MARKETING SCIENCE
Vol. 24, No. 1, Winter 2005, pp. 81–95
ISSN 0732-2399 | EISSN 1526-548X | 05 | 2401 | 0081
DOI 10.1287/mksc.1040.0087
© 2005 INFORMS

Differences in Dynamic Brand Competition Across Markets: An Empirical Analysis

Jean-Pierre Dubé, Puneet Manchanda
Graduate School of Business, University of Chicago, 1101 East 58th Street, Chicago, Illinois 60637
{jdube@gsb.uchicago.edu, puneet.manchanda@gsb.uchicago.edu}

We investigate differences in the dynamics of marketing decisions across geographic markets empirically. We begin with a linear-quadratic game involving forward-looking firms competing on prices and advertising. Based on the corresponding Markov perfect equilibrium, we propose estimable econometric equations for demand and marketing policy. Our model allows us to measure empirically the strategic response of competitors along with economic measures such as firm profitability. We use a rich dataset that combines sales, marketing mix, factor cost, and advertising cost data for eighteen geographic markets in the frozen entrée category.

We find that larger markets tend to be less price-sensitive and more profitable than smaller markets. We also find evidence of positive carryover of own advertising on own demand. In terms of consumer substitution patterns, we find that the role of advertising (in our data) seems to be more category-building (complementary) than share-stealing (competitive). The complementary role is stronger in larger markets. On the supply side, we find that firms make smaller adjustments to own advertising as goodwill goes up. Consistent with cross-advertising effects on demand, firms make smaller (larger) adjustments to advertising in response to competitive goodwill in the less competitive larger (in the more competitive smaller) markets. Finally, we find that consumer welfare decreases (increases) in larger (smaller) markets when firms move to a zero-advertising regime.

Key words: competition; advertising; multiple geographic markets; structural models; Markov perfect equilibrium; dynamics; packaged goods
History: This paper was received September 4, 2001, and was with the authors 10 months for 4 revisions; processed by James Hess.

1. Introduction

Consumer goods manufacturers typically compete in various geographic markets. Recently, research has begun to focus on geographic differences in responses to marketing-mix variables (Boatwright et al. 2004) and the potential dependencies of marketing efforts across neighboring regional markets (Bronnenberg and Mahajan 2001). In consumer goods markets, marketing policies typically consist of three types of strategic instruments: prices, promotions (in this paper, we use "promotion" to refer to nonprice promotion only), and advertising. These instruments usually have strong carryover effects in demand (Leeflang and Wittink 1992, Clarke 1976), requiring firms to be forward looking. Thus, competitive marketing decisions are not only market specific, they are also inherently dynamic. The extant empirical research in marketing has not formally disentangled the supply and demand responses to dynamic marketing effort. Little attention has been paid to the measurement of market-specific differences in optimal marketing decisions, especially in a dynamic environment.

We wish to empirically measure the long-run profitability of marketing effort, pricing, and advertising for a consumer packaged goods (CPG) category and to describe the differences in such efforts across the largest U.S. markets. A novel feature of our empirical analysis is the data we use to estimate the model, collected from the frozen entrée industry. Our data comprise three years of weekly sales, prices, promotions, and advertising gross ratings points (GRPs) for 18 major U.S. city-markets. We supplement these data with market-specific information on both production costs (wages and factor prices) and advertising costs (cost per GRP), which provide exogenous sources of variation in the marketing variables.

To guide us in the formulation of the econometric specification, we begin with an economic model of profit-maximizing firms. The model accounts for a decision-making process that spans several strategic marketing instruments and a long-run planning horizon (Vilcassim et al. 1999, Slade 1995). In the model, we account for firms' strategic responses to intertemporal changes in their own and their competitors' marketing effort. We base our econometric specification on the corresponding Markov perfect equilibrium (MPE) in prices and advertising. After fitting the model to marketing data, we then carry out policy experiments to quantify the value of advertising to firms and consumers.

Our results show that the pattern of demand, margins, and profits varies significantly across markets. We find that larger markets tend to be less price sensitive and more profitable than smaller markets in this industry. With respect to advertising, we find that own current and past advertising has a positive effect on own demand. The role of advertising (in our data) seems to be more category building (complementary) than share stealing (competitive). The complementary role of advertising is much stronger in the larger markets relative to the smaller markets, possibly because media availability in smaller markets is much lower, leading to firms behaving more competitively with regard to advertising.

On the supply side, we find that firms make adjustments to own advertising in response to current goodwill—as goodwill goes up, advertising adjustments are smaller. We find that the adjustment to advertising as a function of competitive goodwill is consistent with the cross-advertising effects on demand—we find larger adjustments in the more competitive smaller markets. In particular, the evidence suggests that when competitive advertising is complementary, firms lower their own advertising in response to competitors' goodwill. Because smaller markets tend to have less complementarity, advertising tends to be more competitive. Firms also condition their adjustments of the cost of GRPs in each market, with the three firms adjustments' depending on the cost of different dayparts.

We use the model to compute the change in long-run profits in response to current investment in advertising goodwill. The direct effect of advertising (arising through the carryover in demand) is positive for large markets for all the products in our data. This is not true in the small markets. Interestingly, we find the direct effect of advertising to be an order of magnitude larger than the strategic effect (arising through competitive reactions). Thus, the total effect of advertising tends to be driven more by the direct influence of carryover effects than the strategic influence of competitive response.

We also look at the welfare implications of setting advertising to zero each period. Consumers benefit from advertising in smaller markets where advertising is fairly competitive. Intuitively, competition on advertising erodes market power and thus lowers equilibrium prices. In contrast, in larger markets where advertising is more complementary, we find that consumers are harmed by advertising. While advertising tends to expand the product category, in equilibrium firms tend to free-ride off one another's advertising investments as competitive advertising increases own market power and thus prices.

The rest of the paper is organized as follows. We describe our model and the econometric specification in §2. Section 3 describes the data. We discuss the results in §4 and conclude in §5.

2. Model and Econometric Specification

We present a dynamic oligopoly model to describe the frozen entrée industry. We base the econometric specification on the corresponding equilibrium conditions of the model. The link to a model helps us control for the endogeneity of strategic variables during estimation. It also allows us to measure empirically the long-run profitability of advertising while controlling for competitive response.

2.1. Aggregate Demand

We model consumer demand for the J brands using the convenient linear demand system, a model that has been used frequently in the marketing literature (see, for instance, Roy et al. 1994, Vilcassim et al. 1999, Kadiyali et al. 2002). Specifically, we model total consumer demand for brand j in a market at time t as

$$Q_{jt} = \alpha_j + \sum_{k=1}^{J} \beta_{jk} p_{kt} + \phi_j F_{jt} + \sum_{k=1}^{J} \delta_{jk} G_{kt} + \gamma_j y_t + \zeta_{jt}, \quad (1)$$

where p_k is the price of brand k, F_j is the current promotion level for brand j, G_k is the current stock of accumulated advertising goodwill for brand k, y is the total income in the market, and ζ_{jt} is a random demand shock capturing aggregate demand-shifting variables that are unobserved by the researcher. As we assume demand and competition are independent across markets, we omit the market subscript to simplify notation. An important feature of this demand system is that it allows for different own and cross-effects of advertising on each of the demand curves because we do not impose any restrictions on the sign of the advertising effects. The existing literature has documented that, in a multiproduct market, a competitor's advertising could be category building or share stealing (e.g., Roberts and Samuelson 1988, Vilcassim et al. 1999, Gasmi et al. 1992). We also include own promotion as one of the demand shifters (e.g., Boatwright et al. 2004, Montgomery 1997).[1] The set $\{\alpha_j, \beta_{jk}, \phi_j, \delta_{jk}, \gamma_j\}_{j,k=1}^{J}$ consists of parameters to be estimated.[2]

[1] In the context of city-level aggregate data, it is difficult to measure promotion accurately (we use the share of items sold on promotion), and hence we view its inclusion only as a control.

[2] While it is straightforward to treat promotions as an additional policy variable in the supply-side model below, it is not clear whether this would be a reasonable assumption. In this industry, promotions are funded by manufacturers while the quarterly promotional calendar is worked out by retailers with varying levels of manufacturer involvement. In the empirical analysis, we control for the potential endogeneity of promotions using instrumental variables—but we do not model promotion decisions explicitly.

