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This research uses Procter & Gamble's value pricing initiative as a context for testing whether actual competitor and retailer response to a major policy change can be predicted using a game-theoretic model. We first estimate demand functions for P&G and competitor brands from the period before value pricing was initiated. We then formulate a dynamic manufacturer-retailer Stackelberg model that includes P&G, a national-brand competitor, and a retailer. The model takes P&G's move as given and prescribes the price and promotion response of the competitors and the retailer. We substitute the estimated demand parameters into the model to obtain prescriptions for each competitor and the retailer, and see whether these prescriptions are related to the actual response. We find that the dynamic game-theoretic model calibrated with empirical estimates of demand parameters has significant predictive power. We also test the predictive power of two benchmark models. The first is based on the reaction function approach of Leeflang and Wittink (Leeflang, Peter S. H., Wittink, Dick R. 1992. Diagnosing competitive reactions using (aggregated) scanner data. *Internat. J. Res. Marketing* **9** 39–57.), and the second is a simplification of our dynamic model where the retailer is not strategic. The dynamic game-theoretic model performs better than either benchmark.

Key words: dynamic game-theoretic models; manufacturer-retailer Stackelberg; competitor response; retailer response; pricing decisions; promotion decisions
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1. Introduction

Game-theoretic models have significantly enhanced the study of competitive response. These models prescribe the actions firms should take in response to moves by other firms. Researchers have applied this approach to vertical channel relationships (e.g., Kim and Staelin 1999) and horizontal "interbrand" competition (e.g., Lal 1990), and shown, for example, that retailers should decrease prices when national-brand cross elasticities increase or that national brands should promote to limit competitive encroachment. Researchers have also developed dynamic game-theoretic models that prescribe pricing and promotion policies for manufacturers and retailers based on a forward-looking analysis (e.g., Kopalle et al. 1999). Such models are particularly important because promotion has several dynamic effects, including consumer "wear-out" to repetitive promotions (Foekens et al. 1999; Kopalle et al. 1999), stockpiling (van Heerde et al. 2000), and retail forward buying (Blattberg and Neslin 1990).

In summary, game-theoretic models have been extensively used to *prescribe* optimal competitive response. A natural next step is to consider whether game theory combined with empirical analysis can actually *predict* this response a priori. The purpose of this paper is to investigate this question. Specifically, we develop a dynamic game-theory model, empirically estimate the demand function that drives this model, substitute the demand parameters into the game-theoretic model, and generate predictions of competitor and retailer response. We then test whether these predictions correspond to reality. To the extent that this exercise is successful, we will have identified a methodological approach to predicting competitive behavior that can be used to guide managerial decision making.

The context we consider is the response to Procter & Gamble's "value pricing" strategy, which entailed P&G making major cuts in promotions and providing a lower everyday price to retailers and consumers (Shapiro 1992). The move was well-publicized and counter to industry trends. It therefore provides a strong exogenous stimulus and a valuable opportunity to see whether we can predict the response of competing national brands and retailers to a major policy change by a market leader.

Previous research suggests that predicting competitive response is a challenge. First, Leeflang and Wittink (1992) show that competitive response is not always "simple." A change by a firm in Marketing Instrument X may evoke a competitive change in Marketing Instrument Y (Kadiyali et al. 2000, Putsis and Dhar 1998). Second, Leeflang and Wittink (1996) show that firms may "over-react" or "under-react" to competitive moves. Third, it is unclear whether managers actually employ the strategic thinking suggested by game-theoretic models. Montgomery et al. (2005) find that managers often do not consider competitor reactions when deciding on their own move, although they are more likely to do so for major, visible decisions, especially pricing-related ones. Therefore, the predictive ability of a game-theoretic model is definitely worth testing, but it is by no means a given.

We base our game-theoretic model on the manufacturer-retailer Stackelberg framework. We place a Stackelberg game in a dynamic channel interaction framework similar to that of Kopalle et al. (1999). Our model is significantly more comprehensive in that it endogenizes (a) the national-brand competitor's price and promotion decisions; (b) the retailer's price decision for P&G, the national-brand competitor, and the private label; (c) the retailer's private-label promotion decision; and (d) the retailer's forward-buying decision for P&G and the national-brand competitor. The result is a "dynamic structural model"—dynamic in the sense of including *temporal* response phenomena and decision making; structural in the sense of modeling the *process* by which decisions are made by profit-maximizing agents.

Dynamic structural models are particularly appropriate in the case of a major policy change because they are better suited to predict how agents adapt their decisions to a new "regime," compared to reduced-form models that attempt to extrapolate from the past (see Keane 1997). The cost, however, is added complexity plus the difficult decision of how all-encompassing to make the model. We therefore compare the predictive ability of our model with two benchmarks. The first is the reaction function approach (Leeflang and Wittink 1996). Reaction functions are reduced-form models that might be better suited to short-term incremental changes than to major policy changes (Vanden Abeele 1994), but this is an empirical question to be investigated. The second is a dynamic model with a simplification in that the retailer is considered to be nonstrategic. Considering this model gets at the question of how detailed the structural model needs to be to predict actual response. As noted by Moorthy (1993), comparing models of varying complexity and realism enhances our understanding of phenomena.

We conduct our analysis for a local market because packaged-goods companies are known to adapt trade-deal policies to local conditions and both competitor and retail reaction can vary substantially across markets (e.g., Kadiyali et al. 2000). We use the scanner database of the *Dominicks* grocery chain in Chicago and wholesale price and trade-deal data for the Chicago market from *Leemis Marketing Inc.* The results show that a game-theoretic model combined with strong empirics does have predictive power. Our model's prescription of how competitors should change wholesale price and trade dealing and how the retailer should change retail price in response to P&G's move is a significant predictor of the actual changes made by competitors and Dominicks in the Chicago market. Our model has better predictive ability than both benchmark models, suggesting that, in the context of a major pricing policy change, managers' actions are more consistent with strategic competitive reasoning than with an extrapolation of past reactions into the future, or with ignoring retailer reaction.

The paper proceeds as follows. We describe the game-theoretic model and our dynamic optimization approach in §2. Section 3 describes the data and the prediction process used in our empirical analysis and §4 presents our results. We conclude with a discussion and implications for researchers and managers in §5.

