E C O N O M I C S B U L L E T I N

Dynamic strategic responses among advertisers: the case of meat products

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Abstract

The case of strategic advertising response is examined for branded and generic meat products (beef, pork, and poultry). A dynamic conceptual model is developed to identify the determinants of advertising expenditures. A time-series model is then used to examine the competitive behavior of branded and generic meat advertisers. The results identify two types of advertising strategies; those based upon changes in revenues and those based upon changes in competitor advertising expenditures. Most groups employ a mix of revenue-based and advertising-based strategies. The results identify examples of both strategic substitutes and strategic complements. No long-run response to generic advertising by brand advertisers in the same commodity group is found.

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1. Introduction

Millions of dollars are spent each year in the U.S. to advertise meat products. Many have analyzed meat advertising, primarily to determine its impact on consumer demand for meat. Fewer have considered how advertising by one group influences another's advertising. The objective of this research is to explore the nature of the dynamic strategic responses among five groups of meat advertisers: brand and generic beef, brand and generic pork, and brand poultry. The primary focus is on understanding how competitor advertising and revenues influence a firm's advertising expenditures rather than how advertising impacts consumer demand. This paper represents an important contribution to the literature as a first look at strategic responses in a complex advertising arena comprised of industry-level advertising (generic) and firm-level advertisers (brand).

The case of meat advertising is particularly interesting. Considerable amounts of both branded and generic advertising expenditures are made for pork and beef products while poultry advertising expenditures are used to promote branded products. The competitive dynamics between brand and generic advertising are not well understood. Some previous research has considered the interaction between generic advertising and branded advertising of the same commodity (e.g., Krishnamurthy, 2000) or between generic advertising of different commodities (e.g., Alston, Freebairn, and James, 2001).

In the case of meat advertising the relationships between brand and generic advertising are complicated by cross commodity effects because meat commodity groups are typically viewed as substitutes. As a result, the generic (and possibly brand) promotional activities of firms in one commodity group may influence the demand faced by other commodity groups. Carey and Bolton (1996) showed that collective (generic) advertising decisions may depend upon the level of spillovers that exists between firms. Analyses of the significance of spillover impacts of meat advertising have been inconclusive (Kinnucan, 1996; Kinnucan and Miao, 2000; and Kinnucan, Xiao, and Hsia, 1996).

It is clear that a variety of factors influence strategic advertising behavior. In the case of meat advertising it is likely that these behaviors will be influenced by the presence of generic and brand advertising, spillover effects of advertising, and responses to changes in market shares (Lim and Ong, 1989; Thomas, 1999). The following section develops a conceptual model of the factors influencing strategic advertising behavior. Then, an empirical model that captures the behavior implied by the conceptual model is developed and estimated.

2. Conceptual Model

Most related studies have established a static game theory model to develop advertising reaction functions. See for instance Alston, Freebairn, and James (2000); Lim and Ong (1989); and Boyer and Moreaux (1999). Tirole (1989) provides a static representation of the reaction function. In his static case, the Nash equilibrium is always achieved and in no time period do the firms deviate from that point. However, he points out that the problem becomes more complex under dynamic conditions. It is further complicated when there are more than two firms in the market. Here, we develop the static, two-firm model. We then introduce dynamics into the model. Finally, we discuss the dynamic, n-firm conceptual problem.

2.1 Static, Two-Firm Reaction Functions

Consider Firm 1, who behaves as a profit-maximizer, choosing advertising expenditures. Firm 1's profit function can be characterized as follows,

$$\Pi^1 = \Pi^1(a_1, a_2) \tag{1}$$

where a_1 and a_2 are advertising expenditures by Firms 1 and 2. Firm 1's optimal advertising expenditures must meet the first-order condition, $\Pi_1^1(a_1^*, a_2^*) = 0$, where Π_1^1 denotes the first derivative of the profit function with respect to a_1 and the asterisks denote the optimal levels of advertising. The first-order condition for a_1^* yields Firm 1's advertising reaction function, R_1, the slope of which is

$$R_1' = -\frac{\Pi_{12}^1}{\Pi_{11}^1}. \tag{2}$$

Assuming a negative denominator (indicating decreasing marginal returns to advertising), the sign of the slope of the reaction function is determined by the cross-partial in the numerator. Tirole (1989) and Varian (1992) point out that if the numerator is positive, then the actions are "strategic complements." In this case, increased advertising expenditures by the rival firm leads to an increase in own advertising. If negative, then the actions are "strategic substitutes."

2.2 Dynamic, Two-Firm Reaction Functions

Now consider the case in which profits are a function of current and lagged advertising. Also, advertising expenditures are a function of lagged revenues, which provide a pool of resources to be used for advertising and other promotional activities. In this case, Firm 1's profit function in period t is

$$\begin{aligned}&\Pi_t^1(a_{1,t}(\Gamma_{1,t-1},...,\Gamma_{1,t-n}),...a_{1,t-m}(\Gamma_{1,t-m-1},...,\Gamma_{1,t-m-n}),\\&a_{2,t}(\Gamma_{2,t-1},...,\Gamma_{2,t-l}),...,a_{2,t-k}(\Gamma_{2,t-k-1},...,\Gamma_{2,t-k-l}))\end{aligned} \tag{3}$$

where Γ is the revenue of the firm. The effects of advertising impact profits for m and k periods for Firm 1 and Firm 2, respectively. Also, advertising is a function of lagged revenues, whose effects last for n and l periods, respectively.

