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Retail Food Store Inventory Behavior

Stephen E. Miller

A stock-adjustment model is applied to monthly retail food store inventory data from 1968 through 1988. Estimates of the speed-of-adjustment coefficient (.34 to .75) are higher than estimates from previous research, indicating that periods of inventory disequilibrium in food retailing are short-lived. The results indicate that inventories are insensitive to financial carrying costs. The hypothesis that parameters of the model are constant over the sample period cannot be rejected, indicating that changes in food retailing (e.g., electronic scanning and diversification of product mixes) have not affected inventory behavior.

Key words: retail food store inventories, stock-adjustment model.

Previous research has indicated that retail food stores can be quite slow in adjusting their inventories to desired levels. Blinder (1981) found that retailers may require up to seven months to make half of desired inventory changes, thus there may be prolonged periods of inventory disequilibrium in food retailing. Such slow inventory adjustments indicate that retailers face substantial costs in adjusting their inventories to changing economic conditions. Blinder (1981) used aggregate seasonally adjusted data in his analysis. He acknowledged that the use of seasonal data would have been preferable, but such data were not available at the time of his study (p. 477). Removing the seasonal pattern from the data can obscure important aspects of inventory behavior (Summers). Presumably, firms find seasonal variations in demand relatively easy to predict and can adjust their inventories accordingly. Deseasonalized data can mask such adjustments and result in lower estimates of the speed at which retailers make inventory changes (Irvine 1981b). Thus, Blinder's (1981) results may overstate the time required for retail food store inventory adjustments.

Blinder's (1981) study was based on data through 1980. Since that time, there have been dramatic changes in food retailing, which have potentially further complicated inventory

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The author acknowledges the helpful comments of Kandice Kahl, Webb Smathers, Gary Wells, and the anonymous reviewers. management. There have been changes in store formats, including the development and expansion of "superwarehouse" and "hypermarkets" (U.S. Department of Agriculture, pp. 33–38). Grocery stores stocked an average of 6,800 items in 1963 (National Commission on Food Marketing, p. 21). Chain grocery stores carried an average of 10,883 items in 1983, a 60% increase in 20 years, and 16,516 items in 1987, a 52% increase in only four years (*Progressive Grocer* 1988a). This is due to both an increase in the number of new food items (Connor, p. 354) and diversification of store product mixes to include nontraditional grocery items.

On the other hand, inventory management potentially has been facilitated by new retailing technologies. Hand-held computers for entry and transmission of inventory counts and electronic scanning at checkout have given retailers means by which sales and inventories can be monitored on virtually an instantaneous basis. The adoption of these technologies has been rapid. The estimated year-end dollar volume of scanning stores as a percentage of total grocery business grew from a negligible amount in 1977 to 55% in 1987 (*Progressive Grocer* 1983, 1988b).¹ Other technical changes such as improved refrigeration and packaging also may have improved inventory management.

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¹ There are no "hard" data on the extent to which scanning data are used for automated reordering purposes. Anecdotal evidence indicates that while these data are used for merchandising purposes, their use in automated reordering is limited (Groves).

This article presents an econometric model of aggregate retail food store inventories using data from 1968 through 1988. The objectives are twofold. The first is to add to the understanding of the factors which explain retail food inventory behavior and the speed at which inventories are adjusted to changing economic circumstances by using seasonal data which have become available since Blinder's (1981) study. The second objective is to assess whether recent changes in food retailing have resulted in structural change(s) in aggregate inventory behavior.

Previous Research

The literature contains a broad array of normative inventory models which are applicable at the firm level. These models allow for single or multiple supply sources, single or multiple inventory items, deterministic or stochastic demand, and can incorporate various restrictions, such as storage space and capital constraints (Banks and Fabrycky). However, only two models have been used in econometric analyses of aggregate retail inventory behavior—the stock-adjustment and S, s models.