2. Game-Theoretic Model

2.1. Demand Function
Unit sales of brand i in week t in store s, S_{its}, are given by:

$$S_{its} = \alpha_{is} + \sum_{k=1}^{K} \beta_{iks} \text{RP}_{kts} + \sum_{k=1}^{K} \gamma_{iks} \text{RD}_{kts} + \delta_{1is} \text{CD}_{its}$$

$$+ \delta_{2is}(\text{CD}_{its})(\text{RD}_{its}), \tag{1}$$

$$\text{CD}_{its} = \lambda_i \text{CD}_{its-1} + (1 - \lambda_i)\text{RD}_{its-1}, \tag{2}$$

where $i, k = 1, 2, 3, \ldots K$, and K is the number of brands in the category;

RP_{kts}, RD_{kts} = Regular retail price and deal amount per unit, respectively, of brand k in week t in store s;

CD_{its} = Cumulative dealing, i.e., exponentially smoothed average of past retail deal amounts, for brand i in week t in store s;

λ_i = Exponential smoothing parameter for the cumulative dealing of brand i;

α_{is} = Intercept for brand i in store s;

β_{iks}, γ_{iks} = Effect of brand k's retail price and deal amount, respectively, on brand i's sales in store s;

δ_{1is} = Effect of cumulative dealing of brand i on sales of brand i in store s;

δ_{2is} = Effect of cumulative dealing of brand i on the effectiveness of its current retail deal in store s.

We use a linear specification primarily to ensure tractability of the dynamic optimization problem, but this appears defensible, as van Heerde et al. (2004) do not find large nonlinearities when they use non-parametric estimation with store-level data. Note that we distinguish between consumer response to regular price changes and temporary deal price cuts and allow for separate cross-price and cross-deal effects of each competitor. We also capture stockpiling through the CD term (van Heerde et al. 2000) and promotion wear-out, i.e., a possible reduction in the impact of a current deal if there has been a stream of deals in the recent past, through the interaction between CD and RD (Foekens et al. 1999, Kopalle et al. 1999).

2.2. Channel Structure and Decision Variables

We model the channel structure as a dynamic series of Manufacturer-Retailer Stackelberg games solved by forward-looking players. We consider two manufacturers, P&G (Brand 1) and a competitive national brand (Brand 2), selling through a common retailer who also sells a private label (Brand 3). In each period, the manufacturer takes into consideration how the retailer will react in this period as well as the maximum profit he (the manufacturer) will be able to make in the series of Stackelberg games in subsequent periods, conditional on his decision in this period. In turn, the retailer takes into consideration the manufacturer's decisions in this period as well as the maximum profit he (the retailer) will be able to make in the subsequent series of Stackelberg games, conditional on his decision in this period. Both players develop expectations about future actions that are fulfilled in equilibrium because, in equilibrium, neither player has an incentive to deviate from their chosen strategy.

Since P&G's move was primarily a pricing and promotion strategy, we consider competitor reactions in terms of wholesale price and what deal amount, if any, to offer. The retailer decides (a) whether and how much to order from each manufacturer; (b) whether to order enough to satisfy future demand as well as current demand (forward buying); (c) retail prices of P&G, the national-brand competitor, and the private label; and (d) what retail deal amount, if any, to offer on the private label.[1]

Two assumptions deserve mention. First, we consider P&G's actions to be exogenous, and hence not decision variables. This is defensible because the company clearly announced its intention to implement value pricing (e.g., Shapiro 1992), and then went on to do so. It is possible that P&G subsequently modified its strategy in response to the reaction it encountered in the market. However, incorporating such a

response by P&G would make our model intractable. Therefore, we conduct our analysis in a period during which such endogenous response by P&G is less likely to have occurred. Second, we follow Silva-Risso et al. (1999) and assume that when the retailer places an order during a trade-deal period, he provides a fixed percentage of the trade-deal amount to the consumer in that period. However, since the retailer can decide whether or not to forward-buy, total trade-deal pass-through is endogenous and varies across brands and categories. We discuss these points in more detail subsequently.

2.3. Objective Functions and Dynamic Program Formulation

Retailer's Objective Function. The retailer's and the manufacturer's objectives are to maximize their respective sum of profits over a finite time horizon, 1 to T. Given a manufacturer's wholesale price and trade-deal amount during $t = 1, \ldots, T$, the retailer decides prices, RP_{1t}, RP_{2t}, RP_{3t}; whether to place an order with the manufacturer during each period; if so, what the order quantities X_{1t} and X_{2t} should be; and the retail deal amount, if any, for the private label, RD_{3t}. Therefore, the retailer's objective function is:[2]

$$\max_{\substack{RP_{1t}, RP_{2t}, RP_{3t} \\ RD_{3t}, X_{1t}, X_{2t}}} \sum_{t=1}^{T} \left[\sum_{i=1}^{2} [(RP_{it} - kD_{it}I_{it})S_{it} - (WP_{it} - D_{it})X_{it} \right.$$
$$\left. - h_i INV_{it}] + (RP_{3t} - VC - RD_{3t})S_{3t} \right], \quad (3)$$

where sales, S, for each brand are given by the demand function in Equation (1), WP is the wholesale price, D is the trade-deal amount offered by the manufacturer, k is the percentage of the trade-deal amount that the retailer offers to consumers in the weeks when he orders on trade deal, h is the retailer's unit inventory holding cost per period, VC is the variable cost of the private label to the retailer, I is an order indicator variable which is equal to 1 if an order is placed and 0 otherwise, and INV is inventory, given by:

$$INV_{it} = INV_{i, t-1} + X_{i, t-1} - S_{i, t-1}, \qquad i = 1, 2.$$

In Equation (3), the first three terms apply to the national brands ($i = 1, 2$). They represent, respectively, the retailer's revenues, acquisition, and inventory costs in period t for brand i. The fourth term is

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[1] We assume that the retailer does not engage in diversion of product.

[2] We do not discount future profits because we consider a fairly short time horizon of 15 weeks, but that can be easily incorporated through a discount factor. Also, we assume without loss of generality that fixed costs are zero, or that contribution to fixed costs is being maximized. Finally, we drop the store subscript s for simplicity of exposition.

the retailer's profit in period t from the private label. We assume initial inventory levels and the salvage value of any inventory held at the end of the time horizon are zero.

Retailer's Dynamic Programming Formulation. For a given manufacturer's wholesale price and trade-deal amount in period t, we formulate the optimization as a dynamic programming problem, where the state space consists of L_{it}, the period before t in which an order was last placed for Brand i, $i = 1, 2$; $WP_{L_{it}}$, the wholesale price for brand i when it was last ordered by the retailer prior to period t; $D_{L_{it}}$, the trade deal for brand i when it was last ordered by the retailer prior to period t; and CD_{1t}, CD_{2t}, and CD_{3t}, the cumulative retailer deals.

