Retail Meat Feature Pricing: Enhancing Meat-Case Revenues?

James Pritchett and Kamina Johnson

Retail meat managers have many pricing tools to encourage product purchase, including the feature price, syndicate price, and the percent discount. Given seasonal demands and a large, diverse set of meat cuts, meat managers may form strategic pricing groups when choosing the feature-price, syndicate-price, and percent-discount levels. This research inductively determines these groups using a principal-components method and examines the role feature pricing plays in determining the volume sold and syndicate price. Seemingly unrelated regression (SUR) models are used to simultaneously estimate the impacts of featuring strategy decisions among cluster groups.

Retail managers encourage product purchases and generate revenues with in-store promotions, coupons, frequent-buyer discount cards, and features. In particular, feature pricing is a percentage markdown from a product's syndicate (shelf) price in which savings are realized when the product is scanned at the checkout lane.

Feature pricing is gaining prominence in the retail meat case as a means of segmenting customer groups and boosting revenues. Retailers feature specific meat cuts according to seasonal consumption and holiday events, with particular attention on the cross-feature price interactions between meat-animal species (pork, poultry, and beef) and between various cuts from the same species (e.g., hamburger vs. sirloin tip). The relationship between feature prices, syndicate prices and percent discount is central to the current research.

Similar to feature pricing, coupons are a price discrimination tool (Narasimham 1984) boosting sales both as a price discount and as an additional advertising tool (Ward and Davis 1978). Coupons can support a higher syndicate price and increased revenues (Vilacassim and Wittink 1987) while encouraging product-category sales (Raju 1992). A goal of the current research is to determine if retail meat managers use feature pricing in much the same way that they use coupons. In particular, two objectives of the current study are to determine the importance of feature pricing, as well as the percent markdown from the retail price, in determining the volume of retail meat sold, and to determine if higher syndicate prices are associated or maintained with feature pricing.

Pritchett is assistant professor and Johnson is graduate research assistant, Colorado State University, Fort Collins.

Presumably, the strategic pricing of individual meat cuts is seldom performed in isolation. Rather, retail managers categorize meat cuts into strategic groups and then, understanding the cross-price effects between groups, price accordingly.

Features are one tool of strategic pricing, but these are jointly determined with the syndicate price and the percent discount from the syndicate price. So without a priori expectations on the pricing strategy, further objectives of the research include using factor analysis to elicit the underlying strategic price behavior of retail managers according to principal components found in the data, and clustering meat cuts into strategic price groups according to these principal components.

Cluster analysis is used to form strategic price groups, and these groups are the unit of analysis when exploring the first two objectives. The next section describes the time-series/cross-sectional data used in the analysis and is followed by a description of the principal-components method. The principal components are used to cluster the retail meat observations into strategic price-cluster groups, and these clusters are described in detail. In the subsequent section, retail meat-sales volume and syndicate-price determinants are discussed. Concluding remarks focus on research shortcomings and opportunities for future work.

Retail Meat Price and Volume Data

The data for this study are drawn from a recently developed USDA/ERS scanner data set focusing on the feature price, syndicate price, total-volume index and feature-volume index for selected cuts of beef, pork, and chicken (see USDA-ERS 2003 for detailed data descriptions). Forty-three cuts of meat from the data set are used in this study (Table 1). This scanner data is voluntarily contributed by stores with more than $2 million in annual sales each and whose overall sales account for twenty percent of supermarket sales in the United States. Because the scanner data is taken at the point of purchase, the database includes observations on feature products sold (both prices and the percentage of total sales volume that was sold on feature) under frequent-shopper discounts or as part of the retailer's advertised specials. The monthly time series extends from January 2001 to April 2004, resulting in 40 observations per meat cut, or 1720 total observations.

Principal Components

Retailers have three basic pricing tools: feature prices, syndicate prices, and the percent discount (calculated as 1 – feature price / syndicate price). A research objective is to identify potential retail meat groups according to these price variables and determine if each strategic group's sales respond differently to feature pricing.