We assume that aggregate consumer response to advertising variables exhibits carryover effects (e.g., Clarke 1976, Lodish et al. 1995). To capture these long-run effects, we model current accumulated goodwill as $G_{jt} = ad_{jt} + \sum_{\tau=1}^{\infty} \eta^{\tau} ad_{jt-\tau}$, which consists of current advertising effort measured in GRPs, the historic goodwill stock, and $\eta \in (0, 1)$, a depreciation factor (assumed to be the same for all firms) for past advertising. Hence, we can think of goodwill as

$$G_{jt} = ad_{jt} + \eta G_{jt-1}. \tag{2}$$

2.2. Prices and Advertising

We now discuss the supply side of the model, consisting of competing manufacturers setting both prices and advertising each week. We do not model the downstream retailers' decisions, which could be interpreted as assuming a competitive retail environment or constant retail mark-ups (e.g., Vilcassim et al. 1999). The firms' decisions consist of setting prices, p_{jt}, and adjusting their advertising levels, Δad_{jt}, on a market-by-market basis. Our decision to model advertising decisions as an adjustment, versus a level effect, was based on our understanding of media planning in this industry. We expect high-frequency (weekly) changes in advertising to reflect an adjustment to a baseline rate determined at a much lower frequency (quarterly). Our understanding is that firms determine a baseline ad rate well in advance. However, over time, they monitor their own and their competitors' advertising behavior and brand performance. As a result, they periodically adjust their advertising decisions (up or down) accordingly. Similar adjustment models have been used for pricing (Slade 1995), demand (Karp and Perloff 1989, Roy et al. 1994), and market shares (Sorger 1989).

To determine the appropriate solution concept for the model, we spoke with several industry experts about media planning in CPG industries. This discussion indicated that firms adjust marketing instruments on a periodic basis in this category in response to changes in the market. Specifically, even though manufacturers choose a network advertising schedule over an accounting period (typically a quarter), they use spot markets to make adjustments to their chosen advertising levels on a weekly basis across markets (as discussed later, expenditure on spot TV advertising represents a high proportion of all advertising expenditure in this industry). These adjustments are based on tracking of recent own and competitive advertising efforts, where the latter are monitored to account for competitive dilution of own ad efforts. In the model below, we make the additional assumption that firms know the goodwill formulation process (2).

Given this industry behavior, we use the MPE solution concept. MPE, or "feedback," strategies are state-dependent, where the state is defined as the payoff-relevant historic information. Thus, current marketing decisions are based only on the current state variables (e.g., own and competitors' goodwill). Empirically, the state-dependence of the feedback strategies accommodates the types of dynamic competitive responses one would expect to observe in competitive environments (Leeflang and Wittink 1992, 2001; Erickson 1995). Theoretically, such strategies must, for any starting date t, constitute a Nash equilibrium for the remaining subgame (i.e., they are subgame perfect). For linear-quadratic games, feedback strategies also have the attractive feature that they are linear in the state.

Firms incur variable marketing and production costs. For production decisions, firm j faces marginal costs

$$mc_{jt} = p_t^Q c_j' + \eta_{jt}, \tag{3}$$

where p^Q are factor prices, c_j' is a vector of firm j factor intensities, and η_{jt} is a mean-zero random component capturing aspects of firm j marginal cost that are unobserved to the researcher (cf. Horsky and Nelson 1992). For advertising decisions, firm j faces advertising costs

$$C_{jt}^{ad} = p_t^{\mathrm{GRP}}(ad_{jt}) + \tfrac{1}{2} g_j (\Delta ad_{jt})^2, \tag{4}$$

where p_t^{GRP} is the market price of GRPs and g_j is firm j's cost of adjusting advertising. Note that this formulation implies that advertising involves a financial cost, based on the price of GRPs and the level of GRPs purchased, as well as an adjustment cost, based on the size of the weekly ad adjustment. Similar to Slade (1995) and Vilcassim et al. (1999), we use a quadratic advertising cost structure to capture the diminishing returns of marketing effort on firm profits. Another interpretation of the quadratic component is that it reflects the extra workload of market monitoring and negotiation required to acquire rating points on the spot market. The larger the required changes, the larger the additional workload. Given the capacity contstraints to advertising (e.g., only so many GRPs are available at a moment in time), we also expect upward-sloping costs in obtaining large quantities of GRPs. The period t profits facing firm j are thus

$$\pi_{jt} = (p_{jt} - mc_{jt}) Q_{jt} - p_t^{\mathrm{GRP}} ad_{jt} - \tfrac{1}{2} g (\Delta ad_{jt})^2. \tag{5}$$

We now summarize the payoff-relevant history in a state vector $S_t = (G_t', \xi_t)'$ where $G_t = (G_{1t}, \ldots, G_{Jt})'$ and $\xi_t = (p_t^Q, p_t^{\mathrm{GRP}})'$. We assume the state, S_t, is observed by all players. We also assume that the exogenous state variables are distributed i.i.d. according to $\xi_t = \bar{\xi} + v_t$, where $E(v_t) = 0$ and $var(v_t) = \Sigma$. Firms observe this mean level, $\bar{\xi}$, and know the distribution of v_t. Finally, from (2), we can show that goodwill stock evolves over time as $G_{jt} = [G_{jt-1} + \Delta ad_{jt} +$

$\eta\Delta ad_{jt-1}+\eta^2\Delta ad_{jt-2}+\cdots]$. Given these laws of motion for G_t and ξ_t, we can therefore write the law of motion of the state vector in the matrix form

$$S_t = AS_{t-1}+\sum_{j=1}^{J}\sum_{\tau=0}^{\infty}B_j(\Delta ad)_{jt-\tau}+u_t. \tag{6}$$

The matrices A and B consist of cells of known values corresponding to the laws of motion described above and $u_t=(0_J, \nu_t)'$.

Because current prices do not affect future profits of the firm, the optimal prices can be solved out by maximizing current profits gross of advertising costs (note that we did not find any evidence of price carryover effects in our data). The optimal period prices satisfy the system of first-order conditions:

$$p^*_{jt}=mc_{jt}+\frac{1}{\beta_{jj}}Q_{jt}, \quad j=1,\ldots,J. \tag{7}$$

Although we solve prices statically, they will be influenced indirectly by dynamics in advertising decisions; i.e., dynamics in advertising decisions generate dynamics in the equilibrium prices. Moreover, a one-time change in advertising will also impact future goodwill levels directly, as well as future advertising and goodwill levels indirectly, via competitive response, generating a long-run impact on prices. Using the optimal set of prices, we can reparameterize the firm's profit function in terms of advertising adjustments. The corresponding per-period profit function can be written in linear-quadratic form[3]:

$$\pi_{jt}(S_t,\Delta ad_{jt})=\tfrac{1}{2}S_t'\Omega_j S_t-\chi_j S_t-\tfrac{1}{2}g_j(\Delta ad_{jt})^2, \tag{8}$$

where Ω and χ are matrices containing the parameters to be estimated. The profit function, (8), has a linear-quadratic structure in the state and policy variables.

We now focus on the optimal advertising decision. Because current adjustments to advertising affect future demand through carryover in goodwill, firms make forward-looking decisions over some sufficiently long planning horizon of length $T\le\infty$ and with a discount factor $\mu\in(0,1)$. Firms optimize the net present value of their future stream of profits subject to the law of motion of the state (6). Formally, firm j solves the optimization

$$\max_{\Delta ad}\sum_{t=1}^{T}\mu^t E_t(\pi_{jt}), \tag{9}$$

subject to

$$S_t = AS_{t-1}+\sum_{j=1}^{J}\sum_{\tau=0}^{L}B_j(\Delta ad)_{jt-\tau}+v_t.$$

[3] The authors thank the AE and an anonymous reviewer for suggesting that we derive these relationships explicitly. The detailed derivations are in a technical appendix available at http://mktsci.pubs.informs.org.

This optimization problem can be rewritten as the optimization of the current Hamiltonian each period:

$$H_{jt}=\pi_{jt}(S_t,\Delta ad_{jt}) + \lambda_{jt}\left(S_t-AS_{t-1}-\sum_{j=1}^{J}\sum_{\tau=0}^{L}B_j(\Delta ad)_{jt-\tau}-v_t\right). \tag{10}$$

Given the linear-quadratic form of period profits, it is well known that such games yield optimal feedback policies that are linear in the state and, under certain conditions, are unique. This linear optimal policy still holds in our specific case in which some of the states, such as random demand and cost shifters, are stochastic. Because solutions to general forms of linear-quadratic games are well known (see Fornell et al. 1985, Chintagunta and Jain 1995), we refer the more interested reader to Basar and Olsder (1998) or Fudenberg and Tirole (1991) for a formal discussion of the derivation and properties of the solutions. We write the optimal advertising policy function as

$$\Delta ad_{jt}=\sigma_j+\rho_j S_t+\varpi_{jt}, \tag{11}$$

where σ_j and ρ_j are parameters to be estimated. We add the mean-zero random term, ϖ_{jt}, to capture the impact of states that are unobserved by the researcher. For instance, if the unobserved component of demand, ζ_{jt}, is observed by firms, then it would also constitute part of the state vector. This completes the characterization of our model. In the empirical section, we treat the ad policy, (11), as a linear regression of ad adjustments on the state variables.[4]

