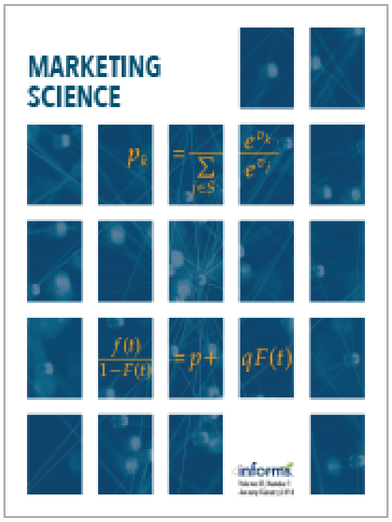

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Practice Prize Paper—Marketing-Mix Recommendations to Manage Value Growth at P&G Asia-Pacific

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Practice Prize Paper

Marketing-Mix Recommendations to Manage Value Growth at P&G Asia-Pacific

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Procter & Gamble (P&G) Asia-Pacific is interested in managing value growth. Only after fully understanding the true effects of the marketing-mix variables can P&G managers make strategic decisions answering questions such as the following: (1) Are the P&G brands in the detergent market inelastic or elastic with respect to price? How has the price elasticity changed over time? Can P&G increase the price of its brands to gain value growth? (2) What are the price, distribution, and sizing combinations needed to achieve the desirable value growth? (3) How can P&G gain market share from its competitors without cannibalizing its own brands? P&G Asia-Pacific approached us to develop a value growth framework to answer these questions. To generate the answers for the above questions, we develop a three-step weighted random coefficient estimator that captures the heterogeneity across cross sections (different stock-keeping units and states) and the endogeneity of distribution. Based on the parameter estimates, we provide strategic recommendations to P&G for a field test to validate our suggestions. We developed a simulator for P&G managers so that they can generate appropriate marketing-mix strategies for achieving the desired value growth. As a result, P&G gained over $39 million in value growth over a one-year period by implementing the recommendations from our modeling approach.

Key words: marketing mix; price elasticity; distribution; random coefficient model; system of equations; sales value; revenue; sales volume
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1. Introduction

Procter & Gamble (P&G) has been present in the Indian laundry detergent market for almost a decade. P&G achieved sales volume growth at the beginning by cutting prices over time. However, the category growth for laundry detergents has been marginal in recent years, and the price-cutting strategy became less effective, especially because of the aggressive competition. Many strong brands (mostly domestic) have been in existence in the market for many years when compared to the P&G brands Ariel and Tide. In general, the market was quite price elastic at the beginning of the study period, the year 2000. This means that for most companies, the trend in the category has been to decrease the price to gain volume share. However, it is a different story with value growth (i.e., revenue growth). Because of the two major price decreases, the value growth has been minimal or even nonexistent. A key question for P&G Asia-Pacific (responsible for India, China, Australia, and other countries in that region) is how to realize value growth (not just volume share growth) from both the P&G brands in this category. Specifically, the questions posed by P&G include the following:

- Are the P&G brands in the detergent market inelastic or elastic with respect to price? How has the price elasticity changed over time? Can P&G increase the price of its brands to gain value growth?
- What are the price, distribution, and sizing combinations to achieve the desired value growth?
- How can a higher-tier P&G brand (Ariel) gain share from the lower-tier brands without cannibalizing P&G's own brand in the lower tier (Tide)?

To answer these marketing-mix questions, P&G approached us[1] to develop a value growth framework by measuring elasticities; investigating the pricing, distribution, and sizing (package size) strategies for achieving the desired value growth for each P&G brand; and evaluating the draw of sales from the lower-tier brands, including P&G's own lower-tier brand (i.e., cannibalization effect). We measure the

[1] Here, "us/we" means the academic authors; "P&G" refers to the P&G company or the executives and their marketing team.

price and distribution elasticities by developing a system of equations for our same-tier sales response models and up-tiering sales response models (to evaluate the draw of sales from the lower-tier competitors), we will call them "same-tier" and "up-tiering" models throughout the paper. Therefore, the joint effect of various marketing-mix variables including price, distribution, commercial innovation, as well as those from competition in different tiers, can be evaluated together in this system. To incorporate the cross-sectional differences in the overall response coefficients and the heterogeneity in response for different stock-keeping units (SKUs) and states, we use a three-step weighted random coefficient regression (RCR) approach to estimate the models. This is the first time in the literature that this weighted estimator is used for the case of a system of equations, and we also show the properties of this estimator in the Technical Appendix, located at http://mktsci.pubs.informs.org. The results revealed that price elasticities were very low (all below one) by the end of the study period, and distribution played a critical role in sales volume. These findings indicate the potential to achieve value growth by increasing price and expanding distribution. Given that no significant additional cost was incurred to increase the distribution, it should ultimately lead to the profit growth. Based on our model results, we develop a sales volume and value simulator for each of the two P&G brands—Tide and Ariel. These simulators enable the marketing managers at P&G to develop the desired pricing/distribution/sizing strategies instantly, find out which competitive brands and SKUs they are actually competing with, and develop proactive marketing strategies to manage value growth. From 2006 to 2007, P&G conducted a field test to evaluate our recommendations. They increased the prices for all the packages at different levels according to their individual elasticities. As a result, P&G gained over $39 million in value growth over a one-year period by implementing our recommendations.

The rest of the article proceeds in this manner. In §2, we discuss the project background and the main ideas behind our approach. Section 3 provides the details on our analytic approach, which includes the description of the data and model development process. The findings and strategic recommendations are described in §4, and the field test is addressed in §5. Section 6 evaluates the implementation and its impact, and discusses potential suggestions for future research.

