Forecasting Item Movement with Scan Data: Box-Jenkins Results

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Preliminary forecasts using the Box-Jenkins methodology for supermarket scan data for ground beef and roast item movement are described. The functional form and the accuracy of the forecasts vary by product. Results suggest that further analyses incorporating price and advertising may increase the accuracy of the forecasts.

Accurate forecasts of sales can be a key determinant of the economic viability of any business. This is especially important in the highly competitive supermarket industry. Low profit margins necessitate very careful management of inventories, scheduling of labor, and timing of shipments. The introduction of scanners was heralded as a technology that could generate sales data for use in managerial decisions in these areas, thereby reducing costs.

While some progress has been made, the supermarket industry has lagged other retailers in using these data (McLaughlin and Lesser; *Supermarket Business* October 1989). Reasons often cited for the relatively slow supermarket application of scan data to managerial decision making include the following. First, the volume of data is much larger than that of other retailers (Capps 1987). Second, the expense of generating a scan database can be a deterrent. Many items do not have Universal Product Codes (UPC), so store-generated bar codes and other special codes are used. This makes it more difficult to adapt external UPC-oriented software to a specific supermarket. These programs would have to be rewritten or modified. Third, variable-weight items, which do not occur in other retail industries, are more difficult to manage (Eastwood).

Agricultural economists are beginning to use scan data to conduct demand analyses (e.g., Capps 1989; Capps and Nayga; Eastwood, Gray, and Brooker; Jensen and Schroeter). Such studies have focused on the structure of consumer demand, direct- and cross-price responses, and advertising effects. These research efforts shed new light on our knowledge of consumer behavior. However, there are few reported attempts to use these data for forecasting. Given the high volumes and low profit margins that typify supermarkets, the cost savings could be quite extensive. Accurate forecasts would enable supermarkets to trim their inventory levels and rely on more just-in-time deliveries. Labor could be scheduled to accommodate periods of peak demand to restock shelves. Savings in these areas would have significant effects on costs because of the high volume and perishable nature of many foods.

This paper presents results from employing the Box-Jenkins technique to forecast weekly item movements of foods with highly variable sales that have been particularly difficult to incorporate into scan databases. The approach is motivated by the realization that traditional demand-estimation techniques may not be feasible for most supermarkets. Very little information about the socioeconomic characteristics of food shoppers at retail outlets is available to managers. Some stores can be characterized by the types of neighborhoods in which they are located, but most draw shoppers from a variety of backgrounds. Furthermore, the stores are not able to match individual customer sales to socioeconomic characteristics. However, scan data do represent a record of sales. If these data can be extrapolated into the future, then supermarket management will have access to a powerful tool to control cost and to be responsive to customers.

Scan Data

Variable-weight items have been difficult to incorporate into supermarket data management systems (Eastwood). Prominent among the problems

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The authors wish to thank Dr. Daniel L. McLemore for his helpful comments on the research. However, responsibility for the paper rests with the authors.

are the absence of UPCs for these products and the need to modify computer programs to handle such foods. Day-to-day management pressures and deadlines, along with the additional cost of generating the requisite scanner and data management programs to accommodate these foods, have curtailed managements' uses of these data. Inventory management programs were originally developed by vendors for UPC master files, thereby omitting non-UPC-bar-code foods from the realm of conventional forecasting.

Most variable-weight items are found in the fresh meat, fish, and poultry; fresh produce; and deli departments of supermarkets. Taken together, they accounted for just over 48 percent of supermarket sales in 1989 (*Supermarket Business* September 1990). The perishable nature of these products, along with fluctuating sales, makes these departments costly to manage. These considerations suggest there is a need to explore forecasting possibilities for these foods.

The functions of scanners can be separated into two areas. One is the operation as a cash register to compute customers' bills. The other is the manipulation of these purchases into sales records via data management systems. Most scan data management systems do not record the weights of packages, because the management software was developed for fixed-weight products. The number of times a bar code is read (i.e., item movement) is the equivalent of recording quantity. However, variable-weight foods require the quantity or expenditure to be registered along with the unit price. Expanding scanners to handle variable-weight foods resulted in corporate-level software that could not easily process these foods, even though store-level scanners tied to computerized checkout procedures could generate accurate customer bills. An easy, quick solution to expanding the data management function was for the corporate-level programs to continue with item movement for variable-weight foods.