A principal-components methodology may be used to isolate underlying patterns in a data set without establishing a priori causal relationships between the variables. Principal components seek to explain the variance-covariance structure of data through linear combinations of the original variables, and these principal components may then be used to cluster data into groups. Fader and Lodish (1990) use a similar technique when they cluster grocery items according to promotional activity. The cluster groups may then be used to test for differences in response to feature-price variation. The upper half of Table 2 presents the correlation matrix for the three pricing variables—feature price (featprice), syndicate price (synprice), and the percent discount (perdisc)—as well as the two volume variables, volume index (vol) and the percentage of the volume that is sold as under a feature price (featvol). The first column of the table indicates the correlation between the feature price and other data. As might be expected, the feature price and feature volume are negatively correlated, but interestingly, the feature price and total volume sold have a small positive correlation. The feature price and the syndicate price are highly correlated with one another.

Table 1. Retail Meat Cuts Used in the Research, Categorized by Species.

Beef	Beef	Chicken
Brisket – Select	Bone-in Round Steak- Choice	Legs/Drumsticks
Brisket - Choice	Bone-in Round Steak - Select	Thighs
Bone-In Chuck Roast - Select	Boneless Round Roast - Choice	Breasts (Boneless/Skinless
Bone-In Chuck Roast - Choice	Boneless Round Roast - Select	
Boneless Chuck Roast - Select	Bone-in Ribeye Steak - Choice	**Pork**
Boneless Chuck Roast - Choice	Bone-in Ribeye Steak - Select	Center Cut Bone-in Chop
Bone-In Chuck Steak - Select	Boneless Ribeye Steak - Choice	Center Cut Boneless Chop
Bone-In Chuck Steak - Choice	Boneless Ribeye Steak - Select	Boneless Ham
Boneless Chuck Steak - Select	Bone-in Rib Roast - Choice	Bone-in Ham
Boneless Chuck Steak - Choice	Bone-in Rib-Roast - Select	Rump Ham
Ground Beef	Boneless Rib Roast - Choice	
T-Bone Steak - Select	Boneless Rib Roast - Select	
T-Bone Steak - Choice		
Bone-In Sirloin Steak - Select		
Bone-In Sirloin Steak - Choice		
Boneless Sirloin Steak - Select		
Boneless Sirloin Steak - Choice		
Boneless Round Steak - Choice		
Boneless Round Steak - Select		

Table 2. Correlation Matrix and Principal Components for Selected Variables.

	featprice	synprice	perdisc	featvol	vol
featprice	1.000				
synprice	0.946	1.000			
perdisc	-0.572	-0.299	1.000		
featvol	-0.291	-0.134	0.572	1.000	
vol	0.006	0.018	0.031	-0.004	1.000

Variable	Eigenvalue	Variance Proportion	Cumulative Proportion
pcomp1	2.456	0.4912	0.4912
pcomp2	1.137	0.2275	0.7187
pcomp3	0.998	0.1996	0.9183
pcomp4	0.401	0.0801	0.99814
pcomp5	0.008	0.0016	1.00000

The lower half of Table 2 shows the eigenvalues associated with the principal components labeled pcomp1 through pcomp5. The first and second principal components have eigenvalues greater than one, and these principal components explain nearly seventy-two percent of the variance in the data. For these reasons, the principal component vectors comprising pcomp1 and pcomp2 will be used to cluster the retail meat observations.[1]

Cluster Procedure

The first two principal components are used to cluster observations creating strategic-pricing groups from the retail meat observations in the data set. Ward's hierarchical clustering method (also known as incremental sum of squares) is used to cluster, and a dendogram is used to reduce the number of clusters to five. Selected descriptive statistics and information for each cluster are presented in Table 3.

Groups A, B, and E represent meat-price clusters whose mean feature price ranges between \$2.43 per lb. and \$3.42 per lb., a relatively low price compared to Groups C and D, whose mean feature prices are well above \$6.00 per lb. A distinguishing feature between Groups A, B, and E is the average size of the feature discount–for Group A the mean percent discount is quite small (1%), while the mean percent discount grows for Group B (19%) and Group E (31%). Of these three clusters, Group A sells the smallest proportion of its total sales volume under a feature price (4.7%), followed by Group B (30.9%) and Group E, which sells more than half of its volume under a feature price.