For such problems, Wagner and Whitin (1958) have derived "zero inventory ordering" and "period-covering" properties that show the retailer places orders only when existing inventory is exhausted, and that orders will cover total demand over some integer number of sequential future periods. The number of future periods for which orders are placed measures the retailer's forward buying. We can therefore restate the retailer's problem in Equation (3) as a dynamic programming problem in discrete time (Stokey and Lucas 1989):

$$\pi_{Rt}^*\left(L_{it}, WP_{L_{it}}, D_{L_{it}}, CD_{3t}, CD_{3t} \mid WP_{it}, D_{it}, i = 1, 2\right)$$

$$= \max_{\substack{I_{1t}, I_{2t}, \\ RP_{1t}, RP_{2t}, \\ RP_{3t}, RD_{3t}}} \left\{ \begin{array}{l} I_{2t}(1 - I_{1t})[(RP_{1t} - WP_{L_{1t}} + D_{L_{1t}} - h_1(t - L_{1t}))S_{1t} \\ \quad + (RP_{2t} - WP_{2t} + (1 - k)D_{2t})S_{2t} \\ \quad + (RP_{3t} - VC - RD_{3t})S_{3t}] \\ + I_{2t}I_{1t}[(RP_{1t} - WP_{1t} + (1 - k)D_{1t})S_{1t} \\ \quad + (RP_{2t} - WP_{2t} + (1 - k)D_{2t})S_{2t} \\ \quad + (RP_{3t} - VC - RD_{3t})S_{3t}] \\ + (1 - I_{2t})I_{1t}[(RP_{1t} - WP_{1t} + (1 - k)D_{1t})S_{1t} \\ \quad + (RP_{2t} - WP_{L_{2t}} + D_{L_{2t}} \\ \quad \quad - h_2(t - L_{2t}))S_{2t} \\ \quad + (RP_{3t} - VC - RD_{3t})S_{3t}] \\ + (1 - I_{1t})(1 - I_{2t}) \\ \quad \cdot [(RP_{1t} - WP_{L_{1t}} + D_{L_{1t}} - h_1(t - L_{1t}))S_{1t} \\ \quad + (RP_{2t} - WP_{L_{2t}} - h_2(t - L_{2t}))S_{2t} \\ \quad + (RP_{3t} - VC - RD_{3t})S_{3t}] \\ + V_{Rt+1}(L_{it+1}, WP_{L_{it+1}}, D_{L_{it+1}}, CD_{it+1}, \\ \quad CD_{3t+1}, i = 1, 2), \end{array} \right.$$

$$(4)$$

where:

$\pi_{Rt}^* = $ Retailer's maximum profit from period t through T given brand i's wholesale price (WP_{it}) and trade deal amount (D_{it}), $i = 1, 2$, in period t;

$I_{it} = 1$ if the retailer places an order for brand i in period t;

$= 0$ if the retailer carries forward inventory of brand i from period L to period t.

The first four major terms in Equation (4) compute current-period profit depending on four ordering possibilities in period t (ordering Brand 2 but not Brand 1, ordering both brands, ordering Brand 1 but not Brand 2, and not ordering either brand). If the brand is ordered in period t, the retailer offers to consumers $k\%$ of any trade deal in that period; i.e., when $I_{it} = 1$, $RD_{it} = kD_{it}$, and so adds $(1 - k)D_{it}$ to his profit margin. If brand i, $i = 1, 2$, is not ordered in period t, the retailer supplies demand through product that was forward-bought earlier, in which case $D_{L_{it}}$ is added to its margin if there was a trade deal the last time the brand was ordered. Also, if the brand is not ordered in period t, the retailer subtracts a holding cost for the inventory it has forward-bought to satisfy this period's demand.[3] The last term, V_{Rt+1}, is the maximum profit the retailer can expect to make, given the decisions he makes in period t. This is evaluated at the manufacturer's *optimal* decisions in period $t + 1$ (WP_{2t+1}^* and D_{2t+1}^*), given P&G's actions in $t + 1$, WP_{1t+1} and D_{1t+1}, and the retailer's actions in period t. Thus:

$$V_{Rt+1}\left(L_{it+1}, WP_{L_{it+1}}, D_{L_{it+1}}, CD_{it+1}, CD_{3t+1}, i = 1, 2\right)$$

$$= \pi_{Rt+1}^*\left(L_{it+1}, WP_{L_{it+1}}, D_{L_{it+1}}, CD_{it+1}, CD_{3t+1}, \right.$$
$$\left. i = 1, 2 \mid WP_{1t+1}, D_{1t+1}, WP_{2t+1}^*, D_{2t+1}^*\right). \quad (5)$$

The state variables CD_{jt+1} ($j = 1, 2, 3$) are as given in Equation (2). The other state variables in period $t + 1$ are given by ($i = 1, 2$):

$$L_{it+1} = I_{it}t + (1 - I_{it})L_{it};$$

$$WP_{L_{it+1}} = I_{it}WP_{it} + (1 - I_{it})WP_{L_{it}}; \quad (6)$$

$$D_{L_{it+1}} = I_{it}D_{it} + (1 - I_{it})D_{L_{it}}.$$

We make three points about the state variables. First, keeping track of L_{it}, time of last order of brand i, removes the need to track all possible levels of inventory for brand i, while allowing us to uniquely determine the cost to the retailer for that brand in any period. Second, since Brand 2 is strategic, the retailer determines his optimal ordering of Brand 2 for all possible values of that brand's wholesale price and deal amount decisions, while taking into consideration P&G's actions, i.e., WP_{1t} and D_{1t}. In contrast, P&G's actions are exogenous and assumed to be known to Brand 2 and the retailer, so the retailer can solve for CD_{1t} and I_{1t} ex ante.[4] Third, L_{1t} and L_{2t} take on values 1 through $T - 1$ representing weeks; $WP_{L_{2t}}$, $D_{L_{2t}}$,

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[3] Note that the wholesale prices, retail prices, and deal amounts differ depending on which of the four order scenarios the retailer undertakes. Therefore, we cannot factor out S_{it}, for example, in writing Equation (4).

[4] Since P&G made the nature of its value-pricing move clear in public announcements, we are confident that competitors knew the

CD_{2t}, CD_{3t} are discretized at 10 levels around their respective initial values to keep computing time manageable; $WP_{L_{1t}}$, $D_{L_{1t}}$, CD_{1t} are based on P&G's actual values.

Competing Manufacturer's Objective Function and Problem Formulation. In each period t, the profit for Brand 2 depends on whether the retailer buys now from Brand 2 or carries Brand 2 forward from the last purchase order. Hence, Brand 2's objective function is:

$$\max_{WP_{2t}, D_{2t}} \sum_{t=1}^{T} \{ I_{2t}(WP_{2t} - VC - D_{2t})S_{2t}$$
$$+ (1 - I_{2t})(WP_{L_{2t}} - VC - D_{L_{2t}})S_{2t} \}. \quad (7)$$

The first term is Brand 2's profit if the retailer places an order in period t at the given wholesale price and trade-deal amount. The second term is Brand 2's profit if the retailer fulfills demand for Brand 2 in period t from inventory carried forward from a past period, L_{2t}. Similar to the retailer's case, we can reformulate the manufacturer's problem in Equation (7) as a dynamic programming problem in discrete time with state vector $\{L_{it}, WP_{L_{it}}, D_{L_{it}}, CD_{it}, CD_{3t}, i = 1, 2\}$:

$$V_{Mt}(L_{it}, WP_{L_{it}}, D_{L_{it}}, CD_{it}, CD_{3t}, i = 1, 2)$$
$$= \max_{WP_{2t}, D_{2t}} \left\{ \begin{array}{l} (I_{2t}(WP_{2t} - VC - D_{2t})S_{2t} + (1 - I_{2t}) \\ \cdot (WP_{L_{2t}} - VC - D_{L_{2t}})S_{2t}) \\ + V_{Mt+1}(L_{it+1}, WP_{L_{it+1}}, D_{L_{it+1}}, \\ \qquad CD_{it+1}, CD_{3t+1}, i = 1, 2) \end{array} \right\},$$
$$(8)$$

where V_{Mt} is the manufacturer's maximum profit from period t through T.