2.3. Econometric Specification

We use the system (1), (7), and (11) to build an empirical model to describe our data. The data itself consist of a balanced panel of N markets with T weeks and J products per market. Stacking the system of three equations, we write

$$Y_j = x\beta_j+\varepsilon_j, \quad j=1,\ldots,J,$$

where β_j is a vector of all model parameters,

$$y_j=\begin{bmatrix}Q_j\\ p_j\\ \Delta ad_j\end{bmatrix}$$

is the $(3NT\times 1)$ vector of dependent variables, and x is a $(3NT\times K)$ matrix of regressors. The stochastic $(3NT\times 1)$ vector

$$\varepsilon_j=\begin{bmatrix}\zeta_j\\ \eta_j\\ \varpi_j\end{bmatrix}$$

[4] To evaluate g_j, we combine the parameter estimates of σ_j and ρ_j with a set of matrix conditions (Ricatti conditions) implied by the model.

captures the effect of states that are unobserved by the econometrician corresponding to the demand, cost, and ad-related shocks discussed in the model section. Stacking the stochastic term across the J products for a given market n in a given period t, we assume them to be jointly distributed with zero mean and covariance $E(\varepsilon_{nt}\varepsilon'_{nt}) = \Sigma$, which is a finite $(3J \times 3J)$ matrix. We jointly estimate the system

$$Y = X\beta + \varepsilon, \tag{12}$$

where $Y = (Y_1, \ldots, Y_J)'$, $X = I_J \otimes x$, $\varepsilon = (\varepsilon_1, \ldots, \varepsilon_J)'$ and the parameter vector $\beta = (\beta_1, \ldots, \beta_J)'$. The model presented in the previous section also provides a set of restrictions on the own-price parameters as well as the advertising policy parameters. We impose the cross-equation restrictions that the price-response parameters in the demand function (1) must correspond to the parameters in (7).[5]

We estimate (12) using nonlinear three-stage least squares. We also account for the endogeneity of current prices, quantities, and advertising effort through the use of appropriate instrumental variables. Note that although we do not model the underlying strategic game determining promotion levels, we acknowledge that these decisions could be endogenous to pricing and advertising decisions. We therefore use instrumental variables to correct for the possibility that current promotions may be correlated with the demand shocks, ζ_{jt}. The precise instruments used are discussed in the data section below.

Finally, we control for market-specific differences in several of the model parameters. Our cross-section of 18 markets is insufficient to approximate a random coefficients distribution across markets (e.g., Hoch et al. 1995). We use the demographics to cluster the 18 markets (details in §4). We then estimate cluster-specific parameters.

3. Data

The sales and marketing instruments we use were collected by various firms (e.g., ACNielsen, Competitive Media Research) and made available to us by Management Science Associates. The data consist of three years (January 1991 to January 1994) of weekly (156 weeks) sales and marketing-mix variables across 18 (ACNielsen's SCANTRAK) markets in the frozen entrée product category. The overall descriptive statistics of our data, along with the market demographics (from the annual March census)[6] and the factor costs (based on the Producer Price Indices available at www.bls.gov), are reported in Table 1. The list of markets is given in Table 2.

Table 1 Descriptive Statistics

	Mean	Std. dev.
Quantity ('00000)	1.05	0.85
Price ($)	2.03	0.34
GRP (100 points)	0.23	0.58
Promotion	0.34	0.22
Population (MM)	5.51	2.73
College (%)	31.0	10.0
Median family size	3.23	0.22
Median income ($)	34.87	5.84
Median poverty	3.34	0.54
White (%)	81.0	9.0
Wages ($/hr)	11.27	1.74
Frozen meat	109.67	3.32
Turkey	131.87	7.70
Frozen vegetables	130.49	2.95
Frozen entrée (wholesale)	129.99	2.20
Frozen fish	146.54	3.22
GRP costs ($)	171.14	119.54

The frozen entrée market was worth $1.4 billion in retail sales (average across the period 1991–1994). The average volume growth was about 4%–5% during this period (*Frozen Food Executive*, December 1992–1994). There were no significant brand introductions or withdrawals during this period. The average expenditure on advertising was $127 million—thus the ad-to-sales ratio was about 10% (*Leading National Advertisers*). More than 60% of the total sales in this category were accounted for by three main brands: Budget Gourmet (BG), Stouffer's (ST), and Swansons (SW). At that point, they were marketed by the All American Gourmet Company (a fully owned subsidiary of Kraft), Nestle, and Campbell Soup, respectively. We therefore consider these three brands in our analysis. Their respective mean shares—based on units sold—across all markets (relative to a three-brand market) during this period were 33.4%, 36.9%, and 29.7%. However, as can be seen from Table 2, sales (and shares) of the three brands vary significantly across the 18 markets.

In terms of the marketing-mix variables, the price we use is the average weekly shelf price per single-serving unit (typically between 8 oz.–11 oz). BG is

[5] However, we do not impose the Ricatti conditions implied by the supply side of the model during estimation. Instead, we take the estimated parameter vector, β, and use the Ricatti conditions to compute the market-specific adjustment cost parameters for each firm, g_j. This two-step approach is used for computational tractability to allow us to accommodate the large state vector.

[6] In the CPS data, the poverty level of a household is reported as the ratio of income to a "low-income" level. For each market year, we take the median poverty level across households. We convert the output into a categorical variable with the following values: 1 if level < 1.75, 2 if level $\in (1.75, 1.99)$, 2.5 if level $\in (2, 2.49)$, 3 if level $\in (2.5, 2.99)$, 3.5 if level $\in (3, 3.49)$, 4 if level $\in (3.5, 3.99)$, 4.5 if level $\in (4, 4.49)$, 5 if level $\in (4.5, 4.99)$.

Table 2 Mean Weekly Quantity, Price, Advertising, and Promotion

	Quantity (100,000 units)			Price ($)			GRP (100 points)			Promotion (%)		
Market	BG	ST	SW	BG	ST	SW	BG	ST	SW	BG	ST	SW
Atlanta	0.57	0.74	0.17	1.72	2.18	1.90	0.09	0.51	0.05	0.09	0.06	0.05
Boston	0.78	1.34	0.99	1.74	2.12	1.94	0.034	0.58	0.16	0.19	0.17	0.15
Chicago	1.74	2.05	1.12	1.69	2.17	1.96	0.13	0.49	0.16	0.26	0.19	0.16
Cincinnati	0.48	0.50	0.42	1.70	2.31	1.90	0.02	0.40	0.05	0.12	0.09	0.07
Dallas	0.78	0.82	0.63	1.69	2.30	1.94	0.13	0.42	0.05	0.21	0.14	0.10
Denver	1.02	0.66	0.68	1.72	2.29	2.01	0.41	0.41	0.04	0.21	0.11	0.09
Houston	0.73	0.48	0.49	1.77	2.61	2.06	0.05	0.36	0.06	0.16	0.08	0.08
Los Angeles	3.02	3.04	2.29	1.82	2.52	2.06	0.14	0.43	0.17	0.25	0.13	0.13
Miami	0.57	1.12	0.57	1.59	1.98	1.83	0.03	0.66	0.05	0.14	0.08	0.10
Minneapolis	0.30	0.41	0.63	1.64	2.02	1.79	0.03	0.01	0.07	0.18	0.18	0.14
New York	1.34	2.66	2.32	1.88	2.39	2.26	0.14	0.61	0.01	0.30	0.19	0.21
Philadelphia	0.86	2.02	1.63	1.89	2.36	2.20	0.17	0.79	0.18	0.25	0.19	0.19
Phoenix	1.07	0.62	0.71	1.70	2.41	2.03	0.29	0.12	0.01	0.27	0.08	0.12
Seattle	1.43	0.65	1.07	1.83	2.33	2.02	0.14	0.01	0.06	0.26	0.14	0.11
San Francisco	1.42	1.19	1.28	1.93	2.87	2.35	0.12	0.48	0.20	0.18	0.09	0.09
St. Louis	0.80	0.24	0.25	1.75	2.52	2.01	0.27	0.01	0.08	0.29	0.15	0.17
Tampa	0.83	1.08	0.72	1.62	2.11	1.79	0.10	0.82	0.06	0.07	0.05	0.08
Washington	1.16	1.22	0.81	1.75	2.46	1.97	0.17	0.59	0.11	0.22	0.13	0.15

the lowest-price brand (average share-weighted price $1.72), with SW at a 14% premium to BG ($2.03), and ST is the most expensive brand at a 33% premium to BG ($2.26) (see Table 2). With respect to promotion, we have data on the number of units sold on promotion (feature advertising or display, or feature advertising and display) during a week. The number of units sold under promotion varies by brand. On average, BG sells about 20% of its units under promotion, while ST and SW sell 13% and 12% under promotion (Table 2). A limitation of our aggregate data is that we cannot decompose the price and promotion sensitivities into brand switching, timing acceleration, and quantity increases (cf. van Heerde et al. 2003).