The basic assumptions of the stock-adjustment model are that demand is stochastic and costs are quadratic. Under these conditions, firms have incentives to use inventories to "smooth" orders over time and as buffer stocks against unexpected sales (Blinder 1981, 1986a).² This model hypothesizes that firms have a desired inventory level which may differ from the actual inventory level. The desired inventory level is a function of expected sales and inventory carrying costs. Inventory adjustment toward the desired level is only partial because of the costs and delays associated with changing inventory levels (e.g., construction of new display and/or storage facilities, the time required between the order and receipt of goods). The model includes a measure of unexpected sales to accommodate the buffer stock role of inventories. In other words, the stock-adjustment model is a partial adjustment model with unexpected sales as an additional explanatory variable.

The S, s model assumes that retailers face fixed ordering costs and constant marginal costs of ordering. Under these and other assumptions detailed in Blinder (1981), it is optimal for a firm to allow inventories to drop to a minimum safety-stock level, s, and then replenish the inventories to a maximum level, S. The S, s model is straightforward when applied as a normative decision rule for individual firms. Application of the model for positive analysis of aggregate data is complicated since the distribution of carry-over stocks across firms affects aggregate inventory investment. Blinder (1981) derived two alternative equations (both nonlinear in the parameters) based on the S, s model for analysis of aggregate retail inventories. The first equation is based on the assumption that shocks (e.g., a change in the interest rate) cause changes in S, with s fixed. For the second equation, shocks are assumed to cause equal changes in S and s. Explanatory variables common to the two models are lagged inventory investment, expected and unexpected sales, inventory carrying costs, and the ratio of buying to selling prices.

Both the stock-adjustment and S, s models have advantages and disadvantages for use in meeting the objectives of this study. Stockadjustment models have a more substantial "track" record of empirical applications to aggregate inventory data (Blinder 1981; Irvine 1981b; Robinson; Trivedi). That record has been criticized by Blinder (1981, 1986a, b) on the grounds that estimates of the speed-of-adjustment coefficient (the ratio of actual inventory adjustment to desired inventory adjustment) are implausibly low and there is no indication that inventories play a buffer stock role. Blinder's (1981) estimated speed-of-adjustment coefficients based on seasonally adjusted monthly data for all retailing; food and three other nondurables (apparel, general merchandise, other nondurables); and four durables (automobiles, furniture and appliances, lumber and hardware, other durables) ranged from a high of only .14 (for other nondurables) to a low of .03 (for other durables). He found little evidence of the use of inventories as buffer stocks. Results more favorable to the stockadjustment model were obtained by Irvine (1981b) from seasonal monthly inventory data for all retailing, all durables, and all nondurables. His estimates of the speed-of-adjustment coefficient ranged from .53 (for all nondurables) to .12 (for all durables). Irvine (1981b) estimated his model for total retailing

² The stock-adjustment model of aggregate retail inventories has been borrowed from the literature dealing with aggregate manufacturing inventories. Other models of aggregate manufacturing inventories include the target-adjustment model of Feldstein and Auerbach, Euler equations used by Miron and Zeldes, and Hay's model which is based on linear decision rules.

with both seasonally adjusted and unadjusted data. The estimated speed-of-adjustment coefficient was only .04 from adjusted data, versus .45 to .49 from seasonal data. Irvine (1981b) also found evidence of the use of retail inventories as buffer stocks. His study is one of the few (for either aggregate retail or manufacturing data) indicating significant inventory carrying cost effects on inventory investment. Aggregation across firms is a potential problem in empirical application of the stock-adjustment model. Such aggregation in partial adjustment models may result in slower estimated speeds of adjustment than estimates from data for individual firms (Griliches).

An advantage of the S, s model is that it allows for fixed ordering costs. Its major disadvantage is that the econometric problems associated with the aggregation of S, s rules across items and firms are not well understood (Lovell; Summers). Blinder's 1981 study is apparently the only empirical application of the S, s model to aggregate retail data. Based on the same seasonally adjusted inventory data. he obtained standard errors from the S, s model which were comparable to those of his stockadjustment model. His estimated speeds of adjustment were higher in the S, s model, but there was little evidence that aggregate inventories were sensitive to either expected or unexpected sales or inventory carrying costs.

Because of the relative simplicity of the stockadjustment model, its success in explaining other seasonal aggregate retail inventory behavior (Irvine 1981b), and the less well-understood consequences of aggregation for estimation and interpretation of the S, s model, a stock-adjustment model was used here for the empirical analysis.