The Sample

These considerations point to a need to investigate the feasibility of forecasting item movement for variable-weight foods. Two categories are selected for this initial work based upon conversations with store and corporate-level managers. One is fresh ground beef and the other is beef roasts. The former is chosen because it can be characterized as a high-volume product, whereas the latter has more stable sales.

Item movement refers to the number of times scanners read respective bar codes. For variable-weight items, this does not translate directly into quantity or sales information. However, assuming that the distribution of package sizes does not change, variations in item movement represent variations in quantities and sales. Information from the retailer indicates that this is the case. The distribution of package sizes of ground chuck changes very little from week to week.

Five local supermarkets in a metropolitan area in the Southeast that are part of a multiregional chain generated the scan data. The data are weekly item movements that have been transferred to corporate headquarters. No smoothing algorithms or other manipulations were used. Thus, the observations represent "raw data" in the form conventionally available to management. Five-store averages of weekly item movements are used below.

A weekly time period has several advantages with respect to forecasting. Much of management's decision making is on a weekly basis. Advertising usually is by week. Consumers' shopping patterns generally follow a seven-day period as well. The time period is 14 May 1988 through 11 November 1989. Stockouts of the products did not occur during the period. Missing data in two weeks necessitated the use of estimates. The averages of the immediately preceding and following weeks were used. Two subperiods were created to allow for a trial forecast period. The first comprised the historical record for estimating the relationships. It ended with 30 September 1989. This provided sufficient time to examine trial forecasts for several weeks prior to the extended holiday season. Forecasts for two-week periods were generated because they are considered to be most appropriate for stocking highly perishable items, reordering, and labor scheduling.

Figures 1 and 2 display the weekly item movements for ground beef and roasts. Ground beef item movement was consistently higher than that for roasts. The weekly five-store averages were 1,815 and 397 item movements, respectively. Variations in item movements were relatively smaller for ground beef than for roasts. The former's coefficient of variation was 0.31, whereas that for roasts was 0.39. Both series displayed evidence of stock-adjustment consumption patterns. Peaks were followed by periods of low item movement. With respect to ground beef, the highest item movement occured for weeks ending 4 March 1989 (week 43) and 9 September 1989 (week 70), and the slowest weeks were those ending 19 November 1988 (week 28) and 22 July 1989 (week 63). Roast item movement, on the other hand, had a slight downward

