Sales Anticipations, Planned Inventory Investment, and Realizations

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1. Introduction

The impact upon inventory investment of errors made by firms in anticipating sales volume is an important but hackneyed topic. The topic is significant, because inventory investment—a much more volatile component of private investment spending than either new construction or producer durables—constitutes a critical link in the generation of fluctuations in economic activity. But the topic has constituted the theme of numerous theoretical and empirical studies. The assumption that inventories are drawn down below planned levels when sales volume is underestimated at the start of the production period constitutes the cornerstone of the Lundberg (1955) and Metzler (1941) aggregative inventory cycle models and their multisector generalizations.[1] The empirical problem of explaining how inventory

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[1] The multisector generalizations of Lovell (1962) and Foster (1963) were concerned with the stability properties of dynamic input-output models in which each industry responded to errors made in anticipating sales volume in essentially the same manner as assumed by Lundberg and Metzler for the aggregate. Complete bibliographical references are given at the end of the paper.

investment is related to anticipated sales volume constituted virgin territory when Modigliani and Sauerlander presented their pioneering paper (1955) some ten years ago at an earlier National Bureau Conference. Today we can look back upon a multitude of empirical studies of inventory behavior.[2] In addition, our knowledge is buttressed by numerous studies of anticipatory data, including Robert Ferber's study of the *Railroad Shippers' Forecasts* (1953) and the many notable papers in *The Quality and Economic Significance of Anticipations Data* (1960).

My excuse for revisiting the topic is provided by the new and exciting data now available from the quarterly manufacturers' inventory and sales anticipations survey conducted by the Office of Business Economics, Department of Commerce. In earlier empirical studies of inventory behavior it was necessary either to rely upon grossly imprecise measures of sales anticipations or to resort to surrogative procedures. Furthermore, considerable detective work was necessary in deriving inferences about the nature of the discrepancy between measured inventories and their desired level. The OBE survey now provides us with data on anticipated sales and planned inventory investment for both a three-month and a six-month horizon. In addition, an index of surplus inventories is provided.

The richness of the new OBE data facilitates the investigation of such problems as the structure of sales anticipations and inventory plans and the determinants of desired inventory levels. Research on these topics is currently under way, and this paper is only a preliminary report on one aspect of a larger study. But the results obtained to date, while preliminary, are surprising to say the least. Specifically, the new evidence suggests that the magnitude of the forecasting errors made by firms is not nearly as large as previous empirical studies had suggested. Firms now appear to be much more precise in predicting sales volume than is customarily assumed in theoretical models of the inventory cycle. Equally important, I find that deviations of actual from anticipated sales volume do not generate discrepancies between planned and actual inventory investment in the way that has customarily been assumed in theoretical and empirical investigations.

In the next section of this paper the new data provided by the OBE survey will be discussed. Then, in section 3, the accuracy of these *ex ante* data will be contrasted with the evidence of earlier empirical surveys of anticipations. Section 4 summarizes the basic equations of

[2] For an attempt to summarize this literature, see Lovell (1964).

TABLE 1

Industry Code and Variables Utilized in Study

Industry Code

Durables

1. Primary iron and steel
2. Primary nonferrous metals
3. Electrical machinery
4. Machinery except electrical
5. Motor vehicles and equipment
6. Transportation equipment, excluding motor vehicles and equipment
7. Other durable goods

Nondurables

1. Food and beverage
2. Textiles
3. Papers
4. Chemicals
5. Petroleum
6. Rubber
7. Other nondurable goods

Variables (million dollars)

IN	=	actual inventory at end of quarter
ASIN	=	short inventory anticipation (anticipated end-of-quarter inventory)
ALIN	=	long inventory anticipation (anticipated inventory at end of next quarter)
SALE	=	actual sales of quarter t
ASSALE	=	short sales anticipation (sales volume anticipated for current quarter)
ALSALE	=	long sales anticipation (sales volume anticipated for next quarter)
COND	=	condition of inventory (proportion of firms reporting inventories high in relation to total sales and unfilled orders backlog less percentage reporting inventories low)
FIN	=	actual finished goods inventory at end of quarter
PMGIP	=	purchased materials and goods in process
UOR	=	unfilled orders at end of quarter

Note: Approximately half the questionnaires are returned to the OBE by the end of the first month of the quarter. Since the smaller companies generally answer sooner than the larger ones, an average response date weighted by company size is probably the tenth day of the second month of the quarter.

the buffer-stock model of inventory behavior. In sections 5 and 6 the model is used in analyzing finished goods and aggregate inventory behavior. The argument of the paper is summarized in the concluding section.

2. *The New Data*

The manufacturers' inventory and sales expectations survey, initiated by the OBE in the fall of 1957, is currently conducted every quarter. Respondents are asked to report both the expected level of inventories at the end of the current quarter and the level anticipated for the end of the next quarter; in addition, they report on actual inventory at the beginning of the current quarter and the previous quarter.[3] The survey also inquires as to expected sales volume in both the current and the immediately following quarter. Further, information on the discrepancy between desired and actual inventory stocks is provided in terms of the percentage of firms reporting inventories as high, about right, and low relative to total sales and the unfilled orders backlog.

I have been privileged to have access to the data in raw form for the seven durable and seven nondurable industries identified in Table 1. In the present study, data are used for the twenty-one surveys conducted through the second survey of 1963, but there are only eighteen observations on short anticipations for inventories and sales as the first three surveys did not inquire about short-run three-month prospects. The anticipations data used here are adjusted to industry benchmarks by the OBE.[4] But unlike most other anticipatory series, the figures utilized in this study have not been adjusted by the compiling agent in

[3] In designing the questionnaire, the OBE benefited from our prior experience with the railroad shippers' survey. By avoiding reference to the corresponding quarter of the previous year, the respondents were in no way encouraged to simply extrapolate from their experience in the same season of last year.

[4] Foss (p. 234) explains that for each industry the firms in the sample are partitioned into two cells on the basis of size. For each size cell of each industry, the anticipated inventory figure is multiplied by a blowup factor. The blowup factor for inventories is simply the ratio of the inventory figure for the regular larger monthly survey to the inventory figure reported by firms in the anticipations survey for the quarter in which the anticipations figure is formulated. A similar procedure is employed for sales. There are certain advantages in employing the benchmark data, for without such an adjustment the observed forecasting error may be distorted as a result of fluctuations in response rates between the survey in which the *ex ante* figures are collected and the subsequent survey in which the *ex post* realizations are reported.

an attempt to eliminate systematic biases or to improve the forecasts.[5] The sample is reasonably large, consisting in 1961 of from 1,250 to 1,400 manufacturing firms, with better than 80 per cent coverage of larger firms with assets over $10,000,000.

Admittedly, quarterly time series covering only five years do not provide as many observations as we would like to have. But the difficulty is mitigated by the breadth of industry coverage. Furthermore, many earlier investigators of expectations behavior, with the notable exception of studies based on the railroad shippers' forecast data, have also had to work with extremely short time series. It would have been useful to have had the inventory figures broken down by stage of fabrication.[6] For the durable and nondurable aggregate, it was possible to utilize the published inventory by stage of fabrication data, but the anticipated inventory figures I utilized were not broken down in this way.[7]

One of the most serious problems involved in collecting *ex ante* data arises from the possibility that the reported figures do not reflect the actual anticipations of individuals making operating decisions for the firm. The questionnaire for the OBE survey is generally submitted by company controllers and treasurers or their assistants, and there exists the distinct possibility that these figures do not correspond to a simple aggregate of expectations of production and purchasing departments. But Murray Foss does report that seven out of every eight respondents reported that the sales anticipations figures "played an important part

[5] The published inventory anticipations figures, in contrast, are adjusted with the aid of the inventory conditions variable in an attempt to eliminate apparent systematic biases. Similar adjustments for systematic biases are made by the OBE-SEC in publishing the results of the survey of business plant and equipment expenditures, and when these data have been used in econometric studies of expectational behavior, the results may have been distorted as a result of the compiling agents' attempt to improve the forecasting ability of the *ex ante* series. Similarly, the raw survey results are subjected to adjustment by some of the regional boards of the American Railway Association in an attempt to improve their accuracy.

[6] The survey does inquire into the condition of inventories (high, low, or about right) by stage of fabrication, and these figures are published for the durable and nondurable aggregates, but this information was not provided to me on an industry basis.

[7] In utilizing the published finished goods aggregates for durables and nondurables, it was necessary to adjust for the fact that the coverage of the individual industries fell short of the published sector totals. The durable and nondurable finished goods aggregates utilized in this study were obtained by multiplying the total inventory figure obtained from summing the component industries by the current ratio of published finished goods to published total inventory. The Department of Commerce now publishes data on industry stage of fabrication, but the new figures are based on a more recent Standard Industrial Classification and are not directly comparable with the industry classification of the anticipations data.

in the company's production and purchasing policies" when this question was raised as a supplemental question on one of the earlier surveys. The proportion was somewhat higher in durables and lower in nondurables; in the food and beverage industry, more than one in three firms answered in the negative. Foss also reports that five out of every six firms reported that they utilized the inventory forecast in production and purchasing policies. Field interviews conducted by the Office of Business Economics confirmed that the sales forecast lies at the heart of most companies' future plans; firms consider the inventory anticipation to be much more difficult to make than the sales projection.[8]

Two questions of ambiguity about the interpretation of the data deserve mention. As with some earlier *ex ante* surveys, there is the question of whether the forecasts are made in terms of current dollars or of the price level anticipated three or six months hence. Fortunately, the period covered by our data has not been marked by sharp inflationary trends. Furthermore, Murray Foss found, early in the history of the survey, that adjusting the inventory data under the assumption that respondents were making the forecast in present prices had only minor effects on the series. The second ambiguity arises from the possibility that the anticipations may have been reported on a seasonally adjusted basis. But when firms were asked, in a supplementary question, to give reasons for the anticipated change, approximately 50 per cent of them indicated "normal seasonal change" as one factor influencing their forecast.[9] The data used in this study have not been seasonally adjusted.

3. *On the Accuracy of Sales Anticipations*

Early studies of short-term anticipatory data suggested that business firms are remarkably poor forecasters of future sales volume. Ferber (1953) reported in his pioneering study that a simple procedure for extrapolating from the past yielded much more precise forecasts than the anticipated carload shipments data collected by the Regional Ship-

[8] See Foss (p. 237) for additional information on the relevance of the forecasts for company planning.

[9] Early in the history of the survey Foss compared the anticipations figures without seasonal adjustment with the seasonally adjusted realizations, but did not find any decisive improvement in the accuracy of the forecasts. Of course, to the extent that the seasonal adjustment procedures are *idempotent,* subjecting a series to repeated seasonal adjustment will have only minor effects upon the series. For inventories, a marked seasonal pattern is observed only in the food and beverage industry, but seasonal movements are somewhat more pronounced in sales volume.

pers' Advisory Board of the American Railway Association. Modigliani and Sauerlander (1955) were also quite pessimistic about the direct forecasting ability of business firms, although they noted that anticipatory data compiled in *Fortune* and in Dun and Bradstreet surveys implied that firms were not quite as unsuccessful at forecasting as the railroad shippers' data suggested. More recently, examination of anticipatory data compiled by the Securities and Exchange Commission and the Office of Business Economics in their annual survey of plant and equipment intentions has suggested that firms are considerably more precise at forecasting annual sales volume than the earlier investigators had concluded.[10] The new data provided by the OBE quarterly survey suggest that businessmen's anticipations of sales volume are much more precise than economists had been led to believe on the basis of the earlier evidence.

ANTICIPATIONS VERSUS NAIVE FORECASTS

A naive forecast is a convenient yardstick by which the accuracy of anticipatory data may be measured. The accuracy of anticipations might be judged by comparing their forecasting accuracy with a naive extrapolation from either the immediately preceding quarter or the corresponding quarter of the preceding year. Ferber (1953) and Modigliani and Sauerlander (1955) used a slightly more complicated naive projection in evaluating their anticipatory data. Specifically, they compared the accuracy of the anticipations forecast with

$$E_t^{**} = A_{t-4}(A_{t-1}/A_{t-5}), \tag{1}$$

where E_t^{**} is the naive forecast and A_{t-i} is the actual realization i quarters previously. For testing six-month anticipatory data, the Ferber naive forecast may be appropriately modified to

$$E_t^{**} = A_{t-4}(A_{t-2}/A_{t-6}). \tag{2}$$

In either form, the naive forecast amounts to adjusting the same quarter of the immediately preceding year by recently observed trend. Or to put it another way, the Ferber test elaborates on the simpler naive forecast of "same as current quarter" by adjusting for the change observed last year.[11] Thus it constitutes a crude adjustment for seasonal movements.

[10] See Modigliani and Weingartner (1958). On the other hand, Pashigian (1964) suggests that the sales anticipations can be beaten by an artfully designed naive model.

[11] This may be observed by writing (1) as $E_t^{**} = A_{t-1}(A_{t-4}/A_{t-5})$.

TABLE 2

Accuracy of Anticipations Data Relative to Ferber's Naive Test: Ratios of Average Absolute Errors

(per cent)

	ASSALE	ALSALE	ASIN	ALIN
Durables				
1	8	36	31	46
2	45	54	64	61
3	49	48	77	57
4	66	47	57	57
5	15	29	48	69
6	58	55	93	53
7	96	89	89	73
Aggregate	15	42	60	57
Combined	25	43	58	59
Nondurables				
1	87	115	309	195
2	68	70	206	162
3	70	80	108	187
4	64	65	233	122
5	110	102	151	123
6	83	71	54	57
7	59	60	123	101
Aggregate	59	64	301	196
Combined	73	73	135	101

Ferber computed the average absolute percentage error (AAPE) for both the naive forecast and for the actual railroad anticipatory data.[12] For the most part, the AAPE was considerably larger for the

[12] In other words, AAPE $= 100\ \Sigma(E - A)/n$, where n is the number of observations, E the forecast change, and A the realized change. An alternative measure would be the root mean square error, $[\Sigma(E - A)^2/n]^{1/2}$. The root mean square error penalizes extreme errors more severely than the AAPE and is appropriate if the loss function is quadratic. I have computed both measures of accuracy for the OBE quarterly data, but report only the AAPE as these figures are comparable with other studies. In any case, the basic conclusions are quite insensitive to the measure selected.

railroad anticipations data than for the naive forecast. For the prewar period, 1929–41, the naive forecasts were more accurate than observed anticipations for the total nonfarm aggregate and for each of the five component industries that he considered. For the period 1946–50, the forecasts of the nonfarm aggregate had a 23 per cent larger AAPE than the naive forecast, although the anticipatory data were at least marginally superior to the naive forecasts in three industries—iron and steel, flour, and cement.

The accuracy of the new OBE anticipatory data relative to Ferber's naive forecast is shown in Table 2 for individual industries as identified in Table 1, for the durable and nondurable aggregates, and for the individual industries combined. Inspection of the table reveals that in durable manufacturing entrepreneurs are particularly accurate forecasters. For iron and steel, the AAPE for the three-month sales forecast is only 8 per cent of the AAPE of the naive projection; the six-month forecast has an AAPE ratio of 36 per cent. Contrast this with the figure of 79 per cent reported by Ferber for the same industry for the 1946–50 period on the basis of the railroad shippers' forecast data. For only one industry—petroleum—does the ASSALE forecast do worse than the Ferber extrapolation. For two nondurable industries —food and petroleum—the Ferber extrapolation is marginally superior to the ALSALE forecast.[13]

CORRELATION OF ACTUAL WITH ANTICIPATED CHANGE

A second yardstick frequently used in evaluating the precision of expectational data is provided by computing the correlation between the predicted and the actual change. A correlation coefficient that is not significantly different from zero would imply that a naive prediction of a constant percentage change for each period constitutes as good a predictor as the anticipatory series. On the other hand, a high correlation may be obtained with a quite poor predictor, for the correlation test is a weak one in that it automatically corrects for any systematic linear bias between anticipated and actual change; the correlation coefficients measures the potential forecasting ability after correction for systematic bias.

On Table 3, where the correlation coefficients obtained with the OBE data are reported,[14] it may be observed that the coefficients

[13] In no case does an alternative to the Ferber naive extrapolation (same as last quarter) do as well as the ASSALE forecast, but for textile and petroleum a naive extrapolation (same as two quarters back) does as well as ALSALE.

[14] The correlation coefficients are adjusted for degrees of freedom.