Solving the first-order conditions for the optimal advertising level for Firm 1 in period t, $a_{1,t}^*$ yields

$$a_{1,t}^* = a_{1,t}^*(a_{1,t-1},...,a_{1,t-m}, a_{2,t}^*,...a_{2,t-k}, \Gamma_{1,t-1},...,\Gamma_{1,t-m-n}, \Gamma_{2,t-1},...,\Gamma_{2,t-k-l}) \tag{4}$$

where an asterisk represents the optimal choices for each firm in period t. In other words, Firm 1 chooses its advertising expenditures based upon its own past advertising and revenues as well as its rival's past advertising and revenues.

2.3 Dynamic, n-Firm Reaction Functions

The dynamic reaction function in the n-firm case follows directly from Equation 4. Firm 1 would choose its advertising expenditures based jointly upon each rivals' lagged advertising and revenues, illustrating the dynamic nature of the problem of estimating firm reaction functions. Static analyses do not capture the strategic interactions that may exist. Therefore, we employ a time-series approach which allows us to specify a dynamic model and estimate both short- and long-run responses between meat advertisers.

3. Empirical Model

Our analysis employs a vector autoregression (VAR) estimation framework. The general form of the VAR model is shown in Equation 5.

$$y_t = \mu + \Gamma_1 y_{t-1} + \cdots + \Gamma_p y_{t-p} + \sum_i \Pi_i x_{t-i} + \varepsilon_t \qquad (5)$$

Here, y_t is an n x 1 vector of current period advertising expenditures and y_{t-1} through y_{t-p} are the first through the p^{th} lags of advertising expenditures. The x_{t-i} are n x 1 vectors of lagged retail revenues. The Γ and β matrices are coefficients to be estimated using a system of seemingly unrelated regressions (SUR). Each of the n equations in the system includes the same set of independent variables. Thus, the coefficient estimates are the same as would be obtained with ordinary least squares (OLS) equations estimated individually. Estimating the equations within an SUR system incorporates the assumption that the errors, ε_t, are uncorrelated with y_{t-p-j}, where j > 0, i.e., p lags of the dependent variables are sufficient to explain the dynamics found in y (Hamilton, 1994). The lag structure, including the choice of p, is an empirical concern.

Once the coefficients in Γ and β have been estimated, they can be used to calculate dynamic multipliers, which map out impulse-response functions and long-run multipliers for each equation. The dynamic multipliers show the affect of a one-unit change r periods in the past on the current period's value of advertising expenditures or, conversely, they can show the impact of a one-unit shock today on advertising expenditures r periods in the future. The long-run multiplier shows the total impact of the one-unit shock after its effects completely work through the system. For details on calculating dynamic and long-run multipliers, the interested reader should see Hyde and Foster (2003). Note that we convert the multipliers to elasticity values by multiplying the multiplier by the relevant ratio of sample means.

4. Data

The data used for this study are quarterly and cover the period of 1970-1993[1]. The data include advertising expenditures for beef (brand and generic), pork (brand and generic), and poultry (brand only) from *Class/Brand QTR $* (Leading National Advertisers, 1970-1994). Per capita meat consumption data were obtained from the *Livestock and Meat Situation and Outlook Report* (USDA/ERS, 1970-1994), price indices for the meat commodities were obtained from *CPI Detailed Reports* (USDL/BLS, various years), and population statistics were obtained from the U.S. Department of Commerce's *Survey of Current Business* (BEA, 1986-1994).

Table 1. Summary statistics and variable definitions

Variable	Description	Mean	Std. Dev.	Min.	Max.
Beeftr	Indexed per capita beef retail revenues	1752	410	912	2356
Porktr	Indexed per capita pork retail revenues	1190	343	611	1871
Pltrytr	Indexed per capita poultry retail revenues	1600	723	516	3190
Bbadv	Per capita branded beef advertising	2.4	2.7	0.0	12.5
Gbadv	Per capita generic beef advertising	9.4	13.7	0.1	56.6
Bpadv	Per capita branded pork advertising	32.5	17.5	7.3	85.2
Gpadv	Per capita generic pork advertising	3.2	4.3	0.0	16.2
Cadv	Per capita poultry advertising (branded)	29.4	19.6	2.7	86.3

Variables representing meat revenues were created by multiplying the price indices by per-capita meat consumption. Because the meat consumption data are reported on a per-capita

[1] The data were used by Brester and Schroeder (1995). We appreciate their making the data available for this research.

basis, the advertising expenditures were divided by population for consistency among the data. The definitions and descriptive statistics of the variables used in the analysis are shown in Table 1. The dependent variable for each equation was one of the five advertising expenditure variables described in Table 1. The independent variables included lags of those five variables as well as lagged indexed retail revenues for all three meats and dummy variables representing quarters 2, 3, and 4.

5. Results

Results are presented in two sections. First, the short-run effects, including the coefficient estimates and the impulse response functions, are presented and discussed. The second section presents the long-run effects, including the long-run elasticities and the results of Granger causality tests.

To determine the appropriate lag structure, a model that included the first through the fourth lags of the endogenous (predetermined) and exogenous variables was estimated. Likelihood ratio tests were used to specify the appropriate lag length and structure. The tests resulted in specifications that included the first and fourth lags of the predetermined and exogenous variables as well as the quarterly dummy variables. Thus each of these variables was included as independent variables in each of the five equations estimated.

