*	(2) (7)	-.633	(6) (7)	4.631*
(2) (8)	-2.267	(6) (8)	6.654*	(2) (8)	-1.366	(6) (8)	3.898*
(2) (9)	-8.943*	(6) (9)	-.021	(2) (9)	-4.629*	(6) (9)	.635
(2) (10)	-11.040*	(6) (10)	-2.119	(2) (10)	-4.327*	(6) (10)	.937
(3) (4)	3.100*	(7) (8)	-.604	(3) (4)	1.247	(7) (8)	-.733
(3) (5)	.483	(7) (9)	-7.280*	(3) (5)	.843	(7) (9)	-3.966*
(3) (6)	-8.133*	(7) (10)	-9.377*	(3) (6)	-4.747*	(7) (10)	-3.694*
(3) (7)	-.875	(8) (9)	-6.675*	(3) (7)	-.116	(8) (9)	-3.263*
(3) (8)	-1.479	(8) (10)	-8.773*	(3) (8)	-.849	(8) (10)	-2.961*
		(9) (10)	-2.097			(9) (10)	.302

*Significant at $\alpha \leq .05$ (test value = 3.085 and 2.450 for MARE and MSRE, respectively).

TABLE 6

SALES FORECAST ERROR DIFFERENCES BETWEEN BACKLOG-TO-SALES GROUPS

Model	MARE Delivery Period Group Differences[a]			MSRE Delivery Period Group Differences[a]		
	S-M	M-L	S-L	S-M	M-L	S-L
(1)	.004 (.167)	.015 (.625)	.019 (.792)	.031 (1.069)	.008 (.275)	.038* (1.310)
(2)	.023 (.958)	.020 (.833)	.043** (1.792)	.030 (1.034)	.020 (.690)	.050** (1.724)
(3)	.019 (.792)	.017 (.708)	.036* (1.50)	.043 (1.483)	.007 (.241)	.050** (1.724)
(5)	.024 (1.000)	.043** (1.792)	-.021 (-.875)	.033 (1.138)	-.026 (.896)	.007 (.241)
(7)	.001 (.004)	-.084** (-3.500)	-.083** (-3.458)	.034 (1.172)	-.036 (-1.241)	-.002 (.069)
(8)	.040** (-1.667)	-.007 (-.292)	-.033* (-1.375)	.038* (1.310)	-.009 (.310)	.039* (1.345)

[a]Delivery period group differences are summarized from Tables 2 and 3; S, M, and L refer to short, medium, and long delivery period groups, respectively.

t-statistics are in parentheses.

**Significant at $\alpha \leq .05$ (two tailed test)
*Significant at $\alpha \leq .10$ (two tailed test)