When Wal-Mart Enters:
How Incumbent Retailers React and How This Affects Their Sales Outcomes

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ABSTRACT

The authors examine incumbent retailers' reactions to a Wal-Mart entry and the impact of these reactions on the retailers' sales. They compile a unique dataset which represents a natural experiment consisting of incumbent supermarket, drug, and mass stores in the vicinity of seven Wal-Mart entries and control stores not exposed to the entries. The dataset includes weekly store movement data for 46 product categories before and after each entry and allows them to measure reactions and sales outcomes using a before-and-after-with-control-group analysis. They find that, overall, incumbents suffer significant sales losses due to Wal-Mart entry, but there is substantial variation across retail formats, stores, and categories both in incumbent reactions and in their sales outcomes. Moreover, they find that a retailer's sales outcomes are significantly affected by its reactions, and the relationship between reactions and sales outcomes varies across retail formats. These findings provide valuable insights on how retailers in different formats can adjust their marketing mix to mitigate the impact of Wal-Mart entry.

Keywords: Wal-Mart effect, incumbent reactions, marketing mix activities, competitive response, reaction effectiveness, natural experiment.

Consumer packaged goods (CPG) retailing has become increasingly competitive in the last two decades. Traditional supermarkets and drug stores face intense competition not only from one another, but also from the fast growing large discount formats that generally embody three main features – everyday low prices, one-stop shopping for a large variety of product categories, and limited assortment of brands within most categories. It is important to understand the impact of the entry of such large discount stores on incumbent retailers. The behemoth of discount formats is Wal-Mart, the world's largest retailer with more than 4,000 stores in the United States employing approximately 1.4 million workers. More than 127 million consumers visit one of Wal-Mart's stores each week (Wal-Mart Facts 2008), and the company's 2005 U.S. revenues exceeded those of the next five U.S. retailers combined (Schulz 2006). Therefore, it is not surprising that consumers, incumbent retailers, and the local economy are significantly affected when Wal-Mart opens a new store.

Researchers have studied the impact of a Wal-Mart entry on consumer purchase behavior (Singh, Hansen, and Blattberg 2006), the labor market (Basker 2005a), average retail prices (Basker 2005b; Hausman and Liebtag 2007; Noel and Basker 2007), market level retail sales (Stone 1995), entries and exits by other retailers (Basker 2005a; Jia 2005), and shareholder value of other retailers (Gielens et. al. 2008). Table 1 highlights the major findings from this research.

<Insert Table 1 About Here>

There has been little academic research, however, on how individual retailers adapt their marketing mix in reaction to Wal-Mart entry. Retailers have multiple marketing mix variables at their disposal, yet prior research has primarily focused on market prices with little attention given to other marketing mix variables or to differences between individual retailers. Further, most CPG retailers carry a large number of product categories with varying degrees of vulnerability to Wal-Mart, but little is known about how reactions might vary across these categories. Moreover, we are not aware of any research that examines how the sales outcomes of incumbent retailers are affected by the way they react to a Wal-Mart entry.

In this paper, we study incumbent stores' reactions to a Wal-Mart entry into their local markets, and the consequences of these reactions for the stores' sales outcomes. Our specific objectives are to: (i) quantify how incumbents change their pricing, promotion, and product assortment in reaction to the entry and how their sales are affected by the entry; (ii) examine how these reactions and sales outcomes vary across retail formats, stores, and product categories; and (iii) investigate whether and how incumbents' reactions influence their sales outcomes.

We compile a unique large-scale dataset to conduct this research. We ascertain the locations of seven first-time Wal-Mart entries in 2000-2002 and identify incumbent stores in the vicinity of the entries. We also identify stores belonging to the same retail chains and market areas that are not exposed to the entry. These experimental and control stores are from six retail chains in three retail formats: supermarkets, drug stores, and mass merchandisers (hereafter "mass stores"). For each store, we obtain weekly store movement data for a large number of product categories both before and after the entry. This dataset represents a natural experiment and allows us to perform before-and-after-with-control-group analyses.