Table 2. Parameter estimates for the vector autoregression model[a]

	Equation				
Variable	BBADV	GBADV	BPADV	GPADV	CADV
Constant	-3.060*	1.074	4.566	-1.758	-16.248**
$BBADV_{t-1}$	0.352**	0.249	0.066	-0.076	0.710
$BBADV_{t-4}$	0.410**	0.066	0.422	0.035	0.715
$GBADV_{t-1}$	-0.009	0.491**	-0.196*	-0.040*	0.096
$GBADV_{t-4}$	-0.023	0.120	-0.128	0.030	0.197*
$BPADV_{t-1}$	-0.061**	-0.008	0.156	-0.069**	0.098
$BPADV_{t-4}$	0.054**	-0.001	0.269**	-0.019	-0.045
$GPADV_{t-1}$	0.034	0.429	0.095	-0.231*	-1.407**
$GPADV_{t-4}$	-0.047	-1.981**	0.092	0.035	-0.492
$CADV_{t-1}$	-0.032	-0.114	0.166*	-0.012	0.200**
$CADV_{t-4}$	0.012	0.020	0.156	0.009	0.453**
$BEEFTR_{t-1}$	-0.005*	-0.029**	0.006	-0.010**	0.004
$BEEFTR_{t-4}$	0.005*	0.008	-0.023	-0.005*	-0.008
$PORKTR_{t-1}$	0.009**	0.020	-0.013	0.010**	0.015
$PORKTR_{t-4}$	-0.001	-0.013	0.035*	0.010**	0.002
$PLTRYTR_{t-1}$	-0.002	0.017*	-0.006	0.004**	0.007
$PLTRYTR_{t-4}$	-0.002	0.006	0.013	0.003*	-0.002
D2	-0.191	2.402	1.817	0.511	6.879*
D3	0.790	-1.306	-1.845	1.130	4.785
D4	-0.721	1.639	4.900	-0.190	10.423**
R^2 =	0.771	0.795	0.860	0.908	0.891
Durbin's h	-0.435	-0.375	-0.614	-0.529	-0.334

* = 10% significance, ** = 5% significance

[a] Estimated equations are represented in the columns of this table.

Notes: System R^2 = 0.99. D2-D4 represent quarterly dummies indicating second, third, and fourth quarters.

In general, the individual equations explain much of the variation in the dependent variables, with each R^2 greater than 0.77. The system R^2 is 0.99, and the system is shown to be stable, as the greatest eigenvalue of the Π_0 matrix is 0.901. Furthermore, the errors were analyzed for potential autocorrelation using Durbin's h test (Harvey, 1981). For each equation, we fail to reject the null hypothesis that the errors are asymptotically normally distributed.

5.1 Short-Run Effects - VAR Results and Impulse Response Functions

Turning attention to individual equations and associated impulse response functions, the VAR results are presented in Table 2 and the impulse response functions are presented in Figures 1-6. For the sake of brevity, we present and discuss only those relationships in which at least one of the estimated coefficients are significantly different from zero. These are denoted as relationships that are statistically significant in the short-run. It is important to note that short-run significance is neither necessary nor sufficient to determine the long-run significance of a given relationship. Below, we summarize short-run results in three categories; intra-group effects, cross-group effects, and revenue effects.

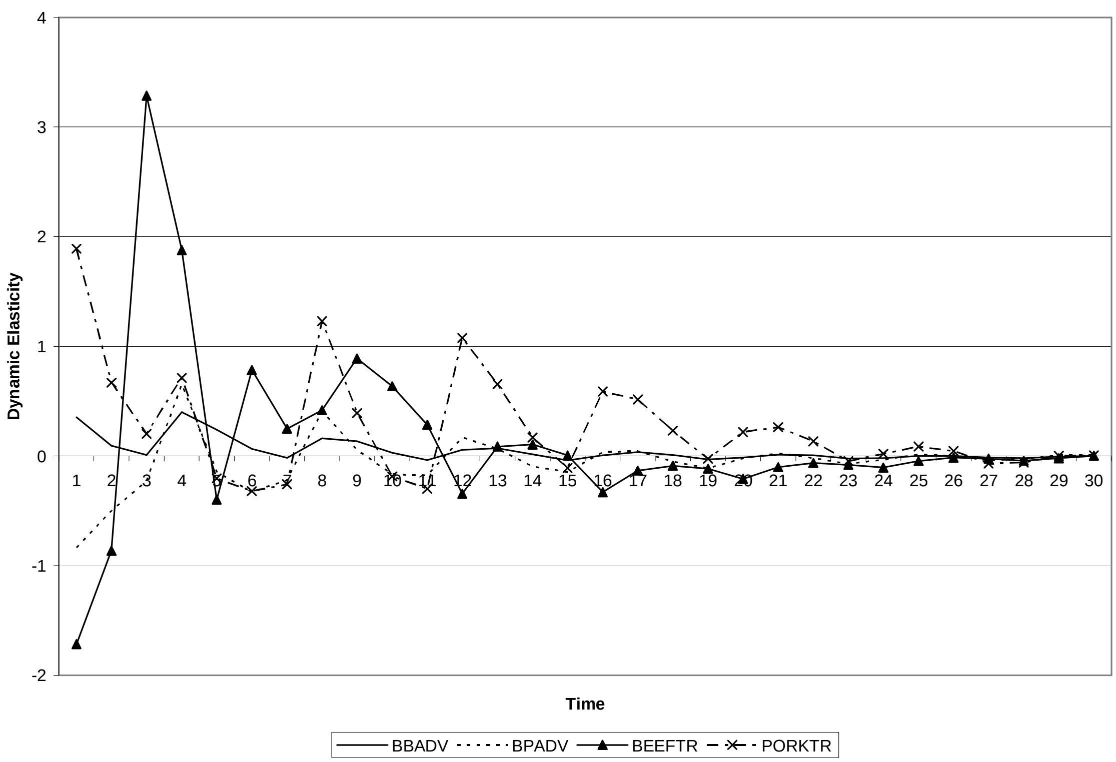

Figure 1. Impulse response functions related to brand beef advertising

5.1.1 Short-Run Intra-Group Effects

With respect to the intra-group effects, all groups except GPADV have at least one positive, significant coefficient and no negative, significant ones. BBADV, GBADV, and CADV have a significantly positive first lag of own advertising while BBADV, BPADV and CADV have a significantly positive fourth lag. Thus, it appears that the groups tend to increase own advertising when experiencing an initial positive shock. With regard to the brand advertising groups, this may well be due to intra-group advertising dynamics, although our aggregate data constrain us from testing this hypothesis. For GBADV, this might be an indication that the initial advertising shock was successful in increasing sales and, therefore, the pool of money from which future advertising expenditures could be made.