2. Background

2.1. Study Context

The Indian detergent market is quite complex. It consists of three distinctive price tiers: super premium (Tier 1—average price around 100 Rs/kg), premium (Tier 2—average price around 50 Rs/kg), and popular tier (Tier 3—average price around 20 Rs/kg). There are a total of 11 brands, of which P&G has two—Ariel (in Tier 1) and Tide (in Tier 2). Within each brand, there are two package forms that a customer can choose from—bags and sachets. The packages that weigh less than 100 g are considered sachets, which are designed for a one-time use. The packages that weigh more than 100 g are considered bags, which are designed for long-term use. Within a package form, there are different sizes—e.g., 200 g, 500 g, and 1,000 g for the bags, and 20 g for the sachets. This market is divided into 10 states by P&G for the purpose of data collection process and management by regions. These 10 states vary in terms of culture and economic environment. Data are collected at the state level for all the brands and SKUs.

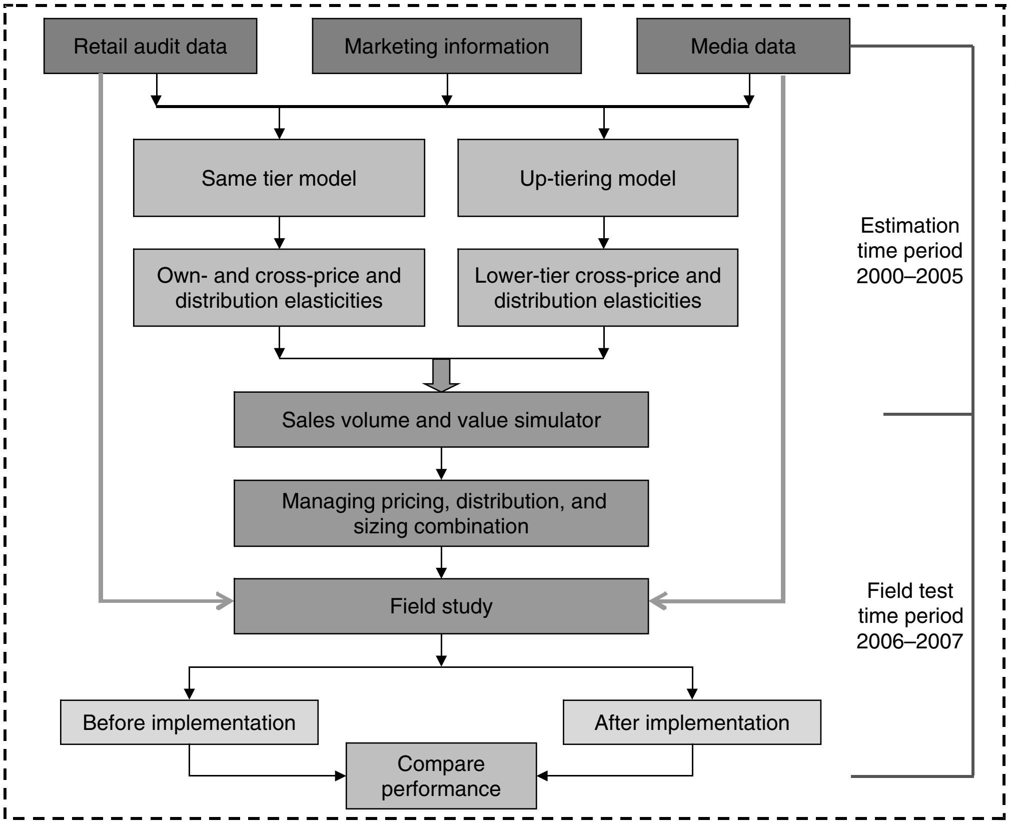
P&G entered this market later than other brands, and they had two major price cuts to expand their market share. However, P&G wants to find out the best way to achieve their desired value growth because a dramatic price cut would be very costly for them. A low-price strategy will not induce value growth, especially when the price elasticity is smaller than one. Therefore, the goal of our project is to manage P&G's value growth through the appropriate allocation of marketing-mix resources. Without inducing extra costs, the value growth will lead to the profit growth.

2.2. Value Growth Framework

We believe that all the marketing-mix variables impact the volume and value growth. To achieve a desired value growth, we have to disentangle the effects of these variables on the sales volume, and allocate the resources accordingly. Therefore, we develop a value growth framework in which we first develop marketing-mix models to estimate the parameters (the effects of the marketing-mix variables on sales volume). These marketing-mix variables include P&G brand's variables as well as P&G's same-tier and adjacent-tier competitors' variables. Then we convert the parameter estimates of all these variables into universal elasticity measures in terms of sales volume. Using these elasticities, we create a sales volume and value simulator as a tool for generating the strategic guidelines. Finally, P&G implemented our recommendations and tracked the results in 2006 and 2007.

Figure 1 illustrates how we achieve the desired value growth. We have three sources of information that we use in this framework: retail audit data, media data, and marketing information. Combining these three sources of information, we develop two types of models: same-tier and up-tiering models. More specifically, in the same-tier model, dependent variables

Figure 1 Implementing Value Growth Framework



are P&G brands' sales and distribution, and independent variables are marketing-mix variables of P&G brands and their same-tier competitors. The existing literature exhibits the presence of asymmetric competition among different price tiers (Kumar and Leone 1988, Blattberg and Wisniewski 1989). Therefore, we develop an up-tiering model to explain the competition across different price tiers. In the up-tiering model, dependent variables are Tier 2 or Tier 3 brands' sales and distribution, and independent variables are marketing-mix variables of Tier 2 or Tier 3 brands and their higher-tier competitors. We believe that looking at price alone is not a good marketing strategy. Reibstein and Farris (1995) argue that distribution is a combined result of various marketing activities including brand preference, brand loyalty, and "push" programs. We develop the model with sales and distribution as a system of equations because we tested and confirmed the endogeneity of distribution in our preliminary analysis. The same test was used to test the endogeneity of price, which was found not to be significant. We also tested the cross-effects between nonadjacent tiers, but they are not significant due to the fact that all three tiers are very distinct from each other (Tier 1 contains super premium brands with average price around 100 Rs/kg, Tier 2 contains premium brands with average price around 50 Rs/kg, and Tier 3 contains popular brands with average price around 20 Rs/kg).