TABLE 3

Accuracy of Anticipations Data: $\bar{R}^2$ of Actual with Predicted Percentage Change

	ASSALE	ALSALE	ASIN	ALIN
Durables				
1	.9667	.8969	.6444	.5257
2	.7233	.2904	+0	.0439
3	.9225	.4180	.8157	.6732
4	.9185	.7363	.6685	.7149
5	.9812	.8430	.7367	.1891
6	.6834	.3249	.2831	.5571
7	.6558	.5367	.7231	.7738
Aggregate	.9618	.7377	.8267	.7185
Combined	.9396	.8208	.5800	.4479
Nondurables				
1	.7814	.8023	.9115	.8912
2	.2801	+0	.7908	.7529
3	.1540	.4522	.3229	.5646
4	.7173	.5583	.7243	.6860
5	.5962	.2345	.8225	.7579
6	.7050	.3079	.6913	.6909
7	.7988	.6720	.7281	.7068
Aggregate	.6196	.4830	.1009	.0831
Combined	.6304	.3737	.7499	.7264

obtained for sales are higher for short than for long anticipations, as might be expected. Durable sales on the average yield a tighter fit than nondurables. Inventory investment is anticipated with less precision than sales volume.

The evidence of Table 3 reveals that sales anticipations are more precise than had been suggested by earlier studies. When anticipated changes reported in the railroad shippers' survey for the 1927–41 period were correlated with actual changes, the correlation coefficients were negative approximately half the time; this reflects the notorious tendency for anticipatory series to predict short-run movements in the reverse direction from actual developments. In contrast, the correlation coefficients for the OBE quarterly survey are all positive. With the postwar Dun and Bradstreet survey data, Modigliani and Sauerlander obtained correlation coefficients for the postwar period of .03 for durables and .10 for nondurables. The *Fortune* survey did considerably better, Modigliani and Sauerlander reported, with a correlation coefficient of 0.80 for durables, but the OBE data yield a considerably higher figure of R^2 of .96 and .74 for short and long durable sales anticipations, respectively.

While the high correlations between the anticipated and the actual sales and inventory changes reported in Table 3 demonstrate that the OBE *ex ante* data constitute more precise predictors of actual realizations than earlier anticipatory series, they do not suffice to establish that the new *ex ante* series are useful forecasters in their own right. It will be remembered that the Ferber naive test makes a simple allowance for seasonal movements. In contrast, the simple correlation coefficients reported in Table 3 do not reveal the extent to which the suggested forecasting precision of the *ex ante* data arises from the seasonality in the data. In order to investigate the net forecasting ability of the OBE data, over and above seasonal movements, the following regression equation was fitted to the individual industries and the durable and nondurable aggregates:

$$\frac{\mathrm{IN} - \mathrm{IN}_{-1}}{\mathrm{IN}_{-1}} = b_1 + b_2 s_1 + b_3 s_2 + b_4 s_3 + b_5 t + b_6 \left(\frac{\mathrm{ASIN} - \mathrm{IN}_{-1}}{\mathrm{IN}_{-1}}\right) + e. \tag{3}$$

Here the s_i are seasonal dummy variables that equal unity in the i^{th} quarter and zero in all other quarters; the variable t denotes trend.[15] Similar regressions were run for ALIN, ASSALE, and ALSALE.[16] If the forecasters were sufficiently clairvoyant to know the seasonal pattern, the seasonal and trend terms in the regression would be insignificant. In fact, however, the dummy variables are generally large relative to their standard errors, suggesting that there is a consistent seasonal pattern in the discrepancies between actual and anticipated changes. Indeed, the anticipated change variable was insignificant in the majority of the nondurable regressions, suggesting that knowledge of the anticipated change would make a negligible contribution toward predicting

[15] This implies a fixed multiplicative seasonal pattern, for equation (3) is equivalent to $\mathrm{IN} = (b_1 + b_2 s_1 + b_3 s_2 + b_4 s_3 + b_5 t + 1 - b_6)\mathrm{IN}_{-1} + b_6\mathrm{ASIN} + e\mathrm{IN}_{-1}$. Seasonality is not marked when represented in additive form.

[16] For the ALIN and ALSALE regressions, a six-month rather than a three-month lag was introduced.

TABLE 4

Accuracy of Anticipations Data: Partial $\bar{R}^2$ Actual with Predicted Percentage Change[a]

	ASSALE	ALSALE	ASIN	ALIN
Durables				
1	.8290	.6735	.4631	.3456
2	.2867	.1015	.0150	–
3	.4588	.2367	.2187	.2945
4	.2958	.1969	.1462	.2813
5	.7566	.5065	.5165	.1244
6	.1858	.2424	.2470	.2975
7	–	–	.2365	.2309
Aggregate	.5517	.4436	.5517	.3932
Nondurables				
1	–	–	.0229	.0928
2	.0221	–	.0026	–
3	.0414	.0931	.1831	.1965
4	.0543	–	.0604	–
5	–	.0350	–	–
6	.0946	–	.2114	.1731
7	.1468	.0967	–	–
Aggregate	.0220	–	–	.1123

Note: Blanks denote negative adjusted partial correlation coefficients.

[a]Partial with respect to seasonality and trend.

the actual change if the seasonal pattern were known.[17] The squared partial correlation coefficients of actual with anticipated change, net of the effects of seasonality and trend but adjusted for degrees of freedom, are presented in Table 4. While these partial coefficients are quite high in a number of durable industries, it is apparent from the table

[17] In the durables, the anticipated change variable appeared with a significant coefficient in all regressions with the exception of ASSALE and ALSALE for industry 7 (all other) and ASIN and ALIN for industry 2 (primary nonferrous metals). For nondurables, on the other hand, ASSALE is significant only for the industry 6 regression, ALSALE only for industries 3 and 7, ASIN in industries 3 and 6, and ALIN only for 1, 3, and 6.

that the anticipated change makes a negligible contribution toward predicting the seasonally adjusted actual change in most nondurable industries.[18]

CONCLUSION

The new *ex ante* data compiled by OBE constitute a much more precise predictor of actual realization than the quarterly anticipations data analyzed in earlier studies. In terms of the two yardsticks applied in previous investigations of quarterly anticipatory data, the Ferber naive comparison and the correlation of actual with anticipated changes, entrepreneurs seem to be much more precise at predicting short-run sales developments than had been suggested by earlier studies. In terms of a tougher test, however, my analysis of the new data suggests that entrepreneurs in a number of industries are not particularly adept at anticipating seasonal movements in sales and inventory volume. They do considerably better at predicting sales and inventory developments than they would by employing the simple Ferber procedure for roughly adjusting for seasonal effects in projecting from current levels; but in terms of a rather invidious comparison with a seasonal pattern estimated from the whole sample period, we find from Table 4 a rather mixed record of achievement. While entrepreneurs still appear to be quite good at predicting actual changes in a number of durable industries, they are apparently much less adept at predicting developments in the nondurable sector.

Why are the *ex ante* data compiled by the Office of Business Economics more precise predictors of actual realizations than the quarterly sales anticipatory data analyzed in earlier studies? We might expect the ASSALE forecast to be more accurate than the railroad shippers' anticipations because the OBE questionnaire is circulated after the beginning of the quarter while the American Railway Association survey data is gathered during the middle of the preceding quarter. But the lead time on the ALSALE forecast is longer than that of the American Railway Association survey, and yet the ALSALE forecasts are also considerably more accurate than the railroad shippers anticipatory data. It is possible that the greater accuracy of the new survey is in part due to a continued improvement in the ability of firms to forecast demand conditions. Support for this argument is provided by

[18] The partial coefficients of Table 4 are identical to those that would be obtained by correlating seasonally adjusted actual change with seasonally adjusted predicted change if (1) the two series were adjusted separately by a least-squares multiplicative procedure and (2) correct allowances were made for the loss of degrees of freedom resulting from the process of seasonal adjustment.

the fact that the shippers' forecasts were somewhat more accurate after World War II than during the interwar period. But a third and more likely explanation is provided by the fact that the *ex ante* data compiled in the railroad shippers' forecasts are reported in terms of anticipated carload usage by the responding firms traffic manager. Even if the traffic manager is informed about anticipated sales volume, the process of converting forecasted sales into an estimate of carloading requirements may well tend to introduce considerable imprecision. The raw carloading anticipatory data, my earlier research suggested, had a grossly unsatisfactory forecasting record because the errors made by firms with regard to sales anticipations were confounded with additional noise resulting from errors made in converting sales figures into carloading requirements.[19] It may well have been a mistake to interpret the poor forecasting record of the railroad shippers' *ex ante* data on anticipated carloadings as evidence that firms were extremely poor at forecasting sales volume.

4. Buffer-Stock Inventory Behavior

In theoretical models of the inventory cycle it is customarily assumed that inventory investment deviates from its planned level as stocks are run down when entrepreneurs are surprised by a sales volume that exceeds anticipations; in other words,

$$\text{IN} = \text{ASIN} - (\text{SALE} - \text{ASSALE}). \tag{4}$$

This elementary version of the realization concept is subject to the obvious objection that no allowance is made for the revision of plans during the quarterly observation period. As errors in anticipating such variables as sales volume become apparent during the quarter, it may be possible for the firm to at least partially revise production schedules and the delivery dates for purchased materials. The possibility of plan revision has received explicit consideration in many empirical studies of inventory behavior, including both the Modigliani and Sauerlander (1955) and the Lovell (1961) papers. A detailed theoretical analysis

[19] See Lovell (1964, pp. 216–220) for a more detailed presentation of this argument. There I showed, for the cement industry data, that if the anticipated carloadings figures are transformed into sales forecasts, the sales forecasts are considerably more accurate predictors of actual sales volume than the *ex ante* carloading figures are predictors of actual carloadings. It is interesting to note that while the Modigliani and Sauerlander study (1955) reported on the inaccuracy of the carloading forecasts, these *ex ante* figures were transformed into sales forecasts, measured in barrels, for purposes of explaining cement inventory behavior; the latter series may have been much more accurate.

of the effects of plan revision on production and inventory levels is to be found in Modigliani and Cohen (1961). I shall briefly summarize the theory in this section and then, in subsequent sections of the paper, evaluate it in the light of the new data provided by the OBE survey.

Let us begin, as has been customary in many studies of inventory behavior, by postulating that the desired level of end-of-quarter inventories, IN^d, is a linear function of current and the next period's sales. Thus we shall assume:

$$\mathrm{IN}^d = \beta_1 + \beta_2\mathrm{SALE} + \beta_3\mathrm{SALE}_{+1} + \epsilon_2. \tag{5}$$

Because SALE and SALE_{+1} are unknown at the beginning of the period, the anticipated level of desired inventory is

$$\mathrm{AIN}^d = \beta_1 + \beta_2\mathrm{ASSALE} + \beta_3\mathrm{ALSALE}_{+1} + \epsilon_3. \tag{6}$$

Anticipated sales volume as well as the realized volume of sales will be regarded as exogenous. Planned inventory investment may be expected to deviate from the desired level because of costs involved in adjusting stocks. If, as is customary, it is assumed that only a partial adjustment of stocks toward the desired level is attempted, we have for the planned inventory stock

$$\mathrm{ASIN} = \delta\mathrm{AIN}^d + (1 - \delta)\mathrm{IN}_{-1} + \epsilon_4, \tag{7}$$

where δ, the adjustment coefficient, lies between zero and unity. Substituting from equation (6) in order to eliminate the unobserved variable AIN^d yields:

$$\mathrm{ASIN} = \delta\beta_1 + \delta\beta_2\mathrm{ASSALE} + \delta\beta_3\mathrm{ALSALE}_{+1} + (1 - \delta)\mathrm{IN}_{-1} + \epsilon_5, \tag{8}$$

where $\epsilon_5 = \delta\epsilon_3 + \epsilon_4$.

If no revision of production plans or delivery schedules is feasible, actual inventories will deviate from planned levels by the amount by which actual sales depart from the anticipated level, in accordance with equation (4). On the other hand, in the case of *complete flexibility,* inventory investment would be unaffected by any error in anticipating current sales volume and, in addition, actual inventory would be determined by end- rather than beginning-of-period anticipations of sales in period $t + 1$. In other words, end-of-period knowledge of current sales and end-of-period anticipations of next-quarters sales volume, rather than initial anticipations, would be the relevant determinants of inventory investment. With sufficient flexibility, then, we would have:

$$\mathrm{IN} = \delta\beta_1 + \delta\beta_2\mathrm{SALE} + \delta\beta_3\mathrm{ASSALE}_{+1} + (1 - \delta)\mathrm{IN}_{-1} + \epsilon_6. \tag{9}$$

In practice, plans may be only partially subject to revision during the three-month observation period. If we are permitted to assume that the effect of plan revision is to cause actual inventory investment to be an average (with weights λ and $1 - \lambda$, respectively) of the extremes suggested by equations (4) and (9), we shall have:[20]

$$\begin{aligned} \text{IN} = {} & \lambda[\text{ASIN} + \text{ASSALE} - \text{SALE}] + (1 - \lambda)\delta\beta_1 + (1 - \lambda)\delta\beta_2\text{SALE} \\ & + (1 - \lambda)\delta\beta_3\text{ASSALE}_{+1} + (1 - \lambda)(1 - \delta)\text{IN}_{-1} + \epsilon_7. \quad (10) \end{aligned}$$

The *realization function* is obtained by a slight modification of equation (10). Specifically, let us add and subtract from the right-hand side of the last equation $(1 - \lambda)$ASIN, as given by equation (8). This yields

$$\begin{aligned} \text{IN} = {} & \text{ASIN} + [(1 - \lambda)\delta\beta_2 - \lambda](\text{SALE} - \text{ASSALE}) \\ & + (1 - \lambda)\delta\beta_3(\text{ASSALE}_{+1} - \text{ALSALE}_{+1}) + \epsilon_8, \quad (11) \end{aligned}$$

where $\epsilon_8 = \epsilon_7 - (1 - \lambda)\epsilon_5$.

The realization function explains the discrepancy between actual inventory and its planned level in terms of both the *surprise* effect of errors made in anticipating current sales volume and the *revision* of anticipations of sales volume expected during the following quarter. Observe that if $\beta_3 = 0$, desired inventories being a function of only current rather than the next period's sales, the above equation reduces to (4). A positive effect upon inventories might be generated when sales volume exceeds anticipations, but only if production plans are extremely flexible; i.e., if $\lambda < \delta\beta_2/(\delta\beta_2 + 1)$, the coefficient of the surprise term SALE $-$ ASSALE in equation (11) is positive.

It will be observed that a limitation of the realization function approach is that its application does not yield estimates of the individual parameters of the model. An alternative approach is to work in terms of a reduced-form equation for inventories. It will be observed that, while equations (8) and (10) constitute a system of two simultaneous equations, they are fortunately triangularly recursive. Although the current value of ASIN appears in both equations, actual inventory does not appear in (8). If we use equation (8) to eliminate ASIN from (10), we obtain as the reduced-form equation for inventories[21]

$$\begin{aligned} \text{IN} = {} & \delta\beta_1 + \lambda(1 + \delta\beta_2)\text{ASSALE} + \lambda\delta\beta_3\text{ALSALE}_{+1} \\ & + (1 - \lambda)\delta\beta_3\text{ASSALE}_{+1} + [\delta\beta_2 - \lambda(\delta\beta_2 + 1)]\text{SALE} \\ & + (1 - \delta)\text{IN}_{-1} + \epsilon_9, \quad (12) \end{aligned}$$

[20] If $\lambda = 1$, plans are completely rigid, and this equation reduces to equation (4); with $\lambda = 0$, we again have (9).

[21] Note that since the system is triangular, the structural and reduced-form equations for ASIN are identical.

where $\epsilon_9 = \epsilon_7 + \lambda\epsilon_5$. This reduced-form equation must be employed when observations on planned inventory investment are not available.