Solving for Optimal Decisions. In each period, we have a Stackelberg game with the manufacturer as the leader and the retailer as the follower, but to solve that game for each period, we need to take into account future profits that depend on the actions taken in each period. The optimization is done through a process of backward induction, with the retailer's decision problem embedded within the manufacturer's decision problem, and vice versa. The retailer's decisions in any period are predicated upon the manufacturer's wholesale price and trade-deal amounts in that period and what the retailer expects the manufacturer's wholesale price and trade-deal amounts to be in

future periods. The manufacturer's decisions in any period are predicated on the retailer's pricing and forward-buying decisions in that period, depending on what actions the manufacturer takes, plus what the manufacturer expects the retailer's future pricing and forward buying to be. The optimization algorithm is available from the authors upon request.

3. Empirical Analysis

3.1. Data

We use weekly retail-level price, deal, and sales data from stores in the Chicago market belonging to the *Dominicks* grocery store chain, and we obtain weekly wholesale price and trade-deal data in the Chicago market for P&G and other national brands from *Leemis Marketing Inc.*, a company that specializes in tracking wholesale prices and trade deals in several U.S. markets. Like Ailawadi et al. (2001), our analysis is at the level of a manufacturer in a product category. We aggregate the UPCs for a manufacturer up to one "umbrella brand." Studying response at the umbrella brand level is consistent with packaged-goods manufacturers' emphasis on category management and with the strategic nature of the managerial situation. Value pricing was a companywide policy change made by P&G, and the response to this type of far-reaching policy change could also be expected to be strategic and broad-based.[5]

We were able to compile data for nine product categories in which P&G is a player. *Dominicks* sold a private-label brand in six of these nine categories throughout the period of our analysis. The number of brands for which both wholesale and retail data are available varies across categories, ranging from three to six. In total, we have 43 brands across the nine categories (nine P&G brands, 28 national-brand competitors, and six private-label competitors).

P&G announced its value-pricing strategy at the end of 1991 (Shapiro 1992) and implemented it over the next few years. The company's annual reports during the period from 1992–1993 to 1994–1995 explicitly discuss the company's move to value pricing. They state that by 1993, 90% of the company's brands were under this program, the process of reducing prices and cutting costs continued in 1994, and value pricing was a fundamental strategy at P&G as of 1994–1995. Thus, it appears reasonable to assume that P&G's actions were exogenous at least until 1994. We also examined changes in P&G's pricing

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general thrust of the policy (i.e., reduction in deals and a lower everyday price). They may also have known exact weekly actions a quarter ahead through their salespeople and retailer contacts. Our best approximation to what competitors knew is what P&G actually did. However, to the extent that this is inaccurate our predictions will suffer.

[5] We recognize that demand function estimates can be biased if UPCs with heterogeneous prices and promotion are aggregated (Christen et al. 1997). To examine the impact on our results, we repeated our analysis by aggregating only those UPCs of each manufacturer whose retail prices are strongly positively correlated (Besanko et al. 2005). There was no substantive change in our findings.

Table 1 **List of Variables and Definitions**

Variable	Definition	Source
Wholesale price	Wholesale price per equivalent volume in a given week.	Leemis Marketing
Wholesale deal amount	Wholesale dollar deal amount per equivalent volume in a given week.	Leemis Marketing
Retail price	Regular retail price per equivalent volume in a given week: Equal to net price paid when brand is not on retail promotion, and equal to the maximum net price paid during the previous four weeks and next four weeks in weeks when brand is on retail promotion. Not all promotions are flagged in the Dominicks data. Following Gedenk and Neslin (1999), we flag a promotion in a given week if the net price paid is at least 5% lower than the maximum price paid in the previous four weeks and the subsequent four weeks.	Dominicks Data
Retail deal amount	Regular retail price minus net price paid.	Dominicks Data
Unit sales	Number of equivalent units sold in a given week.	Dominicks Data
Variable cost	Average value of: (1 minus percent retail margin on private label) times (retail price of private label).	Dominicks Data
Small player	Equals 1 if the market share of the brand is less than 5% of the total share of the top three brands in the category; 0 otherwise.	Dominicks Data
Multimarket contact	Equals 1 if the firm competes with P&G in more than two of the categories, 0 otherwise.	Dominicks Data
Category advertising	Average annual media advertising expenditure in the category.	Leading National Advertisers
Category dealing	Average percentage of sales in the category made on some type of retail deal.	IRI Market Fact Book
Category purchase cycle	Average number of days between consecutive purchases of the category.	IRI Market Fact Book

Note. Price and deal variables are averaged across all UPCs for a manufacturer.

and dealing over the 1991–1996 period in Chicago and nationwide. After a sustained pattern until 1994, there was an uptick in deals in 1995–1996, suggesting a possible modification of strategy based on market reaction. Interestingly, there is no mention of value pricing in the company's annual report for 1995–1996. We therefore study the changes made from 1991 to 1994 to be sure that the assumption of P&G exogeneity is reasonable and yet able to cover the bulk of the changes made under value pricing. The following timeline summarizes:

Year	Weeks	Use
1991	1 to 5	Initialization of all long-term smoothed variables
	6 to 37	Estimation of demand functions and reaction functions
	38 to 52	Optimization period before implementation of value pricing
1992	1 to 52	Value pricing being implemented, data not used
1993	1 to 52	Value pricing being implemented, data not used
1994	1 to 37	Value pricing being implemented, data not used
	38 to 52	Optimization period after implementation of value pricing
1995	1 to 52	Possible modification of P&G strategy, data not used
1996	1 to 52	Possible modification of P&G strategy, data not used

As the timeline shows, we use retail data from the first 37 weeks of 1991 to estimate our demand functions and reaction functions, and changes between the last 15 weeks of 1991 and the last 15 weeks of 1994 to test our predictions. Thus, there is a clean separation between the estimation and prediction portions of our analysis, in that the same data are not used for estimation and for prediction. We use the same 15 weeks in 1991 and 1994 to control for possible seasonality. There are two reasons for using a 15-week horizon in our optimization. First, our interviews with grocery retailers suggest that this reflects reality in that manufacturers and retailers do tend to look ahead one quarter when they make pricing and promotion decisions. In fact, a typical promotion-planning calendar is for a quarter. Second, given that we have to run our model twice (1991 and 1994) for each brand, we need to keep the computational burden reasonable. For example, with a 15-week horizon each run takes about 17 hours on a dedicated UNIX machine, while a 25-week horizon takes over 48 hours.