This paper makes several contributions to the literature on response to large store entry. First, we study the reactions of multiple incumbents on a full array of marketing mix variables. As such, we can provide more complete substantive insights compared to prior studies that have focused on market level prices or sales. The data in prior research are either at the market level averaged across retailers or limited to a single store, and do not lend themselves well to studying individual incumbent reactions. Second, prior research has generally employed a before-and-after analysis. Our before-and-after-with-control-group analysis allows us to rigorously quantify reactions and sales outcome effects, separating them from other chain-specific, regional, or temporal factors, and alleviating potential bias due to endogeneity of Wal-Mart entry. Third, the broad scope of our analysis across multiple entries, retail formats, stores, and product categories means that our results are more generalizeable than those in prior research. We are able to provide insights on why some stores and categories are affected more strongly by a Wal-Mart entry than others. Fourth, ours is the first study to link the impact of entry on a retailer's sales outcomes to the way the retailer reacted to the entry. This analysis provides guidance on how retailers can adjust their marketing mix to minimize the negative impact of Wal-Mart entry.

The rest of the paper is organized as follows. First, we present our conceptual framework. Next we discuss the data, hypotheses, and methodology. This is followed by our empirical findings and a discussion of their key implications.

CONCEPTUAL FRAMEWORK

Overview

When Wal-Mart enters a market, an incumbent store in that market can react by adjusting one or more elements of its marketing mix, and it can make different adjustments in the various product categories it carries. The major marketing mix elements at a retailer's disposal include price, promotion, and assortment. For each marketing mix variable in each category, an incumbent can react in three possible ways – doing nothing, significantly decreasing, or significantly increasing the variable. Decreasing price and increasing promotion and assortment are all intended to defend the incumbent's sales, and are termed "retaliatory" reactions in the literature (Steenkamp et al. 2005; Ramaswamy, Gatignon, and Reibstein 1994; Shankar 1999). Analogously, increasing price and decreasing promotion and assortment are called "accommodating" reactions.

A common theme in the literature is that incumbents are more likely to retaliate in response to a large entry (a) when the incumbent's motivation to retaliate is high, which is influenced by (i) how vulnerable the incumbent is to the entry and (ii) how important the affected market is to the incumbent; and (b) when the incumbent has the ability to retaliate effectively. These are the three building blocks of our conceptual framework in Figure 1.

<Insert Figure 1 About Here>

The incumbent's vulnerability to the entry, the importance of the affected market, and the ability of the incumbent to react all increase the likelihood of retaliation. Further, the incumbent's sales outcome is a function not only of its vulnerability but also of its reactions (Gatignon, Robertson, and Fein 1997; Kuester, Homburg, and Robertson 1999). Finally, there is feedback from sales outcomes to reactions, as incumbents may make subsequent adjustments based on the effectiveness of their initial reactions (Horvath et al. 2005; Pauwels 2004).

The literature has examined three sets of antecedents of competitive reaction – entrant characteristics, incumbent characteristics, and market characteristics (Bowman and Gatignon 1995; Ramaswamy, Gatignon, and Reibstein 1994; Shankar 1999). In the context of retailers' reactions, these antecedents translate to characteristics of the entrant store; characteristics of the incumbent stores; and characteristics of the product markets, i.e., the different categories sold by the incumbents. We discuss below the key characteristics in each group that influence the three building blocks of our framework. Subsequently, we will draw on this discussion to propose hypotheses specific to our data.

Vulnerability to the Entry

An incumbent who is affected more by the entry should be more motivated to retaliate to it (Leeflang and Wittink 1996). Incumbents in close proximity to the Wal-Mart entry, in terms of physical distance or in terms of format, assortment, and positioning overlap should be more adversely affected (Cleeren et al. 2008; Gielens et al. 2008; Stone 1995; Zhu and Singh 2007). Conceptually, this relates to Chen's (1996) market commonality and resource similarity, both of which increase the likelihood of retaliation. Large incumbents may also be less vulnerable than small ones (Basker 2005a; Gielens et al. 2008).

Staple and/or traffic building categories are more likely to be emphasized by Wal-Mart because they can drive where the consumer purchases his/her entire shopping basket, making incumbents more vulnerable in these categories. Wal-Mart may also emphasize large, growing, and profitable categories but incumbents may have more cushioning in such categories so it is not clear if they are more or less vulnerable. Incumbent retailers are more vulnerable in categories where they have more competition and that are dominated by a few high consumer pull brands. In such categories, manufacturers have considerable leverage and consumers have strong preferences for the top few brands, which are most likely to be carried by Wal-Mart.