5. *Finished Goods Inventory Behavior*

The distinction between finished goods inventories and purchased materials and goods in process has been stressed in many empirical studies of inventory investment behavior. When anticipations data have been utilized in earlier studies of inventory investment, the primary focus has been upon finished goods. It is possible for us to replicate on the new data models employed by Modigliani and Sauerlander (1958) and Lovell (1964). In addition, it will be possible to exploit the ASSALE versus ALSALE distinction now provided by the new survey. Of course, it will be necessary, as in the earlier studies, to finesse the planned inventory position variable, as data were not available on planned inventory by stage of fabrication. For this reason, we must work with reduced form equation (12). We must also content ourselves with an examination of the durable and nondurable aggregates, for it has not proved convenient to work with stage of fabrication data by individual industries.[22]

First, we will consider the restricted case in which desired inventory depends upon current rather than the next period's anticipated sales volume, i.e., $\beta_3 = 0$. In an earlier study of durable and nondurable finished goods manufacturing inventory data covering the period 1948–55, it was necessary for me to invoke this assumption since the crude measure of anticipated sales that I derived from railroad shippers' forecast data referred only to short anticipations. Equation (12) was tested in the form:

$$\Delta\text{FIN} = \delta\beta_1 + \delta\beta_2\text{SALE} - \lambda(\delta\beta_2 + 1)(\text{SALE} - \text{ASSALE}) - \delta\text{FIN}_{-1} + \epsilon. \qquad (13)$$

The coefficient of the surprise term, SALE − ASSALE, was at least three times its estimated standard error in both the durable and the nondurable regressions. The point estimates obtained for λ of .11 for durables and .10 for nondurables were sufficiently large relative to the estimates of δ and β to imply that inventories are reduced when actual sales exceed the anticipated level. I also pointed out that these estimates would be biased toward zero if, as Albert Hart has suggested, there

[22] Although the OBE now publishes stage-of-fabrication data by individual industry, the industry classification is not comparable to that of the inventory anticipation survey.

exists a tendency for the railroad shippers' forecast data to systematically exaggerate the errors made by firms in forecasting sales volume. In addition, regressions were run on the cement industry for the period 1947–56, and here the coefficient of the surprise term was larger than one-half and more than twice its standard error.[23]

The replication of this same model on the new OBE data yields the following regressions for finished durable and nondurable goods, respectively:

$$\begin{aligned}\Delta\text{FIN} = \underset{(1089.7)}{53.0} + \underset{(.0345)}{.0799}\text{SALE} - \underset{(.1385)}{.0474}(\text{SALE} - \text{ASSALE}) \\ - \underset{(.1655)}{.3303}\text{FIN}_{-1} + e.\end{aligned} \qquad (14a)$$

$$\bar{R}^2 = .2903,\ d = 1.52,\ \bar{S}_{\text{est}} = 280.85,\ df = 13,$$
$$\delta = .3303,\ \beta_1 = 160.5,\ \beta_2 = .2421,\ \lambda = .0439.$$

$$\begin{aligned}\Delta\text{FIN} = \underset{(540.0)}{449.0} + \underset{(.0213)}{.0886}\text{SALE} - \underset{(.0484)}{.1034}(\text{SALE} - \text{ASSALE}) \\ - \underset{(.0970)}{.4574}\text{FIN}_{-1} + e.\end{aligned} \qquad (14b)$$

$$\bar{R}^2 = .5508,\ d = 1.47,\ \bar{S}_{\text{est}} = 104.3,\ df = 13,$$
$$\delta = .4574,\ \beta_1 = 981.6,\ \beta_2 = .1937,\ \lambda = .0950.$$

For the durable regression, the coefficient of the surprise term is less than half the size of its standard error, but of positive sign. For nondurables, the coefficient is somewhat larger in magnitude and twice its standard error. The implied values of the adaption coefficient, .044 for durables and .095 for nondurables, are of extremely small magnitude, suggesting that production plans are extremely flexible. It will be observed that the estimates imply that for nondurable manufacturing an increase in sales above anticipated volume leads to a reduction in finished goods inventory stocks, while the reverse is true for durables. It was suggested by Modigliani and Sauerlander (1955), when they originally tested this model, that the omission of the effect of the revision of expectations with regard to the next period's sales volume (i.e., the assumption that $\beta_3 = 0$) may contribute to a downward bias in the estimation of λ. It will also be noted that the presence of the lagged endogenous variable means that even if β_3 is in fact zero, the applica-

[23] This evidence appears in Lovell (1964, pp. 196–197). My approach was quite similar to that of Modigliani and Sauerlander (1955), who had already tested with considerable success on eleven observations on nondurable inventories this same expression, modified by the assumption that $\beta_1 = 0$, and normalized by dividing all terms by FIN_{-1}.

tion of least squares yields parameter estimates that are subject to Hurwicz bias, although they will constitute maximum-likelihood estimates if the stochastic disturbance is normally and independently distributed.

With the new data it is possible to elaborate on the approach of earlier studies by using observations on ALSALE as well as ASSALE in working with reduced-form equation (12). It is no longer necessary to suppress the effects of the revision of anticipations of the next period's sales volume. However, a slight complication is introduced in working with the reduced-form equation by the fact that equation (12) is "overidentified." Specifically, the direct application of least squares to equation (12) yields six regression coefficients while there are five parameters to estimate.[24] My approach has been to work with a slight modification of the standard regression procedure that yields maximum-likelihood estimates of the five parameters under the assumption that the stochastic disturbance is normally and independently distributed. This involves finding the values of λ, δ, β_1, β_2, β_3 that minimize the standard error of the estimate of:[25]

$$\begin{aligned}\text{FIN} = {} & \lambda(\text{ASSALE} - \text{SALE}) + \delta\beta_1 + \delta\beta_2[\lambda\text{ASSALE} + (1-\lambda)\text{SALE}] \\ & + \delta\beta_3[\lambda\text{ALSALE} + (1-\lambda)\text{ASSALE}_{+1}] + (1-\delta)\text{FIN}_{-1} + \epsilon. \quad (15)\end{aligned}$$

[24] The direct application of least squares to equation (12) yields six regression coefficients. Adding the coefficient of ASSALE and SALE yields an estimate of $\delta\beta_2$. Dividing the coefficient of ASSALE by this estimate plus unity yields an estimate of λ. But a second estimate of λ may be obtained from the coefficients of ALSALE_{+1} and ASSALE_{+1}. Thus, there is no unique way of obtaining estimates of the parameters of the model from the regression coefficients.

[25] The theory of Mann and Wald (1943), summarized by Johnston (1963), for obtaining maximum-likelihood estimates from equations involving lagged dependent variables requires a slight modification because of the restrictions upon the parameters. The problem is to find, given our sample observations, the values of the unknown parameters λ, β_1, β_2, β_3, and δ that maximize the likelihood

$$L = (2\sigma^2\pi)^{-n/2}\exp(-\sigma^{-2}/2)\sum_{t=1}^{T}\epsilon_t^2$$

where T is the number of observations and

$$\begin{aligned}\epsilon_t = {} & \text{FIN} - \delta\beta_1 - \lambda(1+\delta\beta_2)\text{ASSALE} - \lambda\delta\beta_3\text{ALSALE} - (1-\lambda)\text{ASSALE}_{+1} \\ & - [\delta\beta_2 - \lambda(\delta\beta_2 + 1)]\text{SALE} - (1-\delta)\text{IN}_{-1};\end{aligned}$$

IN_0 is regarded as nonstochastic. Taking logarithms reveals that maximizing L with respect to the parameters of interest is equivalent to minimizing

$$\begin{aligned}\hat{\sigma}^2 = \frac{1}{n}\sum_{t=1}^{T} & [\text{FIN} - \delta\beta_1 - \lambda(1+\delta\beta_2)\text{ASSALE} - \lambda\delta\beta_3\text{ALSALE}_{+1} \\ & - (1-\lambda)\text{ASSALE}_{+1}\,[\delta\beta_2 - \lambda(\delta\beta_2+1)]\text{SALE} - (1-\delta)\text{IN}_{-1}]^2\end{aligned}$$

The maximum-likelihood estimates of the parameters thus involves the method of least squares.

By the application of a search procedure over λ, we obtain for durable manufacturing.[26]

$$\begin{aligned}
\text{FIN} = {} & .055(\text{ASSALE} - \text{SALE}) - \underset{(1083.4)}{465.6} \\
& + \underset{(.0246)}{.0727}[.055\text{ASSALE} + .945\text{SALE}] + \underset{(.0273)}{.0376}[.055\text{ALSALE}_{+1} \\
& + .945\text{ASSALE}_{+1}] + \underset{(.1338)}{.6031}\text{FIN}_{-1} + e. \qquad (16) \\
& d = 1.31,\ \bar{S}^2 = 262.47.
\end{aligned}$$

The maximum-likelihood estimates of the parameters are $\lambda = .055$, $\delta = .397$, $\beta_1 = 1172.8$, $\beta_2 = .183$, and $\beta_3 = .095$. It must be emphasized that these estimates, as indeed those reported earlier for the case in which it was assumed that $\beta_3 = 0$, are subject to Hurwicz bias as a result of the presence of the lagged dependent variable. Furthermore, the standard errors in parentheses and the Durbin-Watson coefficient should be regarded with extreme suspicion. While the parameter estimates themselves, since they are obtained by the method of maximum likelihood, are consistent, this property can provide little solace when dealing as here with an extremely small sample. For nondurable manufacturing, we have:

$$\begin{aligned}
\text{FIN} = {} & .13(\text{ASSALE} - \text{SALE}) + \underset{(482.6)}{543.7} \\
& + \underset{(.0311)}{.0476}[.13\text{ASSALE} + .87\text{SALE}] + \underset{(.0255)}{.0459}[.13\text{ALSALE}_{+1} \\
& + .87\text{ASSALE}_{+1}] + \underset{(.085)}{.507}\text{FIN}_{-1} + e. \qquad (17) \\
& d = 1.60,\ \bar{S} = 95.5.
\end{aligned}$$

The maximum-likelihood estimates of the parameters are $\lambda = .13$, $\delta = .493$, $\beta_1 = 1102.8$, $\beta_2 = .0966$, and $\beta_3 = .0931$. It will be noted that the relaxation of the assumptions that $\beta_3 = 0$, permitted by the availability of data on ALSALE, leads to an increase in the maximum likelihood estimate of λ. This is in conformity with the conjecture of Modigliani and Sauerlander. But the increase is quite small, and the parameter estimates still imply that production plans are extremely

[26] Although the problem of finding maximum likelihood estimates of the unknown parameters constitutes a least-squares problem (see footnote 25), the computations cannot be performed directly by standard regression procedures unless the value of λ is specified. Since $\min_{\lambda,\delta,\beta_i} \hat{\sigma} = \min_{\lambda}[\min_{\delta,\beta_i} \hat{\sigma}]$, the obvious approach is to search over λ for the value minimizing the standard error of the estimate. At each point in the search procedure, a regression is run for the given valued λ.

flexible. In particular, we again find for durables that an increase in current sales volume above the level anticipated for the quarter leads to an increase in finished goods inventories.

In concluding, it is interesting to contrast the results obtained with the sales anticipatory data provided by the OBE survey with the degree of success that can be obtained utilizing a proxy procedure that has sometimes been employed when anticipations variables have not been observable. By such a comparison, it will be possible to evaluate the suggestion of Modigliani and Sauerlander[27] that whatever the direct forecasting value of anticipatory data, *ex ante* sales observations may be both relevant and useful in explaining short-run inventory movements. Substitution of the actual change in sales for the forecast error in equation (13), under the assumption that errors in forecasting sales volume are proportional to actual changes, yields for durable manufacturing:

$$\begin{aligned}\Delta \mathrm{FIN} = \underset{(1133.6)}{180.7} + \underset{(.0394)}{.0616}\mathrm{SALE} + \underset{(.0314)}{.0106}(\mathrm{SALE} - \mathrm{SALE}_{-1}) \\ - \underset{(.1612)}{.2683}\mathrm{FIN}_{-1} + e. \end{aligned} \tag{18a}$$

$$R^2 = .2901,\ d = 1.58,\ \bar{s} = 280.89,\ df = 13.$$

For nondurables, we have:

$$\begin{aligned}\Delta \mathrm{FIN} = \underset{(567.9)}{306.9} + \underset{(.0300)}{.0471}\mathrm{SALE} + \underset{(.0412)}{.0639}(\mathrm{SALE} - \mathrm{SALE}_{-1}) \\ - \underset{(.1318)}{.2477}\mathrm{FIN}_{-1} + e. \end{aligned} \tag{18b}$$

$$R^2 = .4878,\ d = 1.604,\ \bar{S} = 111.3,\ df = 13.$$

In contrast to my experience with 1948–55 data, the sign of the change in sales term is positive.[28] Comparing the standard errors of the estimates with those obtained utilizing the ASSALE *ex ante* data—equations (14a) and (14b)—we find that there is virtually no effect for durables; with nondurables, on the other hand, information on ASSALE's does lead to a reduction in the standard error of the estimate over what can be achieved with the proxy procedure. The advantages of utilizing *ex ante* data are somewhat more substantial, however, when data on ALSALE are used together with ASSALE, as in regressions (18a) and (18b), for the standard error of the estimate of each

[27] 1955, p. 350.

[28] Equations (18a) and (18b) constitute a replication over a new sample period of the model originally reported in Lovell (1961).

of those equations is considerably below that obtained with the corresponding proxy procedure.[29]

A few additional complications of the basic model were examined. In particular, I considered the effects of production smoothing. This concept, which reflects the effects of costs of adjusting production schedules, is taken into account by adding the change in production as an additional explanatory variable.[30] But, in contrast to my earlier efforts, the coefficient of this term now has an inappropriate sign.

6. *Aggregate Inventory Behavior*

By focusing attention on the inventory aggregate, rather than partitioning inventories by stage of fabrication, it will be possible to take advantage of the observations provided by the new OBE survey on desired inventory position and anticipated inventory investment. While this approach permits the direct evaluation of a number of the basic equations discussed in section 4, it must be observed that treating inventories as a conglomeration, rather than restricting attention to finished goods inventories, constitutes a refocusing of the theoretical model. When we were considering finished goods inventory behavior, the process of plan revision involved the reorientation of production plans as developments during the quarterly observation period suggested errors in initial sales anticipations. Now that inventories are to be treated in the aggregate, the process of plan revision will concern the rescheduling of deliveries of raw materials. In this section I shall first discuss the determinants of the inventory condition variable, which constitutes an index of desired inventory position. I shall then turn to an evaluation of the planned inventory investment equation and the realization function concept. Since there are, from an econometric point of view, certain disadvantages involved in working separately with these equations, I shall conclude by applying the principle of maximum likelihood to the task of obtaining point estimates of the parameters of the model discussed in section 4. This approach will yield preferred estimates based on a larger number of degrees of freedom, an important consideration given the limited number of observations avail-

[29] The significance of the improvement has not been tested. Theil (1961, Ch. 6.2) has suggested that, in deciding between two alternative structures, one is more likely to select the correct one if he chooses that which gives the smallest standard error of the estimate. However, Theil's analysis is based on the assumption that the explanatory variables are nonstochastic.

[30] See Lovell (1964, p. 97).

able for the study. The results of this and earlier sections of the paper will be summarized in section 7.

INVENTORY CONDITION

The inventory condition variable, COND, is derived from the question of how the responding company views its current inventory position. Specifically, it is the excess of the proportion of respondents reporting their end of period inventory as "high" over those who regard them as "low" in relation to "total sales and the unfilled orders backlog." This attitudinal variable constitutes a rough index rather than a precise measure of the excess of actual stocks over desired inventory, discussed in section 4. The wording of the questionnaire presupposes that sales and the order backlog are the determinants of desired inventory. Given current and anticipated sales volume and the order backlog, we would expect COND to be larger the higher the current inventory stock; given the level of current inventories, we would expect COND to be inversely related to sales and orders.

For the durable aggregate, we have:

$$\begin{aligned} \text{COND} = \underset{(54.05)}{32.55} + \underset{(.000736)}{.000044\text{SALE}} - \underset{(.0007)}{.0028\text{ASSALE}_{+1}} \\ - \underset{(.0009)}{.0035\text{ALSALE}_{+2}} - \underset{(.00082)}{.00032\text{UOR}} + \underset{(.0024)}{.0090\text{IN}} + e. \end{aligned} \tag{19a}$$

$$\bar{R}^2 = .638,\ d = 1.93,\ \bar{S}_{\text{est}} = 5.66,\ df = 12.$$

With the exception of the SALE variable, which is exceedingly small relative to its standard error, all the coefficients are of the anticipated sign. It is interesting to observe that the coefficient of UOR is quite small relative to its standard error; while this is not consistent with other empirical studies which have suggested that unfilled orders are a critical determinant of inventory investment, it is possible that in earlier studies the important role attributed to unfilled orders actually resulted from its influence upon expectations rather than as a direct determinant of inventory position.[31] When the unfilled orders term is dropped from the regression, the coefficient of SALE assumes the anticipated negative sign. Equations of the same form as (19a), but without the unfilled orders variable, were fitted to the data for the individual component durable industries; practically all the coefficients were of the anticipated sign, although the fits were poorer in several industries than for the aggregate.

[31] This point will be elaborated upon in the second part of section 6.