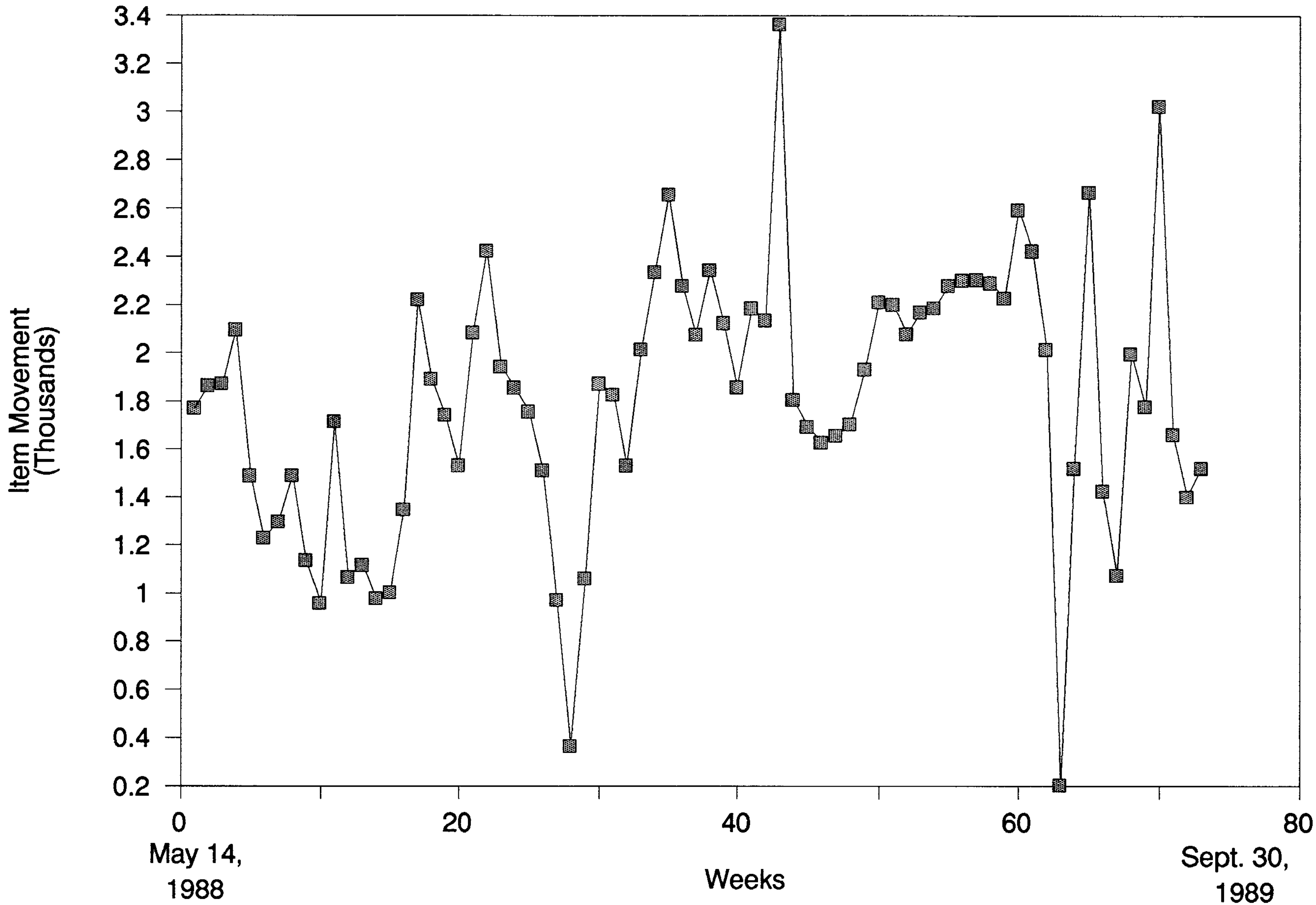

Figure 1. Ground Beef Item Movement Per Week

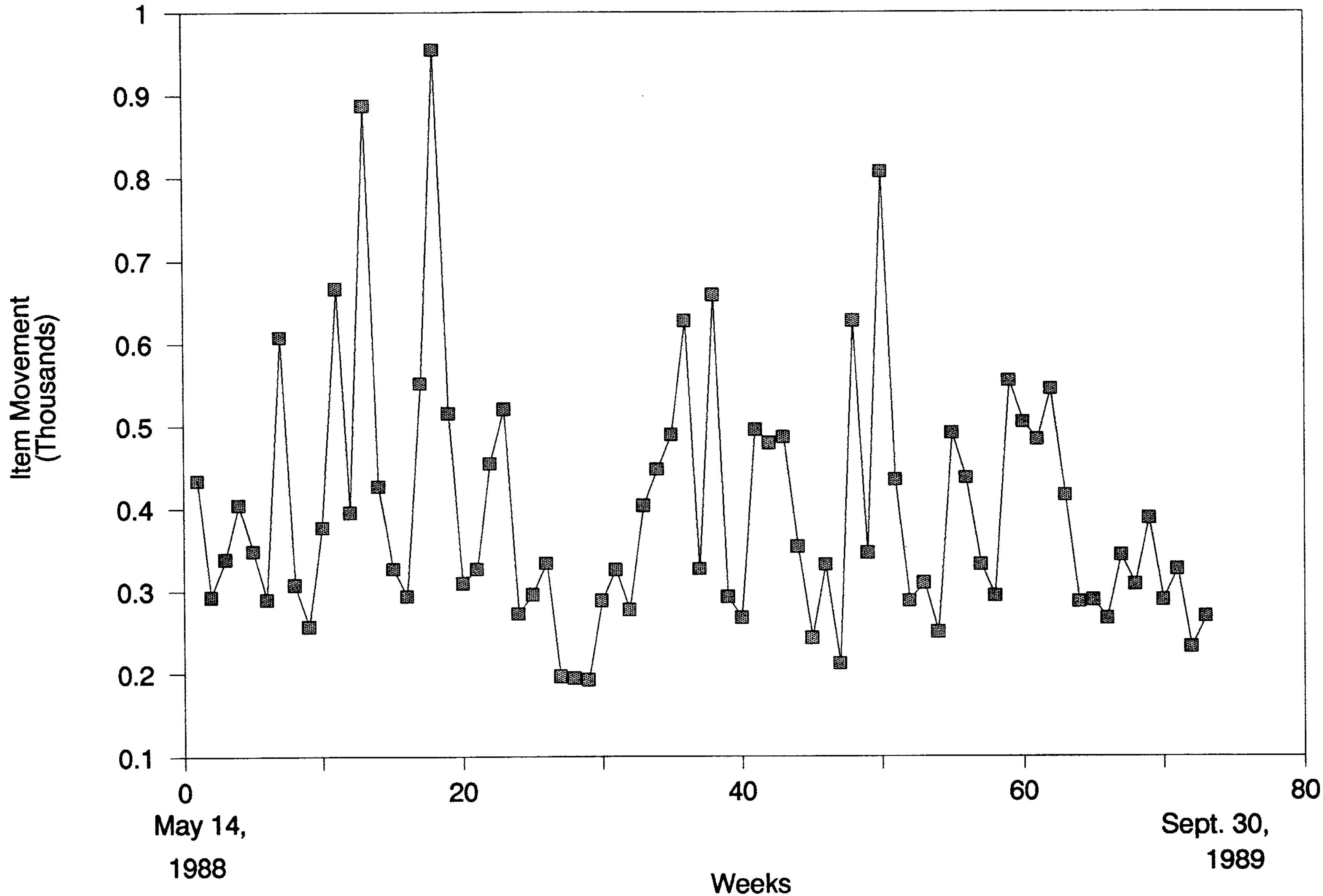

Figure 2. Roast Item Movement Per Week

trend, and there was more variability during the last half of the time period. Relatively high peaks occurred for weeks ending 6 August 1988 (week 13), 10 September 1988 (week 18), and 22 April 1989 (week 50). A three-week low occurred during the last three weeks of November 1988 (weeks 27–29).

Box-Jenkins Forecasts

There are two fundamentally different approaches to forecasting. One uses demand theory to develop theoretical relationships, specifies empirical counterparts, and uses results to make forecasts. The other extrapolates the historical record of interest without any consideration of causal relationships. More recently, blends of the two approaches are beginning to be used, but no applications have been reported in the agricultural economics literature.

Forecasts based on demand theory for selected meat groups using supermarket scan data have been reported by Capps and Nayga. They found the accuracy of their forecasts varied considerably by fresh-meat group. This paper reports on an alternative forecasting methodology for item-movement data, which is the only series available to many chains. Its choice is based on the realization that most supermarkets are not able to associate the socioeconomic characteristics of their customers to the scan data they receive.

Box-Jenkins forecasting could be a useful technique for supermarkets. It assumes that the time series being studied contains all of the information that is needed in order to make forecasts. The current value is considered to be composed of a moving average of past values and/or an autoregressive error (Granger and Newbold). It automatically incorporates a base level for the series through the constant term. The procedure assumes the series has a constant variance and no trend, or that the series is stationary. If nonstationarity is found, then the data must be transformed in some manner (e.g., differencing) to obtain stationarity. The stationary series is examined in various ways to identify the autoregressive and moving-average components.

Since the Box-Jenkins technique involves simulation of the observed time series with alternative lag structures, several were tried. Identification of the best structure was based on the AIC, computed chi squares of lagged autocorrelations, plots of autocorrelations and partial autocorrelations, and the significance of autocorrelation coefficients. These values were calculated for each alternative using the residuals from the fitted models.