Categories that are more responsive to the entrant's marketing strategy are also more vulnerable. Since Wal-Mart's value proposition is everyday low prices (EDLP), price sensitive categories are more likely to be affected. Finally, incumbents may be less vulnerable where they have strong consumer equity, e.g., health products for drug stores, food products for supermarkets, and household products for mass stores (Inman, Shankar, and Ferraro 2004).

Importance of Market

Incumbents are more motivated to protect their position in markets that are attractive and of strategic importance to them (Bowman and Gatignon 1995; MacMillan, McCaffery, and van Wijk 1985; Shankar 1999). Large, high-growth, and profitable stores are more important for incumbents, and so are large, high-growth, and profitable product categories (Bowman and Gatignon 1995; Debruyne and Reibstein 2005; Shankar 1999). It is also likely that incumbents will view staple and traffic building categories as more important to defend (Dhar, Hoch, and Kumar 2001). Additionally, retailers may consider categories where they have a strong position to be more important for their long-term stability.

Ability to Retaliate

Incumbents are less likely to retaliate if they believe they have only a small chance of doing so effectively (Chen 1996; Chen and Miller 1994; Gatignon, Anderson, and Helsen 1989; Leeflang and Wittink 1996). Large and profitable retailers should be more capable of retaliating against Wal-Mart. On the other hand, reactions may be less effective for those in close physical or strategic proximity to Wal-Mart. For instance, Wal-Mart's price advantage is so significant that it may attract away price sensitive consumers from a store located close by, rendering ineffective any price cuts by the incumbent (Cleeren et al. 2008; Zhu, Singh, and Dukes 2006). Retaliation may also be less effective for stores whose format and/or positioning overlaps with Wal-Mart and thus brings them in direct comparison.

Large and profitable categories provide resources for retailers to retaliate (Smith et al. 1991) and retaliation may also be more effective in categories where the retailer is strong. In contrast, categories with more competition and manufacturer pull allow less leeway for effective retaliation. Retaliation may also be less effective in price sensitive categories since they fit with Wal-Mart's value proposition.

Other Forces Driving Reactions

The framework above is grounded in prior research on competitive response but there are some other drivers of reactions that may not fit neatly within it. First, some incumbents may feel pressured to imitate the entrant irrespective of whether it is optimal for them to do so. Smith et al. (1991) propose that firms with less slack in resources are more likely to imitate other firms. According to Lieberman and Asaba (2004) and Mukherji et al. (2009), firms imitate others in their strategic group to maintain their relative position and imitation is more likely when they overlap in product lines and markets. Wal-Mart is a strong and successful player with a clear everyday low price and moderate-to-narrow assortment strategy. Thus, weaker incumbents and those in close proximity to the entrant may cut regular prices but also reduce promotion and/or assortment, and they may de-emphasize top price tier products.

Second, incumbents may aim to maintain profit in addition to, or instead of, defending sales or market share (Bell and Carpenter 1992). Thus they may not retaliate in all categories or with all marketing mix instruments. The proposed framework provides guidance on which categories should see retaliation and which ones should see accommodation, but not variations across marketing mix instruments. A concern with profit may mean that incumbents retaliate with one instrument but cut costs with another. Steenkamp et al. (2005) find that simple reactions are most likely to be retaliatory. This suggests that incumbents would be most likely to cut price, but they may try to control costs by reducing promotion and/or assortment.

Third, incumbents may be constrained by inter-dependency between various reactions. For instance, if they want to decrease overall price, they may be reluctant to add high price tier brands. They may also be constrained by their corporate positioning. For instance, a store belonging to an EDLP chain may not increase everyday prices and significantly expand promotions even if it is optimal for it to do so. Promotion decisions across categories may also be constrained by the fact that retailers distribute the same weekly flyer in wide market areas. These factors make it difficult to predict reactions across multiple marketing mix variables.