We have price and distribution in different units. To compare the effects of these two variables in drawing sales volume from same-tier and lower-tier brands, we convert all the parameter estimates into elasticity measures. We especially want to examine the effect of price on value by checking whether the price elasticity is greater than one.

The goal of the framework is to provide a tool for P&G managers to evaluate the effects of the key marketing-mix variables as a system. Therefore, using all the response coefficients/elasticities, we design a sales volume and value simulator for Ariel and Tide, respectively. It incorporates all the key marketing-mix variables and calculates their effects on sales volume and value systematically. P&G managers can use this simulator directly to calculate the predicted sales volume and value as a result of planned price and distribution change. Based on the elasticities from the same-tier model, the simulator can tell the managers how much volume/value gain or loss will occur due to the changes in P&G's or its same-tier competitor's price, distribution, or commercial innovation; similarly, based on the elasticities from the up-tiering model, the simulator can provide the managers with information about how much volume/value gain or loss is expected from each lower-tier competitor when P&G changes its price, distribution, or commercial innovation.

By using the simulator, we investigated which SKUs have the highest potential to achieve sales volume and value gain and provided strategic recommendations to P&G. Then, P&G adjusted the prices and introduced a few commercial innovations for each of their SKUs. Distribution also increased because of this. After the implementation, P&G collected the same set of data that we used for our model development to conduct the impact analysis.

3. Analytic Approach

In this section, we will discuss the data used in this study and the development of models.

3.1. Data

P&G provided us with the state-level monthly data for 11 brands at the SKU level in a five-and-a-half year period (July 2000–December 2005), giving us a total of 8,485 observations. Because P&G also wants to know the sales volume change in each state, our same-tier model is built at the SKU-state level. The sales volume for each SKU is reported in stock units (SUs) normalized for the variations in package size. The price is measured as the average price per SU. The distribution is a retailer-calculated measure of the percentage of stores in a state that are selling the item weighted by the stores' total turnover (see details in Technical Appendix, located at http://mktsci.pubs.informs.org). The distribution for all the brands and SKUs are defined in the same way.

In such a competitive market, the sales volume for all three tiers is growing over time. Tier 2 has the highest growth rate at 120%, followed by Tier 1 at 78%, and Tier 3 at 67% from July 2000 to December 2005. One potential reason why Tier 2 has the highest growth rate, whereas Tier 3 has the lowest, could be that Tier 2 is drawing sales from Tier 3 (which has the highest sales volume among the three tiers) when the prices of Tier 2 brands were decreasing over time. There are two major price drops for Tide and Ariel over the five-and-a-half year period. P&G expected the price drops to bring them significant value growth. However, the value growth of P&G is minimal.

3.2. Model Development

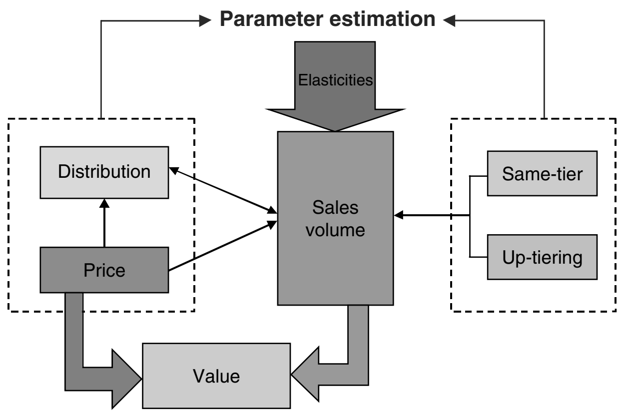
In this market, detergent sales also highly rely on the breadth of distribution because most detergents are sold in convenience stores that are omnipresent in this region. We treat distribution as an endogenous variable because it is largely determined by customer demand and the storeowners' brand preference/loyalty. To test for the endogeneity of price and distribution, we have to find the instrumental variable (IV) for them first. An IV has to be (a) correlated with the endogenous variable and (b) not correlated with the error terms in the system of equations. Because most stores are small convenience stores in this market, the sales volume is determined by the customers' request and storeowners' preference. Because of the severe competition between convenience stores, the storeowners were quite aware of what was popular in the market. When the sales volume increases, the storeowners who were not selling this product started to sell, whereas those who were already selling this product tend to keep more of the product in stock. Therefore, the sales volume growth will induce increase in distribution. Thus, we use various sales growth rates (monthly sales growth, two-month moving average, three-month moving average, etc.) as the candidates for the IV of distribution besides some demographic variables (e.g., population density, average income level, etc.).

To test for the two IV conditions stated above, we first check for the exogeneity condition. It is not easy to find exogenous variables that are not correlated with the existing independent variables in the model. We tried various variables, including demographic variables. The demographic variables are all correlated with the residuals from the preliminary ordinary least squares regression. When we tried the moving average of sales volume growth variables mentioned above, the correlations are not significant. Then we checked these IV candidates for their relevance by calculating their partial R2 (Hall et al. 1996, Shea 1997) and found that the three-month moving average has the highest partial R2. Therefore, we use it as our instrumental variable in the model.

For "price," we follow the same procedure and found that the three-month moving average of the sales value growth rate is a good instrument for price (value growth might influence the firm's pricing but not sales volume). However, using the Hausman endogeneity test, we found that price is not endogenous.

To measure the effects of marketing-mix variables accurately, we have to take the endogeneity of distribution as well as both the same-tier and up-tiering effect into account in our models. The conceptual framework of our approach is shown in Figure 2. We build the same-tier models and up-tiering models for each Ariel bag, Ariel sachet, Tide bag, and Tide sachet due to the fact that customers do not have the same purchase patterns for different brands and package forms. The modeling framework is shown in Figure 3. To get different responses from each of the cross sections (i.e., SKU-state combination for the same-tier model and brand-SKU-state combination for up-tiering model), we estimate each of these models by a three-step weighted RCR estimation.