Table 1 provides definitions and sources of all the variables used in the analysis. Three points deserve mention. First, we obtain estimates of the variable cost of brands in each category using *Dominicks* gross margin on its private label in each category. If the retailer produces its own private label or buys it in a perfectly competitive supplier market, we can assume the cost of the private label to the retailer is the variable cost. We compute this variable cost from the retail price

and retail gross margin on the private label, and apply it to all brands in a category. Second, based on conversations with four retail managers, we assume that a brand's unit holding cost per month is 5% of its wholesale price. Third, we assume that in the weeks when the retailer orders under a trade deal, he offers 120% of the trade deal to consumers (i.e., $k = 1.2$ in Equations (3) and (4)). The retailer also forward-buys product for satisfying consumer demand in future weeks. In those weeks, the retailer offers no discount to consumers, although the retailer's cost is the same trade-deal cost. Thus, to be comparable with Besanko et al. (2005), we calculate "pass-through" for a given brand in a given quarter as the average of 120% during the retailer discount weeks and 0% during the forward-buy weeks. Since the amount of product forward-bought differs by manufacturer due to differences in deal amounts, holding costs, demand, and own and cross effects (Moorthy 2005), pass-through also varies by brand. The median pass-through in our model is 82%, which is very close to the median of 83% reported by Besanko et al. (2005).[6]

3.2. Demand Function Estimation

We estimate the demand function in Equation (1) separately for each brand in each category, using data pooled across stores. However, since stores differ in size, we follow van Heerde et al. (2004) in dividing the dependent variable, S_{its}, by the total category sales in that store, so that the magnitudes of all the demand parameters are proportional to category volume. We also include store-specific dummy variables to account for differences in the base level of brand sales across stores (Kopalle et al. 1999). The model is estimated using all available data from each Dominicks store in the first 37 weeks of 1991. As noted earlier, the first five weeks are used to initialize the cumulative dealing variable (CD) and create lags for the price and deal variables. We employ 2SLS to control for possible endogeneity in price and deal variables, using the five weekly lags of the price and deal variables as instruments (e.g., Kadiyali et al. 2000), and do a grid search to find the value of the smoothing parameter λ that maximizes R^2 for each brand.[7] We constrain the signs of "own" effects since incorrect signs resulting from possible multicollinearity would cause problems in the optimization

model that is calibrated using these coefficient estimates.[8] This is in the spirit of Blattberg and George (1991), who advocate shrinkage estimation to avoid incorrect signs and of conjoint research showing that constrained parameter estimation improves predictive ability (e.g., Moore et al. 1994, Van der Lans et al. 1992).

3.3. Benchmark Models and Prediction Procedure

Benchmark Models. We compare the predictive ability of our model to two benchmarks. The first is based on reaction functions and embodies an extrapolation of past interactions in that it assumes competitors and the retailer will continue to react to P&G and to each other in the wake of value pricing the same way they did before P&G's move. Our reaction function specification incorporates cross-instrument reactions because Leeflang and Wittink (1992) find that reactions are not necessarily "simple." Further, manufacturers take account of their own, competing manufacturers', and the retailer's past actions, and the retailer takes account of his own past actions and the past and current actions of the manufacturers. Finally, we follow Leeflang and Wittink (1992, 1996) in taking the first difference of log of price and the first difference of deal amount, and Kopalle et al. (1999) in using a parsimonious decay specification for the impact of past prices and deals instead of multiple lags. The specifications of the reaction functions are available from the authors upon request.

The second benchmark incorporates the dynamic effects in our full game-theoretic model, with the exception that the retailer is nonstrategic. It is assumed that the retailer will add a constant markup to the wholesale price and pass through a constant percentage of the wholesale trade-deal amount with no forward buying. The national-brand competitor makes wholesale price and deal decisions in response to P&G's actions, taking into consideration consumers' immediate and dynamic response, but not the retailer's. Therefore, this benchmark model embodies the possibility that national-brand competitors do not engage in strategic competitive reasoning—they react to P&G, but do not consider possible retailer reactions to their own decisions (Montgomery et al. 2005).

Prediction Procedure. All predictions are made for a prototypical store using average values of all the variables, i.e., prices, deals, and category size. We compute the optimal values of the decision variables for the last 15 weeks of 1991, at which time P&G

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[6] We also repeated all of our analysis with $k = 80\%$ instead of 120%. The median pass-through in that case was 62% and the predictive ability of our model remained unchanged.

[7] NEIO models often specify and estimate both supply-side and demand-side models. However, it is not necessary to estimate the supply side in order to control for endogeneity in the demand side (e.g., Chintagunta et al. 2002). We thank Vrinda Kadiyali for helping us to sort out this issue.

[8] Please note that constraining these demand parameters does not put the game-theoretic model at an advantage or disadvantage over the benchmark models because we use the same parameters in the nonstrategic retailer benchmark too, and they are not relevant at all in the reaction function benchmark.

had not yet implemented value pricing, and for the last 15 weeks of 1994, by which time value pricing had been implemented. We ignore the last two weeks to alleviate end-game effects, compute the average optimal values for the remaining 13-week periods in both 1991 and 1994, and subtract these averages. That difference is represented as PREDCHG_{ij}, the predicted change in decision variable i for brand j. This is compared to ACTCHG_{ij}, the actual change in variable i for brand j similarly computed over the same 13-week periods in 1991 and 1994. Note that our objective is not to predict week-to-week changes, but to predict broader changes over time in response to the value-pricing move. That is why we average the weekly predictions in 1991 and 1994 and examine the change in those averages instead of examining the predictions in each week.

For our dynamic optimization model and the non-strategic retailer benchmark, initial values of the cumulative dealing variable (CD) are based on the previous quarter of 1991. We then plug into the dynamic optimization the demand parameters and the actual values of P&G's wholesale price and deal amount during the last 15 weeks of 1991 and obtain optimal values of each brand's decision variables during this 15-week period. This is done via a wide grid search around average values of all the decision variables to find values that maximize the sum of the relevant player's profits over the 15 weeks. We repeat the process for the last 15 weeks of 1994, using initial values of the CD variable from the previous quarter of 1994.

For the reaction function benchmark model, initial values of all variables are based on the previous quarter of 1991. We then plug in actual values of P&G's wholesale price and deal amount for the last 15 weeks of 1991, and get predicted values of all the decision variables for each week. Predicted values of each decision variable in one week are used to update the long-term smoothed value for the next week. We repeat the same process for the last 15 weeks of 1994. Note that because the reaction function predictions are unbounded and can go below zero as well as to very high positive values, while predictions from the other two models are bounded by the width of the grid search, we truncate the reaction function predictions to the same bounds.