The nondurable regression is unsatisfactory:

$$\begin{aligned} \text{COND} = {} & \underset{(93.81)}{82.85} - \underset{(.0046)}{.0058\text{SALE}} + \underset{(.0045)}{.0032\text{ASSALE}_{+1}} \\ & - \underset{(.0053)}{.0033\text{ALSALE}_{+2}} - \underset{(.0110)}{.0098\text{UOR}} + \underset{(.0154)}{.0121\text{IN}} + e. \end{aligned} \tag{19b}$$

$$\bar{R}^2 = .0601,\ d = .5513,\ \bar{S}_{\text{est}} = 7.77,\ df = 12.$$

The coefficient of multiple determination is exceedingly small; none of the explanatory variables is significant. The component nondurable industry regressions were, for the most part, equally unsatisfactory; even the inventory term had the wrong sign in a number of cases.

How is this evidence to be interpreted? The wording of the questionnaire *presupposes* that sales and unfilled orders are the determinants of desired inventories. Consequently, the success in explaining the COND variable in the durable sector in terms of these variables does not suffice to establish that they in fact are the major determinants of desired inventory position, although the insignificant coefficient for the unfilled order backlog suggests that this variable is not of critical importance. Conversely, given that respondents are asked about the condition of inventories relative to sales and orders, the unsatisfactory results for nondurables do not suffice to demonstrate that desired inventory position is not determined by sales and orders. Perhaps the difficulty stems from working with a variable that is not weighted by size of firm. Nonetheless, it is disappointing to find that the COND variable, the first index that we have of desired inventory position,[32] cannot be explained in nondurables by the variables customarily assumed in many prior empirical studies to be the determinants of desired inventory. Essentially the same results are obtained when the COND variable is regressed upon the ratios of SALE − ASSALE, ALSALE, and UOR to IN, suggesting that the difficulties do not stem from the linear specification of regressions (19a) and (19b).

ANTICIPATED INVENTORY INVESTMENT

In earlier studies of inventory behavior it was not possible to test directly the determinants of planned inventory investment, for that variable had not been observed prior to the new OBE survey. It will be remembered from equation (8) that we argued that planned inventory investment should be a linear function of current anticipations with regard to sales volume expected in the next two quarters and the

[32] An indirect measure of surplus inventories for a number of durable industries was presented in Lovell (1961).

lagged inventory stock. But because we are now dealing with total inventories, including purchased materials and goods in process as well as finished goods, the hypothesis that anticipated inventory is also influenced by the backlog of unfilled orders also deserves consideration, for earlier empirical studies have suggested that this variable is an important determinant of inventory investment.

Turning first to planned inventory investment for durable manufacturing, we obtain:

$$\begin{aligned} \text{ASIN} - \text{IN}_{-1} = {} & \underset{(2041.8)}{1639.9} + \underset{(.0262)}{.0959}\text{ASSALE} + \underset{(.0357)}{.0936}\text{ALSALE}_{+1} \\ & - \underset{(.0349)}{.0102}\text{UOR} - \underset{(.0860)}{.3320}\text{IN}_{-1} + e. \end{aligned} \tag{20a}$$

$$\bar{R}^2 = .5161,\ dw = 2.38,\ \bar{S} = 215.2,\ df = 13,$$
$$\beta_1 = 4939.,\ \beta_2 = .2889,\ \beta_3 = .2819,\ \beta_4 = -.0307,\ \delta = .3320.$$

For nondurables, we have:

$$\begin{aligned} \text{ASIN} - \text{IN}_{-1} = {} & \underset{(1093.1)}{2284.1} + \underset{(.0364)}{.0679}\text{ASSALE} + \underset{(.0494)}{.0012}\text{ALSALE}_{+1} \\ & - \underset{(.1431)}{.0980}\text{UOR} - \underset{(.0983)}{.2593}\text{IN}_{-1} + e. \end{aligned} \tag{20b}$$

$$\bar{R}^2 = .3893,\ dw = 2.24,\ \bar{S} = 97.8,\ df = 13,$$
$$\beta_1 = 8809.,\ \beta_2 = .2619,\ \beta_3 = .0046,\ \beta_4 = -.3779,\ \delta = .2593.$$

It will be observed that both the short and the long anticipatory sales terms have the anticipated sign; for durables, their regression coefficients are large relative to their standard errors. The estimated values of δ, the speed of adjustment coefficient, suggests that durable manufacturing firms plan to correct approximately one-third of their inventory imbalance, on the average, within the quarter; for nondurables, the coefficient is one-quarter. These coefficients are somewhat larger than those obtained in earlier studies.

The surprising factor is the negative coefficient for unfilled orders. The appropriate test is one-tailed, and the evidence suggests that we should reject the hypothesis that unfilled orders have a direct influence on planned inventory investment. In an earlier study I argued:[33]

If unfilled orders represent an established demand, indeed a possible committal to deliver at some future date, entrepreneurs may well consider it advisable to carry additional stocks when unfilled orders are large as a hedge against possible shortage and price commitments. In addition, a rise in the

[33] 1961, p. 298.

TABLE 5

Durable Manufacturing: Regression Coefficients of Inventory Equations

ASIN on C, ASSALE, $ALSALE_{+1}$, IN_{-1}	Durables 1	2	3	4	5	6	7	Aggregate Regression	Pooled Regression	Separate Intercept Regression
Degrees of freedom	14	14	14	14	14	14	14	14	122	116
R^2 adjusted	0.8142	0.8769	0.9087	0.8944	0.7441	0.8386	0.8188	0.9646	0.9958	0.9961
Standard error	81.74	24.26	91.83	86.90	140.05	79.55	85.75	208.09	96.47	93.22
Durbin-Watson coefficient	1.400	2.270	1.843	1.738	2.064	1.569	1.479	2.297	1.918	1.796
Variable 1	886.166	-25.513	189.167	1455.497	250.897	643.093	412.936	1144.104	21.812	336.505
	363.397	170.092	336.452	466.694	423.031	742.566	274.426	1096.570	21.978	102.648
Variable 2	-0.053	-0.041	0.099	0.031	0.003	0.085	-0.202	0.094	-0.040	-0.024
	0.026	0.113	0.091	0.052	0.040	0.131	0.116	0.024	0.012	0.015
Variable 3	-0.036	0.007	0.121	0.175	0.075	-0.117	-0.048	0.088	0.038	0.045
	0.036	0.099	0.120	0.057	0.037	0.136	0.094	0.028	0.012	0.016
Variable 4	0.806	1.058	0.609	0.473	0.743	0.860	1.168	0.681	0.985	0.845
	0.106	0.104	0.194	0.121	0.198	0.114	0.193	0.071	0.012	0.044

$F = 1.77$ with 24, 98 degrees of freedom if all coefficients are identical.

$F = 1.49$ with 18, 98 degrees of freedom if all coefficients are identical except intercepts.

TABLE 6

Nondurable Manufacturing: Regression Coefficients of Inventory Equations

ASIN on C, ASSALE, $ALSALE_{+1}$, IN_{-1}	Nondurables 1	2	3	4	5	6	7	Aggregate Regression	Pooled Regression	Separate Intercept Regression
Degrees of freedom	14	14	14	14	14	14	14	14	122	116
R^2 adjusted	0.7163	0.6934	0.9686	0.9483	0.2172	0.7899	0.7284	0.9896	0.9875	0.9893
Standard error	158.24	84.64	19.28	51.32	87.44	30.88	118.69	95.92	140.47	130.35
Durbin-Watson coefficient	2.365	1.629	1.928	2.092	1.401	1.429	1.672	2.079	2.049	1.943
Variable 1	532.318	438.817	119.225	1776.183	1455.869	268.297	635.568	1637.143	57.716	869.959
	809.116	395.389	73.642	285.329	850.984	114.689	442.620	539.879	35.834	201.711
Variable 2	0.522	0.083	–0.133	–0.073	–0.131	–0.277	–0.412	0.077	–0.016	0.029
	0.102	0.153	0.076	0.051	0.097	0.097	0.097	0.033	0.044	0.046
Variable 3	–0.394	–0.342	0.251	0.293	0.125	0.229	0.289	–0.018	0.024	0.046
	0.095	0.175	0.082	0.064	0.069	0.106	0.079	0.040	0.044	0.044
Variable 4	0.519	1.197	0.674	0.164	0.572	0.822	1.067	0.782	0.954	0.535
	0.159	0.211	0.125	0.137	0.309	0.157	0.262	0.077	0.024	0.095

$F = 8.04$ with 24, 98 degrees of freedom if all coefficients are identical.

$F = 7.80$ with 18, 98 degrees of freedom if all coefficients are identical except intercepts.

backlog of unfilled orders may be expected to lead to an acceleration of production that is felt first in terms of an increase of goods in process. . . .

In my earlier investigation with 1948–55 data, and in subsequent studies, the unfilled orders term generally appeared with a highly significant positive coefficient. Because anticipated sales volume was not measured, the question of whether unfilled orders have a direct influence upon desired inventories or only an indirect one through the influence of the order backlog upon anticipated sales volume remained open. It now appears that, if unfilled orders influence inventory investment, it is only indirectly, via their effect upon sales anticipations, rather than as a direct determinant of the desired inventory stock.

Let us now turn to the individual industries. The results of running regression (8) on the seven durable and seven nondurable industries are reported in Tables 5 and 6, respectively. Each column of the tables constitutes a regression. The first seven regressions report results for the individual industries identified in Table 1. The aggregate regression was run on data obtained by summing for each observation over all seven component industries. The pooled regression was obtained by pooling the observations for the component industries under the assumption that there are no interindustry differences in the parameters of the realization function. The separate intercept regression was also run on pooled data, but with industry dummy variables introduced. The standard error of the estimate and the coefficient of multiple determination are adjusted for degrees of freedom. The regression coefficients, with standard errors immediately below, appear in the middle of the table. The two F-statistics provide an approximate test of the hypothesis that there are no interindustry differences in the parameters of the realization function.[34]

The evidence is rather mixed. While they conform with what was expected in certain industries, we find that for several industries the regression coefficients relating planned inventory to short- and longer-run sales anticipations are not both of the expected positive sign; for one durable and two nondurable industries, the negative coefficient is more than twice its standard error in magnitude. Furthermore, the estimated δ coefficients are slightly negative in two durable and two nondurable industries. While the F-statistic is sufficiently low in durable

[34] In order for the F-test to be precise, it would be necessary (but not sufficient) for the disturbances to be free of serial and interindustry correlation and that their variance be the same in all industries. The Durbin-Watson statistics for the pooled regression were not computed with precision in that the computer program treated the sequences of observations from successive industries as a single time series.

manufacturing to suggest that the hypothesis of no interindustry differences in the parameter values is tenable, the pooled regressions yield negative point estimates of β_2. It is conceivable, of course, that β_2 should in fact be zero. After all, the inventory planned for the end of the current quarter, ASIN, consists of goods to be available in subsequent periods; so the forward-looking firm may well plan its end-of-quarter inventory with regard to sales anticipated in the succeeding rather than the current quarter, i.e., ALSALE rather than ASSALE. But this rationalization does not serve to explain negative values of β_3.

THE REALIZATION FUNCTION

As explained in section 4, the realization function appears in its most elementary form in theoretical models of the inventory cycle. It is customarily assumed in constructing such cycle models that inventory investment deviates from its planned level as stocks are run down when entrepreneurs are surprised by a sales volume that exceeds anticipations—this is equation (4). For purposes of evaluating this elementary realization function concept, consider the following regression equation:

$$\mathrm{IN} = b_1 + b_2\mathrm{ASIN} - b_3(\mathrm{SALE} - \mathrm{ASSALE}) + \epsilon. \qquad (21)$$

The version of the realization function employed in inventory cycle models requires that b_2 and b_3 equal unity, for no allowance is made for the revision of production plans or delivery schedules within the production planning period. It will be noted that if $b_1 = 0$, equation (21) constitutes a special case of equation (11) in which $\beta_3 = 0$; i.e., desired end-of-period inventory depends only upon current rather than the next period's sales.

The results of fitting equation (21) on individual durable and nondurable industries and the aggregates are presented in Tables 7 and 8. Clearly, they are not in conformity with the elementary formulation of the realization function underlying the theory of the inventory cycle, for while the coefficient of ASIN is always fairly close to unity, the coefficient of the surprise term is of extremely small magnitude and indeed positive in a majority of the regressions. The low values of the F-statistics suggest that pooling the data may not be inappropriate, but the results of the combined regressions yield a negative coefficient for the surprise term only for nondurables, and here the coefficient is statistically insignificant and of such small magnitude as to suggest that errors in anticipating future sales volume have a negligible effect in explaining deviations of inventories from their planned level. Small

TABLE 7

Durable Manufacturing: Regression Coefficients of Realization Functions

IN on C, ASIN, SALE-ASSALE	Durables 1	2	3	4	5	6	7	Aggregate Regression	Pooled Regression	Separate Intercept Regression
Degrees of freedom	14	14	14	14	14	14	14	14	116	110
R^2 adjusted	0.7728	0.8410	0.9490	0.8987	0.8697	0.7658	0.9350	0.9632	0.9971	0.9973
Standard error	100.59	22.08	68.39	86.62	89.17	98.86	52.22	200.82	81.56	78.28
Durbin-Watson coefficient	1.343	1.535	1.300	1.221	1.409	1.925	1.920	1.241	1.332	1.473
Variable 1	102.463	387.649	-28.446	428.445	215.668	409.565	18.984	384.263	-6.841	113.005
	346.610	101.841	244.725	525.423	296.709	492.778	184.957	1180.032	19.013	95.997
Variable 2	0.967	0.702	1.028	0.954	0.969	0.908	1.011	1.004	1.022	0.977
	0.129	0.892	0.061	0.083	0.094	0.126	0.067	0.049	0.005	0.034
Variable 3	0.024	-0.141	-0.060	0.329	0.168	0.004	0.011	0.160	0.101	0.084
	0.081	0.890	0.184	0.114	0.117	0.164	0.088	0.070	0.042	0.041

$F = 1.50$ with 18, 98 degrees of freedom if all coefficients are identical.

$F = 0.93$ with 12, 98 degrees of freedom if all coefficients are identical except intercepts.

TABLE 8

Nondurable Manufacturing: Regression Coefficients of Realization Functions

IN on C, ASIN SALE-ASSALE	Nondurables							Aggregate Regression	Pooled Regression	Separate Intercept Regression
	1	2	3	4	5	6	7			
Degrees of freedom	14	14	14	14	14	14	14	14	116	110
R^2 adjusted	0.9216	0.8752	0.9043	0.9348	0.7440	0.8711	0.7823	0.9614	0.9976	0.9976
Standard error	78.94	54.38	33.64	64.00	43.57	27.58	99.59	181.04	63.56	63.53
Durbin-Watson coefficient	1.370	2.085	2.066	1.641	1.658	0.956	2.315	2.874	1.880	1.891
Variable 1	-14.134	400.746	35.683	-545.746	610.794	-127.006	395.888	-1067.945	-26.122	102.144
	414.231	248.189	132.359	319.067	400.111	125.256	358.161	1128.955	15.229	107.400
Variable 2	1.029	0.865	0.991	1.155	0.831	1.126	0.888	1.070	1.028	0.983
	0.083	0.893	0.081	0.077	0.120	0.109	0.116	0.054	0.005	0.035
Variable 3	-0.086	0.200	0.042	0.085	0.015	-0.006	-0.117	0.156	-0.019	-0.017
	0.099	0.102	0.099	0.076	0.062	0.110	0.118	0.080	0.034	0.035

$F = 1.31$ with 18, 98 degrees of freedom if all coefficients are identical.

$F = 1.43$ with 12, 98 degrees of freedom if all coefficients are identical except intercepts.