The Stock-Adjustment Model

The following stock-adjustment model is adapted from Irvine (1981b). The behavior of monthly retail inventories is described by

(1)
$$H_t - H_{t-1} = \gamma(H_t^* - H_{t-1}) + cFERR_{t-1} + e_t$$

where $H_t(H_{t-1})$ is the actual inventory quantity at the beginning of month t (t - 1); H_t^* is the desired inventory quantity at the beginning of month t; $FERR_t$ is the unexpected sales quantity (forecasted sales quantity – actual sales quantity) in month t - 1; and e_t is a disturbance term. Equation (1) says that the observed change in inventories during month t

-1 is the sum of three components: a component used to adjust inventory by some proportion γ , $0 < \gamma < 1$, of the difference between desired and actual inventories; a component used to meet some proportion $c, 0 \le c \le 1$, of unexpected sales during month t - 1; and a component representing random influences. The parameter γ , the speed-of-adjustment coefficient, reflects delivery-smoothing motives and measures the speed at which inventories adjust to desired levels. The parameter c measures the extent to which inventories are used as buffer (safety) stocks against sales shocks. Suppose that actual sales in month t-1 are higher (lower) than forecasted. In this case, H_t should decrease (increase) if inventories are used as buffer stocks. If unexpected sales are met exclusively from inventories, c would equal unity. On the other hand, if unexpected sales are met entirely by adjusting orders (or other actions exclusive of inventory adjustment), c would equal zero.

The desired inventory level is assumed to be a linear function of the expected sales quantity and financial costs of carrying inventories:

(2)
$$H_t^* = a_0 + a_1 ECC_t + a_2 ES_t$$

where ECC_t is the expected cost of carrying inventories over the inventory planning horizon; ES_t is the expected sales quantity over the inventory planning horizon; and a_0, a_1 , and a_2 are fixed parameters. The *t* subscripts for ES and ECC indicate that expectations are formed at the beginning of month *t*. The desired inventory level is expected to be negatively related to expected inventory carrying costs, $a_1 < 0$, and positively related to expected sales, $a_2 > 0$.

The variables ES and ECC are unobservable and must be proxied. The proxy for expected carrying costs is given by

(3)
$$FCC_t = (P_{t-1}/CPI_{t-1}) [r_{t-1} - FI_t],$$

where FCC_t is the forecast of real costs of holding one unit of inventory capital, exclusive of costs of physical storage and depreciation; P_{t-1} is retail food price in month t-1; CPI_{t-1} is the consumer price index for all items in month t-1; r_{t-1} is the short-run nominal interest rate in month t-1; and FI_t is the forecasted ownprice inflation rate for month t as measured by $[(P_{t-1} - P_{t-13})/P_{t-13}] * 100$. Capital cost represented by FCC_t is an increasing function of both the relative price of the goods held in The proxy for expected sales in month t is given by

(4)
$$FSO_t = S_{t-12} \{ [(S_{t-1}/S_{t-13}) + (S_{t-2}/S_{t-14}) + (S_{t-3}/S_{t-15})]/3 \},$$

where $FS0_i$ is the forecast of sales quantity in month t; and S_{t-i} is the actual sales quantity in month t - i. The forecast of sales is sales in the same month of the previous year adjusted by the sales experienced in the most recent three months relative to sales in those months in the previous year. In order to allow for a two-month inventory planning horizon, expected sales in month t + 1 are proxied by $FS1_i$, where $FS1_i$ is derived as in equation (3) with S_{t-11} replacing S_{t-12} on the right-hand side (i.e., the term in braces is held constant).⁴ $FERR_{t-1}$ is calculated as $FS0_{t-1}$ minus S_{t-1} .