Diagnostics led to the inference that the ground beef series was stationary. The autocorrelations had a dampened cyclical pattern that died out quickly. Partial autocorrelations also indicated a stationary series. The sample was divided into two subgroups of equal size, variations were computed for each, and an F test was conducted to determine whether there was a significant difference in the series. Results led to the inference of a constant variance.

The roast series appeared to be nonstationary. Its autocorrelation pattern was wave-like and did not dampen, which are characteristics of a nonstationary series. Furthermore, the F test suggested the variation was not constant. The sample variations for the two roast subgroups were 30,199 and 18,227, respectively. These considerations prompted two alternative ways of obtaining a stationary series. One was to calculate first differences, which removed the trend. The other was a log transformation of the original time series. Examination of these transformed series led to inferences of stationarity.

Additional Box-Jenkins analyses were conducted for both transformed roast series in order to determine which one forecasted better. The best first-differenced series turned out to be marginally superior than the best log-transformed series with respect to the AIC and Theil's inequality coefficient. This is not surprising, as Nazem notes that one subgroup variation should be at least 200 times larger than the other before nonstationarity of variances is pursued.

Table 1 presents the estimated functions. The statistics lead to inferences of significant relationships. For ground beef, the previous week's sales have a negative impact on the current week's sales, followed by seven- and eight-week lags that have positive and negative impacts, respectively. The roast beef relationship is a positive, but declining influence over a four-week period.

Forecasts

Figures 3 and 4 present the actual and predicted Box-Jenkins item-movement forecasts for the estimation subperiod. The mean actual values are 1,815.8 and 395.6 item movements for ground beef and roasts, respectively. Corresponding forecast averages are 1,814.8 and 397.0 item movements. Coefficients of variation for the respective actual series are 0.31 and 0.39 for ground beef and roasts, respectively, and those for the predicted series are 0.16 and 0.22. Average absolute errors are 355.5 and 121.1, respectively. These data indicate that the units of ground beef sold are approximately six times higher than those for roasts, and the varia-

Table 1. Box-Jenkins Results for Ground Beef and Roasts[a]

Ground Beef

Equation[b] $GB_t = .50B(1) + .26B(7) - .26B(8)$ AIC = 1,112
(-4.85) (2.01) (-1.98) I-squared = .24

Error Diagnostics

Lag	Chi Squares	Autocorrelations for First 24 Residuals					
6	2.53	.023	−.082	.045	.128	.037	−.032
12	3.81	.005	.018	−.061	−.028	−.078	.061
18	5.68	.023	.041	.029	−.000	.071	.105
24	12.79	.195	−.050	.008	.084	−.104	−.098

Beef Roasts

Equation[b] $R_t - R_{t-1} = 1.0 + .66B(1) + .43B(2) + .48B(3) + .33B(4)$ AIC = 942
(5.72) (3.33) (3.72) (2.89) I-squared = .74

Error Diagnostics

Lag	Chi Squares	Autocorrelations for First 24 Residuals					
6	1.17	−.032	−.063	−.042	−.019	−.088	−.014
12	6.94	.011	−.035	−.129	−.097	−.122	.156
18	8.47	−.036	−.058	.009	−.096	−.000	.047
24	10.95	.017	.048	.021	−.107	.067	.064

[a]Computed t values are in parentheses below the respective coefficients.
[b]GB_t is ground beef item movement in period t; R_t is roast item movement in period t; and $B(L)$ is backshift operator of length L.

bility is relatively higher for roasts. The Box-Jenkins forecasts have somewhat less variability and, on average, are close to the units sold.

Focusing on turning points, the actual ground beef series has 34 and the roasts series has 48. The respective values for the forecasts are 37 and 39 turning points, respectively. However, there are respectively only 3 and 9 matched turning points. The forecasted direction of change (positive or negative) is correct 27 and 29 times, respectively. This information suggests that the Box-Jenkins forecasts are relatively close to the actual values, especially for ground beef, but the functions do not consistently predict small week-to-week changes.