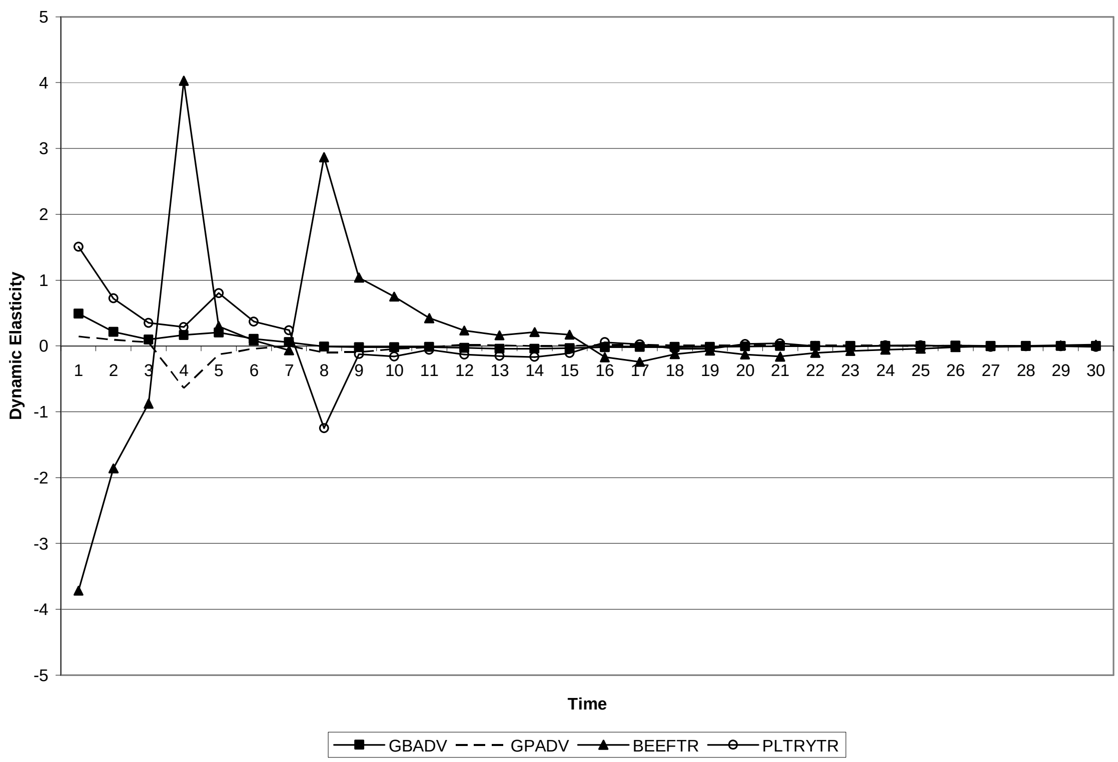

Figure 2. Impulse response functions related to generic beef advertising

5.1.2 Short-Run Cross-Group Effects

The cross-group effects are more complex. However, it is clear that most responses occur within one period of a shock. Of the eight cross-group relationships in the figures, five are initially negative. Those indicate the equations in which the first lag of the associated variable was negative and statistically significant. Of the three that were positive, only one was statistically significant. Looking at the coefficients on the fourth lags of the associated variables, only three are statistically significant, with two positive and one negative. Thus, it appears that most groups respond quickly to an increase in advertising by other groups, but the response is typically to reduce advertising expenditures. This may be some indication that the groups attempt to determine the impact of the advertising shock before developing an appropriate response. It may also indicate a strategy of simply accommodating the shock by either decreasing or making no change to expenditures.