A linear time-trend variable, T_t , is added to equation (1) to measure secular movements in inventories not captured by the variables listed above. This variable may go part way in capturing the effects of physical storage costs and improvements in storage technology (e.g., improved refrigeration and packaging) in so far as those factors are correlated with time. Including a trend variable also follows the recommendation by Griliches (p. 46) to account for trend when the data used in estimation have strong trends (see figure 1).⁵ Substitution of proxies for expected capital costs and sales in equation (2), subsequent substitution of equation (2) in equation (1), and rearranging of terms results in

5)
$$H_t = \gamma a_0 + \gamma a_1 FCC_t + \gamma b_1 FS0_t + \gamma b_2 FS1_t + (1 - \gamma)H_{t-1} + cFERR_t + dT_t + e_t,$$

where $b_1 + b_2 = a_2$. To recapitulate, the expected coefficient signs and magnitudes from estimation of equation (5) are $0 < (1 - \gamma) < 1$; $a_1 < 0$; b_1 , $b_2 > 0$; and $0 \le c \le 1$. The specification of inventory carrying costs

in equations (3) and (5) imposes the restriction that the nominal interest and forecasted inflation rates have coefficients equal in absolute value but opposite in sign. Blinder (1981) argued that this restriction need not hold if firms use first-in, first-out (FIFO) pricing. If firms do not change the prices on goods once the goods are placed on the shelf, the firms do not capture price appreciation, and the nominal interest rate should be used to measure financial carrying costs.⁶ Also, Irvine (1981a) pointed out that the nominal interest and inflation rates need not have equal coefficients if the degree of uncertainty differs between interest and inflation rates. Risk-averse firms likely would experience more uncertainty regarding the expected inflation rate and would thus give it less weight in forecasting the financial costs of carrying inventories. In line with these arguments, alternative versions of equation (5) were estimated in which nominal interest and inflation rates were treated as separate variables.

Of particular interest in this study are the effects of recent changes in food store retailing on inventory behavior. One possible effect of new retail technologies would be a change in the parameter γ over time. If new technologies have increased the speed at which retailers adjust their actual inventories toward desired levels, γ would be expected to increase over time, all else constant. On the other hand, expansion of the number of items carried in inventory complicates inventory management and may have slowed inventory adjustment. Which of these effects has predominated is an empirical issue.

³ Some writers (e.g., Alfandary-Alexander) identify "transactions," "precautionary," and "speculative" motives for holding inventories. In this article, the "transactions" motive is reflected in the desired inventory level (expressed as a function of expected sales) and the "precautionary" motive corresponds to the buffer stock role of inventories. The expected own-price inflation term of equation (3) is treated here as a "negative" component of inventory carrying costs but also can be thought of as reflecting a "speculative" motive.

⁴ Irvine (1981b) allowed for longer planning horizons by adding a proxy for expected sales in month t + 2 as an explanatory variable. This proxy was omitted here because of the relatively rapid inventory turnover times in food retailing [U.S. Department of Commerce (USDC), Bureau of the Census]. Preliminary analysis including such a proxy resulted in anomalous signs in estimated models. Irvine (1981b) also considered ARIMA forecasts as alternatives to extrapolative forecasts. His extrapolative forecasts performed as well as the ARIMA forecasts.

⁵ The omission of the time-trend variable results in slower estimated speed-of-adjustment coefficients than those reported in table 2.

⁶ One of the advantages of scanning technology is that prices can be changed by shelf labels and scanner programming, rather than by remarking individual items. Thus, Blinder's (1981) argument may not hold for food retailing, at least in recent years.

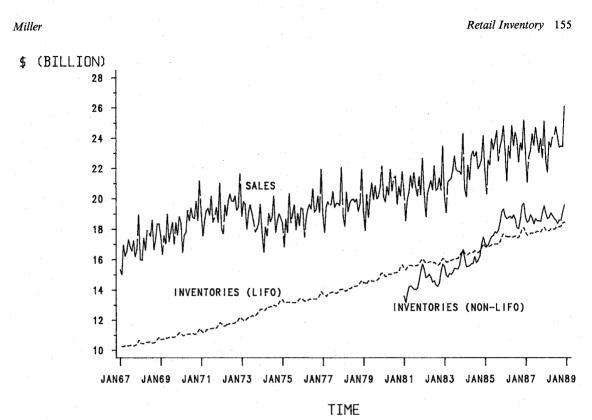


Figure 1. Deflated retail food store sales and inventories

Empirical Analysis

Data and Estimation Strategy

Estimation of equation (5) requires measures of quantities of retail food store sales and inventories. The monthly constant-dollar (deflated) sales and inventory data reported in the Survey of Current Business (USDC) provide these measures but only after seasonal adjustment. Such adjustments may obscure important facets of inventory behavior (Irvine 1981b; Ghali; Summers). As a consequence, nominal seasonally unadjusted sales and inventory data were deflated to obtain constant-dollar series without seasonal adjustment. Two nominal monthly inventory value (i.e., book value) data series are available from the USDC-an unpublished series based on last-in, first-out (LIFO) accounting methods available from January 1967 onward and a second series based on nonLIFO inventory values published from December 1980 onward.7