DATA AND HYPOTHESES

As mentioned previously, we analyze seven first-time Wal-Mart entries that occurred during 2000-2002. All the entries in our data are supercenters, the first one in mid 2000 and the last one in early 2002. We use weekly store data on 46 product categories from a total of 90 experimental and control stores belonging to six retail chains, covering the period from December 1999 to one year after each Wal-Mart entry. The data are provided by Information Resources Inc. and span a wide range of grocery, health, beauty, and general household categories in three supermarket chains, two drug store chains, and one mass chain.

Selection of Markets, Experimental, and Control Stores

We first used market information from IRI and store opening information from Wal-Mart's website to identify some IRI markets where (i) Wal-Mart opened a store during 2000-2002 and (ii) there was no existing Wal-Mart within a 15-mile radius of the new store. We identified seven such "first-time" entries in markets within a three-state region in the eastern U.S.

Next, based on the location of all supermarket, drug and mass stores covered by IRI in those markets, we selected stores that (i) were within a 15-mile radius of the Wal-Mart entry, and (ii) either did not previously have a Wal-Mart within a 15-miles radius, or if they did have a pre-existing Wal-Mart, it had opened more than five years ago.[1] This resulted in 40 "experimental" stores from six chains, of which 25 did not have prior exposure to Wal-Mart within 15 miles, and 15 had prior exposure but had undergone a "cooling off" period of at least five years since the last entry, thus allowing any prior effects to stabilize. 16 of the experimental stores are supermarkets, 19 are drug stores, and 5 are mass stores.

Finally, we identified control stores for each of the six chains. These are stores in the same markets and from the same chain that either did not have a Wal-Mart within a 15-mile radius, or, if they did, that entry was at least five years ago. The former set of 35 stores serve as controls for experimental stores without prior exposure to Wal-Mart, and the latter set of 15 stores are controls for experimental stores with prior exposure. Thus, we match control and experimental stores on three dimensions – chain, markets, and prior exposure to Wal-Mart.

Variables

We study price, promotion (breadth and depth), and product assortment (size and composition) reactions. Price is measured as the average regular price per unit volume to avoid confounding it with promotion. Promotion breadth is measured by the percentage of SKUs on price promotion in a given period, and promotion depth by the average percentage of price discount. We measure assortment size by the number of SKUs in a category, and assortment composition by the percentage of national brand SKUs in top and bottom price tiers, and by the percentage of SKUs that are private labels. In addition to reactions on these seven marketing mix variables, we quantify the impact of entry on incumbent stores' sales revenue in each category and measure several store and category characteristics derived from our conceptual framework. Definitions of all variables are provided in the Appendix and mean values of the marketing mix variables and sales revenue for the three retail formats are provided in Table 2.

<*Insert Table 2 About Here*>

Hypotheses

Table 3 lists the incumbent store and category characteristics used in our analysis, links them to the conceptual framework of Figure 1, and summarizes our hypotheses about their expected association with incumbent reactions and sales outcomes. We develop our hypotheses by considering the association of each characteristic with the incumbent's vulnerability, the importance of the market to the incumbent, and the incumbent's ability to retaliate. Although we do not actually measure these three constructs, we can combine expectations of the intervening associations to hypothesize how each characteristic should affect the extent of retaliation (see Geyskens, Gielens, and Dekimpe 2002 and Narasimhan, Neslin, and Sen 1996 for similar logic in other contexts).

<*Insert Table 3 About Here*>

Incumbent store characteristics. The weekly sales revenue of an incumbent store is a measure of its size. Large stores are likely to be less negatively affected by the entry, they are more important to the incumbent, and their reactions are likely to be more effective. Hence, we hypothesize that a store's weekly sales revenue will be positively associated with retaliation. Financially strong incumbents are more capable of retaliating (Gielens et al. 2008), so we hypothesize that the Return on Assets of a retailer will be positively associated with retaliation. Unfortunately, we do not have data on individual store growth or profitability to include in the empirical analysis.

We measure physical proximity by the driving distance from the incumbent store to the entering Wal-Mart, and by whether it is the store's first exposure to Wal-Mart. The shorter the distance, the more severely the store will be affected, but retaliation may also be less effective especially on price. So the association between distance and likelihood of retaliation is unclear. If a store has had prior exposure to Wal-Mart, it may have already adjusted to the competition, and the impact may be smaller (Gielens et al. 2008). Thus, we hypothesize that stores with first exposure to Wal-Mart are more likely to retaliate than those with prior exposure.