Theil's inequality coefficient provides a more objective measure of forecast accuracy. The computed I-squared values are .24 for ground beef and .74 for roasts. An inference is that the ground beef forecasts are far superior to no-change forecasts, whereas those for roasts are only slightly better. Decompositions of I-squared values indicate that the forecast errors contain no bias and that most of the error is due to random fluctuations in both series. This is expected because the Box-Jenkins methodology is designed to pick up the systematic variation. Thus, these results suggest that an appropriate functional form has been identified. Furthermore, they indicate that the ground beef forecasts are quite accurate, whereas those for roasts are not as good.

Trial Forecasts

Two-week trial forecasts were generated. This forecast period was chosen to reflect the normal amount of time available to management for forecasting; that is, the store-level scan data must be transmitted to corporate headquarters, analyzed, and forecasts generated. Starting with September 30, two-week trial forecasts were obtained. Then the historic record was increased by one week, a new Box-Jenkins equation estimated, and another two-week forecast generated. The results are shown in Tables 2 and 3 under the successive trial-forecast periods. For example, period 1 refers to forecasts generated with the scan data through September 30 for weeks ending October 7 and 14. Trial forecast 5 refers to the two forecasts using data through October 28 and projections for November 4 and 11.

With respect to ground beef, the actual values from October 7 through November 11 have two very extreme values. The first week experienced nearly record item movement and that of October 28 was very low. Consequently, the forecasted levels of item movement are quite different than