Finally, we have advertising data that consists of gross rating points (GRPs) representing the combined weight of advertising from different TV sources—network, spot, syndicated, and cable (Table 2). TV advertising dollars accounted for 72% and spot TV dollars accounted for 35% of total advertising dollars in this category during this period (*Leading National Advertisers*). ST is the clear leader in average advertising with 43.3 GRPs per week, followed by BG with 16.5 GRPs per week, and SW with 9.76 GRPs per week. Table 2 shows, however, that different brands focus the weight of advertising in different cities—BG focuses on Denver, Phoenix, and St. Louis; ST focuses on Boston, Miami, New York, Philadelphia, Tampa, and Washington; and SW focuses on Boston, Chicago, Los Angeles, Philadelphia, and San Francisco. Casual observation suggests that BG is focusing on relatively small markets, whereas ST focuses on large and intermediate markets, and SW focuses only on large markets. In terms of competitive behavior vis-à-vis advertising, a simple correlation of the mean levels across markets shows that BG advertising is somewhat negatively correlated with ST and SW advertising ($\rho_{(\mathrm{BG,ST})} = -0.23$, $\rho_{(\mathrm{BG,SW})} = -0.19$), while ST and SW advertising is somewhat positively correlated ($\rho_{(ST,SW)} = 0.30$). There is also substantial variation across markets and brands in the volatility of advertising over time—the standard deviation of weekly GRP changes is 35.03 (BG), 74.93 (ST), and 28.12 (SW).

A key feature of our model is the focus on advertising effort, captured through gross rating points (GRPs). With the exception of a few recent studies (e.g., Vilcassim et al. 1999), most prior research has used advertising expenditure to capture the effects of advertising on sales. However, advertising expenditures typically are *accounting* measures and therefore may not accurately represent true advertising effort at each temporal unit in the data. On the other hand, weekly GRPs are a *marketing* measure of advertising effort in each temporal period and therefore are likely to be more accurate. In addition, GRPs also represent measures that are adjusted for market size.

As mentioned earlier, we also control for the endogeneity of marketing variables in our model. The exclusion restrictions in our model yield three sets of instrumental variables—demographics, production costs, and GRP costs. The production costs consist of monthly factor price indices and a monthly, market-specific wage index data obtained from the Bureau of Labor Statistics (see www.bls.gov for details on how these are computed). The GRP costs are list prices

($ per GRP) for each market (across different times of the day) obtained from the *Media Market Guide*. The use of advertising cost data makes it unnecessary to estimate the cost of each GRP from the data (cf. Vilcassim et al. 1999). We find that our instruments perform quite well. The first-stage regressions of prices and advertising levels on these instruments produced R^2 values of about 0.35 to 0.69. Although not reported, we also experimented with marketing variables from other markets as instruments (cf. Hausman 1997), which were found to provide lower R^2 values.

4. Results and Discussion

In this section, we discuss the empirical results arising from the specified model. We use cluster analysis to group the 18 markets into clusters based on the demographics (using the `Proc Cluster` procedure in SAS via the Ward method). The clustering variables we used were all the demographic variables except total income. Clustering provides a parsimonious way of interacting market demographic variables with marketing instruments. We find that three clusters accounted for 93% of the variance in the clustering variables (using the R^2 measure reported by the procedure). The three clusters that we find are (1) Atlanta, Cincinnati, Dallas, Denver, Houston, Miami, Minnesota, Phoenix, Seattle, Tampa, and Washington; (2) Boston, Chicago, New York, Philadelphia, and San Francisco; and (3) Los Angeles. The main clustering variable seems to be market size (population). As can be seen from the above and Tables 2 and 3, Cluster 1 comprises the small markets, Cluster 2 the bigger markets, and Cluster 3 just one very large market.[7] We summarize the demographics and marketing instruments for each cluster in Table 3.

Clustering provides a parsimonious way of controlling for differences across markets. We do not have enough degrees of freedom to estimate all parameters as cluster-specific parameters. We therefore estimate a subset of our parameters as cluster specific. For demand, we estimate cluster-specific parameters for all the own and cross-prices and goodwill. On the supply side, we estimate cluster-specific mean intercepts in the cost function and own- and cross-goodwill parameters in the advertising policy equation. However, as markets could differ even though we have cluster-specific parameters, we retain the market-specific demographics in the demand and advertising policy equations.

Table 3 Cluster-Level Descriptive Statistics

	Cluster 1 (Atlanta)	Cluster 2 (Boston)	Cluster 3 (Los Angeles)
Population (MM)	4.02	7.27	14.59
College (%)	32	32	24
Family size	3.20	3.22	3.76
Median Income ($ '000)	35.3	35	27.3
Median Poverty (%)	3.35	3.50	2.50
White (%)	82	78	83
BG qty ('00000)[a]	0.81	12.34	3.02
ST qty ('00000)[a]	0.71	18.71	3.04
SW qty ('00000)[a]	0.60	14.78	2.29
BG price ($)[a]	1.71	1.83	1.82
ST price ($)[a]	2.29	2.38	2.52
SW price ($)[a]	1.94	2.14	2.06
BG GRP ('00)[a]	0.18	0.14	0.14
ST GRP ('00)[a]	0.36	0.60	0.44
SW GRP ('00)[a]	0.07	0.15	0.17

[a]Weekly averages.

We also simplify our treatment of the goodwill formulation as $G_{jt} = ad_{jt} + \sum_{\tau=1}^{L} \eta^{\tau} ad_{jt-\tau}$, where L is a cutoff point after which we assume past advertising effects cease to persist (cf. Erdem and Sun 2002, Vilcassim et al. 1999).

4.1. Demand

We begin by discussing the results for the demand system. The estimates from the demand function are detailed in Table 4. The responses to prices are all significant. The own-price effects are negative and the cross-price effects are positive, which is consistent with economic theory in categories with substitute products. We also find that the demand sensitivity to prices varies across our three clusters (see Table 5). We find Cluster 3 to be the most price inelastic, Cluster 2 to be intermediate, and Cluster 1 to be relatively price elastic, in line with the own-price parameters in the demand system. In other words, the smaller the market, the more price elastic it is likely to be. This may be because the mean price level is higher in the larger markets (Table 3). In addition, the coefficient of variation is also higher in the larger markets. In terms of the three brands, there are some noticeable differences across clusters (Table 5). Consumers seem to have similar price sensitivities across all three brands in Cluster 3. We find that consumers have the lowest price sensitivity for BG in Cluster 1 markets, whereas in Cluster 2, consumers have the lowest price

[7] In terms of the clustering procedure, three issues are noteworthy. First, a model with clusters had a better fit in terms of prediction (lower root-mean-square error) relative to a model with no clusters. Second, this cluster configuration was stable across many different sets of clustering variables. These included subsets of the demographics as well as response variables from simpler models. Third, in every clustering scheme we tried, Los Angeles was identified as a unique cluster. In the retained scheme, separating Los Angeles into a unique cluster explained 65% of the variance, and then separating out the large markets (Cluster 2) accounted for an additional 28% of the variance across the clustering variables.

Table 4 Demand Coefficients

	Budget Gourmet		Stouffer's		Swanson	
	Parameters	Std. error	Parameters	Std. error	Parameters	Std. error
Income	4.52E-10	3.16E-10	1.17E-09[a]	4.14E-10	3.16E-09[a]	2.63E-10
Price BG1	−2.18[a]	0.05	0.16[a]	0.07	0.58[a]	0.04
Price BG2	−2.19[a]	0.05				
Price BG3	−1.74[a]	0.08				
Price ST1	0.33[a]	0.04	−2.38[a]	0.06	0.62[a]	0.03
Price ST2			−2.40[a]	0.06		
Price ST3			−2.17[a]	0.08		
Price SW1	0.65[a]	0.06	1.42[a]	0.08	−2.09[a]	0.049
Price SW2					−1.72[a]	0.04
Price SW3					−1.50[a]	0.06
Promo BG	0.81[a]	0.08				
Promo ST			−0.08	0.12		
Promo SW					−0.15[b]	0.09
Goodwill BG1	0.08[a]	0.01	0.05[a]	0.01	0.05[a]	0.01
Goodwill BG2	0.06[a]	0.03	0.22[a]	0.03	0.11[a]	0.02
Goodwill BG3	0.31[a]	0.06	0.01	0.08	0.08[b]	0.05
Goodwill ST1	−0.04[a]	0.01	−0.03[a]	0.01	−0.04[a]	0.01
Goodwill ST2	−0.01	0.01	0.13[a]	0.01	0.07[a]	0.01
Goodwill ST3	0.08[a]	0.04	0.13[a]	0.05	0.08[a]	0.03
Goodwill SW1	0.04[a]	0.02	−0.03	0.03	−0.02	0.02
Goodwill SW2	0.04[a]	0.01	−0.01	0.02	−0.01	0.01
Goodwill SW3	0.10[a]	0.03	−0.02	0.04	0.01	0.03

Notes. For the sake of brevity, the intercept, seasonality, and demographic parameters are not reported here (but are discussed in the text).
[a] $p < 0.05$.
[b] $p < 0.10$.

sensitivity for SW. Thus, it seems that BG (the low-price, low-quality brand) is well entrenched in the smaller markets, while SW (the midprice, midquality brand) is well entrenched in the bigger markets, while all three brands have similar pricing power in the largest market.