Nominal sales values in month t were deflated by concurrent values of P_t , the consumer price index for food consumed at home by urban wage earners and clerical workers (1982-84 = 100), to obtain values of S_t (\$ billion). The producer price index for processed foods and feeds (1982 = 100) was used in deflating both nominal inventory series to obtain alternative measures of H_t (\$ billion).⁸ Procedures for deflating nominal inventory values depend on the inventory accounting method used in generating the data (Feldstein and Auerbach, pp. 394–96; Hinrichs and Eckman). Deflation of nonLIFO nominal values depends on the age composition of goods in inventory. The more rapid is inventory turnover, the more closely nominal nonLIFO values correspond

⁷ Reported inventory values are end-of-month and are treated here as beginning-of-month values for the succeeding month.

Through December 1986, the USDC also reported inventory "book values" in the *Survey of Current Business* but without specification of inventory accounting method. Irvine (1981b) used these data under the assumption that the data were based on the FIFO accounting method.

⁸ The deflated series are subject to possible measurement error since the price indices used for deflation do not measure the price changes of nonfood items carried by retail food stores.

to current values. Since monthly inventory-tosales ratios have been less than unity (USDC, Revised Monthly Retail Trade Sales and Inventories), reported nominal nonLIFO values are approximately equal to current values. Thus, nonLIFO inventory values were deflated by the concurrent values of the producer price index. The LIFO method assumes that inventories on hand at the end of a period are made up of the oldest costs incurred in building inventories to current levels. LIFO inventory book values are comprised of base stocks (the time at which the LIFO method was adopted) plus (less) subsequent additions (deletions). The LIFO book values were deflated as follows. The base stock was arbitrarily selected to be that reported for January 1967.9 The LIFO book value for that date was treated as a nonLIFO book value and was deflated accordingly. Subsequent changes in LIFO book values were deflated by the ratio of the concurrent producer price index to the January 1967 producer price index level and then cumulated from the deflated base stock.

The deflated sales and inventory data are shown in figure 1. Each series has trended upward over time. There is a seasonal pattern in each series, with the LIFO series exhibiting less seasonality than the other two. Sales are highest in December and lowest in February and are higher in the summer months than in the fall and winter months. Inventories tend to be lower in the fall and peak in December. The simple correlation of the two inventory series is .976 from 1981 onward, indicating that the two deflated series provide comparable measures of constant-dollar inventories.

 CPI_t was measured by the consumer price index (1982-84 = 100) for all items for wage earners and clerical workers. The New York City open market interest rate (%) for six-month commercial paper in month t - 1 was used to measure r_{t-1} . T_t was set equal to one for January 1967 and was increased by unity for each subsequent month.

The sales and inventory data were obtained from the USDC, Current Retail Inventory and Sales Branch upon request. The sales and nonLIFO data also are published in *Survey of Current Business* (USDC) and *Revised Monthly Retail Trade Sales and Inventories* (USDC). The price index data were obtained directly from the U.S. Department of Labor but are published in the *Survey of Current Business* (USDC). The interest rate data were taken from the *Survey of Current Business* (USDC).

Three issues concerning the estimation of equation (5) warrant discussion. First, the monthly data used in estimation have their shortcomings. These data obscure inventory behavior within months and thus do not allow detection of the use of inventories as buffer stocks in meeting week-to-week sales shocks. Also, the use of monthly data may result in slower speed-of-adjustment coefficients than would be the case if weekly data were used in estimation (Griliches, pp. 45–46). However, weekly data were not available.