TABLE 9

Durable Manufacturing: Regression Coefficients of Realization Functions with Anticipation Revision Term

IN on C, ASIN, SALE-ASSALE, $ASSALE_{+1}$ $- ALSALE_{+1}$	Durables							Aggregate Regression	Pooled Regression	Separate Intercept Regression
	1	2	3	4	5	6	7			
Degrees of freedom	13	13	13	13	13	13	13	13	115	109
R^2 adjusted	0.8233	0.8537	0.9502	0.8925	0.8707	0.8437	0.9337	0.9662	0.9971	0.9973
Standard error	88.70	21.18	67.64	89.24	88.81	80.77	52.72	192.31	81.92	78.56
Durbin-Watson coefficient	0.898	1.638	1.192	1.278	1.311	1.860	2.072	1.833	1.330	1.462
Variable 1	562.224	287.350	-171.474	380.893	55.212	665.758	-10.308	-1190.155	-6.563	126.446
	368.321	118.038	272.308	552.120	332.251	412.724	189.803	1539.724	19.574	100.967
Variable 2	0.808	0.778	1.063	0.962	1.017	0.844	1.021	1.068	1.022	0.972
	0.134	0.894	0.068	0.087	0.104	0.105	0.069	0.063	0.005	0.036
Variable 3	-0.117	0.836	0.211	0.363	0.199	-0.379	0.115	0.262	0.100	0.072
	0.095	0.147	0.298	0.141	0.120	0.191	0.150	0.096	0.049	0.048
Variable 4	0.096	-0.818	-0.189	-0.045	-0.044	0.416	-0.087	-0.082	0.001	0.010
	0.043	0.146	0.165	0.103	0.041	0.147	0.102	0.055	0.021	0.022

$F = 2.12$ with 24, 91 degrees of freedom if all coefficients are identical.

$F = 1.82$ with 18, 91 degrees of freedom if all coefficients are identical except intercepts.

TABLE 10

Nondurable Manufacturing: Regression Coefficients of Realization Functions with Anticipation Revision Term

IN on C, ASIN, SALE-ASSALE, ASSALE $_{+1}$ − ALSALE $_{+1}$	Nondurables 1	2	3	4	5	6	7	Aggregate Regression	Pooled Regression	Separate Intercept Regression
Degrees of freedom	13	13	13	13	13	13	13	13	115	109
R^2 adjusted	0.9294	0.8637	0.9024	0.9365	0.7857	0.8678	0.7698	0.9596	0.9975	0.9975
Standard error	74.90	56.40	33.97	63.19	39.86	27.92	102.41	185.09	63.82	63.75
Durbin-Watson coefficient	1.181	2.049	2.059	1.941	1.535	0.737	2.543	2.974	1.873	1.872
Variable 1	−13.887	411.257	0.920	−374.713	677.647	−72.980	308.648	−1585.096	−25.733	115.713
	393.072	274.090	139.701	347.438	367.689	143.224	409.427	1417.921	15.382	111.711
Variable 2	1.027	0.862	1.013	1.114	0.811	1.078	0.915	1.095	1.028	0.979
	0.079	0.202	0.086	0.084	0.111	0.125	0.132	0.068	0.005	0.036
Variable 3	−0.278	0.279	0.142	−0.043	0.085	−0.164	−0.066	0.232	−0.027	−0.034
	0.152	0.210	0.154	0.132	0.067	0.225	0.161	0.146	0.050	0.052
Variable 4	0.167	0.023	−0.134	0.116	−0.099	0.111	−0.066	−0.069	0.009	0.019
	0.105	0.196	0.156	0.100	0.051	0.136	0.135	0.111	0.039	0.041

$F = 1.31$ with 24, 91 degrees of freedom if all coefficients are identical.

$F = 1.37$ with 18, 91 degrees of freedom if all coefficients are identical except intercepts.

negative values of the coefficient of the surprise term suggest that plans are exceedingly flexible. The positive coefficients, it will be remembered from section 4, imply that plans are so flexible that stocks can actually be increased when the sales volume has been underestimated. Thus the evidence suggests that firms are exceedingly adept at adjusting schedules for the delivery of raw materials when developments during the quarter reveal errors in initial anticipations of sales volume.[35]

This elementary version of the realization function may also be used to explain the discrepancy between ALIN and actual inventory investment in terms of the discrepancy between SALE and ALSALE. This involves a three-month longer planning horizon, for the ALIN and ALSALE *ex ante* data are collected approximately five months before the end of the quarter to which the actual realizations refer. Essentially the same results were obtained. The sales forecast error term had the anticipated negative sign in only one durable and four nondurable industries. As might be expected, the realization function yields a poorer fit with the longer planning horizon.

Since the OBE survey provides data on longer-run sales anticipations, it is possible to relax the assumption that desired end-of-period inventories depend only upon current sales, that $\beta_3 = 0$ in equation (11). Tables 9 and 10 report the regressions obtained when the anticipation revision term is added to the elementary realization function concept. The results are rather disappointing, for the coefficient of the anticipation revision term, $\text{ASSALE}_{+1} - \text{ALSALE}_{+1}$, has an incorrect negative sign in a number of these regressions. The coefficient has the correct sign for the pooled durable and nondurable regressions, but is insignificant. Reasonably satisfactory results are obtained for durable industries 1 and 6 (iron and steel, and transportation equipment) and nondurable industries 1, 2, 4, and 6 (food, textiles, chemicals, and rubber). For the other industries we must argue that $\beta_3 = 0$, on the grounds that a one-tailed test is appropriate.[36]

[35] It should be observed that the R^2's are inflated in that if the coefficient of ASIN is constrained to unity, the change in inventory being regressed upon the error in anticipating sales volume, a much lower value of R^2 is obtained; for example, the coefficient of multiple determination for the durable manufacturing aggregate is reduced from .96 to .22; further, the adjusted coefficient of multiple determination is negative for a number of industries.

[36] In order to verify that the difficulties did not stem from the presence of seasonality in the data, the equations were refitted with seasonal dummy variables included; the only improvement was to correct the sign of b_3 for other durables and the paper industries, but the coefficients were not significant. This is equivalent to filtering out a constant seasonal pattern in advance of running the regression.

There are, of course, other aspects of the firm's environment in addition to sales volume that may lead to a revision of planned inventory accumulation. In particular, an increase in unfilled orders might well be expected to generate an increase in purchased materials and goods in process inventory. If we postulate that unfilled orders are a factor influencing desired inventory, the change in unfilled orders should be added to equation (11). The following estimates were obtained when this regression was run on the durable aggregates.

$$\begin{aligned}\text{IN} = &-1392.4 \underset{(1665.5)}{} + \underset{(.0680)}{1.0757}\text{ASIN} + \underset{(.1026)}{.2735}(\text{SALE} - \text{ASSALE}) \\ &- \underset{(.0645)}{.0952}(\text{ASSALE}_{+1} - \text{ALSALE}_{+1}) + \underset{(.0374)}{.0153}(\text{UOR} - \text{UOR}_{-1}) + e.\end{aligned}$$

$$R^2 = .9639,\ dw = 1.79,\ \bar{S}_{est} = 198.8,\ df = 12. \tag{22a}$$

For nondurables, we have:

$$\begin{aligned}\text{IN} = &-1735.4 \underset{(1424.0)}{} + \underset{(0.678)}{1.1024}\text{ASIN} + \underset{(.1474)}{.2119}(\text{SALE} - \text{ASSALE}) \\ &- \underset{(.1128)}{.0924}(\text{ASSALE}_{+1} - \text{ALSALE}_{+1}) + \underset{(.2399)}{.2434}(\text{UOR} - \text{UOR}_{-1}).\end{aligned}$$

$$R^2 = .9597,\ dw = 2.79,\ \bar{S}_{est} = 184.9,\ df = 12. \tag{22b}$$

While the coefficient of the change in unfilled orders term has the expected sign, it is in both cases small relative to its standard error. Further, the first surprise term, SALE − ASSALE, again has the positive coefficient implying extreme plan revision while the second surprise term has the inappropriate negative sign.

A possible explanation for the limited success with the realization concept is provided by Murray Foss's earlier analysis of the data. He suggested that the anticipated inventory figure may be at least in part a target figure rather than an attempted forecast. When inventory stocks are thought to be excessive, the anticipated inventory figure may be deliberately set at a low level in an effort to discourage purchasing agents and other departments from accumulating stock. If there were a consistent understatement, its effect would be absorbed by the constant term in the regression; in any case, the anticipated inventory figures are not consistently biased downward. It is possible, however, that the magnitude of such an effect hinges upon whether current inventories are regarded as excessive or deficient. Consequently, I fitted the following regression to the data:

$$\text{IN} = b_1 + b_2\text{ASIN} + b_3(\text{SALE} - \text{ASSALE}) + b_4\text{COND}_{-1}. \tag{23}$$

It will be remembered that the variable COND denotes the excess of the proportion of respondents who report stocks excessive over those who regard them as deficient. Again, b_3, the coefficient of the surprise term, has a positive sign in the majority of cases; contrary to hypothesis, the coefficient of the inventory condition variable was generally negative. Similar results were obtained when the anticipation revision term, $\text{ASSALE}_{+1} - \text{ALSALE}_{+1}$ was added to equation (23).

MAXIMUM-LIKELIHOOD PARAMETER ESTIMATES

The investigations of the determinants of inventory conditions, of ASIN, and of the realization function have been based on an extremely limited number of observations. Furthermore, the approach has not yielded much information about the magnitude of the parameter λ measuring the extent of plan inflexibility. The anticipated inventory position regressions in the second part of section 6 do not yield any information about the extent to which plans are revised as errors in initial sales anticipations become apparent during the quarter. The realization function construct, examined in the third part of section 6, does not yield a point estimate of λ, although it was possible to infer that plans are subject to quite extensive revision. Of course, it might be possible to use the coefficients obtained from the anticipated inventory regressions in conjunction with the realization function regressions in order to estimate this parameter. But there exists an alternative procedure that yields maximum-likelihood estimates of all the parameters of the inventory model—λ, δ, β_1, β_2, and β_3. An advantage of this method is that the estimates are based on a larger number of degrees of freedom, an important consideration in view of the small number of observations available for the study.

Our strategy, which is analogous to that employed in section 5 when working with finished goods inventories, is easily understood if we first consider a slightly simpler problem. Suppose that the magnitude of the parameter λ were known. We could then proceed to rewrite equation (10) in the form:

$$\begin{aligned}[\text{IN} - \lambda(\text{ASIN} + \text{ASSALE} - \text{SALE})] &= \delta\beta_1[1 - \lambda] \\ &+ \delta\beta_2[(1 - \lambda)\text{SALE}] + \delta\beta_3[(1 - \lambda)\text{ASSALE}_{+1}] \\ &+ (1 - \delta)[(1 - \lambda)\text{IN}_{-1}] + \epsilon_7. \quad (24)\end{aligned}$$

Given the value of λ, the expressions in brackets could be utilized as the variables in a regression yielding estimates of the other parameters, δ, β_1, β_2, and β_3. But the coefficients of equation (25) are identical to those of equation (8). Thus, it would be possible, knowing λ, to

TABLE 11

Maximum-Likelihood Parameter Estimates

	λ	$\delta\beta_1$	$\delta\beta_2$	$\delta\beta_3$	δ	β_1	β_2	β_3	$\bar{S}_{est}$
Durables									
1	.10	371.9	0	.043	.2054	1810	0	.2093	116.2
2	.08	2.462	.0859*	0	.1061	23.20	.8096	0	24.5
3	.68	171.1	.1581*	.1427*	.5070	337.5	.3118	.2815	102.4
4	0	1709**	.0535	.1514**	.5536	3087	.0966	.2735	131.1
5	0	600.9*	.0200	.0892**	.4117	1460	.0486	.2167	140.0
6	.08	66.15	.0090	.0584	.0946	699.3	.0951	.6173	99.8
7	0	309.6	0	.0520	.1749	1770	0	.2973	97.4
Aggregate	0	2374*	.0975**	.0721**	.3411	6960	.2858	.2114	363.9
Pooled	.11	12.37	0	.0262**	.0421	293.8	0	.6223	120.6
Separate intercept	.06	419.1**	0	.0760**	.2464	1701	0	.3084	111.1
Nondurables									
1	.10	409.8	.2004**	0	.6644	616.8	.3016	0	204.0
2	0	803.8	0	0	.2978	2699	0	0	110.3
3	.05	187.9**	0	.1613**	.4505	417.1	0	.3580	30.9
4	.15	1926**	0	.2428**	.8997	2141	0	.2699	91.3
5	.14	1472**	0	.1251	.8004	1839	0	.1563	80.2
6	.22	229.8**	0	.2237**	.5146	446.6	0	.4347	37.2
7	.11	724.5*	0	.2699**	.8812	822.2	0	.3063	151.0
Aggregate	0	1597	.0666	0	.2257	7076	.2951	0	258.7
Pooled	.29	42.0	0	.0043	.0248	1694	0	.1734	138.8
Separate intercept	.20	865.1**	.0323	.0765**	.5361	1614	.0602	.1427	127.5

Note: The single and double asterisks indicate that the regression procedure yielded coefficients at least two or three times their standard errors in magnitude.

pool the two sets of observations in a single regression.[37] Since there are seventeen observations on the variables entering into equation (10)

[37] This would be difficult if the regression program automatically introduced the intercept. The program utilized introduces an intercept by having the first explanatory variable a column of ones. For this application, then, the first variable consists of ones through the observations on equation (8) and then [1 — λ] for the observations on equation (24).

and eighteen on the variables of equation (8), this approach would increase the total number of observations available to thirty-five. Even if we knew λ, of course, pooling the two sets of data might not be appropriate if the disturbances of equations (8) and (10) were not independently distributed. But it is reasonable to assume that this independence condition is satisfied, for the disturbance ϵ_5 of the ASIN equation arises from variables omitted in explaining the generation of beginning-of-period inventory anticipations, while the other disturbance, ϵ_7, results from variables omitted from an equation describing a quite different process, namely, the way in which discrepancies between anticipated and actual inventory are generated by errors in anticipating sales volume. If ϵ_5 and ϵ_7 are independently and normally distributed with equal variances, and λ is known, the application of the straightforward regression approach to the pooled thirty-five observations simultaneously will yield maximum-likelihood estimates of the parameters of the model; such an estimation strategy could be expected to yield more efficient parameter estimates than the regressions reported in the second part of section 6 because of the information provided by the seventeen additional observations.

But how can we proceed when λ is unknown? The application of the maximum-likelihood principle reveals that the appropriate procedure is to search over values of λ, running the pooled regression for each value of λ considered. The value of λ yielding the smallest standard error of the estimate constitutes the maximum-likelihood estimate; maximum-likelihood estimates of the other parameters of the model are provided from the coefficients obtained from that regression.[38] The

[38] Under the assumption that the disturbances of equation (8) are normally and independently distributed, the likelihood of obtaining the n observed values of ASIN is

$$L_5 = \left(\frac{1}{\sigma_{\epsilon_5}\sqrt{2\pi}}\right)^n \exp\left(1 - \frac{1}{2\sigma_{\epsilon_5}{}^2}\,\Sigma\epsilon_5{}^2\right),$$

where the disturbance ϵ_5 is a function of observed variables and the unknown parameters (except) as given by equation (8). Similarly, the likelihood of obtaining the n' observed values of IN is

$$L_7 = \left(\frac{1}{\sigma_{\epsilon_7}\sqrt{2\pi}}\right)^{n'} \exp\left(-\frac{1}{2\sigma_{\epsilon_7}{}^2}\,\Sigma\epsilon_7{}^2\right),$$

where the disturbance ϵ_7 is a function of observed variables and the unknown parameters as given by equation (10). The likelihood of obtaining the combined set of observations, assuming as we have that ϵ_5 and ϵ_7 are independently distributed, is simply $L = L_5L_7$. Taking logarithms, we have

$$\log L = \text{constant} - \frac{1}{2\sigma_{\epsilon_5}{}^2}\,\Sigma\epsilon_5{}^2 - \frac{1}{2\sigma_{\epsilon_7}{}^2}\,\Sigma\epsilon_7{}^2;\ \text{consequently,}$$

the values of δ, β_1, β_2, β_3, and λ that maximize L also minimize

$$\sigma = (\Sigma\epsilon_{5^2} + \rho\Sigma\epsilon_{7^2})/(n + n') \text{ where } \rho = \sigma_{\epsilon_5}{}^2/\sigma_{\epsilon_7}{}^2.$$

estimates derived by this procedure, presented in Table 11, were obtained subject to the constraints that β_2 and β_3 be nonnegative and that λ be nonnegative and no greater than unity.[39] These estimates are likely to be subject to Hurwicz bias, because of the presence of the lagged inventory stock in equation (24). They are asymptotically unbiased and consistent; provided the homoscedasticity condition is met, they should be efficient or nearly so.[40] The estimates for the fourteen component industries and the durable and nondurable aggregates are based on thirty-five observations; those obtained by pooling the data over industries are based on 245 observations. I have not applied the likelihood ratio test procedure appropriate for testing hypotheses; the single and double asterisks over the various parameter estimates indicate that the regression procedure yielded coefficients that were at least two or three times, respectively, their standard errors in magnitude, but these should be interpreted with extreme caution.