Given the Bertrand pricing assumption, these elasticities directly imply price-cost margins, also reported in Table 5. The average margin across all the markets is 38% for BG, 19% for ST, and 37% for SW (this is consistent with prior research; e.g., Mojduszka et al. 2001 find the average margins in this category to be 30%). As expected, margins are much higher in Cluster 3. Also, BG has the highest margins in Cluster 1, whereas ST has the highest margins in Cluster 2.

The demand responses to advertising also show interesting patterns. Recall that advertising enters the demand function as the sum of current GRPs and current goodwill stock. To compute the goodwill stock, we use an exponentially smoothed sum of lagged advertising for five lags.[8] For both BG and SW, we find that own advertising increases demand across all clusters. We find a positive effect for ST as well except for Cluster 1.[9] BG advertising is clearly the most effective in Cluster 1, whereas ST advertising is most effective in Clusters 2 and 3. For SW, we find small and insignificant effects from own advertising.

We also observe interesting cross-advertising impacts. Recall that one of the advantages of our model is that we do not impose any constraints on the direction of cross-advertising effects. In Cluster 1, we find that there are three positive cross-advertising effects and two negative. In contrast, in Clusters 2 and 3 we see only positive cross-advertising effects (four and four, respectively). Thus, the results point to advertising being more complementary (category building) than competitive (share stealing) in the larger markets relative to the smaller markets. This is consistent with previous studies that have found complementary effects of cross advertising on demand (Roberts and Samuelson 1988, Gasmi et al. 1992, Vilcassim et al. 1999).[10]

[8] We used a two-stage approach in our final estimation. In the first stage, we computed a value for the carryover parameter, η, which was then fixed in the second stage. In the first stage, we use two different analyses to arrive at the value of η. Both analyses provided an almost identical "best" value of 0.70.

[9] At this stage, we do not have an explanation for the negative own-response parameter in this cluster. This may be due to an outlier, such as Minneapolis, in this cluster.

[10] This is also consistent with the general move in the industry to try and raise the profile of frozen entrées as a category at this time.

Table 5 Mean Cluster-Specific Own-Price Elasticities, Margins, and Marginal Costs

	Own-price elasticity (%)			Price-cost margins ($)			Marginal costs ($)		
	BG	ST	SW	BG	ST	SW	BG	ST	SW
Cluster 1	−5.89	−10.64	−9.15	0.37	0.30	0.27	1.33	1.99	1.65
Cluster 2	−4.15	−3.93	−2.89	0.56	0.77	0.67	1.26	1.61	1.29
Cluster 3	−1.14	−1.91	−1.42	1.73	1.39	1.31	0.08	1.14	0.54

In terms of the effects of each brand's advertising in each cluster, ST advertising has a negative effect on BG and SW demand in Cluster 1. In the same cluster, BG advertising increases the demand for ST and SW. In Cluster 2, the biggest beneficiary is SW, which benefits from both ST and BG advertising. In Cluster 3, BG and SW benefit from their competitors' advertising. Thus, ST advertising is clearly playing a category-building role in this cluster.

In conclusion, we find that advertising by the firms in this tends to be of a complementary nature in the large markets, but more competitive in the small markets. Therefore, on the supply side, one may expect such complementarities to cause firms to reduce their advertising levels in response to high competitor goodwill. We also find that brand advertising can play different roles in different markets (e.g., ST is complementary in the larger markets, but competitive in the smaller markets).

The promotion results are not very strong. We find that promotion increases own demand for BG but has no significant effect for ST. The SW effect is small but negative. This finding could be due to the manner in which we construct the promotion variable. While we include promotions as a control (for consistency with the literature), it is difficult to interpret the promotion coefficients because it is not a simple indicator variable as is typically used with store-level data.

Not surprisingly, we also find that larger population markets tend to sell more units. In terms of seasonality, we find that fall is the season with the strongest demand. This is consistent with industry information that demand drops in the winter holiday period and that summer demand is low due to higher outdoor activity (Bender 1995).

4.2. Marginal Cost and Advertising Policy

We now discuss our results for the supply side. The marginal cost parameters are reported in Table 6. In general, we find that BG has lower marginal costs than ST and SW. We use the results to compute the average marginal cost: $1.24 (BG), $1.84 (ST), and $1.49 (SW). As expected, the ordering of the mean marginal cost across the three brands is the same as the order of the mean market prices of the three brands ($1.72 (BG), $2.26 (ST), and $2.03 (SW)). We find that wages and most of the factor prices are significant. In particular, ST seems particularly sensitive to wages, explaining the high marginal cost in markets like St. Louis, where wages are relatively high. As a result, ST prices are high in St. Louis and, consequently, demand for ST is relatively low. We also find evidence of a small time trend in all three products' marginal cost.

We also report the cluster-specific costs in the last three columns of Table 5. Interestingly, we find that marginal costs are much lower in Cluster 3. Given the notably higher volume of sales for all three brands in LA, the relatively low costs likely reflect economies-of-scale.[11]

The results for the advertising policy function are detailed in Table 7. We focus our attention on those remaining state variables with statistically significant impact on advertising adjustments.[12] Advertising adjustments seem to be driven heavily by strategic response to goodwill stock. For all three products, we observe significantly negative response to own goodwill stock. Thus, when firms' goodwill stocks are high, they adjust their current advertising level downward. Thus, it seems that the firms' advertising exhibits patterns that are consistent with "pulsing"-like strategies. For BG, the own-response appears to be quite similar across clusters. ST, however, makes much larger adjustments in response to its own goodwill in Cluster 3 than the other clusters. Note that own-goodwill response for SW is insignificant in all three segments. Given the lack of impact of SW advertising on its own demand, this result is not surprising. Note that this does not preclude SW from advertising for competitive reasons because its goodwill levels

BG was trying to establish that frozen entrées were a high-quality item through its advertising (Bender 1995). ST was trying to differentiate itself on taste with the memorable tagline "The first frozen entrée that doesn't taste like the box it came in," while sending the message that frozen entrées were not necessarily low-quality meal alternatives (Wacker 1992).

[11] This may also be because two of the three brands were marketed by firms headquartered in LA—ST by Nestlé and BG by the All American Gourmet Company (a fully owned subsidiary of Kraft at that time).

[12] To conserve space, we do not report coefficients on factor prices which, even when statistically significant, were relatively small in magnitude. We also do not report the daypart parameters if they were not significant for all three brands.

Table 6 Marginal Cost Coefficients

	Budget Gourmet		Stouffer's		Swanson	
	Parameters	Std. error	Parameters	Std. error	Parameters	Std. error
Intercept1	−2.36	1.40	−1.567	2.00	−0.66	1.19
Intercept2	−2.46[b]	1.40	−2.06	2.00	−1.06	1.19
Intercept3	−3.64[a]	1.40	−2.52	2.00	−1.80	1.20
Wages	0.03[a]	0.004	0.11[a]	0.006	0.04[a]	0.004
Frozen meat	−0.01[a]	0.002	−0.003	0.003	−0.006[a]	0.002
Turkey	0.0032[a]	0.0015	0.000	0.002	−0.003[a]	0.001
Frozen vegetables	−0.003	0.005	0.016[a]	0.007	0.012[a]	0.004
Frozen entrée (wholesale)	0.018[a]	0.004	−0.002	0.06	−0.000	0.004
Frozen fish	0.013[a]	0.005	0.01	0.01	0.009[a]	0.004
Time	−0.0029[a]	0.0004	0.0011[b]	0.0006	−0.001	0.0004

[a] $p < 0.05$.
[b] $p < 0.10$.

do affect other firms' demand and thus pricing and advertising decisions.

The responses to competitors' goodwill stocks exhibit some interesting patterns. BG's adjustments to competitors' goodwill are very small and insignificant. This finding is not surprising because BG tends to advertise more aggressively in markets where its competitors do not typically devote much advertising effort (such as Phoenix and St. Louis). ST adjusts its advertising downward in response to BG goodwill in Cluster 1 because BG advertising has a complementary effect on ST demand (see Table 4). In Cluster 3, ST adjusts its advertising upward in response to BG goodwill in Cluster 3, even though BG advertising has no significant effect on demand. ST does not appear to respond to SW goodwill; this is not surprising because we found no cross effects of SW advertising on ST demand. Finally, SW adjusts its advertising downward in response to ST goodwill in Cluster 2, where the effect of ST advertising on BG is complementary.[13] In conclusion, we find that the three players respond to each other's advertising in a manner that is broadly consistent with cross effects on demand. The three firms also seem to condition their advertising on price of different time slots—BG on "prime time," ST on "day time," and SW on "late fringe."