We measure a store's strategic proximity by whether or not its positioning and format overlap with Wal-Mart. We use a dummy variable for EDLP positioning (Gielens et al. 2008) and dummy variables for the supermarket and drug store format. Stores with overlap are more likely to be affected. Although their reactions may be less effective due to the head-on comparison with Wal-Mart, the pressure to retaliate in order to survive will be strong. Therefore we hypothesize that EDLP stores are more likely to retaliate than High-Low stores and mass stores are more likely to retaliate than supermarkets or drugstores.

Category characteristics. We measure category size by U.S. average weekly dollar sales and profitability by average retail gross margin. Further, we use penetration and average purchase cycle as indicators of whether a category is a staple and/or traffic builder (more consumers buying the category more frequently). Large, profitable and staple and/or traffic building categories are more important to retailers (Ailawadi and Harlam 2004; Dhar, Hoch, and Kumar 2001), so incumbents should be more motivated to defend them. Incumbents may also have more leeway to effectively retaliate in large and profitable categories. As discussed previously, it is not clear whether incumbents are less or more vulnerable in such categories. Overall, we hypothesize that weekly sales, margin, and penetration will be positively associated with and purchase cycle will be negatively associated with retaliation.

We measure competitive pressure in a category with several variables. The first is All Commodity Volume (ACV) distribution of the category. The more widely a category is distributed, the more competition a retailer faces. Thus incumbents are more vulnerable to the entry, but it is also more difficult for them to retaliate effectively. The same holds for categories that have high manufacturer concentration and advertising (Ailawadi and Harlam 2004). Therefore, we cannot predict the overall directional effect for these three characteristics.

Private label share in a category is also related to competitive pressure. On one hand, if consumers are loyal to a retailer’s well-differentiated private label, the retailer may be less vulnerable in such categories (Steenkamp and DeKimpe 1997). On the other hand, there is some evidence that heavy private label buyers are price sensitive, may have lower store loyalty, and are more likely to defect to Wal-Mart (Ailawadi, Pauwels, and Steenkamp 2008; Singh, Hansen, and Blattberg 2006). So its association with the expected impact is unclear. But categories with high private label share are more strategically important to retailers. Further, private labels are owned by retailers and often more profitable than manufacturer brands, so they may provide more resources and flexibility for effective retaliation. Overall, we hypothesize a positive association of private label share with retaliation.

We have two measures of sensitivity to Wal-Mart's positioning in a category – price promotion elasticity and promotion intensity (Steenkamp et al. 2005). In categories with high promotion elasticity and intensity, incumbents can react more effectively with promotions to combat Wal-Mart's every day low price. It is not clear, however, whether incumbents will be affected more or less in such categories. To the extent that they are price sensitive, these categories may be more vulnerable. But, consumers do respond differently to promotions versus reduction in regular price and may be less attracted to Wal-Mart's every day low price in such categories. Overall, we predict a positive association of these variables with retaliation.

Finally, categories where a retailer is strong are less vulnerable and strategically more important. Retaliation is also likely to be more effective in such categories. We measure an incumbent's strength in a category as the percentage of US category sales made in the incumbent's format, and hypothesize that it will be positively associated with retaliation.[2]

Assortment Composition Reactions: The hypotheses above relate to four marketing mix reactions – regular price, promotion breadth and depth, and assortment size. A positive association of a store or category characteristic with retaliation implies a negative association with price (i.e., a decrease in price) and a positive association with promotion and assortment size (i.e., an increase in those variables). Assortment composition reactions do not fit into the retaliation-accommodation framework. For instance, it is not clear whether reducing emphasis on bottom-tier SKUs is a retaliatory or accommodating reaction. Therefore, we examine the correlates of assortment composition reactions in an exploratory fashion.