Groups C and D tend to sell at higher feature prices, and unlike the previously discussed clusters, are exclusively composed of higher-value beef cuts from the loin and rib. A primary difference in the clusters is the mean percent discount, which is 3% for Group C's data points and 18% for Group D. Not surprisingly, Groups D sells a greater proportion of its volume under a feature price (46.5% versus 12.8% for Group C).

The five retail meat clusters differ from one another based on the mean feature price level, percent discount from the syndicate price, and the proportion of the total volume that is sold under a feature price. Three of the clusters (Groups A, B, and E) are composed of mixed-species meat cuts and tend to have lower feature prices. The remaining two groups are composed of high-end beef cuts, and differences between these two groups include the percent discount and the proportion of the total volume sold under feature. An interesting follow-up is to determine the responsiveness that each cluster

[1] Principal components with eigenvalues less than one are typically dropped as clustering vectors because they explain less of the underlying variance-covariance patterns of the data than do the original variables. However, some authors have noted that dropping the variables might eliminate useful information, leading to less-than-efficient clustering (Dillon, Mulani, and Frederick 1989)

Table 3. Description of the Retail Meat Clusters.

Group Identifier	Mean Feature Price ($/lb)	Mean Percent Discount	Mean Feature Volume	Example Cuts in Group
Group A (mixed species)	$3.42	1%	4.7%	Chicken Wings Round Steaks
Group B (mixed species)	$2.43	19%	30.9%	Ground Beef Drumsticks
Group C (beef only)	$7.41	3%	12.8%	Ribeye Steak
Group D (beef only)	$6.16	18%	46.5%	T-bone Steak
Group E (mixed species)	$2.75	31%	51.1%	Chicken Breast Pork Chop

groups' sales volume has to its own feature price and the feature price of other clusters.

Feature Pricing's Impact on Volume Sold

Feature pricing is one tool that a retail manager might use to increase volume sold, but the sales-volume response to features may vary across the cluster groups identified in the previous section. To gain insight into feature responsiveness, a five-equation linear system is developed according to:

$$1)\ Vol_{g,i,m} = f(featprice_{g,i,m}, perdisc_{g,i,m}, featvol_{g,i,m}, summer, fall, boneless, choice),$$

where *featprice* is the feature price for group g's retail meat cut i in time period m. The variable *perdisc* is the percent discount from the syndicate price, *featvol* is the proportion of the m^{th} period's total volume sold under a feature price, *summer* and *fall* are dummy variables for the second and third quarters of the calendar year, and *boneless* and *choice* are dummies for retail meat characteristics that may influence sales volume.

The parameters for the system of equations represented in Equation 1 are estimated using a Seemingly Unrelated Regression (SUR) procedure, and a first-order autoregressive process is corrected in the equations concerning Group A and Group B. An F-test is used determine if a variable's coefficients are statistically different from one another across the system of equations, and the only coefficient variable in which a cross-equation restriction may be imposed is on the *choice* variable. This restriction is imposed and the model re-estimated. Results are shown in Table 4.

According to these results, a positive statistically significant relationship exists between the feature price level and the volume sold for all cluster groups, a surprising result. However, the impact is small; for example, a one-cent increase in the own-feature price for Group A results in a 0.16-percent increase in the volume index.

The strongest own feature price effect is for Groups A and E, with lesser effects for Groups C and D. In general, the own-feature price effects dwarf the cross-feature price effects, and these cross-feature price effects have a negative relationship with volume sold. That is, as the cross-feature price increases, the own-volume sold decreases, another surprising result. Again, the cross-price feature effect is small—a one-cent increase in the feature price of Group B results in only a 0.03-percent decrease in the volume of Group A meats.

Examining the relative size of the cross-feature price effects suggests some substitutability between the strategic price groups. Groups A, B, and E respond to one another's cross-feature pricing more dramatically than do Groups C and D. Indeed the cross-feature price impact multipliers for A, B and E range between –1.1 and –7.1, while cross-feature price impact multipliers for Groups C and D are almost always between 0 and –1 and are not statistically significant.