Second, monthly inventories would be expected to be autocorrelated due to inertia of adjusting inventories (Irvine 1981b). Since equation (5) contains the lagged dependent variable as a regressor, use of ordinary least squares would result in the estimated coefficients being inconsistent. Lagged inventory values were replaced by estimates obtained by the instrumental variable technique with the instruments being the exogenous variables lagged one and two months (the two-month lag of T was omitted to avoid exact collinearity). Equation (5) then was estimated by nonlinear least squares in order to mitigate against the "identification problem" associated with distinguishing between an equation with strong autocorrelation and rapid adjustment versus an equation with weak autocorrelation and slow adjustment (Blinder 1986b).10

The third issue is the procedure for testing the stability of the parameters in equation (5). The standard Chow test would be appropriate if there were reasons to hypothesize the points at which the parameters changed. As no such reasons exist here, the Farley-Hinich test (Farley, Hinich, and McGuire) was used instead. A new regressor is added to the original regression for each regressor suspected of parameter change, where the new regressor is the suspect

⁹ Although the choice of the base stock is arbitrary, the choice has no effect on regression coefficients (Feldstein and Auerbach, p. 396).

¹⁰ Some two-step linear procedures used to correct for autocorrelation settle on local minima in the error sum of squares. These local minima are typically associated with strong autocorrelation coefficient estimates. Nonlinear least squares is a maximum likelihood procedure under the assumptions that the disturbances are normal and follow a first-order autoregressive process (Blinder 1986b). Alternative starting values for the autocorrelation coefficient ranging from .00 to .90 in increments of .10 were used here in the nonlinear least squares algorithm. In all cases, the parameter estimates converged to those reported in table 1.

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Table 1.	

	R- se square	.976	<i>TT</i> 6.	166.	166.	666.	666	
	RMSE ^e s	.290	.287	.088	160	.085	.084	
	P ^d	.874	.865	.854	.833	.877	.852	
	Time Trend (T)	0.030** (2.56)	0.030** (2.83)	0.009 * (1.60)	0.015 ** (2.94)	0.009**	0.012** (2.74)	
•	Sales Forecast Error (FERR)	-0.013 (-0.28)	0.014 (0.31)	0.005 (0.35)	0.010 (0.72)	0.021 ** (3.44)	0.016** (2.62)	
	Lagged Inventory ^c (H)	0.356** (2.30)	0.253**	0.552**	0.388** (2.65)	0.659** (4.19)	0.559** (4.29)	
bles	Sales Forecast Month t + 1 (FS1)	0.126** (4.82)	0.119** (4.46)	0.042** (5.17)	0.040**	0.026** (5.54)	0.028** (5.93)	
Independent Variables	Sales Forecast Month t (FS0)	0.136** (5.39)	0.138** (5.45)	0.055 ** (6.82)	0.052** (6.35)	0.058*** (8.70)	0.051**	
Indepen	Inflation Rate (<i>FI</i>)		-0.010 (-0.26)	,	0.014* (1.29)		0.005 (1.10)	68:5 to 1988:12.
	Nominal Interest Rate (r)		-0.074 * (-1.62)		-0.014		0.007 (1.06)	runs from 15
	Real Interest Rate (FCC)	$(-0.002 (-0.60)^{b})$		-0.016* (-1.56)		-0.003 (-0.70)		Sample Period II
	Rea Intercept Ra	-1.480	1.190	3.496	5.065	2.011	2.969	1 to 1988:12.
	Dependent Variable	NonLIFO Inventory (H)		LJFO Inventory (H)				^a Sample Period I runs from 1981:1 to 1988:12. Sample Period II runs from 1968:5 to 1988:1
	Sample Period ^a	Π		Ι		Ш		^a Sample Per

Sample Period I runs from 1981:1 to 1988:12. Sample Period II runs from 1968:5 to 1988:12.
Numbers in parentheses are *t*-ratios. Also, * (**) denotes a significant difference from zero at the 10% (5%) level by one-tailed *t*-test.
Estimated via instrumental variables.
Estimated first-order autocorrelation coefficient.
Root mean-square error.

regressor multiplied by a time index. An *F*-test then is used to evaluate the null hypothesis of no parameter change by jointly testing for significant differences from zero of the coefficients of the new regressors.