METHODOLOGY

First-Stage Analysis: Estimating Reactions and Outcomes

Recall that we have weekly data before and after Wal-Mart entry for sales and seven marketing mix variables for each category in each store of each chain. Further, we have identified experimental and control stores within each chain. We estimate the following model for each marketing mix variable and also for sales revenue in each category and experimental store of each chain. With 46 categories, 40 experimental stores, seven marketing mix variables and sales revenue, we estimate approximately 14,000 equations.

$$\text{(1)} \qquad \text{Variable}^{v}_{its} = \beta^{v}_{0ie} + \beta^{v}_{1ie}\,\text{Expt}_{s} + \beta^{v}_{2ie}\,\text{After}_{te} + \beta^{v}_{3ie}\,\text{Expt}_{s} * \text{After}_{te} + \varepsilon_{its},$$

where $\text{Variable}^{v}_{its}$ = Value of variable v (e.g., regular price) in category i, week t, and store s; Expt_{s} = 1 if store s is an experimental store, 0 otherwise; After_{te} = 1 if week t is after Wal-Mart entry in the market of experimental store e, 0 otherwise; Expt*After = Interaction between the Expt and After variables.

The key features of this model are worth noting. First, we estimate it separately for each category in each experimental store belonging to each chain, hence the category i and experimental store e subscripts on coefficients. The superscript v denotes that the model is for variable v. There are sufficient degrees of freedom to estimate each model separately, although a random effects model estimated using data pooled across categories and experimental stores within a chain provided similar results.

Second, $\hat{\beta}^{V}_{3ie}$ represents the Wal-Mart effect. To see why, note that the average value of a given variable v for control stores before Wal-Mart entry is $\hat{\beta}^{V}_{0ie}$ and the corresponding average after entry is $\hat{\beta}^{V}_{0ie} + \hat{\beta}^{V}_{2ie}$. Similarly, the average value of the variable for an experimental store before Wal-Mart entry is $\hat{\beta}^{V}_{0ie} + \hat{\beta}^{V}_{1ie}$ and the corresponding average after entry is $\hat{\beta}^{V}_{0ie} + \hat{\beta}^{V}_{1ie} + \hat{\beta}^{V}_{2ie} + \hat{\beta}^{V}_{3ie}$. The Wal-Mart effect is thus the difference between "before" and "after" for the experimental store ($\hat{\beta}^{v}_{2ie} + \hat{\beta}^{v}_{3ie}$), minus the corresponding before-and-after difference for the control stores ($\hat{\beta}^{v}_{2ie}$). This "difference in differences" is $\hat{\beta}^{V}_{3ie}$, the so-called treatment effect in classic before-and-after-with-control-group analyses.

Third, each experimental store has several control stores matched by chain, market, and prior exposure to Wal-Mart. The average of the matched control stores serves as the benchmark, which could even out idiosyncratic differences in individual control stores.

Finally, we can estimate this model using different time periods after the entry to obtain the Wal-Mart effect in each of those time periods. For instance, we use the period before entry and up to 12 months after entry to estimate the Wal-Mart effect in the first year after entry. Similarly, we use the period before entry and the first and second six months after entry to estimate the Wal-Mart effect in the first and second six months after entry, respectively. As we discuss below, this is important in our third stage analysis where we must control for potential feedback effects in order to assess how incumbents' reactions influence their sales outcomes.

Second-Stage Analysis: Examining Variations in Marketing Mix Reactions

We estimate a regression model for each marketing mix reaction to explain variation across stores and categories. The dependent variable in each model is a reaction estimated above, and the independent variables are the store and category characteristics identified in Table 3. We allow for correlated errors across categories within a store and compute heteroskedasticity-robust standard errors (White 1980) because the dependent variable is estimated with error. In this analysis and in the third-stage analysis below, regular price and assortment size reactions and sales outcomes are scaled so that they are comparable across categories and stores. Specifically, these variable are divided by their average values in that category and store during the first six months of the data (i.e., before any Wal-Mart entry).

Third-Stage Analysis: Linking Retailers' Reactions to Their Sales Outcomes

In the final stage, we study the effects of these marketing mix reactions on the sales impact for a given category in a given experimental store. The dependent variable for this analysis is an incumbent's sales outcome, i.e., the Wal-Mart entry effect on sales revenue of category i in experimental store e, and the key independent variables are the marketing mix reactions for the corresponding category and store. In addition, we include the store and category characteristics identified earlier because they influence the sales outcome of a given category in a given incumbent store. The "Extent of Vulnerability" column in Table 3 provides our hypotheses for their effects. Of course, all the signs flip direction because the impact of Wal-Mart entry on incumbents' sales is expected to be negative.