As the percent difference between the syndicate price and the feature price increases, so too does the

Table 4. Restricted SUR Results in which Volume Sold is Dependent Variable.

Variable	Group A	Group B	Group C	Group D	Group E
Constant	8.315**	16.992**	3.282*	1.265	19.452**
$Featprice_a$	16.659**	-4.357**	-0.843	-0.325	-4.996**
$Featprice_b$	-3.037**	22.98**	-1.204	-0.464	-7.135**
$Featprice_c$	-1.103**	-2.255**	12.751**	-0.168	-2.585**
$Featprice_d$	-1.313**	-2.687**	-0.520	14.669**	-3.082**
$Featprice_e$	-2.739**	-5.599**	-1.084	-0.418	24.452**
Featvol	1.099**	0.338**	-0.602**	-0.501**	0.0199
Perdisc	1.294**	0.500**	0.287	1.621**	0.961**
Summer	24.453**	19.457**	1.064	15.907**	26.948**
Fall	26.614**	8.915**	-14.639**	27.076**	14.772**
Choice	4.239**	4.239**	4.239**	4.239**	4.239**
Boneless	-38.783**	-31.622**	9.207**	10.718**	-24.823**
Adjusted R^2	0.751	0.606	0.667	0.564	0.401
Durbin-Watson	2.01	2.01	2.02	2.07	1.92

*Statistically significant at the 85% confidence level.
**Statistically significant at the 95% confidence level.

volume sold, suggesting that consumers respond to steeper price cuts with increased purchases. The percentage-discount effect is largest with the Group D meats, a group with relatively high feature prices and a large proportion of volume sold under feature; the smallest effect is found with the Group C meat cuts, a high feature price group with only small price discounts from the syndicate price (1%).

Seasonal variables (*summer* and *fall*) are important when explaining variation for Groups A, B, D, and E, all of which have retail meat cuts that are used in barbecue grilling. In fact, the seasonal effects outweigh the own-feature price effects for groups A, D, and E, supporting the notion that retail meat managers may make strategic group-pricing decisions based on seasonal demands.

In summary, feature pricing has a positive, statistically significant relationship with respect to volume sold, a surprising result to be discussed further in the conclusions portion of this study. These own-feature price effects are substantially larger than the negative cross-feature price effects, but can be dominated by the seasonal demands for meats.

Feature Pricing's Impact on Syndicate Price

The previous section dealt primarily with feature pricing's impact on the volume of retail meat sold. This section considers the relationship between the feature price and the syndicate price, focusing on whether the retail manager may be able to maintain a higher price with features in much the way coupons are used to maintain a higher shelf price (Vilacassim and Wittink 1987). This dual-pricing strategy may differ across the five cluster groups, due in part to varying degrees of consumer responsiveness to the apparent "discount" received. To this end, a five-equation linear system is developed according to

$$2)\ synprice_{g,i,m} = f(featprice_{g,i,m}, perdisc_{g,i,m}, summer, fall, boneless, choice)\,.$$

These five equations are then estimated simultaneously using a Seemingly Unrelated Regression procedure with appropriate correction for autoregressive processes. An F-test is used determine if a variable's coefficients are statistically different from one another across the system of equations. All of the coefficients are determined to be statistically different, so the estimation results of the unrestricted model are presented in Table 5.

From Table 5, it is clear that a positive, albeit small, relationship exists between the syndicate price and feature price for each group. Groups A, B, C, and D have a nearly one-to-one relationship between their respective own-feature price and own syndicate price, and these impacts are statistically significant. A notable own-feature price impact is found in Group E, in which an increase of one cent in the feature price corresponds to a one-and-one-quarter-cent increase in the syndicate price.

In contrast to the volume results discussed in the previous section, cross-feature prices have a minimal effect on the own-syndicate price of the cluster groups. Group D is the only cluster with a statistically significant relationship between its syndicate price and all cross-feature prices, but the cross-feature price impact multipliers are very small, ranging from 0.002 to 0.005. Perhaps, then, retail managers consider the own-feature price when establishing the syndicate price but have little concern for feature prices of other strategic groups.