The results show slightly higher cross response to advertising in the smaller markets. One possible reason for this finding is that managers and media planners react more competitively in markets where the media supply is restricted. The main difference between big and small markets is that of media availability (supply). Big markets typically have many more media outlets than smaller markets.[14] In larger markets, it is thus easier to target various subsegments, and firms spread out their advertising, resulting in lesser competition. In small markets, managers and media planners tend to overreact to the constrained supply, leading to more intense advertising competition.

Finally, we also find market-specific differences based on demographics. For instance, *all else equal*, over time BG will tend to have lower advertising levels in markets with higher median poverty rates and more advertising in markets with a higher proportion of whites. This latter effect helps interpret the emphasis on advertising in Phoenix, for instance, where the white population is the largest. ST also will tend to have lower ad levels in markets with higher poverty rates and larger average family sizes. The latter effect is intuitive because frozen entrées had a higher consumption rate among (older) single-person households (*Frozen Food Executive*, December 1992). Over time, ST will tend to have higher advertising in the larger-population markets. Finally, SW will tend to have lower advertising in markets with more white households and with higher proportions of college education. The seasonality results show that all three brands tend to adjust their advertising upward in the fall and lower it in the winter and summer. BG and ST also adjust advertising upward in the spring, while SW adjusts it downward. These adjustments are consistent with the demand patterns described earlier. In addition, there are some minor variations in temporal advertising patterns: BG and ST target fall and spring, while SW targets only fall.

4.3. Impact of Advertising on Equilibrium Prices

We discuss the impact of current accumulated goodwill on equilibrium prices in Table 8. The numbers

[13] We also find a similar effect in Cluster 1 even though the effect of ST advertising on SW demand is competitive. However, as can be seen from the table, this effect size is small.

[14] A big media market is characterized by the presence of the four national TV networks, at least one strong independent TV station/network, and many cable channels. Smaller markets typically have only three national networks, no independent station/network, and little presence of cable.

Table 7 **Ad Policy Coefficients**

	Budget Gourmet		Stouffer's		Swanson	
	Parameters	Std. error	Parameters	Std. error	Parameters	Std. error
Intercept	−0.63	1.43	12.82[a]	3.08	1.30	1.15
Goodwill BG1	−0.22[a]	0.01	−0.06[a]	0.03	0.0031	0.01
Goodwill BG2	−0.24[a]	0.02	−0.01	0.05	−0.01	0.02
Goodwill BG3	−0.23[a]	0.05	0.22[b]	0.12	−0.02	0.04
Goodwill ST1	−0.01	0.01	−0.25[a]	0.02	−0.0113[b]	0.0065
Goodwill ST2	−0.001	0.01	−0.26[a]	0.02	−0.02[a]	0.0075
Goodwill ST3	−0.006	0.03	−0.53[a]	0.07	−0.03	0.02
Goodwill SW1	−0.01	0.02	−0.05	0.04	−0.24[a]	0.01
Goodwill SW2	−0.01	0.01	0.01	0.03	−0.14[a]	0.01
Goodwill SW3	−0.003	0.03	0.07	0.07	−0.13[a]	0.03
Day time	0.001	0.001	−0.002[a]	0.001	−0.001	0.001
Prime time	−0.0004[a]	0.0002	0.001	0.0004	−0.0002	0.0002
Late fringe	0.0003	0.0004	−0.001	0.001	0.001[a]	0.0003
Winter	−0.02	0.02	−0.23[a]	0.05	−0.085[a]	0.019
Spring	0.06[a]	0.03	0.14[a]	0.06	−0.11[a]	0.021
Summer	−0.05[a]	0.02	−0.21[a]	0.05	−0.13[a]	0.017
Median poverty	−0.06	0.03	−0.09[a]	0.05	0.03	0.021
Median family size	0.03	0.05	−0.30[a]	0.11	−0.04	0.04
White	0.42[a]	0.15	−0.27	0.3165	−0.58[a]	0.12
Median college	−0.04	0.09	−0.22	0.2034	−0.13[b]	0.076
Population	−3.76E-05	6.26E-05	4.65E-04[a]	1.35E-04	4.25E-05	5.04E-05

[a]$p < 0.05$.
[b]$p < 0.10$.

in this table reflect the impact of 100 GRPs of current goodwill on the equilibrium price. Thus, the first column captures the impact of 100 BG GRPs on BG prices, the second column the impact of 100 ST GRPs on BG prices, and so on. Note that to translate these values into the impact of current advertising on future equilibrium prices t periods ahead would require depreciating the reported derivatives by μ^t. For instance, we allow current goodwill to depend on lagged advertising for up to five weeks by using a depreciation rate of $\mu = 0.7$. Thus, a current advertising investment by BG of 100 GRPs would increase its current price in Cluster 3 by almost seven cents, next week's price by five cents, and so on until finally the price five weeks from now would increase by just over one cent. In general, increases in own advertising lead to higher own prices. Referring back to Table 2, we observe that BG and ST advertise most heavily in markets where additional goodwill raises prices (Clusters 1 and 2, respectively). However, if the cost of advertising is too high in a market, the two firms pull back on advertising in the market even if the price increase as a function of goodwill is high (see BG and ST advertising in LA).

4.4. Impact of Advertising Investment on Long-Run Profits

From the above discussion, we see how advertising affects price levels over time. However, the bottom line for assessing the long-run implications of advertising is to relate it to long-run profits. We also wish to explore how these profit implications differ across market clusters. As discussed earlier, we expect the carryover effects of advertising on demand to make strategic advertising decisions dynamic in nature. Thus, current advertising effort will have current and future profit implications for the firms. Recall that the future implications of advertising arise from carryover in advertising effort as well as from the state-dependent policy functions.

Table 8 **Derivative of Equilibrium Price with Respect to Current Advertising Level**

	BG price			ST price			SW price		
Cluster	BG	ST	SW	BG	ST	SW	BG	ST	SW
1	0.014	−0.006	0.010	0.006	−0.003	−0.005	0.008	−0.006	−0.004
2	0.006	−0.006	0.009	0.033	0.020	−0.001	0.021	0.015	−0.005
3	0.070	0.015	0.025	−0.004	0.019	−0.004	0.010	0.016	−0.001

Specifically, we distinguish between the "direct effect" of advertising on profits, captured by the impact of current advertising investments on future goodwill, and the "indirect" or "strategic effect" of advertising, captured by the additional advertising generated via competitive response (cf. Slade 1995). To measure these effects, we consider the impact of an exogenous investment in a firm's ad stock (e.g., one could think of this as an increase in current goodwill), $d(ad_t)$, on profits, $d\pi_j/d(ad_k)$, $j, k = 1, \ldots, J$, while distinguishing the direct and strategic effects. The direct effect of an advertising investment by firm k on the profits of firm j at time t is

$$DE_{jkt} = E_t\left(\frac{\partial\pi_{jt}}{\partial ad_{kt}} + \delta\frac{\partial\pi_{jt+1}}{\partial G_{kt+1}}\frac{\partial G_{kt+1}}{\partial ad_{kt}} + \cdots + \delta^L\frac{\partial\pi_{jt+L}}{\partial G_{kt+L}}\frac{\partial G_{kt+L}}{\partial ad_{kt}}\right), \quad (13)$$

where L is the maximum lag in the goodwill function. Note that in computing the impact of current advertising (and consequent future goodwill) on profits, $\partial\pi_{jt}/\partial ad_{kt}$ $(\partial\pi_{jt+1}/\partial G_{kt+1})$, we take the total derivative of the long-run profit equation at a given start date t, $\sum_{\tau=t}^{T}\pi_{j\tau}(S_\tau, \Delta ad_{j\tau})$ (the derivation of the profit equation is available from the authors on request). Because the profit function is reparameterized in terms of Bertrand prices, we implicitly account for the impact of advertising on equilibrium prices. The indirect, or strategic, effect of an advertising investment by firm k on the profits of firm j at time t is

$$\begin{aligned} SE_{jkt} &= \delta E_t\Bigg[\sum_{l=1}^{J}\frac{\partial\pi_{jt+1}}{\partial\Delta ad_{lt+1}}\frac{\partial\Delta ad_{lt+1}}{\partial G_{kt+1}}\frac{\partial G_{kt+1}}{\partial ad_{kt}} \\ &\quad + \delta^2\Bigg\{\sum_{l=1}^{J}\Bigg[\frac{\partial\pi_{jt+2}}{\partial\Delta ad_{lt+2}}\frac{\partial\Delta ad_{lt+2}}{\partial G_{kt+2}}\frac{\partial G_{kt+2}}{\partial ad_{kt}} + \Bigg[\frac{\partial\pi_{jt+2}}{\partial\Delta ad_{lt+2}} \\ &\quad \cdot\sum_{n=1}^{J}\frac{\partial\Delta ad_{lt+2}}{\partial G_{nt+2}}\frac{\partial G_{nt+2}}{\partial\Delta ad_{nt+1}}\frac{\partial\Delta ad_{nt+1}}{\partial G_{kt+1}}\frac{\partial G_{kt+1}}{\partial ad_{kt}}\Bigg]\Bigg]\Bigg\} \\ &\quad + \delta^3\{\cdots\} + \cdots\Bigg]. \quad (14) \end{aligned}$$

Each term in the "[ ]" represents the indirect effect of a lag period. Using the model estimates described in the previous section, we can measure these long-run impacts of advertising explicitly. We report the direct, strategic, and total effect of advertising by cluster in Table 9.