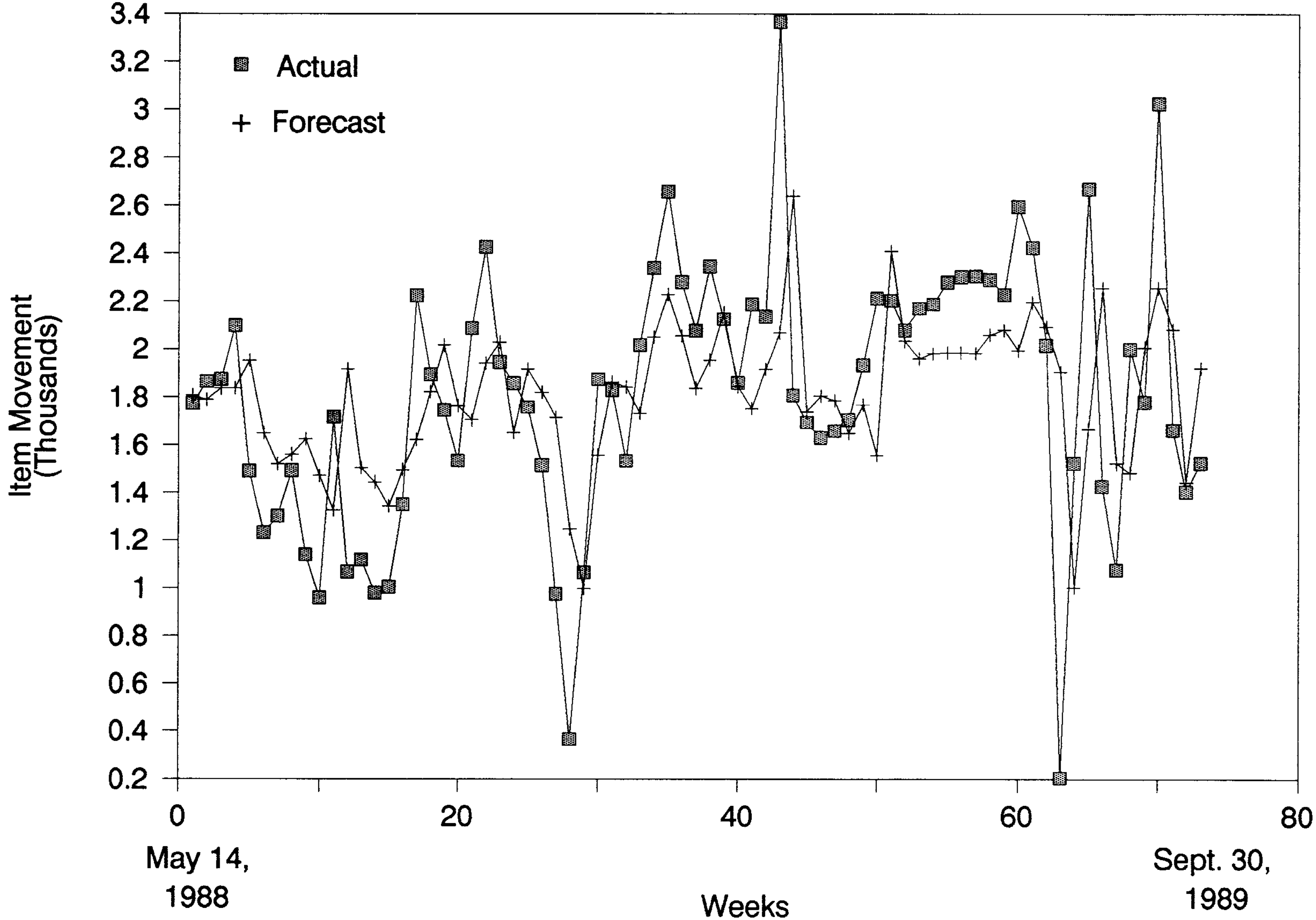

Figure 3. Ground Beef Box-Jenkins Forecasts

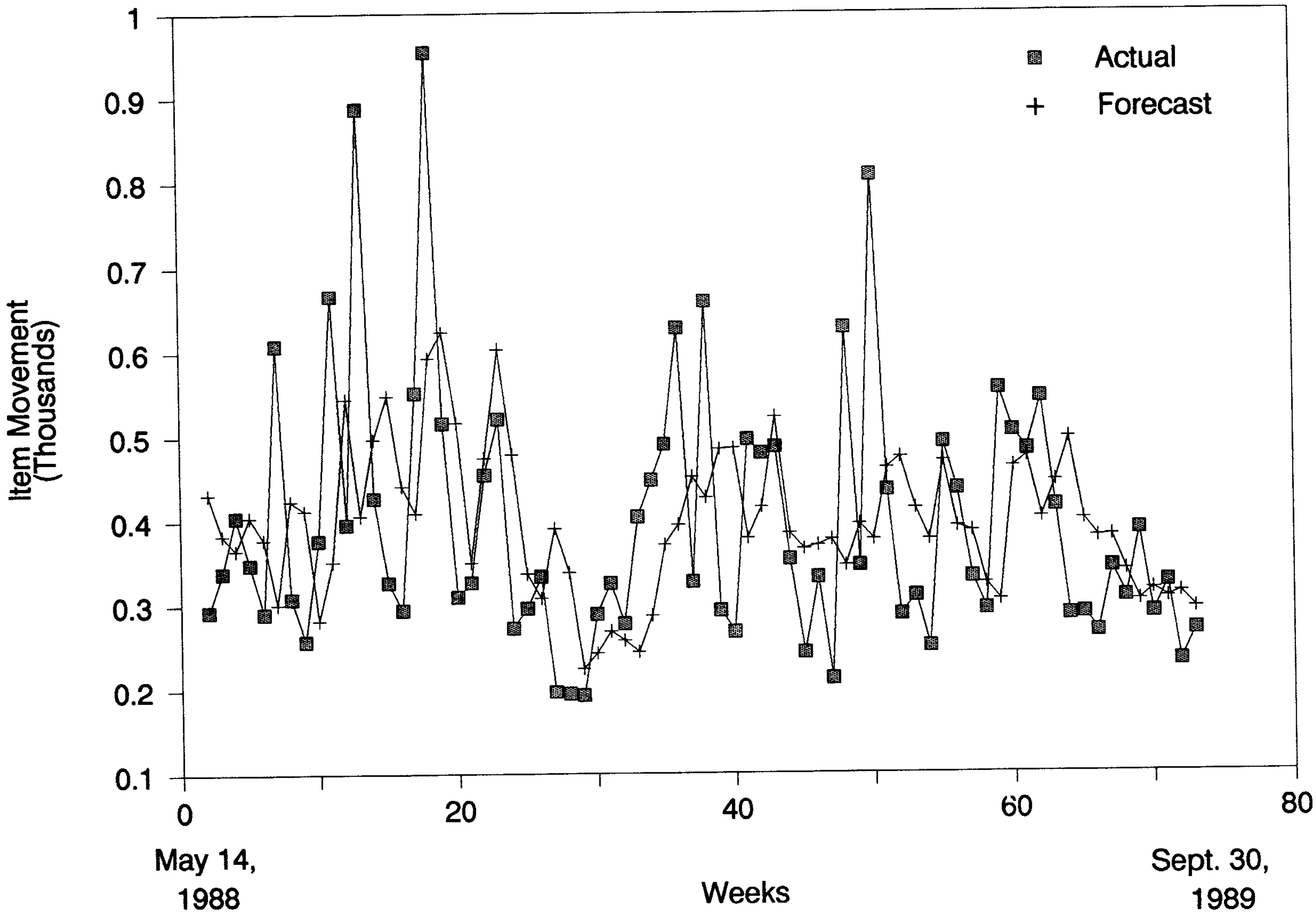

Figure 4. Roast Box-Jenkins Forecasts

Table 2. Box-Jenkins Trial Forecasts: Ground Beef Item Movement

Week	Actual	Trial Forecast 1	2	3	4	5
Sept. 29	1,523					
Oct. 7	3,090	1,754				
14	2,172	1,544	2,203			
21	1,823		2,073	2,058		
28	180			1,569	1,456	
Nov. 4	1,674				2,000	1,444
11	1,227					1,748

the actual levels. Given the structure of the Box-Jenkins equation with backshift operators of periods 1, 7, and 8 (Table 1), the extreme values take some time to work themselves through the forecasts. However, notice that the forecasted values correctly reflect the direction of change for the first three trial-forecast periods. The Box-Jenkins equation has trouble adjusting to the period of very low item movement in the later periods.

Roast item movement is much more stable during the trial forecast period, although the week of October 7 is relatively high. These trial forecasts do not track actual roast item movement as well. This is not unexpected given the poorer results of the Box-Jenkins equation over the initial 14 May 1988 to 30 September 1989 period.

Summary and Conclusions

The highly perishable nature of most variable-weight food items combined with their significant contributions to sales revenue suggest that forecasting customer demand could lead to significant cost reductions and increases in profitability. Scan data can be used as a database for individual products. However, many firms must rely on item-movement records for variable-weight foods. Supermarket management also has very limited information about the socioeconomic characteristics of customers, thereby precluding the estimation of demand equations to be used in subsequent forecasts. Thus, the Box-Jenkins approach may represent the most viable means of projecting product movement.