Examination of the table reveals that the λ coefficient is exceedingly small in most instances, suggesting that plans are subject to extremely rapid revision. Indeed, the parameter is estimated to have a zero value in three durable industries and one nondurable, implying that ASIN is irrelevant in the determination of end-of-quarter inventory position. The evidence suggests that schedules for the delivery of raw materials are, for the most part, subject to extremely sharp revision during the quarterly observation period, when actual sales deviate from their anticipated level. The only notable exception is durable industry 6, electrical machinery, for which $\lambda = .68$. It will be noted that a number of the β_2 coefficients are zero, particularly in nondurables. As may be seen from inspection of equation (4), this implies that desired end-of-period inventories are not affected by current sales volume, a not unreasonable result. The zero values of β_3, on the other hand, do not appear

[39] Because of the restriction $0 \leq \lambda \leq 1$ and the unimodal nature of the minimization problem, it was possible to economize on the computations by employing a Fibonacci search procedure. For a description of this procedure, see Wilde (1964).

[40] Inspection of the residuals for the individual industries suggested that this homogeneity assumption was not grossly violated. If it had, the estimates obtained from the residuals of ρ would have been used in an application of the theory of weighted regression in order to obtain maximum-likelihood estimates. It is interesting to observe that *if* the variance of the disturbance term of equation (8) is exceedingly small, relative to that of equation (10), so that ρ is close to zero, the appropriate weighted regression procedure is equivalent to the use of equation (8) to estimate all of the parameters except λ; an estimate of λ is then obtained with a regression based on equation (10), after simplification with the aid of the parameter estimates obtained earlier of the other parameters; this is, in essence, the two-stage procedure used by Gordon R. Sparks in his paper on residential building cycles in this volume. At the other extreme, when ρ is close to infinity, all the parameters would be estimated from equation (10).

reasonable, for they imply that firms do not look to the future in considering what level of inventories is appropriate.

7. *Summary and Conclusions*

In econometric work we are rarely presented with the opportunity of replicating earlier empirical studies with new data. Given the notorious difficulties involved in attempting to test hypotheses on time series data, the opportunity to replicate prior studies must be welcomed. In this instance, however, the effort has been full of surprises, and in a number of areas we find that points that appeared to be at least tentatively established in earlier work are now open to serious question.

With regard to sales anticipations, the early studies of *ex ante* data had suggested that entrepreneurs' expectations of future sales volume are so imprecise as to yield aggregate anticipations data which are of no direct forecasting value. At the same time, it was concluded that such data might be of considerable use when harnessed with other variables in econometric models involving explicit assumptions about firm behavior. Both of these conclusions now seem questionable. The analysis of the new OBE sales anticipations data presented in section 3 reveals that short-run sales forecasts are considerably more accurate than the earlier studies, based largely on the railroad shippers' forecast data, had suggested. In contrast to the old data, the OBE sales anticipations do considerably better than the Ferber naive model at predicting actual sales volume. The high positive correlations between anticipated and actual changes stand in marked contrast to the negative results of earlier studies. On the other hand, it was found in section 5 that only a marginal improvement could be obtained by using observations on sales anticipations in a model describing the generation of finished goods inventories, rather than resorting to a proxy procedure. Since only a limited number of observations have accumulated for our study, undue pessimism may not be warranted at this time. But the evidence now available suggests that, while sales anticipations are more accurate than the earlier studies had led us to believe, observations on anticipated sales volume may be less useful than we had been led to hope in helping to explain such variables as inventory investment within the context of econometric models.

A second surprise concerns the impact upon inventory position of errors that are made by firms in anticipating sales volume. If firms actually made the substantial errors in forecasting sales volume that the earlier studies suggested, it would doubtless be extremely difficult for them to move far in the direction of error correction within our three-month observation period. But since forecast errors are small in magnitude, error correction is feasible. The evidence suggests that production plans and schedules for the delivery of raw materials are sufficiently flexible to permit considerable adjustment within the quarter to whatever errors are made in forecasting sales volume.

This evidence on the extent of error correction strikes at a basic assumption underlying theoretical models of the inventory cycle. Lloyd Metzler has stated: "The only indispensable assumption in the theory of the inventory cycles is that businessmen do not immediately adapt their production plan to a change in sales."[41] He estimated that the average planning period, the time interval underlying his analysis, has a duration of approximately five months. In examining certain empirical implications of my multisector extension of the Metzler model, I assumed that the average planning period was of three months duration.[42] In contrast, the new evidence suggests that if the planning period is on the order of two or three months duration, then plans must be regarded as being subject to extreme modifications as developments during the quarter reveal errors in anticipating such variables as sales volume. The estimates presented in section 5 suggest that production plans are flexible enough for durable manufacturing to permit an actual *increase* in finished goods inventories when sales volume has been underestimated. Schedules for the delivery of purchased materials, the analysis of section 6 suggests, are so flexible in many industries that terminal inventory stock is virtually unaffected by beginning-of-quarter anticipations of inventories and sales volume.[43] The fact that inventory investment does not lead the cycle must be explained by the willingness of firms to tolerate considerable departures of actual inventory from the desired level, by the flexible accelerator, rather than by errors made by firms in anticipating sales volume.

Can the negative findings with regard to the buffer stock model be attributed to the limitations of the data? As explained in section 2, the OBE inventory and sales anticipations survey constitutes a better source of information than the one available for the earlier studies. For one thing, evidence is provided for the first time on planned inventory investment. In addition, the OBE survey emphasizes a distinction

[41] 1947, p. 11.

[42] See Lovell (1962).

[43] These results are consistent with those of Pashigian (1965), who used a simple accelerator model, unencumbered by the buffer stock complication, in using sales anticipations data collected in the OBE plant and equipment survey in explaining manufacturing inventory investment.

between long and short sales anticipations that was not available in earlier investigations. Admittedly, there is a problem created by the fact that the questionnaire's *ex ante* figures may be furnished by individuals remote from the actual decision-making about purchasing and production scheduling. But as indicated in section 2, there exists at least some evidence that the *ex ante* data are relevant to production and inventory decisions. If my difficulties with the buffer-stock concept are to be attributed to bad data, then surely the earlier studies are equally suspect.

A second possible source of error arises from problems of aggregation. Our inability to distinguish stage of fabrication at the industry level may well have constituted a distorting factor; for example, both sales and inventory may fall short of anticipations as a result of delays experienced in obtaining raw materials. Furthermore, to the extent that one firm sells more than anticipated to another firm within the observed aggregate, total inventories will be unaffected by the error made in anticipating sales volume. But the level of disaggregation provided by the OBE survey is at least as fine as that of most other studies of inventory behavior.[44] In earlier investigations more successful empirical results led to the conclusion that the difficulties of aggregation were not critical;[45] this conclusion is shaken if the difficulties reported in this paper are to be attributed to problems of aggregation.

A major qualification of our analysis concerns possible limitations of the accelerator buffer stock framework. It is apparent that at a number of points my empirical results are not in conformity with what was expected on the basis of earlier empirical work and a priori ideas about the signs of certain parameters. In contrast to earlier empirical studies, the unfilled orders backlog was not found to have an important role in determining desired inventory or anticipated inventory investment; this rather surprising result may well be explained by the possibility that in earlier studies unfilled orders served as a proxy for anticipated sales volume, an unobserved variable, rather than as a direct determinant of desired inventory. But it is less easy to reconcile the difficulties encountered in the first part of section 6 in explaining the inventory condition variable. Furthermore, repeated difficulty was

[44] The primary exception is Edwin Mills' (1957) study based on individual firm data for the interwar period, but here *ex ante* concepts were not observable and the empirical results were not completely consistent with the theory. The cement studies discussed in section 5 above involved a narrower definition of industry than is available from the OBE.

[45] It will be remembered that Moses Abramovitz (1950) had stressed the importance of the aggregation problem.

encountered in an embarrassing number of industries with the signs of the regression coefficients relating desired inventory to current and anticipated future sales volume. While these difficulties may stem in part from the rather limited number of observations available, they should be regarded as symptomatic of a possible misspecification of the basic model. In order to prevent the statistical analysis from degenerating into an exercise in descriptive statistics, repeated experimentation on the basic format of the model suggested in earlier empirical studies was not attempted in this study. But the difficulties encountered suggest that the basic limitations of the buffer stock theory may be critical. It may well be that revisions of price anticipations belong in the realization function. If firms raise prices when demands conditions are buoyant in order to restrict demand to the available supply, the revaluation of existing inventory may create difficulties for us, as the stocks are not measured in physical units and sales are regarded as exogenous. It may be that a primary source of difficulty stems from the possibility that the firm's total inventory picture is subject to much uncertainty because of difficulties in predicting the arrival of raw materials rather than errors made in anticipating future demand.

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COMMENT

On Sachs-Hart and Lovell

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The proper balance in discussion appears to be about nine parts criticism and one part praise. I think it important that the papers contributed to this session on anticipations and investment behavior receive their full quota of praise. The Sachs-Hart study deals with data on capital appropriations that have been extensively described elsewhere but used relatively little; the Lovell paper describes and analyzes data on sales and inventory anticipations that are essentially new. Both papers are thus highly worthwhile efforts to assess and "prove in" important new bodies of anticipations data. They deal extensively with the uses to which the new data can be put, and they provide illuminating comparisons with the results achieved using different and less satisfactory bodies of data.

For this kind of investigation, a rather free-wheeling attitude in sifting hypotheses is warranted. The problem is one of seeking hypotheses more than of testing them, that is to say, of trying to find unbiased simplifications that relate the new data to information already at hand. Until some experience has been gained, however, a priori information is likely to be insufficient to reduce the possible relationships among variables to models simple enough to be rich in empirical content. In such circumstances, the temptation to seek help in the data themselves is well-nigh irresistible, and sometimes unavoidable.

An exploratory investigation in this spirit is plainly fraught with certain dangers. The rule that the "maintained hypothesis," or model, shall be independent of the data under investigation is a categorical necessity of the strict application of the principles of statistical inference. It is, of course, a rule frequently honored in the breach. This occurs when we incorporate in our maintained hypothesis mathematically convenient assumptions such as linearity, normality, and so forth for which we lack evidence. It occurs more outrageously when we provisionally examine the data to assure ourselves that such convenient assumptions are not patently false, and then proceed as if they were true. When we go further and ask the data which hypotheses are worth investigating, the price is likely to be an inability to make any statements at all about the statistical significance of our findings.

A more serious danger, it seems to me, is the failure to consider a suitably wide range of possibilities. Often this failure is due to the enormous computational burdens involved. Where this is the case, computers can break through the impasse. They offer the possibility of systematic exploration of whole classes of simplified models, they permit the running down of purely formal reservations of uncertain empirical importance, and they foster consideration of the degree of inferiority of unpreferred alternatives. In effect, they liberate the researcher from casual empiricism by permitting him to extend a kind of likelihood technique to hypothesis seeking. The penalties for inadequate imagination remain, but they are no longer aggravated by the crippling limitations of computational economy.

Significantly, the authors of both papers make extensive use of the computer, and the result in each case is a far subtler piece of analysis than would otherwise have been possible. Moreover, the spirit of the Sachs-Hart approach appears to be rather close to that outlined above. They write, ". . . the present study should probably be viewed as a reconnaissance: we have looked at so many relations that the degree to which we can claim to have genuinely tested hypotheses is doubtful. But at the very least, we are in a position to enter upon research at the two-digit industry level with fairly well-defined hypotheses."

I think we must ask, however, what these well defined hypotheses are. At another point, the authors tell us that the results of their study "are perhaps best viewed as hypotheses which should stand confrontation with the corresponding data for the two-digit durable goods manufacturing industries. Time lags and relative weights of variables," they say, "should vary from industry to industry. But if our results are meaningful, the two-digit industries stage of the analysis should yield functions with a strong family resemblance to those presented in this study."

What does this mean in terms of the next research stage? If time lags and relative weights remain open, does not the entire field of hypotheses remain open also? Are we then considering a replication of the whole research program for each two-digit industry? If this is the plan, I submit that the statistical significance of what is learned will still be very much open to question. Perhaps the replicates will coalesce about a very characteristic structure, but suppose they do not. Thus while I agree that the present study provides a very illuminating foundation for subsequent work, I think it does so not by providing hypotheses but by providing constraints on subsequent theorizing. For example, one would be suspicious of any theory that makes capital expenditures at time t a function of a single period's authorizations, that implies a rigid determinism between expenditures and any earlier authorization, that fails to make room for capacity utilization and financial variables in addition to authorizations, and so forth. But these, and other similar constraints derivable from the present paper, are insufficient to specify a theory of the role of authorizations in capital expenditures; and a considerable effort at formal model-building must precede the next stage of the investigation if the findings are to be amenable to the usual apparatus of statistical interpretation.

Quite possibly the authors mean their remarks to be interpreted in this sense. If so, I feel that their research strategy is a defensible one. Perhaps another set of investigators would have been willing to stake more on the adequacy of their prior theory of the expenditures-authorizations nexus, but in the present state of knowledge they could hardly object if others fail to share their confidence. What is important is that any research program provide a place for the maintained-hypothesis approach, and this the Sachs-Hart program appears to do.

Turning next to Michael Lovell's paper, one finds the discipline of prior theorizing a good deal more in evidence. Lovell begins, however, with some purely descriptive findings on the accuracy of manufacturers' anticipations in the new OBE survey. To this end he employs the naive-model approach first used by Ferber in 1953 on the railroad shippers' forecasts. This consists of comparing the accuracy of anticipations about a given variable with a mechanical forecast based on recent actual values of the same variable. The formula employed for the naive forecast is presented in the paper as

$$E_t^{**} = A_{t-4}(A_{t-1}/A_{t-5}),$$

which, as Lovell expresses it, "amounts to adjusting the same quarter of the immediately preceding year by the recently observed trend." This provides a one-quarter forecast at the close of period $t - 1$; a two-quarter forecase at the same date is given by

$$E_{t+1}^{**} = A_{t-3}(A_{t-1}/A_{t-5}).$$

By and large, Lovell finds that the new anticipations data are substantially more accurate than naive projections. This finding is uniformly true for durable goods manufacturing industries; it is also generally true of the sales anticipations in nondurable goods manufacturing. The exception is provided by inventory anticipations in nondurable goods manufacturing, which are generally inferior to naive projections.

My own feeling, however, is that the Ferber-Modigliani test against a naive model—ingenious and revealing as it has been in characterizing the nature of *ex ante* data—is no longer definitive. We now recognize that the value of anticipations data depends not on how good they are as direct forecasters but rather on what we can do with them in a behavioristic model. One thing that the "realization function" approach shows us is that there is good reason why one- and two-quarter anticipations should not be accurate: their purpose is to initiate correctable action, not to predetermine action. To put the matter metaphorically, business planning is less a matter of sighting a distant target than it is of launching a guided missile on a path that can be adjusted as more information on an approaching target becomes available. Regarded in this light, anticipations data yield valuable information on the planning process, which in turn provides a foundation for describing the process by which realized magnitudes are shaped. Good evidence on the planning process need not be good evidence as forecasts; it undoubtedly helps to be both, but it is not essential.

I pass now to the heart of Lovell's paper, the realization function approach to inventory behavior. In Lovell's notation, the simplest version of this approach states the following relation between realized and planned inventories

$$\text{IN} = \text{ASIN} - (\text{SALE} - \text{ASSALE}).$$

This implies complete plan rigidity—an idea appropriate, say, to the "Hicksian week." Lovell considers a slight modification reasonable in time periods long enough for surprises to be recognized and reacted to

$$\text{IN} = b_1 + b_2\text{ASIN} - b_3(\text{SALE} - \text{ASSALE}),$$

where b_2 and b_3 are intrinsically positive. He does not, however, consider a positive coefficient of (SALE $-$ ASSALE) reasonable. Why not?

Let us first see that a positive coefficient is not illogical. Suppose that at the beginning of the current period, it is planned that inventory at the end of the period shall be IN^p. We may suppose that this plan depends in a definite way on the sales anticipated for the same period

$$\text{IN}^p = f(\text{ASSALE}).$$

Then, with sufficient plan flexibility, we expect to be able to approximate realized inventory at the close of the period by the first terms in Taylor's expansion

$$\text{IN} = \text{IN}^p + f'(\text{ASSALE})(\text{SALE} - \text{ASSALE}).$$

In the linear case, this becomes

$$\begin{aligned} \text{IN}^p &= \beta_1 + \beta_2\text{ASSALE},\ \beta_2 > 0 \\ \text{IN} &= \text{IN}^p + \beta_2(\text{SALE} - \text{ASSALE}) \\ &= \beta_1 + \beta_2\text{ASSALE} + \beta_2(\text{SALE} - \text{ASSALE}). \end{aligned}$$

With moderate plan flexibility, one would expect to find the statistical coefficient of the term (SALE − ASSALE), say, b_3, *less than* β_2; but it need not be negative. Even inverse movements of the ratio IN/SALE with respect to sales, or cyclical alternations of stock shortages and surpluses, need not make b_3 negative.