Results

After allowing for lags, the estimation period for the LIFO data was from 1968:5 to 1988: 12. The nonLIFO data allowed estimation from 1981:1 to 1988:12. In order to assess the sensitivity of the results to inventory deflation procedure, regressions were also estimated over the latter period using LIFO data. The results are shown in table 1. Looking first at the results based on the nonLIFO inventory data with inventory carrying costs measured by the real interest rate, each of the coefficients has the expected sign except for the FERR coefficient. That coefficient does not differ from zero at conventional levels,¹¹ indicating that food retailers meet sales shocks by adjusting orders or other actions rather than by using inventories as buffer stocks across months. The coefficient for FCC has the expected negative sign but is not significant at conventional levels. The remaining coefficients are significant at or below the 5% level. The estimated speed-ofadjustment coefficient, γ , is .644 (table 2), which is somewhat higher than Irvine's (1981b) estimates for nondurable retailing (.531 to .532) and is much higher than Blinder's (1981) stockadjustment model estimate of .12 for food retailing. When inventory carrying costs are measured separately, the nominal interest rate coefficient has the expected negative sign and is significant at the 10% level. The coefficient for forecasted inflation has an unexpected negative sign but is not significant at conventional levels. The coefficients of the other variables and associated *t*-ratios are little changed by the alternative measurement of carrying costs; however, a higher speed-of-adjustment coefficient (.747) is indicated when carrying costs are measured separately.

Estimation based on LIFO inventory data from 1981–88 results in coefficient estimates which are comparable to those obtained with nonLIFO data over the same interval. All of the coefficients have the expected signs. Over this latter period, the coefficient for FCC is significant at the 10% level. When carrying costs are separated, the nominal interest rate is not significant. As with the nonLIFO data, the coefficients of the other regressors are insensitive to use of alternative measures of inventory carrving costs. Both coefficients for FERR remain insignificant. The estimated speed-of-adjustment coefficients (.448 when inventory carrving costs are combined. .612 when those costs are separated) are lower when LIFO data are used in estimation versus the use of nonLIFO data but not dramatically so. As is the case with the nonLIFO data, separation of carrying costs results in a higher speed-of-adjustment coefficient.

There is no evidence that inventory carrying costs affect inventory over the entire sampling interval (1968:5–1988:12), regardless of how those costs are measured. When those costs are combined, a correct sign is obtained, but the coefficient is not significant. When the costs are separated, the nominal interest rate coefficient has an unexpected positive sign, but both that coefficient and that for forecasted inflation are insignificant. The coefficients for *FERR* have positive signs and are significant under both measurement schemes, indicating that inventories play a buffer stock role across months.

Holding the means of measuring inventory carrying costs constant, the speed-of-adjustment coefficients are larger and the FERR coefficients are smaller in the latter part (1981-88) of the total sampling interval. Also, the absolute values of the remaining regression coefficients are in most cases larger in the latter part of the total sample than over the total interval, as would be expected if the speed-ofadjustment coefficient has increased over time. However, the differences in coefficient estimates are not large across sample periods. Farley-Hinich tests (Farley, Hinich, and McGuire) fail to indicate any parameter changes over the entire sampling interval regardless of how carrying costs are measured. With combined carrving costs, the calculated F for the null hypothesis that each of the regression parameters (other than for T) is constant is .95. When carrying costs are separated, the calculated Ffor the null hypothesis is 1.12. Neither of these ratios is significant at conventional levels.

Table 2 presents selected short- and longrun elasticity estimates evaluated at mean val-

¹¹ Unless otherwise noted, this and subsequent statements as to significance should be read as applying to one-tailed *t*-tests.