Figure 2 The Conceptual Framework



3.2.1. Same-Tier Model. In the process of model development, we first build the same-tier models to see which of P&G brand's or competitors' marketing-mix variables have significant effects on the sales volume of P&G brands. As mentioned earlier, we build our same-tier model at SKU-state level. Thus, our same-tier models are hierarchical models with the combinations of SKUs and 10 states as cross sections. For example, we have four SKUs in the same-tier model of Ariel bags and 10 states. Thus, we have a total of 40 cross sections in this model. This system of equations model is composed of sales and distribution equations. $Sales_{it}$ represents the monthly sales volume of SKU-state combination i at time t, and $Distribution_{it}$ represents the distribution of SKU-state combination i at time t. In the same-tier model for Ariel bags, we use $(Comp\_Price)_{it}$ and $(Comp\_Distribution)_{it}$ to represent Surf Excel's (Ariel's only same-tier competitor) price and distribution in SKU-state cross section i. We tested for the competitive effects from all the tiers but found that lower-tier competitors would not be able to draw sales from higher-tier brands (Kumar and Leone 1988). Thus, lower-tier marketing-mix variables are not included as independent variables. CI is the commercial innovation, which is the most common marketing initiative for P&G. There were two major commercial innovations (CIs) (e.g., the "OxyBlu additive" commercial campaign) in 2004 and 2005, respectively. Both the campaigns were followed by volume growth. Overall, there are 20 variables in each equation. These variables include *Price*, *Distribution*, *Advertising*, *Promotion*, and CI for P&G's own brands and competing brands in the same tier. The system of equations of *Sales* and *Distribution* for the cross section i at time t with a few select variables is shown below.

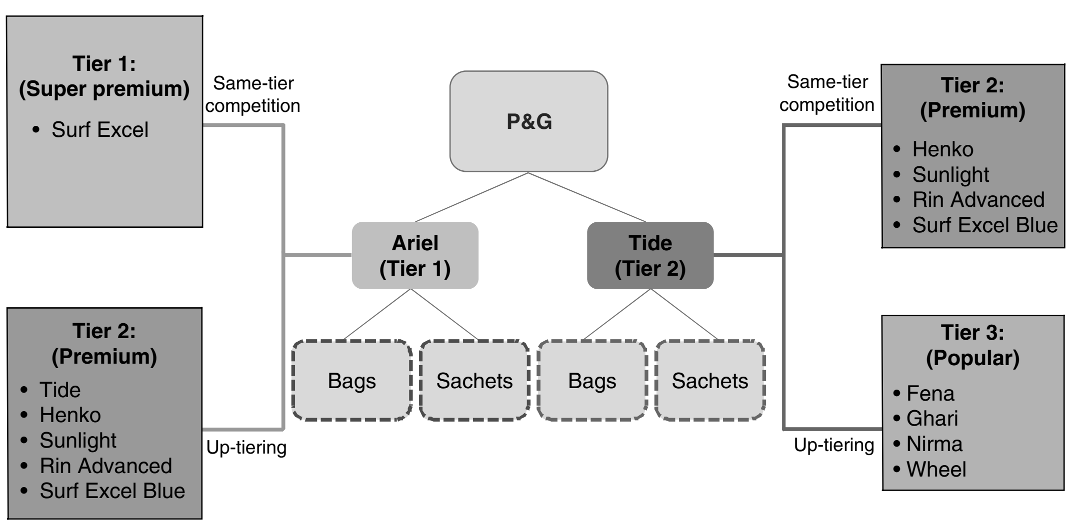
$$\left\{\begin{aligned} Sales_{it} &= \alpha_{0i} + \alpha_{1i}Y02_{it} + \alpha_{2i}Y03_{it} + \alpha_{3i}(Price)_{it} \\ &\quad + \alpha_{4i}(Y02*Price)_{it} + \alpha_{5i}(Y03*Price)_{it} \\ &\quad + \alpha_{6i}(\mathrm{CI})_{it} + \alpha_{7i}(Comp\_Price)_{it} \\ &\quad + \alpha_{8i}(Comp\_Distribution)_{it} \\ &\quad + \alpha_{9i}(Distribution)_{it} + \cdots + \varepsilon_{it}, \qquad (1) \\ Distribution_{it} &= \beta_{0i} + \beta_{1i}Y02_{it} + \beta_{2i}Y03_{it} + \beta_{3i}(Price)_{it} \\ &\quad + \beta_{4i}(Y02*Price)_{it} + \beta_{5i}(Y03*Price)_{it} \\ &\quad + \beta_{6i}(\mathrm{CI})_{it} + \beta_{7i}(Comp\_Price)_{it} \\ &\quad + \beta_{8i}(Comp\_Distribution)_{it} \\ &\quad + \lambda_{1i}(QSG)_{it-1} + \cdots + \xi_{it}, \qquad (2) \end{aligned}\right.$$

where

$$Y02_{it} = \begin{cases} 1 & \text{July 2000} \le month \le \text{December 2002}, \\ 0 & \text{else}; \end{cases}$$

$$Y03_{it} = \begin{cases} 1 & \text{January 2003} \le month \le \text{February 2004}, \\ 0 & \text{else}. \end{cases}$$

Figure 3 The Modeling Framework



We created time dummies in this study to capture the time-varying nature of the price sensitivity and the price drop occasions for Ariel and Tide. For example, we created two time dummies $Y02$ and $Y03$ for Ariel bags to reflect the price regimens caused by the two major price drops in January 2003 and March 2004, respectively. The dummies themselves reflect the effects of price regimens (accounted by the intercepts), and the interactions of the price dummies with price reflect the change in the price effects on sales in the three regimens (accounted by the slope coefficients). According to the literature on RCR (Hsiao and Pesaran 2008), presuming the parameter to change in each time period (month) is not parsimonious and it is not feasible to estimate the model. Therefore, we assume a constant parameter for price in each of the three price regimens.