We first discuss the direct effect of a current investment in advertising on profits. The numbers in the table reflect the net present value of the direct impact, ignoring competitive adjustments, of one GRP of current advertising on long-run equilibrium profits. Note that these numbers provide us with a simple test for our assumed closed-loop feedback advertising strategies relative to an open-loop information structure. If firms are in fact playing an open-loop game, i.e., setting permanent advertising decisions for the entire planning horizon at date zero, then they would want to set the derivative of long-run profits with respect to advertising equal to zero. In other words, in an open-loop game, the firm precommits to long-run advertising decisions that maximize the long-run profit function. In contrast, in the closed-loop game the firm does not precommit to ad levels, allowing for competitive responses to historic decisions. In the table we see that the direct effects differ from zero (these are statistically significant), suggesting that firms are indeed using strategies that are consistent with our feedback policies.

First, we find that the three products have a differential average direct effect of advertising. For BG, this effect is positive for all clusters. Thus, ignoring competitive adjustments, advertising seems to benefit BG in equilibrium. ST, on the other hand, has a positive direct effect in Clusters 2 and 3 but a negative one in Cluster 1. In contrast, SW has an insignificant direct own-advertising effect. This is due to the insignificant impact of own advertising on own demand documented earlier. Second, we see that the complementary or competitive role of advertising on demand is reflected in the "cross"-direct effects. For

Table 9 Effect of Advertising on Long-Run Profits

Effect of advertising	Market group	BG ad			ST ad			SW ad		
		BG	ST	SW	BG	ST	SW	BG	ST	SW
Direct	Cluster 1	78.12	−40.38	36.39	47.91	−29.03	−26.54	45.56	−30.43	−10.08
	Cluster 2	119.64	6.32	54.04	489.19	299.79	−38.08	293.19	168.91	−20.96
	Cluster 3	1,370.28	440.14	450.93	132.58	554.18	−43.88	471.50	400.27	92.61
Strategic	Cluster 1	−7.43	4.90	−2.83	−4.45	3.80	4.01	−4.15	3.89	2.16
	Cluster 2	−14.49	−1.23	−3.81	−58.30	−38.27	3.31	−34.92	−21.56	1.83
	Cluster 3	−113.13	−115.31	−18.60	40.92	−136.55	19.69	−13.47	−100.36	5.33
Total	Cluster 1	70.69	−35.48	33.56	43.46	−25.24	−22.53	41.41	−26.55	−7.93
	Cluster 2	105.15	5.09	50.23	430.89	261.53	−34.77	258.28	147.34	−19.13
	Cluster 3	1,257.15	324.82	432.33	173.50	417.62	−24.19	458.03	299.91	97.95

BG, its advertising generates a substantial benefit to ST and SW profits. These findings are driven primarily by the category expansion effects of BG ads (they increase both own and competitors' demands). The cross-direct effects of ST are mixed. In particular, ST advertising seems to have a negative impact on BG profits in Cluster 1 markets and a positive effect in Cluster 2 markets. To understand the positive effect in Cluster 2, we refer back to Table 8, where we also noted that, in Cluster 2, ST advertising causes SW to raise its price. This price increase draws sufficient additional demand to BG to offset the negative impact of ST advertising. Finally, the cross-direct effects of SW are positive for BG and negative for ST across all clusters. This last finding is important for understanding how SW benefits from advertising, despite the fact it has no significant impact on its own demand. SW advertising indirectly affects ST and BG pricing, which in turn feeds back into SW profits. Thus, while SW advertising might have no immediate benefit on its own demand, it can be used strategically to influence the nature of competition. Looking at the cluster-level numbers, it seems that the direct effect of advertising is positive in the larger markets (Clusters 2 and 3) for all three brands, but that it is positive only for BG in the smaller markets (Cluster 1).

We next examine the role of strategic response. The numbers in this table reflect the indirect or strategic effects of advertising (due to dynamic competitive reactions) on profits. We first discuss the own strategic effects. For BG, the strategic effect is negative in all clusters. Thus, some of the direct benefit of advertising investment for BG is offset once we allow for competitive responses. Strategic response tends to have a positive effect for ST in Cluster 1 and a negative effect in Clusters 2 and 3. The positive effect in Cluster 1 is driven primarily by the relative large negative coefficient in SW's advertising policy function (Table 7) on ST goodwill. Thus, SW tends to adjust its advertising down in response to ST goodwill. Because the direct effect of SW advertising on ST profits is negative, this downward adjustment will benefit ST. Finally, the own-strategic effect of SW advertising is insignificant. In terms of the cross-strategic effects, we find that these effects are relatively very small in Cluster 1. However, in Cluster 2, BG has an effect on ST and SW, while in Cluster 3 ST has a large negative effect on BG and SW.

Two main conclusions can be drawn from these findings. First, the direct effects are about an order of magnitude larger than the strategic effects and therefore tend to drive the total effects. This implies that the carryover effects of advertising on demand are more important in determining firm profits relative to the strategic effects arising from competitive reaction. Second, the total own effect of advertising is positive in the larger markets while it varies by brand in the smaller markets.

4.5. Policy Experiment

We now investigate whether the presence of advertising is beneficial or harmful for consumers. Equilibrium prices and sales are simulated when advertising is set to zero for all markets and weeks. We then compute the corresponding change in Marshallian consumer surplus, the area below the demand curve and above market prices. The change in consumer surplus we report captures consumers' aggregate willingness to pay to keep advertising available at its actual levels versus the hypothetical regime with no advertising.[15] Our aggregate data are not suitable for quantifying the microeconomic impact of advertising on individual consumers. Hence, we wish to restrict our welfare analysis to the implications of the change in prices associated with advertising. Switching to a zero-advertising regime involves both a demand shift due to changes in ad level and movement along the demand curve due to changes in prices. We measure only the latter effect by concentrating on the surplus change associated with movement along the demand curve from the current prices to the zero-advertising prices (i.e., we do not look at the demand-shifting effect). In this way, our analysis makes no assumptions about consumers' inherent utility from advertising.

Table 10 shows the dollar changes in consumer surplus as well as percent changes in prices and quantities sold across product markets obtained by moving to a zero-advertising regime. Overall, we note that removing advertising from the set of marketing instruments available to a firm leads to small, but material, percentage changes in price. Quantity changes, in percent, are even larger. Thus, removing advertising does seem to lead to a noticeable change in the competitive nature of the markets. We also observe patterns across markets. In general, we see prices falling in the relatively larger markets and rising in the relatively smaller markets. Similarly, quantities sold rise in the large markets and fall in the small markets. As expected, consumer surplus rises in the larger markets and tends to fall in the smaller markets when advertising is set to zero. Intuitively, these results can arise from the fact that, in smaller markets, advertising tended to have more of a competitive effect than in larger markets. Thus, the strategic response of a firm to its competitors' goodwill was to raise own advertising. However, because all firms

[15] Marshallian consumer surplus is an approximate measure of consumer welfare. The welfare interpretation in fact requires assumptions such as a constant income effect (see any standard reference such as Varian 1992).

Table 10 Impact of Zero-Advertising Regime

Market	Consumer surplus ($)[a]	Prices (%)			Quantities (%)		
		BG	ST	SW	BG	ST	SW
Atlanta	−16,121	0.3	0.3	0.5	1.5	2.0	3.1
Boston	80,118	−0.7	−2.3	−1.9	−2.3	−8.0	−5.0
Chicago	95,903	−0.9	−2.4	−2.1	−2.7	−7.2	−5.1
Cincinnati	−15,429	0.3	0.3	0.4	1.8	6.1	4.0
Dallas	−9,836	0.1	0.2	0.3	0.6	1.2	1.7
Denver	14,123	−0.7	−0.3	−0.3	−3.1	−2.1	−2.1
Houston	−13,846	0.2	0.2	0.3	1.2	4.4	2.5
Los Angeles	124,704	−4.5	−2.2	−3.2	−4.7	−4.1	−4.4
Miami	−27,566	0.7	0.6	0.8	3.2	2.9	4.4
Minneapolis	981	−0.2	0.0	0.0	−0.8	0.2	−0.1
New York	116,588	−0.8	−2.7	−2.2	−2.4	−7.5	−5.0
Philadelphia	127,627	−1.1	−3.5	−3.0	−3.4	−11.5	−8.0
Phoenix	14,390	−0.6	−0.3	−0.4	−2.6	−1.9	−2.2
Seattle	8,671	−0.4	−0.1	−0.2	−1.9	−1.2	−1.5
San Francisco	87,373	−0.9	−2.3	−2.1	−3.4	−8.5	−6.0
St. Louis	21,938	−0.8	−0.3	−0.5	−4.2	−5.0	−4.2
Tampa	−28,924	0.7	0.6	0.8	3.1	3.2	4.5
Washington	−18,128	0.2	0.3	0.5	0.8	1.6	2.6

[a]Adjusted for advertising effect.

compete on advertising, the net benefit is eroded, leading to lower market power and lower prices. As a result, in smaller markets, advertising seems to be beneficial for consumers who end up paying lower prices. The intuition is likely to be similar for the larger markets (where advertising tends to be more complementary), as consumers seem to be harmed by the presence of advertising as it tends to make prices higher. In other words, it may be that firms tend to lower their own advertising in response to competitors' goodwill and free-ride off one another's advertising. In general, competitive advertising will raise own market power and thus raise own prices. As explained above, our assessment of harmful or beneficial advertising in terms of consumer surplus relates only to the impact of advertising on prices.