Covariates for Predicting Actual Response. In addition to the predictions from the game-theoretic model and the two benchmarks, we consider the predictive ability of some covariates. Multimarket contact and firm size are two key brand characteristics that determine competitive reaction. Multimarket contact (MULTMKT) may increase competitive rivalry (Porter 1980) or lead to mutual forbearance because the competing firms have a high stake in many shared markets (Bernheim and Whinston 1990). Small or fringe

firms (SMALL) may react differently from larger competitors (Putsis and Dhar 1998, Shankar 1999). There may also be differences in reaction across categories, over and above the impact through different sales response elasticities. We include three category characteristics—category advertising (CAD), category dealing (CDL), and category purchase cycle (CPC)—that other researchers have used in cross-category empirical analysis (Narasimhan et al. 1996, Ailawadi et al. 2001). Thus, the regression model for each decision variable i for brand j using each predictive model m is:

$$\text{ACTCHG}_{ij} = \beta_0 + \beta_1 \text{PREDCHG}_{mij} + \beta_2 \text{CAD}$$
$$+ \beta_3 \text{CDL} + \beta_4 \text{CPC} + \beta_5 \text{SMALL}_j$$
$$+ \beta_6 \text{MULTIMKT}_j + \varepsilon_{ij}. \quad (9)$$

4. Results

4.1. Estimates of Brand Sales Model

In order to conserve space, and because the magnitudes of the parameters in the linear brand sales model are difficult to interpret, we do not report the model estimates. To provide a sense of the magnitude of the estimated effects, we use our estimated demand function to calculate the percentage change in each brand's sales in each of the 13 weeks of a quarter, for both a 12% reduction in regular price for the first three weeks of the quarter, and the same 12% reduction offered as a deal discount for the first three weeks of the quarter. Under the deal discount condition, we make two calculations: (a) the sales impact from only the current deal component of our estimated demand function (this yields the current deal effect), and (b) the sales impact from both the current and dynamic components (this yields the net deal effect). We then average the percentage sales change over the 13 weeks of the quarter for each of these three cases. We do the computation with three weeks of discounting instead of just one week so as to allow wear-out in the deal effect to kick in. Similarly, we consider the sales effect over the entire quarter to account for the stockpiling effect that continues after the end of the deal.

Table 2 reports the median and mean values of these three effects for each category, as well as for the overall sample. There is substantial variation in these effects across brands and categories, which would lead to differences in the response predicted for the different brands. As expected, the net deal effect is smaller than the current deal effect due to stockpiling and wear-out, and also closer in magnitude to the regular price effect. The average net deal effect for our sample is 41% of the current effect, but we wish to clarify that this percentage will vary substantially depending on

Table 2   Summary of Price and Deal Effects in Brand Sales Model

Category	Median value across brands			Mean value across brands		
	Price effect (%)	Current deal effect (%)	Net deal effect (%)	Price effect (%)	Current deal effect (%)	Net deal effect (%)
Automatic dishwasher detergent liquid	24	21	10	21	42	15
Automatic dishwasher detergent powder	1	31	8	2	26	6
Dishwashing liquid	0	20	4	0	28	−3
Fabric softener sheets	5	33	10	11	33	12
Laundry detergent liquid	8	82	35	17	68	36
Laundry detergent powder	5	21	21	17	36	30
Paper towels	7	56	44	20	61	36
Toilet tissue	1	52	34	2	118	25
Toothpaste	7	23	11	8	36	17
Overall sample	5	38	12	11	54	22

Note. Average weekly percentage change in sales due to a 12% price cut given for three consecutive weeks at start of a 13-week quarter.

how deeply and frequently a brand is promoted. The wear-out effect, in particular, becomes much stronger as the number of consecutive promotions increases. For instance, if a promotion is offered for five consecutive weeks instead of three, the average net deal effect is only 13% of the current effect and is smaller in magnitude than the regular price effect.

4.2. Predicting the Direction of Change
Figure 1 summarizes the actual changes made by P&G in the Chicago market between the last 15 weeks of 1991 and of 1994. The median change in P&G's wholesale price was −4%. This is perhaps not as strong a reduction as we might have expected given the publicized EDLP nature of P&G's strategy.
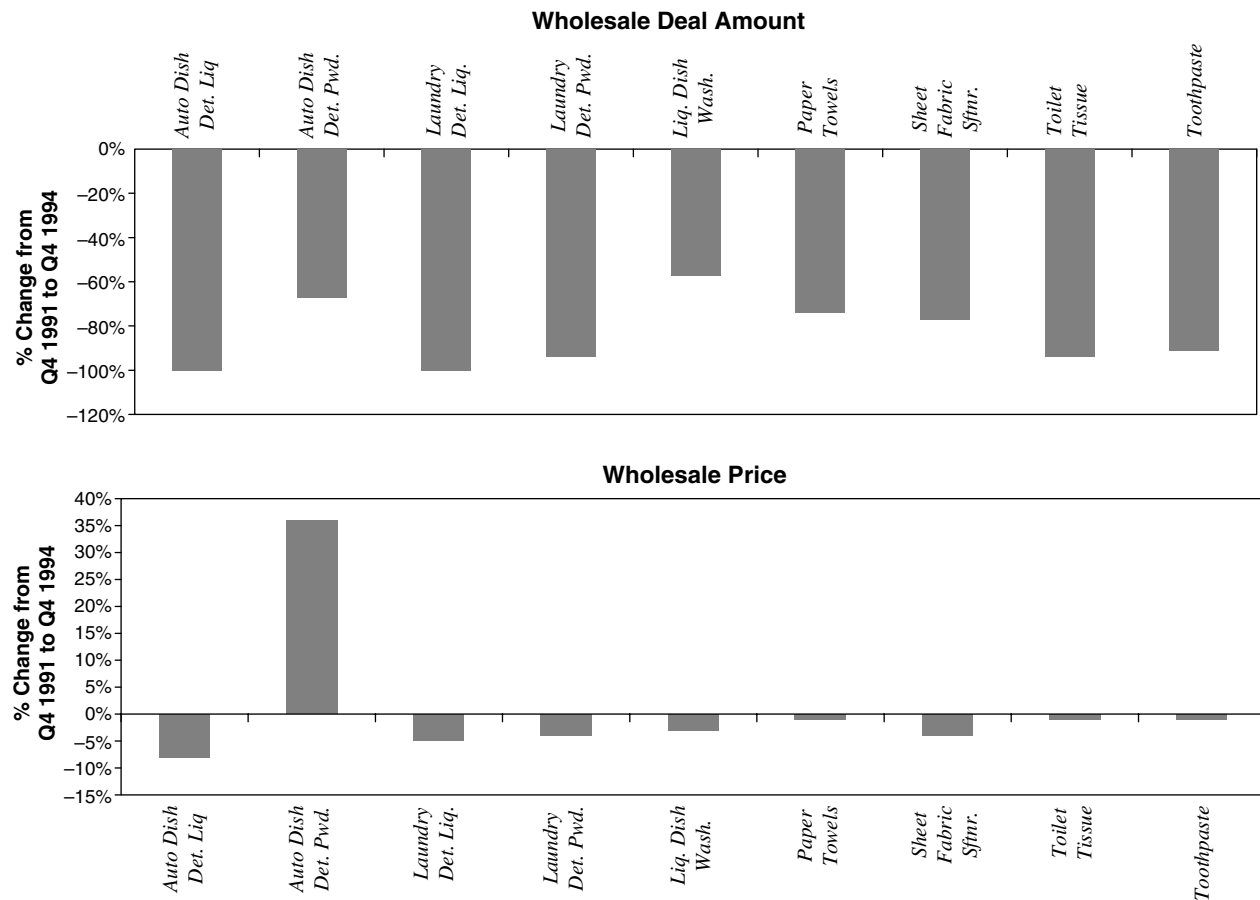
Figure 1   Procter & Gamble's Policy Changes in Chicago