Results in Table 5 also indicate that the steepness of the discount (represented by the Perdisc variable) has an important impact on maintaining a higher syndicate price. For the lower-end meat cut groups (Groups A and B), a one-cent increase in the percent discount allows for a three-cent-higher syndicate price. In contrast, the syndicate prices of the higher value meat groups (Groups C and D) have a larger response to the percent discount. In fact, a one-cent increase in the percent discount leads to more than a seven-cent increase in syndicate price.

Conclusions

Retail meat managers have many pricing tools to encourage product purchase, including the feature price, syndicate price, and the percent discount. Given seasonal demands and a large, diverse set of meat cuts, meat managers may form strategic pricing groups when choosing the feature-price, syndicate-price and percent-discount levels. The current research inductively determines cluster groups using a principal-components method and examines the role that feature pricing plays in determining the volume sold and syndicate price.

Principal components are used to determine five clusters, and these clusters differ by the mean feature price level, the proportion of volume sold under feature, by the perceived value of the cut (high-end versus low-end) and by the number of animal species represented in each group. As an ex-

Table 5. Unrestricted SUR Results in which Syndicate Price is Dependent Variable.

Variable	Group A	Group B	Group C	Group D	Group E
Constant	0.008	-0.119***	-0.003	-0.015***	-0.518**
$Featprice_a$	0.971***	0.017***	0.001	0.004***	0.000
$Featprice_b$	-0.003	1.076***	0.001	0.005***	0.002
$Featprice_c$	-0.000	0.006***	1.002***	0.002***	0.006
$Featprice_d$	-0.001	0.002	0.001	1.001***	0.031***
$Featprice_e$	-0.002	0.001	0.001	0.004***	1.254***
Perdisc	3.171***	3.764***	7.386***	7.346***	5.022***
Summer	0.013***	0.006	-0.006***	-0.021***	0.001
Fall	0.043***	0.019***	0.001	-0.023***	0.006
Choice	0.017**	0.051***	0.003	0.069***	0.158***
Boneless	0.013	0.003	-0.011***	0.051***	0.039***
Adjusted R^2	0.999	0.999	0.999	0.999	0.999

**Statistically significant at the 90% confidence level.

***Statistically significant at the 95% confidence level.

ample, Group A had the lowest-value meat cuts and the lowest mean feature price, while Group C was a beef-only, high-value, high feature-price cluster.

The feature price, percent discount, and seasonal variables all had differing impacts on the volume sold. Interestingly, feature pricing has a positive, statistically significant relationship with the volume sold index. Two possible explanations include the impact of an omitted variable and the complex interaction of the pricing variables. In the first case, feature prices include both the advertised specials and the in-store, non-advertised specials. Conceivably, a retail manager might increase the feature price and advertise the "special" in retail circulars in order to increase the volume sold. Likewise, the manager might lower the feature price after an advertised special, and the volume of sales may decrease in spite of the lower price. Unfortunately, the ERS scanner data set does not contain information on media expenditures; a future research opportunity might be combining a media-index variable with the retail meat data.

A second possible explanation may be the first-order and second-order complexities of the feature price level's impact on the other important variables, including the syndicate price, the percent discount, and total revenues. An interesting alternative to the current analysis would be to posit a revenue function for the meat case. Using this optimized function, the marginal impacts of pricing variables may be estimated within the context of a flexible functional form, and perhaps additional insight gained from parameter estimates.

Feature prices are associated with increasing syndicate prices, suggesting that features might be used as a price-discrimination tool. Practically speaking, retail meat managers can use features to lower retail meat prices below consumers' reference prices occasionally, but still be able extract additional margin from a higher syndicate price when the meat is off feature. It should be noted, however, that the effect of feature prices on syndicate prices is quite small.

The percent discount, or "steepness" of the feature price, has a much larger impact on the syndicate price than do feature prices. The effect differs across groups—the syndicate price of lower-value meat groups is less responsive to the percent discount when compared to groups with higher-value meat cuts.

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