5. Conclusion

We have used a dynamic game framework to capture the dynamic aspects of an industry with competitive prices, advertising, and carryover effects. Empirically, we observe that marketing effort differs considerably across geographic markets. We attribute these patterns to differences in the nature of competition. First, we find that in general, own current and past advertising has a positive effect on own demand. In terms of competitive effects, we find that the role of advertising (in our data) seems to be category building (complementary) rather than share stealing (competitive). The complementary role of advertising is much stronger in the larger markets relative to the smaller markets. We also find some evidence that this role differs across markets for the same product.

On the supply side, we find that firms make adjustments to advertising as a function of existing goodwill. As own goodwill goes up, own-advertising adjustments are smaller, leading to pulsing-like patterns that are frequently observed in consumer markets. The adjustment to advertising as function of competitive goodwill is consistent with the cross-advertising effects on demand, e.g., we find larger adjustments in smaller markets. Firms also condition their adjustments of the cost of GRPs in each market, with the three firms' adjustments depending on the cost of different dayparts.

These findings have interesting implications for firms. We find that the direct effect of advertising (arising through the carryover in demand) is more important in determining firm profits relative to the strategic effects arising from competitive reaction. We also find that the relatively higher competitive nature of advertising in smaller markets leads to firms' profits being competed away. For consumers, we find that advertising may be beneficial in smaller, more competitive markets and harmful in larger, less competitive markets.

We note some limitations of the current analysis. First, we use aggregate market-level data. These data can suffer from some aggregation biases (Christen et al. 1997). Second, we have no data on the information contained in the advertising, so we are unable to interpret the exact consumer response to advertising (e.g., consumption versus information). Third, we assume that returns to advertising are all due to the weight of advertising and that there is no effect of copy. Finally, though our data indicate that there is no spillover effect of price, promotion, and advertising across markets, firms may be allocating resources under an overall budget constraint.

Acknowledgments
The authors are grateful to the co-editors, the area editor, and two anonymous reviewers; Eric Anderson, Dennis Bender, Pradeep Chintagunta, Günter Hitsch, Harikesh Nair, and Peter Rossi; two anonymous reviewers of a preliminary abstract; participants at the MSI Conference on Competitive Response at Boston and the Marketing Science Conference at Wiesbaden for comments and feedback; Mark Dominiak, Mike Duffy, and Suresh Ramanathan for information on advertising planning and execution; and Bob Mariano, Dennis Heldman, Julie Caswell, and Eliza Mojduszka for background information on the frozen entrée industry. The authors also acknowledge the Kilts Center for Marketing at the University of Chicago for providing research funds and the Beatrice Foods Faculty Fund at the Graduate School of Business for research support.

References

Basar, T., G. J. Olsder. 1998. *Dynamic Noncooperative Game Theory, Classics in Applied Mathematics Series*, 2nd ed. SIAM, Philadelphia, PA.

Bender, J. Dennis. 1995. Sales impact of advertising awareness. ARF Scanning Research Workshop paper, Chicago, IL, April 25–26.

Boatwright, Peter, Sanjay Dhar, Peter E. Rossi. 2004. The role of retail competition, demographics and account retail strategy as drivers of promotional sensitivity. *Quant. Marketing Econom.* **2** 169–190.

Bronnenberg, Bart J., Vijay Mahajan. 2001. Unobserved retailer behavior in multimarket data: Joint spatial dependence in market shares and promotion variables. *Marketing Sci.* **20** 284–299.

Chintagunta, Pradeep K., Dipak Jain. 1995. Dynamic duopoly models of advertising competition: Estimation and specification tests. *J. Econom. Management Strategy* **4** 109–131.

Christen, Markus, Sachin Gupta, John C. Porter, Richard Staelin, Dick R. Wittink. 1997. Using market-level data to understand promotion effects in a nonlinear model. *J. Marketing Res.* **34** 322–334.

Clarke, Darral G. 1976. Econometric measurement of the duration of advertising effect on sales. *J. Marketing Res.* **13** 345–357.

Erdem, Tülin, Baohong Sun. 2002. An empirical investigation of spillover effects of marketing mix strategy in umbrella branding. *J. Marketing Res.* **34** 408–420.

Erickson, Gary M. 1995. Differential game models of advertising competition. *Eur. J. Oper. Res.* **83** 431–438.

Fornell, C., W. T. Robinson, B. Wernerfelt. 1985. Consumption experience and sales promotion expenditure. *Management Sci.* **31** 1084–1105.

Fudenberg, Drew, Jean Tirole. 1991. *Game Theory*. MIT Press, Cambridge, MA.

Gasmi, F., J. J. Laffont, Q. Vuong. 1992. Econometric analysis of collusive behavior in a soft-drink market. *J. Econom. Management Strategy* **1** 277–311.

Hausman, J. A. 1997. Valuation of new goods under perfect and imperfect competition. T. Bresnahan, R. J. Gordon, eds. *The Economics of New Goods*. University of Chicago Press, Chicago, IL.

Hoch, Stephen J., Byung-Do Kim, Alan M. Montgomery, Peter E. Rossi. 1995. Determinants of store-level price elasticity. *J. Marketing Res.* **32** 17–29.

Horsky, Dan, Paul Nelson. 1992. New brand positioning and pricing in an oligopolistic market. *Marketing Sci.* **11** 133–153.

Kadiyali, Vrinda, K. Sudhir, Vithala Rao. 2002. Structural analysis of competitive behavior: New empirical industrial organization methods in marketing. *Internat. J. Res. Marketing* **18** 161–186.

Karp, Larry S., Jeffrey M. Perloff. 1989. Dynamic oligopoly in the rice export market. *Rev. Econom. Statist.* **71** 462–470.

Leeflang, Peter S. H., Dick R. Wittink. 1992. Diagnosing competitive reactions using (aggregated) scanner data. *Internat. J. Res. Marketing* **9** 39–57.

Leeflang, Peter S. H., Dick R. Wittink. 2001. Explaining competitive reaction effects. *Internat. J. Res. Marketing* **18**(1–2) 119–137.

Lodish, Leonard M., Magid Abraham, Stuart Kalmenson, Jeanne Livelsberger, Beth Lubetkin, Bruce Richardson, Mary Ellen Stevens. 1995. How T.V. advertising works: A meta-analysis of 389 real world split cable T.V. advertising experiments. *J. Marketing Res.* **32** 125–139.

Mojduszka, Eliza M., Julie Caswell, J. Michael Harris. 2001. Consumer choice of food products and the implications for price competition and government policy. *Agribusiness* **17** 81–104.

Montgomery, Alan L. 1997. Creating micro-marketing pricing strategies using supermarket scanner data. *Marketing Sci.* **16** 315–337.

Roberts, Mark J., Larry Samuelson. 1988. An empirical analysis of dynamic, nonprice competition in an oligopolistic industry. *RAND J. Econom.* **19** 200–220.

Roy, Abhik, Dominique M. Hanssens, Jagmohan S. Raju. 1994. Competitive pricing by a price leader. *Management Sci.* **40** 809–823.

Slade, Margaret E. 1995. Product rivalry with multiple strategic weapons: An analysis of price and advertising competition. *J. Econom. Management Strategy* **4** 445–476.

Sorger, Gerhard. 1989. Competitive dynamic advertising. *J. Econom. Dynam. Control* **13** 55–80.

van Heerde, Harald J., Sachin Gupta, Dick R. Wittink. 2003. Is 75% of the sales promotion bump due to brand switching? No, only 33% is. *J. Marketing Res.* **35** 481–490.

Varian, Hal A. 1992. *Microeconomic Analysis*, 3rd ed. W. W. Norton and Company, New York.

Vilcassim, Naufel J., Vrinda Kadiyali, Pradeep K. Chintagunta. 1999. Investigating dynamic multifirm market interactions in price and advertising. *Management Sci.* **45** 499–518.

Wacker, W. 1992. The demography of tomorrow. *Retail Bus. Rev.* **60** 12.