The truth is that, quite frequently, Lovell does *not* find coefficients of the type b_3 to be negative; and he is much troubled by this outcome. In employing the realization function idea on Dun and Bradstreet data, I got similar results—correction coefficients that were frequently positive and sometimes large. These results were suspect because of the possible influence of inflationary price rises in the period I investigated, 1949–57; but Lovell's data are much less likely to be contaminated in this way.

I therefore recommend that, for total inventories, we steel ourselves to the possibility of having to *accept* this evidence of programming flexibility in manufacturing industry. It begins to have the appearance of an attested fact. I can sympathize with Lovell's concern for the buffer-stock hypothesis; to relax or abandon it threatens some important macrotheories of inventory behavior. But we need to remember that the buffer-stock hypothesis is most plausible for stocks of finished commodities. For stocks of goods in process and even stocks of raw materials, a fairly close correspondence of stocks with sales is to be expected theoretically and has been found statistically by Abramovitz and Stanback. When to these we add finished stocks, the resulting series of total stocks shows at most a short lag behind the turning points of sales; and this phenomenon, as I shall show below, is not incompatible with a positive coefficient for the surprise term (SALE − ASSALE) in Lovell's realization function.

In my initial reaction to Lovell's paper, I was inclined to take a similarly lighthearted view of his dissatisfaction with the coefficients in his equation for investment in finished inventories

$$\Delta\text{FIN} = \delta\beta_1 + \delta\beta_2\text{SALE} + \lambda(\delta\beta_2 + 1)(\text{ASSALE} - \text{SALE}) - \delta\text{FIN}_{-1}.$$

On a closer reading of his paper, however, I am convinced that his concern is warranted. The results he gets are (1) inconsistent with earlier econometric findings of his and others, (2) apparently contrary to the production-smoothing hypothesis, which has strong theoretical and practical support, and (3) difficult to square with Abramovitz' finding, confirmed by Stanback, that finished manufacturers stocks move inversely to sales in short cycles.

Some insight into these difficulties is suggested by a slight transformation of the preceding equation

$$\begin{aligned}\Delta\text{FIN} = {} & \delta\beta_2(\text{SALE} - \text{SALE}_{-1}) + \lambda(\delta\beta_2 + 1)[(\text{ASSALE} - \text{SALE}_{-1}) \\ & - (\text{SALE} - \text{SALE}_{-1})] + \delta\beta_1 + \delta\beta_2\text{SALE}_{-1} - \delta\text{FIN}_{-1},\end{aligned}$$

or in difference notation

$$\begin{aligned}\Delta\text{FIN} = {} & [\delta\beta_2(1 - \lambda) - \lambda]\Delta\text{SALE} + \lambda(\delta\beta_2 + 1)\Delta\text{ASSALE} \\ & + \delta(\text{FIN}_{-1}{}^d - \text{FIN}_{-1}),\end{aligned}$$

where $(\text{FIN}_{-1}{}^d - \text{FIN}_{-1})$ is the discrepancy between actual and desired stocks at the close of the preceding period. This version justifies the earlier assertion that Lovell's model of inventory behavior can show a lag of inventories behind sales at turning points, even when the coefficient $[\delta\beta_2(1 - \lambda) - \lambda]$ is positive. For this implies that ΔFIN lags ΔSALE, and this can happen because ΔASSALE lags ΔSALE and the final term, representing stock disequilibrium, also lags ΔSALE.

More significantly, this formulation shows that Lovell's model of inventory behavior implies the same timid planning reaction to an *ex post* stock disequilibrium, $(\text{FIN}_{-1}{}^d - \text{FIN}_{-1})$, as to an *ex ante* stock disequilibrium, $\beta_2(\text{ASSALE} - \text{SALE}_{-1})$. This can perhaps be seen more clearly by going back to first principles. We have the anticipated level of desired finished stocks,

$$\text{AFIN}^d = \beta_1 + \beta_2\text{ASSALE} + \beta_3\text{ALSALE}_{+1},$$

and the corresponding short-run planned level,

$$\text{ASFIN} = \delta\text{AFIN}^d + (1 - \delta)\text{FIN}_{-1},$$

whence $\text{ASFIN} - \text{FIN}_{-1} = \delta\text{AFIN}^d - \delta\text{FIN}_{-1}$, i.e.,

$$\begin{aligned}\Delta\text{ASFIN} & = \delta(\beta_1 + \beta_2\text{ASSALE} + \beta_3\text{ALSALE}_{+1}) - \delta\text{FIN}_{-1} \\ & = \delta\beta_2(\text{ASSALE} - \text{SALE}_{-1}) + \delta\beta_3(\text{ALSALE}_{+1} - \text{ASSALE}) \\ & \quad + \delta(\beta_1 + \beta_2\text{SALE}_{-1} + \beta_3\text{ASSALE} - \text{FIN}_{-1}).\end{aligned}$$

The final term implies that only a fraction δ of the *ex post* disequilibrium $(\text{FIN}_{-1}{}^d - \text{FIN}_{-1})$ is planned for correction in the next period.

It seems more reasonable to suppose that this correction will be planned for a single period, thus

$$\begin{aligned}\Delta\text{ASFIN} = {} & \delta\beta_2(\text{ASSALE} - \text{SALE}_{-1}) + \delta\beta_3(\text{ALSALE}_{+1} - \text{ASSALE}) \\ & + (\beta_1 + \beta_2\text{SALE}_{-1} + \beta_3\text{ASSALE} - \text{FIN}_{-1})\end{aligned}$$

whence

$$\text{ASFIN} = \delta(\beta_1 + \beta_2\text{ASSALE} + \beta_3\text{ALSALE}_{+1}) + (1 - \delta)\text{FIN}_{-1}{}^d.$$

The derivation of an equation for realized inventories now proceeds exactly as before, and we arrive at the equation

$$\begin{aligned}\text{FIN} = \text{ASFIN} + [(1 - \lambda)\delta\beta_2 - \lambda](\text{SALE} - \text{ASSALE})\\ + (1 - \lambda)\delta\beta_3(\text{ASSALE}_{+1} - \text{ALSALE}_{+1}),\end{aligned}$$

which has exactly the same structure as one shown by Lovell for total inventories. The missing anticipations variable ASFIN can be finessed as before by substituting the foregoing expression for it, which gives, after some manipulation,

$$\begin{gathered}\Delta\text{FIN} = \text{FIN} - \text{FIN}_{-1} = \delta\beta_1 + \delta\beta_2\text{SALE} + \delta\beta_3\text{ASSALE}_{+1}\\ - \lambda(1 + \delta\beta_2)(\text{SALE} - \text{ASSALE}) - \lambda\delta\beta_3(\text{ASSALE}_{+1} - \text{ALSALE}_{+1})\\ + (1 - \delta)(\text{FIN}_{-1}{}^d - \text{FIN}_{-1}) - \delta\text{FIN}_{-1}.\end{gathered}$$

Let us follow Lovell in dropping the long anticipations; then the model becomes

$$\begin{aligned}\Delta\text{FIN} = \delta\beta_1 + \delta\beta_2\text{SALE} - \lambda(1 + \delta\beta_2)(\text{SALE} - \text{ASSALE})\\ + (1 - \delta)(\text{FIN}_{-1}{}^d - \text{FIN}_{-1}) - \delta\text{FIN}_{-1},\end{aligned}$$

which differs essentially from the equation derived by Lovell.

If, as I believe, the implied handling of *ex post* stock disequilibrium in this model represents a gain in realism, it would appear that part of the trouble with Lovell's finished inventories investment function is inherent in a misspecification of ASFIN. Significantly, this misspecification has no effect on the inventory equations in which inventory anticipations enter explicitly; it thus provides no reason to question the equations for total inventories. But it does lead to the neglect of a relevant term in equations from which inventory anticipations have been finessed, viz., $(1 - \delta)(\text{FIN}_{-1}{}^d - \text{FIN}_{-1})$. It is thus possible that the variable SALE serves as a proxy for $(\text{FIN}_{-1}{}^d - \text{FIN}_{-1})$, with which it tends to be positively correlated and which has an intrinsically positive coefficient. In this case $\delta\beta_2$ would tend to be too large, and the derived sum

$$\delta\beta_2 - \lambda(1 + \delta\beta_2) = (1 - \lambda)\delta\beta_2 - \lambda$$

correspondingly too large also.

For estimation purposes, a slight modification of the foregoing equation is convenient

$$\begin{aligned}\Delta\text{FIN} = \delta\beta_2\Delta\text{SALE} - \lambda(1 + \delta\beta_2)(\Delta\text{SALE} - \Delta\text{ASSALE})\\ + (\beta_1 + \beta_2\text{SALE}_{-1} - \text{FIN}_{-1}).\end{aligned}$$

This version shows that the unknown coefficients β_1, β_2, δ, and λ can be estimated uniquely. It also shows that the variable accelerator model, even as modified, depends on surprises—in fact, substantial ones—to generate inverse behavior of finished inventory stocks and sales. Without such surprises, stocks vary directly with sales.

It may be interesting to compare the working of a simple production-smoothing model developed in the same spirit as Lovell's variable accelerator model. Let us introduce the notation PROD for production, APROD^d for desired production in terms of anticipated sales, and ASPROD for short-run planned production. Then we may suppose that desired production equals anticipated sales plus a correction of *ex post* inventory maladjustment

$$\text{APROD}^d = \text{ASSALE} + (\beta_1 + \beta_2\text{SALE}_{-1} - \text{FIN}_{-1}).$$

But production smoothing implies that the firm will make the desired adjustment of production gradually. One possibility, implying a two stage adjustment to realized sales and a multiple-period correction of inventory stock, is the following:

$$\text{ASPROD} = \text{SALE}_{-1} + \delta(\text{ASSALE} - \text{SALE}_{-1}) + \gamma(\beta_1 + \beta_2\text{SALE}_{-1} - \text{FIN}_{-1}),$$

where both δ and γ are less than unity.

Following Lovell's procedure, we posit two extreme hypotheses about the adjustment of production to surprises: PROD = ASPROD, i.e., complete inflexibility, with weight λ; and PROD = ASPROD + δ(SALE − ASSALE), i.e., two-stage adjustment to sales, with weight $1 - \lambda$. Then over all firms in the industry

$$\text{PROD} = \text{ASPROD} + (1 - \lambda)\delta(\text{SALE} - \text{ASSALE}).$$

Now, evidently we have

$$\text{AFIN} = \text{FIN}_{-1} + (\text{ASPROD} - \text{ASSALE}) \text{ and } \text{FIN} = \text{FIN}_{-1} + (\text{PROD} - \text{SALE}).$$

From these we derive

$$\text{FIN} = \text{AFIN} + (\text{PROD} - \text{ASPROD}) - (\text{SALE} - \text{ASSALE})$$

and, substituting from the equation for PROD, we get

$$\text{FIN} = \text{AFIN} - [1 - (1 - \lambda)\delta](\text{SALE} - \text{ASSALE}).$$

Similarly, substituting for ASPROD in the expression for AFIN gives

$$\begin{aligned}\text{AFIN} &= \text{FIN}_{-1} - \text{ASSALE} + \text{SALE}_{-1} + \delta(\text{ASSALE} - \text{SALE}_{-1}) + \gamma(\beta_1 + \beta_2\text{SALE}_{-1} - \text{FIN}_{-1})\\ &= \text{FIN}_{-1} - (1 - \delta)\Delta\text{ASSALE} + \gamma(\text{FIN}_{-1}{}^d - \text{FIN}_{-1}).\end{aligned}$$

Again, by definition, $\Delta\text{FIN} = (\text{FIN} - \text{AFIN}) + (\text{AFIN} - \text{FIN}_{-1})$, whence after substitution from the preceding paragraph

$$\Delta\text{FIN} = -(1 - \delta)\Delta\text{ASSALE} - [1 - (1 - \lambda)\delta](\Delta\text{SALE} - \Delta\text{ASSALE}) + \gamma(\text{FIN}_{-1}{}^{d} - \text{FIN}_{-1}).$$

In this form we see that, for suitably small γ $(0 < \gamma < 1)$, the production-smoothing model yields Abramovitz' findings—inverted behavior of finished stocks in short cycles and conforming behavior with a long lag in major cycles. For in a time of rising sales and sales anticipations, ΔFIN will tend to fall. The only offset to this tendency will be the growth of the discrepancy $(\text{FIN}_{-1}{}^{d} - \text{FIN}_{-1})$, due both to the rise of $\text{FIN}_{-1}{}^{d}$ with sales and to the decline of FIN_{-1} with production smoothing. But given that γ is small, this offset will dominate the movement of ΔFIN only with a considerable lag. A parallel argument holds for declining sales and sales anticipations. Finally, the inverse behavior of sales and inventories does not depend on surprises: given that the coefficient of ΔASSALE is negative, even if $\Delta\text{SALE} = \Delta\text{ASSALE}$, inventory change will be inverse to the change in sales until the discrepancy $(\text{FIN}_{-1}{}^{d} - \text{FIN}_{-1})$ becomes sufficiently large.

As near as I can determine, Lovell's results from fitting his equations for ΔFIN do not yield a test of this model. The above comments suggest that it, or something like it, might be worth investigating.

On Sachs-Hart and Lovell

BY ROBERT EISNER, NORTHWESTERN UNIVERSITY

I presume that the role of a discussant is that of a searching critic who offers the most severe scrutiny of possible pitfalls for the unwary on every road traveled. What is more, he should be a kind of backseat driver constantly asking "Why didn't you take that road?" Where the roads traveled are pioneering and ingeniously constructed, as is apparent in the papers under discussion, the challenge to the discussant is all the greater.

To begin with the Sachs-Hart paper, one usually fruitful avenue of criticism—that of asking the authors why they did not try this or that possibility—might seem cut off since Sachs and Hart have tried them all! Indeed they admit quite candidly that they have indulged in "extensive screening" which may raise some questions about the statistical significance of their findings. Well, since I cannot easily suggest that they should have tried other things, I shall *object* to their having tried everything.

None of us is innocent in this regard, and Sachs and Hart are no more guilty than most; but this is, in my opinion, a really serious and growing problem in the modern age of high-speed digital computers. Without specific reference to the Sachs-Hart paper, what indeed are we to make of a relation reported as significant at a .01 probability level if we are told by the authors that they tried 100 different relations and screened out the 99 that did not prove "significant"? I am not prepared to argue that there should be no examination of data during the process of formulating and developing hypotheses. But there are some serious formal and statistical considerations that must be set forth in view of modern technology, and they should be taken quite explicitly into account in our work.

Turning to more substantive matters, the National Industrial Conference Board appropriations data utilized by Sachs and Hart may be of interest for what they reveal about capital expenditure decisions, may be useful per se for forecasting purposes, may be useful for forecasting along with other contemporaneous variables, or may be useful in a realization function along with other variables subsequent in time to the period at which the decisions underlying appropriations are made. They may be meaningful as factors actually influencing investment or they may merely be useful as conveyors of information to the research worker.

I myself am rather inclined to doubt the importance of appropriations as factors determining investment in their own right. I am rather skeptical in general about the significance of financial considerations in determining the rate or even timing of investment. This is not the place to review the growing econometric literature on the subject, but I might relate a high point of one of my interviews of business executives a number of years ago in an effort to find out about the determinants of capital expenditures. One financial officer of a large manufacturing company had just finished assuring me with some passion of the necessity for him to find appropriate ways to "get the money" if capital expenditures were to be made. At this point his superior in the business hierarchy entered the room. I briefed him on the question I had raised and he quickly interjected, "Oh, financial considerations never stop us from making a capital expenditure that we think is profitable. We'll always get the money. That's his job, to get it for us," he said, pointing to the somewhat embarrassed financial officer.

The inference which I would draw from this and other facts is that monetary considerations are important in the timing of monetary arrangements and hence, very likely, important in the timing of appropriations as well. It is hard to believe that either the fact that money could be raised readily or that, as a consequence, appropriations might be made would lead the large firms that do most of our investing to undertake capital expenditures of inappropriate profitability.