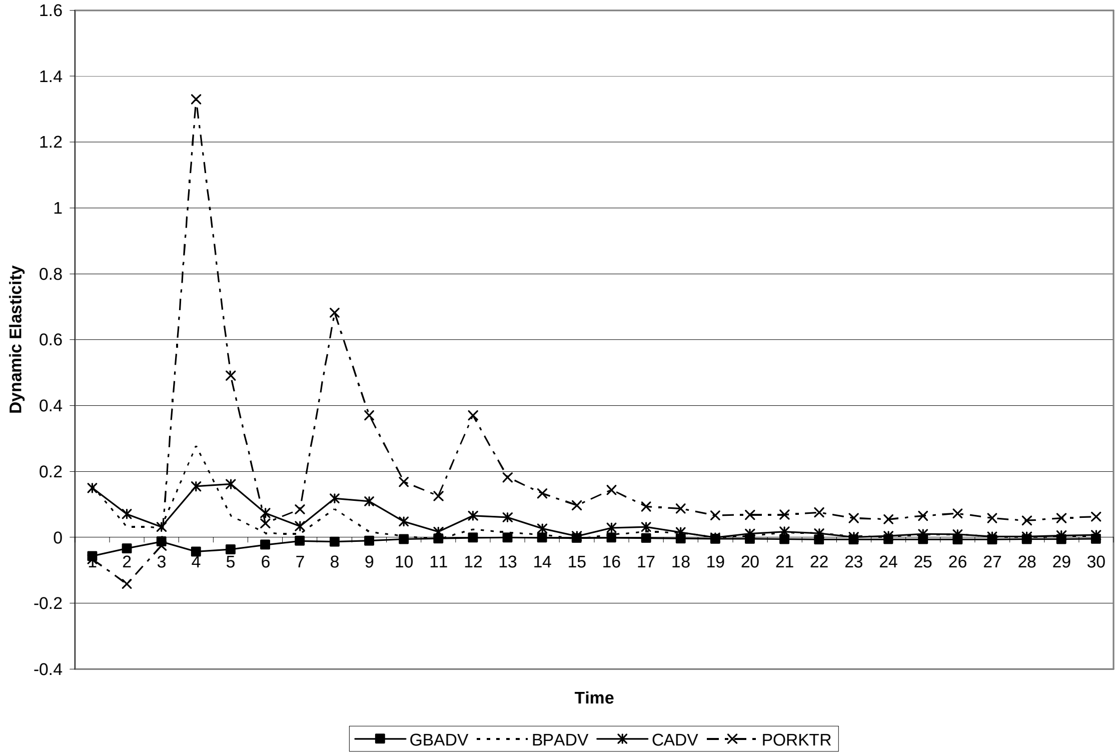

Figure 3. Impulse response functions related to brand pork advertising

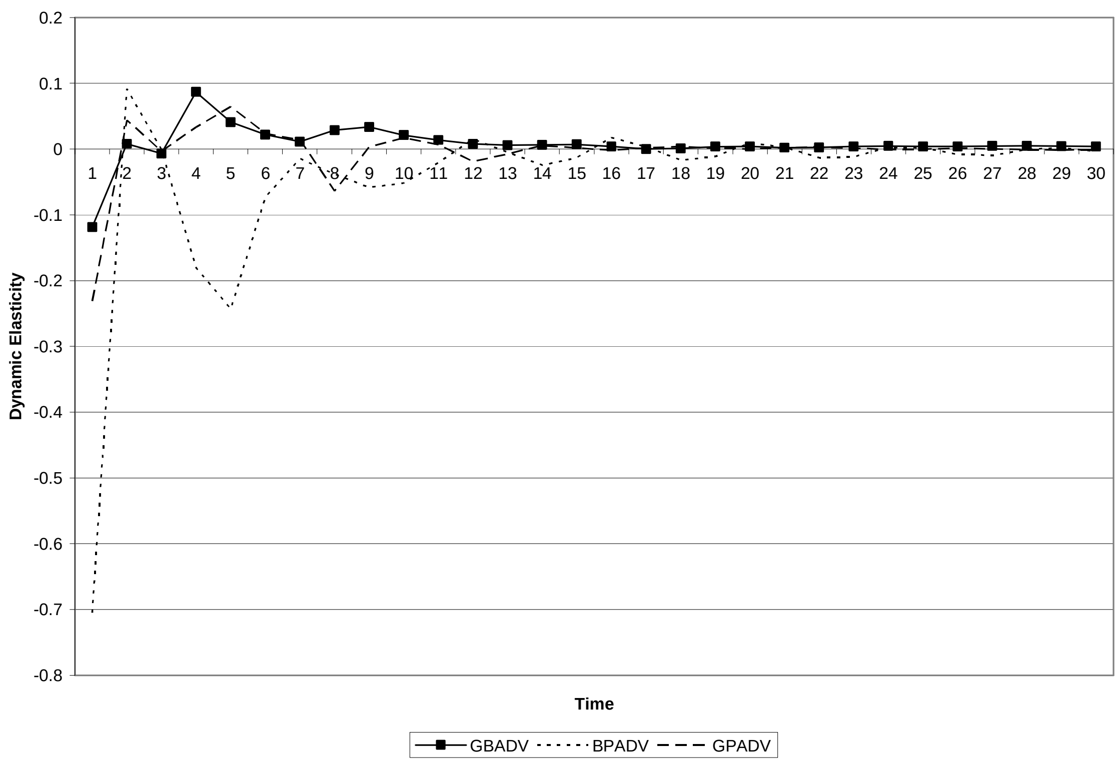

Figure 4. Impulse response functions relating advertising variables to generic pork advertising