After trying various nonlinear model specifications, we converged on the linear model form. This linear model fits the data quite well, and so we retain this simple model. The mean absolute percentage error (MAPE) is the lowest for the linear model. For example, the MAPE for Ariel (500 g) is 4.7% for the linear model, 7% for the log-linear model, and 8.1% for the log-log model. Similar results were observed for the other SKUs, indicating that a linear model provides the best fit for this data set. Advertising is an important element to the sales volume in the consumer packaged goods (CPG) category. P&G spends a huge amount on advertising, especially on TV commercials; so do P&G's competitors. With similar information in their advertising, it is possible for the effect of P&G's advertising to cancel out with those of competitors' advertising, leading to a very little sales gain for P&G (Bass and Pilon 1980). The other reason for advertising not to be significant in our model is that advertising in this market could have reached equilibrium, and the advertising spending was to maintain the equilibrium instead of increasing the sales volume directly. However, the commercials that carry information on innovations about the P&G brands differentiate P&G from its competitors. The effects of this type of advertising will not be cancelled out. In other words, they will have an impact on the sales volume. In our model, CI is the variable that reflects this type of effect. Managers have to maintain their advertising level while working actively on producing advertising involving commercial innovations for differentiating their products from their competitors. We assume the constant effects of CI and *Distribution* over time based on our preliminary analysis. To account for the endogeneity of *Distribution* and get an unbiased estimator for Equation (1), we use $(QSG)_{t-1}$, which is defined as the three-month moving average of monthly sales growth rate as our IV for $Distribution_{it}$. The monthly growth rate of sales volume expands distribution because the convenience store owners are willing to carry the product when they observe an increase in sales. Furthermore, the introduction of CIs will cause the distribution to increase because of the pull from the customers.

To incorporate the cross-sectional differences in the overall response coefficients and the heterogeneity in response for different SKUs, we develop a three-step weighted RCR approach to estimate the four same-tier models. In the first step, we estimate the model by two-stage least-squares (2SLS) estimation at the SKU-state level to get individual parameter estimates for each cross section. Then, we compute the parameters for the regular RCR by weighting the 2SLS parameters we obtained in the first step with the help of a mean squared error (MSE) estimate and a dispersion estimate. The MSE estimate is obtained for each cross section, whereas the dispersion estimate is obtained across the cross sections. The system of equation setup helps us to jointly estimate the interdependencies between sales and distribution responses. However, we will not be able to capture the heterogeneity across different SKUs because there is only one common mean for all the cross sections if we use the regular RCR estimates. To capture the heterogeneity across different SKUs, especially to get different own- and cross-price elasticities for different SKUs, we calculate the weighted average of the coefficients from the pooled RCR and individual 2SLS to get the individual set of parameters for each cross section in the third step. In this weighted estimator, the weight for the pooled RCR is the ratio of MSE to the total (MSE + dispersion), and the weight for individual 2SLS is the ratio of dispersion to the total. It means that when the dispersion is large (i.e., the cross sections are very distinctive from each other), we should give more weight to individual 2SLS, whereas when the MSE is large (i.e., the individual 2SLS estimate is not reflective), we should borrow more information from the pooled RCR. This weighted RCR estimator can help us capture both the common properties of all the cross sections as well as the stochastic character of the individual response (Kadiyala and Oberhelman 1982, Leone et al. 1993). The details of this estimation process are in the Technical Appendix, located at http://mktsci.pubs.informs.org. Following the above process, we get a new set of parameter estimates that vary across different SKUs and states (see the Technical Appendix, located at http://mktsci.pubs.informs.org, for a sample set of estimates).

3.2.2. Up-Tiering Model. One of the key challenges of this project is to effectively draw sales from a lower tier without cannibalizing P&G's own lower-tier brand (Tide). As stated earlier, given the distinct price tiers, only the adjacent tier brands were found to be significantly impacting the sales. We developed an up-tiering model for Ariel (see Figure 3) where the immediate lower-tier competitors' (e.g., Rin, Tide, etc.—belonging to Tier 2) sales volumes is the dependent variable, and the lower-tier brands' marketing-mix variables are the independent variables, in addition to the marketing-mix variables of Ariel and its competitors within the same tier. We also specify similar models for Tide and replicate the analysis for both package forms—bags and sachets. The up-tiering models have a similar, but not exactly the same, data structure as the same-tier model. We stack all the brands in the lower tiers one below the other so that the up-tiering models have three levels of combinations: brand, SKU, and state. These combinations create more cross sections in the model. However, we can use the same estimation approach that we used in the same-tier model—with more cross sections as the only difference between these two types of models in terms of model specification. From the up-tiering model, we can get the parameter estimates of P&G price and distribution to see specifically which P&G SKU is influencing which lower-tier competitors' sales volume the most and to provide the basis to determine the best pricing-sizing combination.

3.2.3. Model Specification Test. We use the RCR with a system of equations to estimate both the same-tier models and the up-tiering models. To verify whether our models are correctly specified, we first use the extra sum-of-squares F-test to see if it is right to have individual parameter estimates for each state. Then, we use the Hausman (1978) specification test to evaluate the appropriateness of our weighted RCR. The results show that the heterogeneity across cross sections was too significant to pool them together. Thus, a natural choice would be an individual 2SLS for each cross section. As explained in §3.2.1, our weighted RCR estimator is a weighted average of 2SLS and pooled RCR, which explains the heterogeneity across individual cross sections by borrowing information from the pooled data. Thus, we use individual 2SLS as our benchmark for comparison because we are more interested in obtaining cross-section–specific effects. More information on the model specification test is given in the Technical Appendix, located at http://mktsci.pubs.informs.org.

The H statistics were computed for each cross section, and the H statistics are all smaller than the critical value of 55.76 at $p = 0.05$ level with 40 degrees of freedom, which shows that our weighted RCR model is correctly specified.[2]

[2] The entire list of parameter estimates can be obtained from the authors upon request.

4. Findings and Recommendations

After obtaining the parameter estimates from the same-tier models and up-tiering models, we calculate P&G's own price and distribution elasticities, as well as its cross-price and distribution elasticities of the same-tier competitor on P&G sales volume from the parameter estimates of the same-tier models. We also calculate the cross-price and distribution elasticities of P&G brands on the lower-tier competitors' sales volume from the parameter estimates of the up-tiering models.