Table 3   Predictive Ability of Models: Direction

Model	Game-theoretic model			Reaction function benchmark		
	Deal amount	Wholesale price	Retail price	Deal amount	Wholesale price	Retail price
Total number of observations	34	28	43	34	28	43
% Admissible predictions (base = total observations)	94%	100%	93%	68%	96%	98%
% Directionally correct predictions (base = admissible predictions)	78%	71%	78%	52%	48%	55%
% Correct "up" predictions (base = admissible "up" predictions)	79%	50%	87%	46%	25%	64%
% Correct "down" predictions (base = admissible "down" predictions)	77%	93%	65%	60%	67%	36%

However, changes in wholesale price go directly against P&G's profit margin. Consistent with value pricing, P&G decreased its dealing drastically in the Chicago market—the median cut across categories is about 90%. Response to these changes varied substantially across brands and categories, and we now evaluate how well our model and the two benchmarks are able to explain these variations in response.

The game-theoretic model and the reaction functions produce wholesale price and wholesale deal predictions for the 28 national brands; retail price predictions for the 28 national brands, the P&G brand in each of the nine categories, and the private label in the six categories where a private label was sold throughout the period of analysis; and retail deal predictions for the private label in those six categories. Since we do not have enough observations to estimate a private-label deal regression separately, we include those observations in the wholesale deal regression. The nonstrategic retailer benchmark model only makes wholesale price and deal predictions for the 28 national brands.

A model's predictions are "admissible" only if optimal values for both 1991 and 1994 do not hit bounds. The nonstrategic retailer benchmark model performed very poorly in terms of admissible predictions, with only 68% admissible predictions for wholesale deal amount and 39% admissible predictions for wholesale price. Therefore, we do not report detailed results for that benchmark, although they are available from the authors upon request. Table 3 summarizes the percentage of brands for which our model and the reaction function benchmark are able to make admissible predictions of change. It also shows the percentage of admissible predictions where the direction of change predicted is in line with the direction of the actual change. Several points should be noted from the table. First, the percentage of predictions that are admissible is higher for the game-theoretic model than for the benchmarks, although we use the same wide bounds for all models. Second, our model's ability to predict the direction of change for all the decision variables is better than chance and substantially higher than the benchmark. Third, our model predicts specific directions of change much better than the benchmark. For example, of the times when our game-theoretic model predicted that competitors would increase wholesale deal amounts, competitors actually increased deal amounts 79% of the time. This compares with 46% correct "up" predictions for the reaction function benchmark.

4.3. Predicting the Magnitude of Change
Table 4 provides estimates of the multiple regression model of Equation (9) using our game-theoretic model predictions as well as the reaction function benchmark predictions. In each regression, we use only those observations for which the model is able to make admissible predictions.[9] Table 5 provides means and standard deviations of all the variables in the model.

Table 4 shows that two of the three regressions using the reaction function predictions do not fit well. The coefficient of PREDCHG is significantly positive only in the deal amount regression. In contrast, our game-theoretic model predictions fit well, with the adjusted R^2 for the three regressions ranging from 0.16 to 0.69. More importantly, the coefficient of PREDCHG is positive and statistically significant for all three regressions, and is the most important driver of the explanatory power of the regression. This is an encouraging result. Using parameter estimates from an initialization period and the stimulus provided by P&G's major policy change, we computed the optimal changes that competing national brands and the retailer should have made in response to P&G's move, and these regressions show that the actual changes made by these agents are significantly associated with the optimal changes prescribed by the model. Interestingly, the covariates are generally not significant in these regressions. Perhaps this is because the effect of all the covariates except multimarket contact is already accounted for in the variation of demand parameters by brand and category that in turn determines PREDCHG.

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[9] PREDCHG is measured with error so our results may understate its true coefficient.

Table 4   Predictive Ability of Models: Magnitude

	Game-theoretic model			Reaction function benchmark		
	Coefficient in ACTCHG regression			Coefficient in ACTCHG regression		
Predictor	Deal amount	Wholesale price	Retail price	Deal amount	Wholesale price	Retail price
Predicted change (PREDCHG)	4.28×10^{-1}*** (1.01×10^{-1})	4.74×10^{-2}*** (2.20×10^{-1})	1.53×10^{-1}*** (1.74×10^{-2})	2.41×10^{-1}*** (9.68×10^{-2})	-2.75×10^{-1} (2.16×10^{-1})	4.75×10^{-3} (1.27×10^{-2})
Category advertising (CAD)	1.47×10^{-5} (5.70×10^{-5})	-7.37×10^{-4}* (4.71×10^{-4})	7.40×10^{-4} (5.21×10^{-4})	1.82×10^{-4}*** (6.08×10^{-5})	1.79×10^{-4}* (2.11×10^{-4})	-1.21×10^{-4} (9.21×10^{-4})
Category dealing (CDL)	5.79×10^{-5} (1.28×10^{-4})	-8.13×10^{-4} (1.1×10^{-3})	3.64×10^{-4} (1.22×10^{-3})	-8.60×10^{-5} (1.31×10^{-4})	9.09×10^{-6} (4.34×10^{-4})	9.75×10^{-4} (2.08×10^{-3})
Category purchase cycle (CPC)	1.32×10^{-4} (1.16×10^{-4})	-1.44×10^{-3} (1.03×10^{-3})	1.05×10^{-3} (1.09×10^{-3})	2.24×10^{-4}** (1.15×10^{-4})	-1.20×10^{-5} (4.15×10^{-4})	-1.66×10^{-4} (1.89×10^{-3})
Small share (SMALL)	2.98×10^{-3}** (1.73×10^{-3})	4.09×10^{-3} (1.56×10^{-2})	-2.01×10^{-2} (1.68×10^{-2})	-1.45×10^{-3} (1.84×10^{-3})	1.39×10^{-3} (6.38×10^{-3})	-1.90×10^{-2} (2.86×10^{-2})
Multimarket contact (MULTMKT)	1.52×10^{-4} (1.61×10^{-3})	1.66×10^{-2} (1.49×10^{-2})	-1.75×10^{-2} (1.40×10^{-2})	-2.27×10^{-3}* (1.43×10^{-3})	3.77×10^{-3} (6.40×10^{-3})	-2.90×10^{-2} (2.41×10^{-2})
R^2 (Adj. R^2)	0.53 (0.42)	0.35 (0.16)	0.74 (0.69)	0.61 (0.47)	0.09 (−0.19)	0.12 (−0.03)
F-stat	4.78***	1.88*	15.30***	4.21***	0.31	0.78
n	32	28	40	23	27	42

Note. Standard errors are in parentheses except in the R^2 row, where adjusted R^2s are in parentheses. ***$p < 0.05$; **$p < 0.10$; *$p < 0.15$.