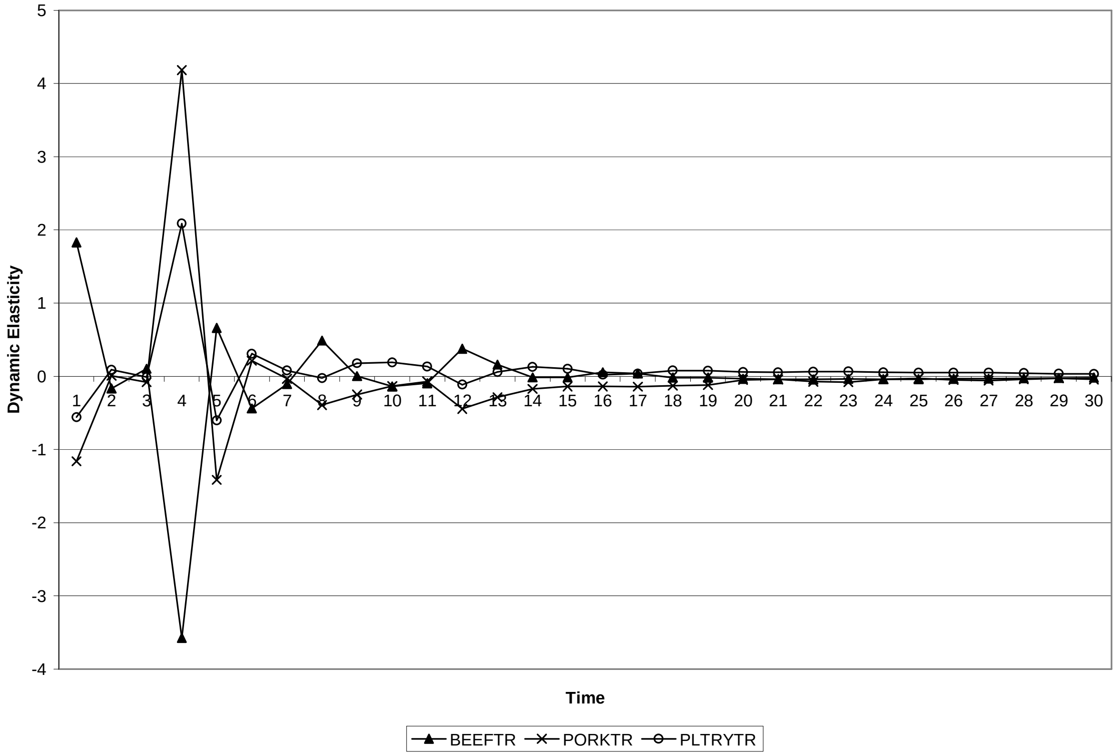

Figure 5. Impulse response functions relating revenue variables to generic pork advertising

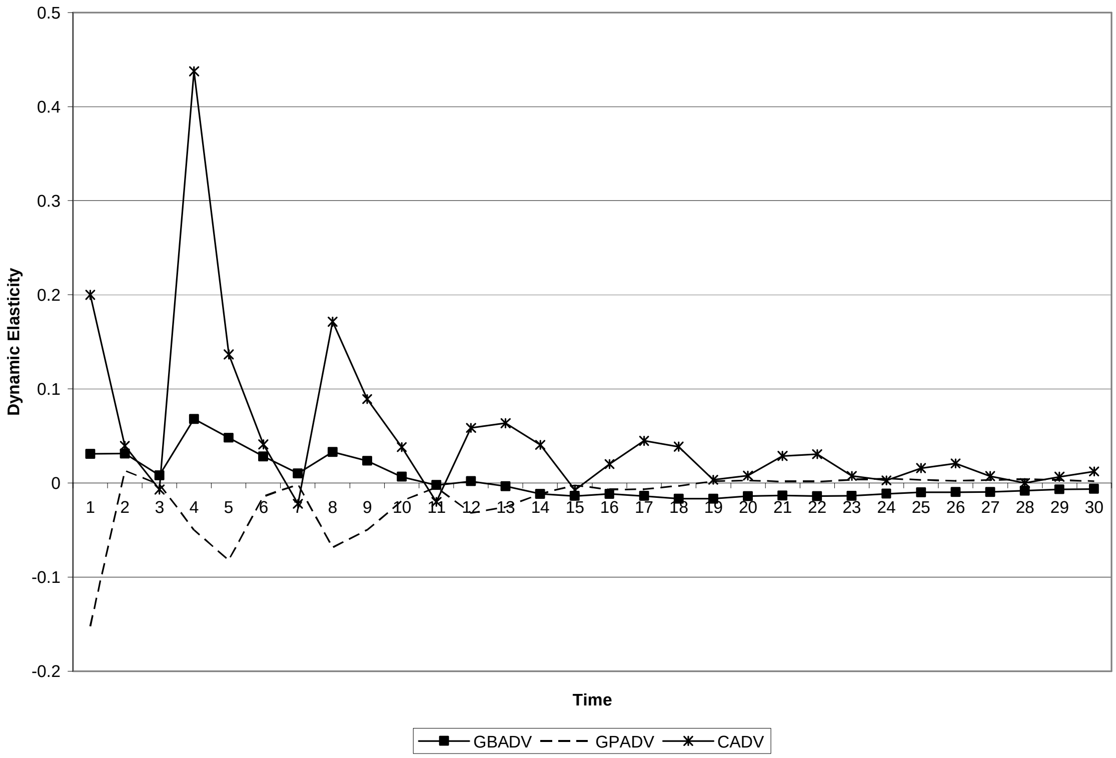

Figure 6. Impulse response functions related to poultry advertising

5.1.3 Short-Run Revenue Effects

Finally, four out of five advertising groups (poultry being the exception) are shown to respond to meat revenues in some fashion. Each of those responds to its own revenues, although the nature of that response differs across groups. In the BBADV equation, the first lag of BEEFTR is negative while the fourth is positive. For GBADV, the first lag of BEEFTR is negative and the fourth is insignificant. Furthermore, both lags of PORKTR are positive in the GPADV equation. Finally, the first lag of PORKTR is insignificant in the BPADV equation, while the fourth lag is positive. Based on these results, it is difficult to draw any general conclusions about the nature of the short-run response of advertisers to their own retail revenues.

There are a few interesting cross-group revenue relationships. For example, GPADV is shown to decline with positive shocks in BEEFTR. All else being equal, this might reflect a capitulation or may simply be a result of reduced funds if consumers are shifting meat expenditures to beef at the expense of pork. However, GPADV increases with positive shocks in PLTRYTR. GBADV also responds positively to shocks in PLTRYTR. Thus, it appears that generic advertisers increase expenditures when poultry revenues increase. This is a direct competitive move.

5.2 Long-Run Elasticities

As noted earlier, it is not always possible to correctly infer a significant long-run strategic relationship based solely on short-run dynamics. Therefore, it is important to consider the longer-term responses separately from those of the short-run. Here, the long-run effects are described as those which reflect the total impact of a shock after its effects are completely dissipated. In the following discussion, we focus on these long-run elasticities. As in the previous section, we discuss intra-group, cross-group, and revenue effects.