As shown in the previous section, our models were developed at the SKU-state level because P&G was interested in the decomposition of sales at the state level as well as the SKU level. The parameter estimates we obtained were also at the SKU-state level. However, P&G required the sales volume and value simulator to be at the national level so that their central marketing department can make the pricing policy changes at the national level. Thus, we used the SKU-state level parameter estimates to calculate the national-level elasticities, which will be then used to obtain the national-level sales volume and value using the simulator. To reflect the instantaneous market conditions, we use the price and sales volume at time t to compute the elasticity at time t. To reflect the strategic uncertainty, we also calculated the confidence intervals for elasticities based on Dorfman et al. (1990). The details of these calculations are shown in the Technical Appendix, located at http://mktsci.pubs. informs.org.

After obtaining all the price and distribution elasticities, we use these elasticities as well as the response effect of CI to generate the volume and value simulator for Ariel and Tide. We use the most recent price elasticity (December 2005) to simulate the effects of price changes. For each SKU, the simulation is done within its price range in the estimation period because the linear model specification and the results are limited to the price range of each SKU in the data in our study period. P&G can use this simulator to estimate the sales volume and value change when they change their prices or introduce any commercial innovations, which will then lead to an increase in distribution. In addition to their own volume and value changes, the impact on the competition brands' sales volume because of these changes is also calculated based on the cross-elasticities we calculated in the previous step. Competitors' price reactions were calculated using Kumar (1994), and competitors' future prices were put in the background calculation sheet of the simulator because they were not controlled by the P&G managers. A portion of the screenshot of the simulator illustrating 500 g Ariel is given in the Technical Appendix, located at http://mktsci.pubs.

informs.org. We demonstrate the utility of the simulator by increasing the price by about 8% and introducing four CIs. This led to an increase in sales volume, resulting in a recommendation for distribution to be increased by about 15%. The monthly volume change is 11,403 stocking units, and the monthly value change is about $200,000. This translates to an annual projected gain of about $2.4 million just for this SKU. If we also include the effect of competitors' price increases in 2006 (which is about 4%), then our simulator predicts the sales increase to be close to $2.9 million. In the field test, the actual gain was about $3 million in 2006.

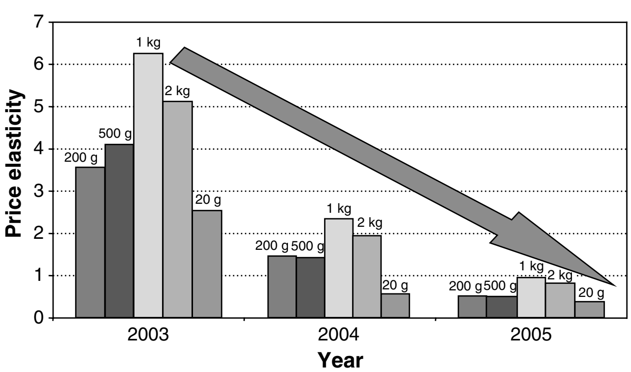
Using the simulator, we developed marketing-mix guidelines for P&G based on their questions.

4.1. Marketing-Mix Strategies

Given the pressure from competitors, firms typically reduce the price to increase the sales volume. However, the ultimate goal of P&G is to manage value growth instead of sales volume. With this comes the question: Should P&G decrease price to increase their sales value? The answer is definitely no, based on the results of our empirical analysis. In general, when the price decreases to some point, the customers become insensitive to the price changes. Combining with the effects of brand loyalty, customers become even more insensitive to price changes. A further decrease in price will not help the sales volume, and it will actually hurt the sales value. Thus, value decreases because the percentage increase in sales volume is smaller than the percentage change in price under this situation. With the P&G brands, there is a clear pattern of decreasing price elasticity over time for all the package forms/size combinations of both brands. We have reasons to believe that price elasticity decreases over time because factors like advertising, brand loyalty, etc., lead to a lower price elasticity (Kaul and Wittink 1995). The trend for Tide elasticity is shown in Figure 4. Ariel follows a similar pattern.

Besides price, another factor that influences the sales volume significantly is the distribution. Because most sales of detergents in this market occur in convenience stores, the breadth of distribution is critical in determining the sales volume. It is especially important when the price is inelastic. Sometimes, the effect of increasing distribution is even more dominant than the effects of lowering or raising price. From our model, we found that even when price increases, an increase in distribution can compensate for the loss of sales caused by an increase in the price. This pushes the sales volume to an even higher level than before while creating opportunities for revenue growth.

Figure 4 Tide Price Elasticity Trend



4.2. Focusing on Key Products for Value Growth

After calculating the price and distribution elasticities and estimating the effects of new-product and market initiatives, it is clear that a prudent strategy to increase the value would be to increase the price and introduce new commerical innovations. Because the model allows for heterogeneity across different SKUs, some SKUs were found to have more potential to lift the value (and profit). Thus, we determined the pricing/distribution/sizing combination for realizing desired value growth.

For Ariel bags, we found that 500 g Ariel is very price inelastic ($\eta_{\text{Ariel\_500}} = 0.09$), so we suggested that P&G increase the price of 500 g packages (for example, P&G increased the price by about 8% in 2006). The amount of price increase is guided by our simulator, which shows that a desired value growth can be achieved by a combination of changes in price, distribution, and new initiatives among other factors. For Tide bags, we found that 500 g Tide is also price inelastic ($\eta_{\text{Tide\_500}} = 0.53$), so we suggested that P&G increase the price of the 500 g package of Tide (for example, P&G raised the price by about 5% in 2006). In addition, the sachets of both Ariel and Tide have very low price elasticity: $\eta_{\text{Ariel\_20}} = 0.299$ and $\eta_{\text{Tide\_20}} = 0.38$. Thus, increasing their prices can also bring a higher sales value. As a result, P&G raised the prices for these two brands and realized a higher value growth. Moreover, P&G prevented the cannibalization of Tide by Ariel.

To display the effect of changes in the marketing-mix elements in our simulator, we calculate the effect of a 5% increase in price, a two-unit increase in CI, and a 15% increase in distribution caused by the total effect of price increase, the CI increase, and the past sales volume growth represented by $(QSG)_{t-1}$ (see Table 1).