5. Discussion

5.1. Summary of Findings

The primary conclusion of this research is that the prescriptions of a dynamic game-theoretic model contribute significantly to the prediction of actual

Table 5   Descriptive Statistics

Variable	Mean	Standard deviation
ACTCHG—Deal amount	2.03×10^{-4}	5.22×10^{-3}
ACTCHG—Wholesale price	-7.42×10^{-3}	3.36×10^{-2}
ACTCHG—Retail price	2.41×10^{-2}	6.96×10^{-2}
Game-theoretic model PREDCHG—Deal amount	-1.15×10^{-4}	7.88×10^{-3}
Game-theoretic model PREDCHG—Wholesale price	-3.97×10^{-2}	2.86×10^{-1}
Game-theoretic model PREDCHG—Retail price	1.22×10^{-1}	3.93×10^{-1}
Reaction function PREDCHG—Deal amount	-8.51×10^{-4}	6.15×10^{-3}
Reaction function PREDCHG—Wholesale price	2.68×10^{-3}	1.39×10^{-2}
Reaction function PREDCHG—Retail price	1.44×10^{-1}	9.09×10^{-1}
CAD ($ mill)	18.3	12.7
CDL (%)	38.9	10.9
CPC (days)	88.7	12.9
SMALL dummy variable	0.19	—
MULTMKT dummy variable	0.38	—

Note. Units of all ACTCHG and OPTCHG variables are $ per equivalent volume.

competitor and retailer response to a major policy change. We constructed our game-theoretic model and "calibrated" it using an empirical analysis of sales data in an initialization period. We then substituted P&G's price and dealing changes from a future period, and obtained optimal changes in the prices and dealing of national-brand competitors and retailers. That the nature of optimal changes corresponded with the nature of actual changes is an important accomplishment, especially given the challenge in formulating the dynamic structural model.

It took a sophisticated dynamic game-theoretic model to obtain predictions that were correlated with actual response. A reaction-function-based model that assumes competitors and the retailer will continue to react to each other's decisions the same way they have in the past, even in the wake of a major policy shift, has some predictive ability but is clearly dominated by our model. Also, a dynamic model that does not consider retailer response performs quite poorly.

The fact that this test is for a major policy change needs to be emphasized. Our findings support the view of Montgomery et al. (2005) that strategic competitive thinking on the part of managers is more likely for highly visible and major decisions, especially in the context of pricing. It also supports the premise noted in the introduction that structural models are preferable to reduced-form models when the agents involved are adjusting to a change in regime. For more typical, ongoing decisions and week-to-week or month-to-month reactions, where managers are less likely to engage in competitive reasoning,

the reaction function approach or a simplified game-theoretic model may have better predictive ability.

5.2. Implications for Future Research

One limitation of our model is that we do not consider retail competition. In our case, we simply did not have data on competitive retailers, but including retailer competition would be a challenge (see Sudhir 2001). Another is that we assume the retailer provides a fixed percentage of the trade deal to consumers during weeks when it buys on trade deal. Although we do endogenize forward buying, which is a primary reason for observed variations in the retail pass-through rate, it would also be worthwhile to make the retail deal decision endogenous. A third is that we assume deterministic demand. Although there is a strong tradition of deterministic models in the literature, introducing stochasticity would also be a valuable endeavor. Fourth, our model assumes exogeneity of P&G's actions and we analyze a period in which this assumption is empirically supported. However, there is some evidence that P&G later started to modify its strategy in response to marketplace reaction. It would be interesting to model such a scenario. Fifth, we only consider price and deal response, but competitors may also have reacted using other marketing instruments like advertising and coupons, on which we did not have data. Overcoming these limitations while keeping the complexity of the model within manageable limits is challenging but would be a fruitful avenue for future research.

Future research could also move beyond the manufacturer-Stackelberg game that we have used in this paper, either by testing other channel interactions like vertical Nash, or by utilizing the New Empirical Industrial Organization (NEIO) paradigm (e.g., Kadiyali et al. 2000, Putsis and Dhar 1998, Vilcassim et al. 1999). In the latter case, researchers could characterize the type of channel interaction using the initialization period and then test its predictions in the 1992–1994 period. The benefit of such an approach is clear since it does not impose a particular game structure a priori. The challenge, however, would be to incorporate in this framework the dynamics that are so important in studying promotion.

Finally, our game-theoretic model does not predict actual response perfectly. Although we compared its predictive ability with two reasonable benchmark models, other theories and models may predict just as well or even better. We encourage future researchers to investigate such alternatives. It would also be valuable to survey managers involved in this response to understand the heuristics they used, and the reasons why their actions corresponded to or deviated from those predicted by our model.

5.3. Conclusion

Methodologically, our study shows that combining a game-theoretic dynamic structural model with empirical estimates of demand functions can pay off in superior predictions of competitor response. Two crucial features of the model are dynamics (stockpiling, wear-out, retailer forward buying, multiperiod decision making) and multiparty decision making (incorporating both the retailer and the competitor). We therefore recommend that future users of this approach incorporate dynamics as well as retailer actions when predicting competitive response. Although closed-form solutions are difficult to obtain for such models, increased computing power and better data do make their use more feasible.

Substantively, our study demonstrates the benefits of examining significant policy changes. First, these are interesting managerially, but second, they are more likely to provide the exogenous change needed to measure competitor and retailer reactions. We believe this exogeneity is crucial. Consider the notion, advanced by Raju et al. (1990), Narasimhan (1988), and others, that promotions are mixed-strategy equilibria. The implication is that, in equilibrium, manufacturers promote randomly and do not respond to each other on a week-by-week basis. This may explain why it is difficult to measure week-to-week competitor response in packaged-goods markets. It takes a major policy change—an out-of-equilibrium move in terms of Raju et al. (1990) and Narasimhan (1988)—to identify competitive response.

Managerially, the promise of our findings is that managers can use game-theoretic models to gauge competitive response. We say "promise" because our findings are initial, and we would advocate replications and extensions before managers can safely make major business decisions based on these predictions. However, our results suggest that empirically calibrated game-theoretic models do have that potential. Finally, this study analyzes but one instance of predicting competitive response to a major policy change—in the packaged-goods industry when a "big player" makes a well-publicized move. We need to generalize beyond this single instance to other industries and other circumstances. Our results provide encouraging evidence that this would be a fruitful endeavor.

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