5.2.1 Long-Run Intra-Group Effects

Of the five intra-group long-run elasticities, four are positive and statistically significant with elasticities that range from 0.83 (BPADV) to 1.47 (BBADV) (Table 3). The one exception, GPADV, is not surprising given the short-run effects noted previously. However, it is interesting to note that although the coefficient on the first lag of GPADV is significant (Table 2), the longer-term dynamics (cycling around zero in Figure 4) cause the long-run effect to be statistically insignificant.

5.2.2 Long-Run Cross-Group Effects

Most of the long-run elasticities are consistent with short-run effects discussed above. There are seven statistically significant cross-group long-run elasticities (Table 3). Three of these are positive. Following Tirole's (1989) definition, a positive long-run elasticity indicates that the actions are strategic complements. The other four, then, are negative, indicating that the actions are strategic substitutes.

Neither BBADV nor GBADV have a strategic complement. One possible explanation suggests that pork or poultry advertising has little impact on the consumption of beef or actually might lead consumers to purchase more beef. This would occur if consumers purchased beef products while at the meat counter as a result of another group's advertising.

Table 3. Long-run elasticity of meat advertising with respect to indicated advertising expenditure source[a]

Source	Brand beef	Generic beef	Brand pork	Generic pork	Poultry
Brand beef	1.47*,[b]	0.25	0.69	-0.61	1.27*,[b]
Generic beef	-1.01	1.06*,[b]	-0.33*,[b]	0.22[b]	0.08*,[b]
Brand pork	0.78[b]	0.76	0.83*,[b]	-1.36*,[b]	0.74
Generic pork	-1.75	-0.67*,[b]	-0.07	-0.10[b]	-0.49*,[b]
Poultry	-2.33	-1.23	1.28*,[b]	-0.92	1.51*,[b]

* = 5% significance
[a] Entries in table represent ε_{ij} where i is the column and j is the row. For example, the elasticity of generic beef advertising with respect to brand beef advertising is 0.25.
[b] Indicates a statistically significant test for Granger causality

The generic advertising groups (GBADV and GPADV) do not view any other advertising as strategic complements. Results indicate that GBADV treats GPADV as a strategic substitute and GPADV treats BPADV as a substitute. These results might indicate that generic advertising expenditures increase only when the relevant commodity group feels that other groups (brand or generic) are not advertising to the extent that they should and thus the spillover effects are absent.

The long-run elasticities also point out that responses are not symmetric across commodities. For example, CADV responds to GPADV as a strategic substitute. However, BPADV responds to CADV as a strategic complement. This is further evidence that generic and brand advertising responses are distinctly different.

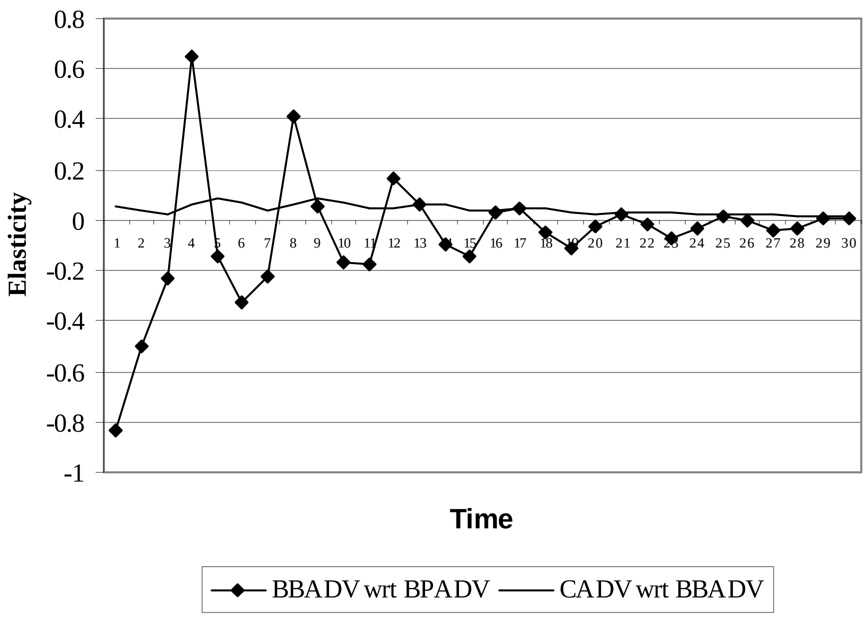

Figure 7. Impulse response function of BBADV with respect to BPADV and CADV with respect to BBADV

With respect to Krishnamurthy's (2000) analytical model, there is no long-run evidence of responses by brand advertising to generic advertising within the same commodity group.

Both long-run elasticities relating own-commodity generic advertising to brand advertising are negative, but statistically insignificant. Thus, although one could hypothesize either a strategic substitute or strategic complement relationship, neither is shown to hold in the long-run in these data.

There are two special cases in which the short-run effects are inconsistent with the long-run elasticities (Figure 7). First, BBADV is shown to have no statistically significant long-run response to BPADV despite coefficients on the first and fourth lags of BPADV being significant in the BBADV equation. In that case, the first lag was negative and the fourth lag is positive, but both are of similar magnitude. It appears that the short-run dynamic effects offset each other over the longer term, resulting in no significant long-run impacts.

Second, the long-run elasticity of BBADV in the CADV equation is positive and statistically significant at a five percent level, despite both coefficients being insignificant at a ten percent level. Figure 7 shows that the impulse response function is strictly positive. Thus, it appears that the sum of many small impacts, in a statistical sense, adds up to an important impact over the long-run.

5.2.3 Long-Run Revenue Effects

There are five significant long-run elasticities relating changes in revenues to changes in advertising expenditures (Table 4). Interestingly, only GPADV responds to own-commodity revenues, with a one percent increase in retail revenues resulting in a five percent long-run increase in GPADV. Although BBADV showed a short-run response to BEEFTR, the long-run elasticity is statistically insignificant (Figure 8). This is another example in which the dynamic cycling pattern around zero results in a net effect of no significant change.