From Table 1, we can see that a 5% price increase caused a slight monthly volume drop but a significant monthly value increase (in '000 Rs). The slight drop in volume will not influence the P&G market penetration because distribution and initiatives such as CI effects are strong enough to support the increasing trend of sales volume. Also, the growth in past sales and the

Table 1 Illustration of the Effects of Price, Distribution, and Commercial Innovation Changes Using the Simulator (500 g Tide)

	Volume change (SU)	Value change ('000 Rs)
(i) Effects of a 5% price increase		
Elasticity		
0.53	−1,740	872.1
(ii) With a two-unit increase in CI		
CI effect		
643.6	1,287.2	809.5
(iii) 15% increase in distribution		
Distribution effect		
546.9	4,220.1	2,654.1
Total effects	3,767.3	4,335.7
Annual value change is equivalent to		US$ 1.4 million

introduction of CI caused a 15% increase in distribution, which is more than enough to recover the volume loss from price increase. Although it is easy to assume that increasing distribution will cause an increase in sales, the right pricing strategy for the right product form-size is critical given the past experience of P&G in this product category. An interesting observation here is to be able to achieve the desired value growth through price increases and to generate higher value with relatively lesser magnitude of increases in distribution (given that it is not easy to convince the retailers to carry all of the P&G products in this category).

From our analysis, we found four SKUs (500 g Ariel, 500 g Tide, 20 g Ariel, and 20 g Tide) to have the lowest price elasticity. Therefore, they can achieve the desired value growth most quickly and with the lowest effort. By narrowing on these four core products and gradually focusing on the other SKUs, P&G can achieve the goal of value maximization most efficiently.

4.3. Evaluating Up-Tiering Effect

Because of the asymmetric effect of price competition between brands from different price tiers, Ariel, as a Tier 1 brand, can attract sales from Tier 2 brands when its price drops; Tide, as a Tier 2 brand, can attract sales from Tier 3 brands when its price drops. Thus, we developed up-tiering models to examine the determinants and magnitude of these up-tiering effects. From up-tiering models, we found that there are some P&G bags/SKUs that can significantly influence the sales of lower-tier brands. From the model estimation results, we observe that Tide sachets (Tier 2) do not have a significant up-tiering effect on the popular tier (Tier 3) sachets in terms of the "value" growth. Tide bags (500 g) have a significant up-tiering effect on the Tier 3 bags; however, Ariel sachets have a significant up-tiering effect on Tier 2 sachets, and 500 g Ariel bags have a significant up-tiering effect on Tier 2 bags. Next, we briefly examine the volume gain of Ariel (500 g bag and 20 g sachet), from a 5% drop in prices as well as their impact on the sales value.

We observe that P&G has volume gains for both 500 g and 20 g (for Ariel) when the prices are reduced by 5%. More specifically, 500 g has a total volume gain of 4,339.4 SUs, and 20 g has a total volume gain of 1,786.0 SUs. These volume gains result from volume pulls from the lower-tier brands, i.e., up-tiering effect and from the same competitors. However, the total value changes are both negative for these two SKUs: −6,975.1 ('000 Rs) for 500 g and −725.8 ('000 Rs) for 20 g, respectively. This is because both SKUs have lower cross-price elasticities compared with their competitors. When they decrease their prices, the volume gains from the same-tier and lower-tier competitors are not enough to compensate for the revenue loss caused by the price drop. Five hundred grams and 20 grams are considered to be the most effective SKUs for up-tiering volume gain but still could not provide a value gain for P&G, which means the correct strategy for P&G is to increase the price instead of decreasing the price for all its SKUs as discussed earlier.

From the findings so far, we can see that the up-tiering effect of volume increase because of price decrease was not able to recover the value loss because of a drop in the price. A drop in the price of Ariel, especially, will introduce a cannibalization effect, and the volume and value of Tide will decrease. Our recommendation is to increase price, bring in new product and marketing initiatives, and induce higher distribution to obtain both volume and value increase. Although up-tiering effect was not significant in this market, the methodology of evaluating same-tier and up-tiering effects together systematically is necessary because the up-tiering effect could be significant for other product categories in this market as well as other markets.

5. Field Test

Although our recommendations (e.g., price increase) were opposite to what was happening in the marketplace (e.g., price decrease), P&G managers conducted a field test because they were eager to implement the findings from the simulator. In the field test, P&G developed different strategies for different SKUs based on the guidelines from the simulator. All the SKUs were kept in the market, and their prices were all changed based on their elasticities. After implementing the recommendations from the simulator, P&G evaluated the effectiveness of our recommendations by collecting the same set of data. We also used the new data to validate our model, and a MAPE is calculated for each model. On average, MAPE is around 10% for Ariel bags across all SKUs, 11% for Ariel sachets, 8% for Tide bags, and 12% for Tide sachets. We made various sales volume and value comparisons between the "status quo" strategy and the recommended strategy in the postimplementation time period. The details are provided in the next section.

6. Implementation and Impact

Based on our model results and suggestions, P&G increased the price and distribution for some SKUs while introducing a few commercial innovations in 2006 and 2007. The results show that, as we predicted, the price and distribution increase together with commercial innovations created an increase in the sales volume and sales value. The value and volume gain for P&G is shown in Table 2.

From these results, we can see that the overall price-increase strategy coupled with distribution increase and new initiatives did support the value and volume growth. One interesting observation is with respect to Tide sachets. The price was increased by 43%, given that it had very low price elasticity. Although the sales and distribution increased initially at the beginning of 2006, in the subsequent months distribution was scaled down slightly based on the model recommendations because of a slight sales drop. Thus, for the entire field test period, the distribution quantity shows a decrease for this SKU. However, the price increase was effective in increasing the sales value and, to some extent, the volume. Overall, there was an increase of $39 million in the sales value when compared with 2005. If P&G had adopted a status quo (where we assume no changes in marketing-mix variables) strategy, the maximum sales value gain would have been about $4 million. However, because of the implementation of our model-based recommendations, the increase was much higher, and significant. Moreover, P&G did not incur any additional marketing cost to achieve the growth in distribution. Therefore, the value growth should lead directly to profit growth. Because the price sensitivities will change after P&G implements the new price-increase strategy, we need to estimate the model again with the new data, calculate the new price elasticities, and update the simulator in the future.