Two fresh beef products were selected for analysis. Ground beef item movement had a relatively stable pattern of weekly item movement, whereas the item movement of beef roasts tended to fluctuate more. In addition, the average number of packages sold per week was much higher for ground beef than roasts. Several notable results were obtained. First, the accuracy of the Box-Jenkins method varies by product. Second, the absence of a uniform forecasting equation indicates that separate equations should be developed for each food. Third, given the large number of variable-weight items carried by the typical supermarket and the first two implications, management should begin its forecasting efforts with those products that have the greatest impact on operating costs. Fourth, the forecasts may be more useful in predicting the direction of the change in item movement, as opposed to the amount. Fifth, supermarkets may have to build more sophisticated databases than those of just scan data. Part of what appears to be random fluctuations in item movement could actually be due to food shoppers' responses to changes in these variables. The inclusion of prices and measures of advertising by bar code would permit the introduction of transfer functions into the forecasting technique.

A final point is that the application of forecasting should be implemented very carefully. The Box-Jenkins technique does not impose any penalty for

Table 3. Box-Jenkins Trial Forecasts: Beef Roast Item Movement

Week	Actual	Trial Forecast 1	2	3	4	5
Sept. 29	269					
Oct. 7	661	296				
14	443	290	417			
21	312		420	429		
28	362			332	291	
Nov. 4	412				336	361
11	213					447

underestimating item movement. Such occurrences could adversely affect customers and, therefore, lead to lost patronage. Consequently, the implementation should be very gradual. A strategy is to focus on forecasting the direction of change initially, followed by levels of change given adequate stocks, and finally on tighter inventory control, deliveries, and labor scheduling.

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