Appropriations data may nevertheless contain useful information for forecasting purposes. They may well give a substantial clue to the desired capital stock for some period in the future (but perhaps a period imprecisely defined). A considerable difficulty remains, nevertheless, in moving from information on desired capital stock to information on investment, which will determine the path of capital over time. It is, of course, possible that there may be some stable distribution function that will transform the stock or flow of appropriations data into subsequent capital expenditures. Interesting work has been done on this matter. Proof of the stability of any such relation cannot come, however, from fits of regressions to past data; it must relate to predictions independent of the data from which estimates are made.

The Sachs-Hart results themselves suggest that much information relevant to investment is lost in the appropriations nexus and that a useful, stable relation of investment and appropriations is elusive. For Sachs and Hart note, most interestingly, that a simple or direct function relating investment to such determinants as accelerator and cash flow-type variables offers a better fit, after appropriate adjustment, than does the relation which makes investment a function of the appropriations function based upon these same determinants.

Sachs and Hart suggest that the marked improvement in the fit of the investment-appropriations relation when lagged investment is added to the independent variables may be a result of "random" but serial correlated disturbances in the investment relation. This may in part be true. I should think, however, that lagged investment is particularly important in taking care of not merely random factors but also the critical question of timing of the investment stemming from any given series of past flows of appropriations. The significant role of lagged investment reminds us, therefore, rather of systematic factors lacking in the investment-appropriations relation. Among these systematic factors may be those relating to the supply of capital goods, an element generally ignored in the Sachs-Hart treatment.

A number of questions are suggested by Sachs and Hart or suggest themselves with regard to the role of "cash flow." They wonder themselves at the relevance of cash flow at a period so late as to cast doubt on its real role in determining investment. I suggest that this may be due to the role of cash flow as a proxy for earlier indicators of expected future demands which operate on investment without manifesting themselves fully in the pure appropriations relation.

A further difficulty in accepting the role of cash flow in the "eclectic model" presented by Sachs and Hart lies in the lack of identifiability of the relation they estimate. It would be a brave man who could assert without doubt that a positive association between cash flow and capital expenditures of the same or proximate quarters in a set of time series observations in manufacturing durables establishes that higher cash flow induces a greater rate of investment. One might as easily infer that higher rates of investment expenditures increase the profits and hence the "cash flow" of the manufacturing durable industries which produce capital goods, not to mention other industries which profit indirectly from higher investment expenditures.

Sachs and Hart express surprise that addition of a variable for lagged cancellation of appropriations results in a better fit than was obtained with appropriations themselves. I might hazard the explanation that this result appears because investment realizations are more sensitive to depressing than to exhilarating changes in underlying economic conditions. I have noted some data bearing on this elsewhere. A confirmation with appropriations data might be found by estimating a relation involving separate coefficients for appropriations when appropriations are rising and when they are falling. This might be done, simply enough of course, by adding a set of appropriations variables which would be identical to the actual appropriations series when appropriations are falling but equal to zero when appropriations are rising. Positive coefficients for this additional set of appropriations variables would confirm the hypothesis that appropriations data and, perhaps, the underlying factors influencing them, are associated more sharply with investment in periods of decline than in periods of rise.

In their discussion of "plan image," Sachs and Hart use very recent cancellations data as the additional arguments necessary to convert their anticipatory function involving appropirations data into a realization function, which would presume to explain the difference between anticipations and realized investment. It seems to me that, since cancellations are themselves nothing but more recent anticipatory variables with regard to investment, they are not proper complements in the creation of a realization function. We should rather have real variables which offer corrections of the expectations which underlay the investment anticipations. A realization function involving such real variables would have the advantage of a tie-in for predictive and analytical purposes with the actual or model-generated nonanticipatory variables which might actually determine investment.

The paper by Sachs and Hart is generally scholarly, tentative, and cautious. Yet in the end they seem to be somewhat carried away in their evaluation of the usefulness of the appropriations data for forecasting purposes. For they base their favorable conclusions on the goodness of fit of their regressions of past investment expenditures on appropriations. Surely, however, the test which the appropriations relation must meet is not that of goodness of fit to the data from which it was estimated. It must rather meet the unhappily more exacting test of prediction of capital expenditures in periods other than those in which it was nurtured.

And if the appropriations data are to be compared for accuracy of forecasting with surveys of anticipated capital expenditures by the McGraw-Hill Department of Economics or the Securities and Exchange Commission and Office of Business Economics of the Department of Commerce, it is not appropriate to compare the "errors" in a regression of actual expenditures on past appropriations with the errors in the raw data of the McGraw-Hill and Commerce-SEC surveys. A proper test might then involve regression of actual expenditures on appropriations data, on the one hand, and anticipated expenditures, on the other, with the critical comparisons relating to the errors in *prediction of current or future capital expenditures* on the basis of the relations estimated from *past* data.

In turning to the Lovell paper, I find myself in my more usual role as a critic. Lovell has not tried everything, at least not yet. In fact, Lovell has been brave in presenting to this Conference on short notice the results of still-continuing research. What is more, he presents results which appear to him, prima facie, to contradict the empirical and theoretically well-oriented findings of his own previous important work on inventory investment. We witness a conflict between the presumably well-established earlier Lovell findings and the current Lovell results. I should like to help rescue Lovell from Lovell by explaining away some of Lovell's current findings and thus restoring at least some of the shine of Lovell's earlier accelerator buffer-stock models.

As is certainly clear to the reader of Lovell's paper, Lovell now suffers from a wealth of "better" data in the form of quarterly anticipations of both sales and inventories. In olden times, when he had to improvise to get measures of relatively short-term sales and inventory anticipations, he did better. But now we have two basic problems; the sales anticipations are too good and the buffer-stock role of inventories is too poor. I shall attempt a common explanation of both of these findings.

In regard to sales anticipations, it should be recalled that previous work in this area has taught us to expect generally poor correlations between actual and anticipated sales changes. Lovell's results now are amazingly good, at least in the manufacturing durables industries. Comparing mean absolute errors of anticipations with mean absolute errors from the Ferber naive-model extrapolation, Lovell finds anticipations doing consistently better, and markedly better—no mean feat. And when coefficients of determination are examined for actual and predicted sales changes, these are found to be correspondingly high.

A clue to part of what is going on may be found in the recognition that, even when average absolute errors of anticipations are virtually as high as those from the naive model extrapolation, as in manufacturing durables industry 7 (where the ratio of mean absolute errors of anticipations to mean absolute errors based on naive model projections is .96, or almost 1), the R^2 of actual on anticipated sales *changes* is still a robust .6558. Now the Ferber naive-model test is essentially a seasonally adjusted extrapolation of the past. The fact that, when the short-run sales anticipation variable ASSALE does little better than the naive-model test, it nevertheless produces a high R^2 of actual on anticipated sales changes indicates that a considerable part of the accuracy of sales anticipations stems merely from their property of catching seasonal variations.

But actually I believe that there is something else at work which can be used to explain not only the relative accuracy of sales anticipations as a forecast but the seemingly poor results of the buffer-stock mechanism in the Lovell inventory model. Recall, of course, that this model indicates that desired holdings of inventories are based upon anticipated sales. Actual holdings of inventories are less than desired holdings of inventories to the extent that actual sales exceed anticipated sales and producers are unable or unwilling fully to adjust production within the period of measurement. If producers or sellers can adjust very quickly, the buffer role of inventories will, of course, disappear. It has indeed been suggested that application of modern computers and sophisticated handling of data on sales and distribution has made the length of this period of adjustment virtually infinitesimal. I doubt it.

My explanation is simply that Lovell's theory has been right all along but that his current data are not what they are cracked up to be. My point implies no disrespect to the worthy OBE collectors of these highly useful series. What I want to stress is simply that, from the standpoint of inventory control, the sales anticipations for any given quarter which are made known close to the middle of that quarter, as are the ASSALE series, are as much reflections of actual sales of that quarter as they are of anticipations. I would interpret the difference between this semi-forecast of sales and actual sales as essentially a random error having little to do either with the anticipations on which inventory decisions are made or the realizations of these anticipations. For inventory decisions in a firm facing substantial costs in rapid fluctuations of production may relate to relatively longer-run expectations of future sales.

If my conjecture is correct, the deviation of actual sales from what is reported as ASSALE, rather than reflecting an error in the anticipation of sales on the basis of which desired inventory holdings were determined, is an improvement in the not fully observed measure of those anticipations. We would then expect a substantial component of this deviation, if not all of it, to be *positively* associated with inventory investment. And this, of course, is consistent with Lovell's current findings. It all stems from the fact that presumably short-run sales anticipations, ASSALE, are as much a measure of actual sales as anticipated sales (and indeed may well be used as such by clever analysts in the Department of Commerce faced with the task of estimating actual sales), while the actual sales figures are really in large part, for our purposes, proxies for future sales anticipations.

Although this line of conjecture may appeal to all of us who hate to discard a useful theory at the first hint of derogatory data, we should look for independent confirmation or contradiction. I believe I can see some confirmation in the relation noted by Lovell in the third part of his section 6, where he shows a negative correlation between his variable COND (measuring the proportion of respondents considering inventory holdings too high) and ALSALE of two periods hence. This suggests that, to the extent firms expect sales well into the future to be higher, they are less likely to consider current inventories too high.

Of course, further tests might be attempted. (There usually *are* more things which a discussant can suggest be tried.) In particular I might urge that SALE (actual sales) be introduced in equation (8). If estimates of this modified equation were to yield a positive coefficient for SALE, they would suggest that actual sales *are* proxying for expected future demand along with the presumably short-term sales anticipation variable, ASSALE. In general, I would suggest checks of the relative role of these purported measures of anticipated and actual sales. In pursuance of this, one might try using the change in actual sales as a measure of surprise or error in anticipation. If, as many of us hypothesize, businessmen tend generally to expect tomorrow to be like today, unless they have very firm knowledge to the contrary, the change in actual sales may be one of the better measures of unanticipated sales that we can find.

On Sachs-Hart and Lovell

BY JAMES MORGAN, UNIVERSITY OF MICHIGAN

Early studies of the Commerce-SEC investment plans indicated a tendency to underestimate investment in the last quarter of good years.[1] I wonder why we do not investigate the possibility that the accounting and tax year affects decisions. It is common for businessmen to say they invest profits before the government gets them. What they mean is that every dollar of investment in new equipment involves some amount—say, a quarter, of outlays—that can be counted as installation expenses for tax purposes. If, as Lovell suggests, the flexibility of adjustment is more rapid than we thought and if, in such adjustment, attention is paid to keeping profits from fluctuating too much, then not only do we have a better chance of explaining fourth-quarter investment, but we may also have to be concerned about the distortion of reported profits figures.

On Sachs-Hart

BY VICTOR ZARNOWITZ, UNIVERSITY OF CHICAGO AND NATIONAL BUREAU OF ECONOMIC RESEARCH

Sachs and Hart use two categories of "causal" variables to explain, first, capital appropriations and, second, capital expenditures (in sections C and D of their paper). The "financial" factors, cash flow and bond yield, compete in this role with the "accelerator-type explanation" represented by the ratio of deflated new orders received by durable goods manufacturers to estimated productive capacity of the durable goods sector. The competition results in a merger: Sachs and Hart find that "eclectic combinations using both financial and accelerator variables are considerably stronger than pure models" (that is, than

[1] See Irwin Friend and Jean Bronfenbrenner, "Plant and Equipment Programs and Their Realization," in *Short-Term Economic Forecasting*, Studies in Income and Wealth 17, Princeton for NBER, 1955, pp. 53–96.

either the financial or the accelerator-type explanation alone). However, when combined with capital appropriations, the financial variables (chiefly the cash-flow term) show more additional explanation than the "accelerator": in fact, "it appears . . . that virtually all the relevant information to be found in the orders-capacity ratio is well represented by capital appropriations."

The purpose of this comment is to point out that, in the context of the aggregative data used by Sachs and Hart, the influence of the orders-capacity ratio can be explained without recourse to the accelerator theory—that the interpretation of the ratio as an "accelerator" variable may, indeed, be quite misleading. The reason is simple. Advance orders for durable manufacturers are dominated by orders for machinery and nonautomotive transportation equipment. These orders, which are essentially commitments to buy capital equipment, accounted for about 70 per cent of the total value of outstanding durable goods orders in recent years.[1] As a consequence, new orders for durables and new orders for investment goods are highly correlated.[2] This being so, durable goods orders, taken with a lead, must be highly correlated with the output of capital equipment, simply because these goods are typically produced to order. In other words, new orders for durables may be regarded as a proxy for equipment orders which precede output and shipments of the corresponding items as a matter of prevailing contractual arrangements that have, as such, nothing to do with the accelerator theory or any other "causal" explanation of investment.

There are a few complications which, however, do not invalidate the above argument. The use of expenditures for capital goods instead of output or shipments matters little, since the association between expenditures and output is demonstrably very close in quarterly terms on a simultaneous basis. Expenditures (and appropriations) include a "plant" as well as an "equipment" component. But durable goods orders are nearly as well correlated with the composite of machinery and equipment orders plus industrial and commercial construction contracts as with the equipment part of that aggregate alone.[3] Finally, there is the

[1] Statistical evidence on statements made in this comment comes mainly from my work on the relations between manufacturers' orders and investment in plant and equipment (part of a manuscript in preparation for the National Bureau of Economic Research). Because of space limitations, only a very few short references to this documentation will be made.

[2] See Department of Commerce, *Business Cycle Developments,* series 6 and 24. A mere inspection of these graphs makes it clear that the patterns of change in the two series are very much alike.

[3] The graphs of these series are conveniently grouped in *Business Cycle Developments* (compare items 6, 24, and 10).

fact that durable orders are not used as a separate independent variable in the Sachs-Hart regressions: the relevant term is rather the ratio of these orders to a capacity index (developed by Frank de Leeuw of the Federal Reserve Board). But the capacity index is, as it should be, a fairly stable series with a relatively strong trend and very weak cyclical and irregular components; hence the changes in the ratio are definitely dominated by those in the numerator, that is, in the new orders which are subject to relatively pronounced fluctuations.

Correlations of the SEC-OBE quarterly plant and equipment expenditures with new investment orders and contracts, taken with a lead of either two or three quarters, yield simple r^2 of about .80 for 1949–62. This is for deflated data; in current dollars, the correlations are somewhat higher and they exceed the correlations between expenditures and the new capital appropriations for manufacturing.[4] The R^2 coefficients resulting from the use of distributed instead of simple lags are appreciably higher. Differences in industry and time coverage prevent direct comparisons of these results with those of Sachs and Hart; the point I wish to make here is merely that all these findings are consistent with my interpretation of the orders variables as representing primarily another "anticipatory" factor (like the appropriations data) rather than a "causal" factor in the sense of economic theory.

As already noted, the addition of orders-capacity ratios to the appropriation terms contributed very little to a statistical explanation of capital expenditures (see section E of the Sachs-Hart paper). This is probably largely attributable to the affinity between orders and appropriations, as both variables share the character of anticipatory data relative to capital expenditures. The financial variables, which were found to provide more additional information, cannot be regarded as being also of this "anticipatory" nature. As the results are presented, some readers could infer that the financial variables have more autonomous predictive power than the "accelerator" variables have, but in the light of our argument such conclusion would clearly be unwarranted.

When orders and appropriations are both viewed as anticipatory or symptomatic variables, the question arises which predicts or "anticipates" capital expenditures more effectively. My results suggest that orders-contracts have some advantage, whether taken singly (see footnote 4) or in combination with various "causal" variables. But the

[4] For 1954–61, the highest r^2 obtained from regressions of plant and equipment expenditures (I) on new capital appropriations in manufacturing was .793 (for a lag of three quarters); the highest r^2 for the relations between I and new investment orders and contracts was .875 (with a lag of two quarters).

advantage is not large and it may depend on the periods used, the lag distributions chosen, etc.[5]

It is important to note that this argument against an interpretation of the orders-capacity ratio as an accelerator variable is cogent only at the aggregative level. When Sachs and Hart extend their study into the two-digit durable goods industries (and we have every reason to welcome their plan to do so and expect interesting results from it), their use of the ratios will be fully justified. For then they will have correctly used orders received by a particular industry, which cannot be confused with orders for the capital goods that are to serve the investment plans of that industry.

[5] The explanatory power of durable goods orders would be expected to be less than that of investment orders-contracts. More importantly, the "deflation" with capacity will reduce the "predictive" efficiency of the orders data. Hence, it is not surprising that the orders-capacity ratios perform weakly alongside appropriations, particularly when several terms of the latter, with different lags, are used simultaneously, as in equation E–3.