There are two econometric issues to address in this analysis. First, we need to account for uncertainty in the dependent variable and the marketing mix reactions because they are estimated by the first-stage analysis. We do so by generating random draws from the univariate distribution of each parameter estimate and using simulated maximum likelihood estimation. Second, incumbents may adjust their reactions based on observed impact on their sales, and we employ an instrument variable approach to control for potential endogeneity in the marketing mix reactions. We divide the one year post-entry period into two halves, specify our model for sales outcomes in the second six months, and use reactions in the first six months as instruments for reactions in the second six months. Clearly, reactions in the first six months cannot be affected by sales outcomes in the subsequent six months. Details of the estimation procedure are described in the Web Appendix. We present below the main model.

Let i = category i, e = experiment store e, and k = retail format k (supermarket, drug, and mass stores). The final model is specified as:

(2) $$S_{ie}^{\tau=2} = \alpha + \hat{X}_{ie}^{\tau=2}\gamma_k + Z_{ie}\theta + \varepsilon_{ie} ,$$

where $S_{ie}^{\tau=2}$ is the impact on sales in category i and store e during the second six months after entry; $\hat{X}_{ie}^{\tau=2}$ is a vector of the predicted values of the seven marketing mix reactions in category i and store e during the same time period, obtained through the instrument variable approach; and Z_{ie} is a vector of the category and store characteristics. We allow coefficients of the reaction variables to be format-specific.

EMPIRICAL ANALYSES

First-Stage Analysis: Incumbent Reactions and Sales Outcomes

For each marketing mix variable and for sales revenue, Table 4 summarizes the percentage of cases in which there is no significant change, a significant increase, or a significant decrease as a result of the Wal-Mart entry. It also reports a meta-analytic Z-statistic to determine whether each reaction (and sales outcome) is significantly different from 0 across stores and categories (Rosenthal 1991, p 93). This summary is provided for each of the three retail formats.

<Insert Table 4 About Here>

Incidence and direction of reaction. Table 4 shows that there is a high frequency of no reactions -- as high as around 80% for promotion in supermarkets and drug stores. Reaction also varies considerably across the marketing mix instruments. In all three formats, reaction is least frequent in promotion breadth and depth, followed by regular price, and is most common in assortment.[3] The low frequency of promotion reaction is consistent with the practice, confirmed in our conversations with retailers, that weekly promotion flyers are not tailored for individual stores, especially not on a category-by-category basis.

When reaction does occur, there is retaliation in some cases and accommodation in others. In general, however, retaliation is more likely in regular price and promotion, and accommodation is more likely in assortment. Incumbents also tend to imitate Wal-Mart's assortment composition by reducing top-tier SKUs. There are, however, substantial differences across retail formats. Mass stores imitate Wal-Mart more frequently than the other two formats – they have the highest incidence of regular price cuts (38% of the time) and assortment size reduction (55% of the time).

Magnitude of reaction. For each marketing mix variable and for sales revenue, Table 5 reports the median percentage change, overall, as well as separately for cases where there was a significant increase or a significant decrease. The base for each percentage is the value of the variable for the same category and store in the first six months of the data. The median magnitude of price reaction ranges from a decrease of .1% for drug stores to a decrease of 2% for mass stores, and is consistent with that reported in prior research (see Table 1). The median is also fairly small in other marketing mix variables.

<*Insert Table 5 About Here*>

The median reactions in cases where there is a significant decrease or a significant increase show that supermarkets are most measured in their reaction. For instance, their median price reaction in cases of an increase is 3.9% and in cases of a decrease is -5.1%. Corresponding numbers for drug stores and mass stores are substantially larger. Drug stores, in particular, are least likely to react, but when they do, the magnitude of reaction is substantial.

Sales outcomes. Wal-Mart entry has a substantial impact on incumbent sales revenue with fairly large differences across retail formats. There is a significant sales decrease in more than 65% of the cases for mass stores but less than 15% of the cases for drug stores. Magnitudes tell a similar story. The median change in sales is a decrease of 40% for mass stores, 17% for supermarkets, and less than 6% for drug stores.