The annual growth of, for example, 20 g Ariel, is 48% in its sales volume and 52% in its value, which is higher than its same-tier competitor—20 g Surf Excel (42% in volume and 41% in value) in the same time period. For the nine competition brands, most of them kept the price unchanged from 2005 to 2006 (fluctuated from 490 Rs/SU to 510 Rs/SU on average). There was a moderate category growth from 2005 to 2006, which leads to a small overall value increase for the competitors. Compared with its competitors, P&G's value growth is very significant.

The promising results from the implementation of this value growth framework illustrate that this framework can help firms to reach the goal of managing value growth instead of competing for market share blindly. For P&G specifically, the use of this modeling approach and the volume and value simulator allowed the P&G managers to identify the price sensitivity of individual SKUs, and estimate sales volume after price changes, distribution changes, and changes in the initiative factors like commercial innovation. Finally, as a result of our advanced modeling and our volume and value simulator, P&G was able to see a significant growth in the value and share of their two detergent products in India.

Although there are some limitations to this study because it was done in one country, the results show the possibility of having both sales volume and value growth simultaneously while increasing price. A limitation of this framework is that the measurements of the elasticities are static. It would be very interesting to develop a dynamic measurement of the elasticities in future research. Moreover, the linear specification of the model might just provide a local solution to the problem; however, different specifications might fit better for other situations. Finally, the new pricing policy might suffer from the Lucas critiques (Lucas 1976) because the market may not be stabilized. To avoid this problem, one solution is to reestimate the model before the other market agents react to the policy changes (Van Heerde et al. 2005). Another solution is to use a structural modeling approach (Erdem et al. 2003, Pauwels 2004). A significant implication of the framework we suggested here is its applicability/

Table 2 **The Effect of Price, Distribution, and Initiative Changes from 2006 to 2007**

Brand	Package	Price (%)	Distribution (%)	CI	Volume (SU) (%)	Value (Rs)	Value (%) (US$)
Ariel	Bags	+9.50	+17.50	+2	+22	310.8 million	+34 ($8.4 million)
	Sachets	+2.60	+40	+2	+48	314.5 million	+52 ($5.5 million)
Tide	Bags	+4.30	+16	+2	+59	725.2 million	+66 ($19.6 million)
	Sachets	+43	−6.50	+2	+19	214.6 million	+71 ($5.8 million)
Total					+1,998,532SUs	1,454.1 million	+$39.3 million

generalizability to other growing/developing markets. Given that Brazil, India, Russia, and China are expected to dominate the economic growth in the next decade, the methodology suggested would go a long way in helping many manufacturers and retailers to better understand and manage the value growth of their brands in these markets, and for all brands in the market used in this study.

References

Bass, F. M., T. L. Pilon. 1980. A stochastic brand choice framework for econometric modeling of time series market share behavior. *J. Marketing Res.* **17**(4) 486–497.

Blattberg, R. C., K. J. Wisniewski. 1989. Price-induced patterns of competition. *Marketing Sci.* **8**(4) 291–309.

Dorfman, J. H., C. L. Kling, R. J. Sexton. 1990. Confidence intervals for elasticities and flexibilities: Reevaluating the ratios of normals case. *Amer. J. Agricultural Econom.* **72**(4) 1006–1017.

Erdem, T., S. Imai, M. Keane. 2003. Brand and quantity choice dynamics under price uncertainty. *Quant. Marketing Econom.* **1**(1) 5–64.

Hall, A. R., G. D. Rudebusch, D. W. Wilcox. 1996. Judging instrument relevance in instrumental variables estimation. *Internat. Econom. Rev.* **37**(2) 283–298.

Hausman, J. A. 1978. Specification tests in econometrics. *Econometrica* **46**(6) 1251–1271.

Hsiao, C., M. H. Pesaran. 2008. Random coefficient panel data models. L. Mátyás, P. Sevestre, eds. *The Econometrics of Panel Data*, 3rd ed. Springer, Boston, 185–214.

Kadiyala, K. R., D. Oberhelman. 1982. Response predictions in regressions on panel data. *Comm. Statist. Theory Methods* **11**(23) 2699–2714.

Kaul, A., D. Wittink. 1995. Empirical generalizations about the impact of advertising on price sensitivity and price. *Marketing Sci.* **14**(3, Supplement) 151–160.

Kumar, V. 1994. Forecasting performance of market share models: An assessment, additional insights, and guidelines. *Internat. J. Forecasting* **10**(2) 295–312.

Kumar, V., R. Leone. 1988. Measuring the effect of retail store promotions on brand and store substitution. *J. Marketing Res.* **25**(May) 178–185.

Leone, R. P., H. D. Oberhelman, F. J. Mulhern. 1993. Estimating individual cross-section coefficients from the random coefficient regression model. *J. Acad. Marketing Sci.* **21**(1) 45–51.

Lucas, R. 1976. Econometric policy evaluation: A critique. *Carnegie Rochester Conf. Ser. Public Policy* **1**(1) 19–46.

Pauwels, K. 2004. How dynamic consumer response, competitor response, company support, and company inertia shape long-term marketing effectiveness. *Marketing Sci.* **23**(4) 596–610.

Reibstein, D. J., P. W. Farris. 1995. Market share and distribution: A generalization, a speculation, and some implications. *Marketing Sci.* **14**(3, Supplement) G190–G202.

Shea, J. 1997. Instrument relevance in multivariate linear models: A simple measure. *Rev. Econom. Statist.* **79**(2) 348–352.

Van Heerde, H. J., M. G. Dekimpe, W. P. Putsis, Jr. 2005. Marketing models and the Lucas critique. *J. Marketing Res.* **42**(1) 15–21.