Table 4. Long-run elasticity of meat advertising with respect to indicated meat revenue[a]

Revenue	Brand beef	Generic beef	Brand pork	Generic pork	Poultry
Beef	0.04[b]	-2.62[b]	-6.68	-0.18**,[b]	2.43
Pork	11.51[b]	-2.22	2.06	5.00**,[b]	4.82
Poultry	-7.39*	4.88**,[b]	4.97	2.80**,[b]	-3.78

* = 10% significance, ** = 5% significance

[a] Entries in table represent ε_{ij} where i is the column and j is the row. For example, the elasticity of brand beef advertising with respect to beef revenues is 0.04.

[b] Indicates a statistically significant test for Granger causality

Note the responses by BBADV and GBADV to PLTRYTR. Brand beef advertisers are shown to decrease expenditures in response to increases in poultry revenues while generic beef advertising expenditures increase. Strategically, beef advertisers may view threats from the poultry industry as damaging beef producers and processors as a whole. Thus, generic advertising could be viewed as the appropriate strategic tool in such a case.

Generic pork advertising is shown to respond to revenues of all three commodity groups. We discussed the response to own revenues earlier. There is a weak negative response to beef revenues, but a strong positive response to poultry revenues. Thus, both generic beef and generic pork advertising respond positively to increases in PLTRYTR in the long-run. As posited earlier, it may be that generic advertising is the best strategic tool for one commodity group to combat another

Finally, poultry advertising does not respond to any revenue signals in a significant manner. It appears, therefore, that poultry advertisers do not account for changes in market position when developing their advertising strategies. Rather, they have a purely advertising-based strategy, responding to other commodity groups' changes in advertising expenditures. The same is true of branded pork advertising. All others, however, employ a mixed strategy based on realizations of both advertising expenditures and retail revenues.

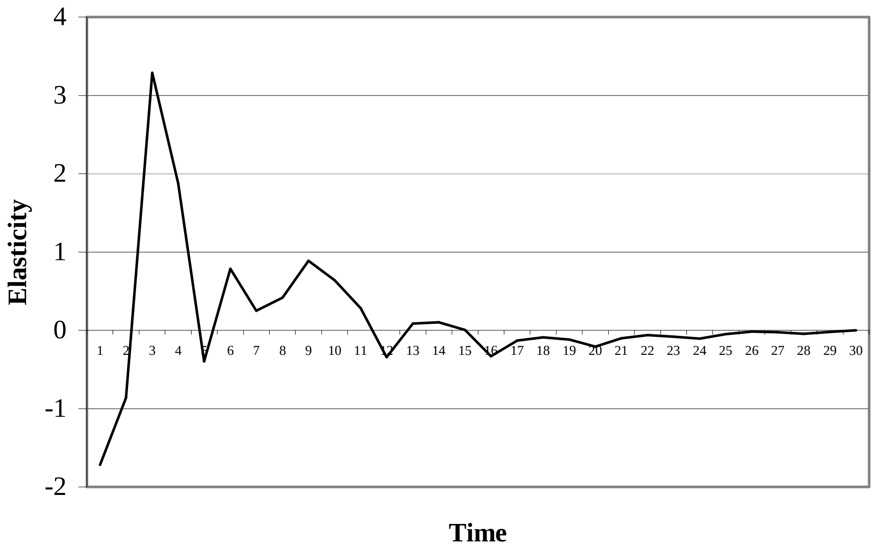

Figure 8. Impulse response function of BBADV with respect to BEEFTR

6. Summary and Conclusion

The analysis employed in this paper sheds light on the dynamic relationships between groups of meat advertisers. A time series econometric approach was employed to assess both short and long-run strategic responses by advertisers to other groups of advertisers or to retail meat revenues. In general, our results provide evidence of significant short and long-term strategic responses. A list of some of the more interesting findings includes the following.

- In the short-run, most groups respond quickly to other groups' advertising, but that response is frequently negative.
- There is no clear pattern indicating how a group responds to shocks in its own revenue
- Generic beef and pork advertisers seem to respond positively to changes in poultry industry revenues; presumably in direct competition.
- Generic advertisers appear to advertise only when others are not advertising at a high level.
- Poultry advertisers appear to follow a purely advertising-based strategy, failing to respond to changes in revenues of other industries.

Taken together, these results suggest clearly that the strategic relationships between poultry and either beef or pork are different from that of the beef-pork relationship. Given that poultry does not have a generic advertising campaign, this makes some sense. Our interpretation of some results suggests that generic advertisers increase advertising when overall industry advertising is low. Because poultry does not have that, it might behave differently toward the other industries.

This research builds off earlier studies by Hyde and Foster (2003), who found evidence of strategic responses in pork advertising. Also, the results found here provide an empirical test of Krishnamurthy's (2000) analytical model. There, it was shown that brand advertising may increase in response to increases in generic advertising in order to gather a share of the expanding market. Our results, however, show no long-run response to generic advertising by brand advertisers.

The main contribution of this paper is that it provides a first look at meat industry advertising dynamics. Analysis of this sort, which provides a long-run view via time-series methods, is absent from the current literature. Although this work represents an important first step in understanding advertising dynamics in the meat industry, it does have a few data issues that should be addressed. The study relies on aggregate data. While it is certainly the case that advertising strategies are set at the firm level, analogous firm-level data are not available. Firm-level advertising data would provide a clearer indication of the presence of strategic responses, but this is left for further research. Additionally, the analysis could be made more contemporary if more recent data, which are very costly to collect, were to be used.

7. References

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