N.	Monthly	Monthly Inventories Measured by:				
	NonLIFO Data	LIFO Data				
Sample Period ^a	I	I	II			
Carrying C	osts Measured by Real Inte	rest Rate				
Speed-of-Adjustment Coefficient	.644	.448	.341			
Short-run Elasticities						
Carrying Cost	001	006	000			
Sales Forecast Month t	.181	.073	.083			
Sales Forecast Month $t + 1$.168	.056	.037			
Long-run Elasticities						
Carrying Cost	001	012	001			
Sales Forecast Month t	.280	.163	.242			
Sales Forecast Month $t + 1$.260	.125	.109			
Carrying Costs Measured	Separately by Nominal Inte	erest and Inflation Ra	tes			
Speed-of-Adjustment Coefficient	.747	.612	.441			
Short-run Elasticities						
Nominal Interest Rate	041	008	.004			
Inflation Rate	002	.003	.002			
Sales Forecast Month t	.183	.069	.073			
Sales Forecast Month $t + 1$.158	.053	.040			
Long-run Elasticities						
Nominal Interest Rate	055	012	.010			
Inflation Rate	003	.005	.005			
Sales Forecast Month t	.245	.113	.165			
Sales Forecast Month $t + 1$.212	.087	.090			

Table 2. Estimated Speed-of-Adjustment Coefficients and Selected Elasticities for Monthly NonLIFO and LIFO Retail Food Store Inventories

^a Sample Period I runs from 1981:1 to 1988:12. Sample Period II runs from 1968:5 to 1988:12.

ues based on the estimates from table $1.^{12}$ The estimated short-run elasticities of inventories with respect to carrying costs measured by the real interest rate are very inelastic but are not out of line from Irvine's (1981b) estimates for nondurable goods, -.012 to -.019. Irvine (1981b) found that inventories for durable goods were relatively more interest-rate elastic than were nondurable inventories. As food items are probably the least durable in the general nondurable category, it is not surprising that those items are relatively more inelastic. The estimated elasticities of food store inventories with respect to forecasted sales are also relatively more inelastic than those estimated for nondurable goods by Irvine (1981b). His elasticity estimates ranged from .558 to .614 for the current month forecast. Again, durable goods inventories were more elastic (1.132 to 1.166) than were nondurable goods inventories. Given the relative nondurability of food items and the rapid inventory turnover in food retailing, the inelastic estimates obtained here make sense.

Implications

This analysis of seasonal aggregate retail food store inventories indicates those inventories reflect order-smoothing properties in that they are affected by expected sales in subsequent months. Estimates of the speed-of-adjustment coefficient (γ) range from .34 to .75, with associated average lags $[(1 - \gamma)/\gamma]$ ranging from 1.94 to .33 months. These estimates are much faster than the previous estimate of .12 (implied average lag of seven months) obtained

¹² Mean values are as follows: for 1981:1-1988:12-H (non-LIFO) = \$16.882 billion; H (LIFO) = \$16.850 billion; FCC = 5.871%; r = 9.363%; FI = 3.492%; FS0 = \$22.420 billion; FSI = \$22.449 billion; FERR = - \$0.004 billion; and T = 217. For 1968:5-1988:12-H (LIFO) = \$14.356 billion; FCC = 2.162%; r = 8.661%; FI = 6.499%; FS0 = \$20.424 billion; FS1 = \$20.449 billion; FERR = \$0.016 billion; and T = 140.5.

by Blinder (1981) using seasonally adjusted data. Thus, this study indicates that periods of inventory disequilibrium in food retailing are short-lived. The results also provide some evidence of a buffer stock role for retail food inventories. Because monthly data were used in estimation, the use of these inventories as intramonth buffer stocks cannot be detected. The estimation results also indicate that retail food store inventories are inelastic with respect to the financial costs of carrying those inventories. These results agree with previous research (Irvine 1981b) which indicates that the elasticity of retail inventories with respect to carrying costs appears to increase with the durability of goods carried in inventory. As food store inventories are among the least durable of all inventories, the elasticity estimates seem plausible.

Food retailing has undergone considerable change in recent years, including optical scanning, improved refrigeration and packaging technologies, and new store formats with expanded and diversified product lines. Despite these changes, there is no evidence of structural change over the last 20 years in the inventory model estimated here. This is not to say that new retail technologies have not facilitated inventory management. The results can be interpreted to indicate that the new technologies have allowed retailers to maintain the speed at which actual inventories are adjusted toward desired levels despite increases in both the number and diversity of items carried in inventory. The model estimated here is not capable of capturing other possible effects of the new retailing technologies. These technologies allow a substitution of capital for labor in providing retail food services and offer the potential for increased retail labor productivity. These effects could be examined by estimating a retail production function (White).

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