Correlations between marketing mix reactions. To examine whether some reactions tend to go together, we report correlations between each pair of reactions for each format in Table 6. In general, the correlations between marketing mix reactions are low, with the following exceptions. There are significant correlations between the assortment composition reactions, but this is by definition. For example, an increase in the percentage top tier SKUs is likely to come at the expense of other tiers and private labels. Similarly, there are significant correlations between assortment composition and price reactions – regular price reaction is positively correlated with % of top tier SKUs reaction and negatively with % of bottom tier SKUs reaction. We also observe modest correlations of assortment size with price and promotion, suggesting that incumbents may be trying to trim costs through assortment reduction when they retaliate on price or promotion. Overall, these significant correlations and the fact that they vary across formats suggest the need to assess the effectiveness of marketing mix reactions in a multivariate model and to allow for inter-format differences.

<Insert Table 6 About Here>

We also examined the incidence of single versus multiple reactions. No reactions on price, promotion, or assortment size (22.1%) and single reactions (37.5%) are most frequent, while concurrent reaction on price, promotion, and assortment size occurs only in 12.3% of the cases. Furthermore, we grouped cases according to whether they accommodated (e.g., significantly decreased price) or retaliated (e.g., significantly increased price) on one or more marketing mix variables, and compared average sales outcomes across groups. Reducing assortment size is associated with the worst sales outcomes, whether as a single reaction or in concert with reactions on price and/or promotion. Reducing promotion also hurts. The most positive sales outcomes are associated with increasing assortment. Complete details of this analysis are available upon request.

Second-Stage Analysis: Explaining Variations in Marketing Mix Reactions

Tables 7 and 8 summarize the association of store and category characteristics with the four marketing mix reactions for which we developed hypotheses.[4] Pooling across formats was rejected so we report results for each format separately. We highlight the key findings below. Given the small number of significant effects, we focus on the important patterns revealed by this analysis rather than on one-on-one comparison with our hypotheses.

<Insert Tables 7 and 8 About Here>

The overall model fit in Table 7 shows higher explanatory power for supermarket and mass store reactions than drug store reactions. Further, promotion depth reaction is the hardest to predict across all formats. But this is not surprising given the high frequency of insignificant reactions in promotion depth (almost 80%, see Table 4).

In general, incumbent store characteristics are better predictors of reactions than category characteristics. The first row of Table 7 shows that, taken as a block, these characteristics are significant in ten out of twelve models. Although category characteristics taken as a block are significant in several models, especially for supermarkets, the impact of many individual category characteristics is not significant. It appears that retailers do not systematically "fine-tune" their reactions in individual categories. This is consistent with our conversations with a few retailers who noted that they distinguish between Wal-Mart zones and non-Wal-Mart zones but react in a more "broad brush" fashion across large groups of categories.

Large stores belonging to profitable companies retaliate more on assortment as we expected, but they resist price and/or promotion wars. Stores that have not been previously exposed to Wal-Mart retaliate more strongly on price. This makes sense as first-time incumbents have to make greater adjustments to calibrate their prices to Wal-Mart levels. They are also more likely to cut assortment size at least in the supermarket format, perhaps in an attempt to cut costs. Similarly, stores located closer to the entry are more likely to cut their assortment size. In the supermarket format, they are also more likely to cut price, whereas in the mass format, they are more likely to increase promotion. Thus, incumbents in close proximity to Wal-Mart tend to focus on closing the price gap while cutting assortment. Supermarkets tend to do so through regular price cuts and mass stores tend to do so through promotions.

EDLP chains, whose positioning overlaps more with Wal-Mart, are more retaliatory on promotion breadth and assortment as we expected, but not on price. In other words, they try to reduce head-on comparisons with Wal-Mart by differentiating rather than imitating. Finally, as we expected, mass stores, whose assortment and format overlap more with Wal-Mart, are more retaliatory. Controlling for other characteristics, they are more likely than supermarkets or drug stores to increase promotion and assortment.

We also examined the association of store and category characteristics with the assortment composition reactions for each format. Since model fits are low and often not statistically significant, we do not report individual coefficient estimates (details are available upon request), but we note a few key findings. Supermarkets tend to emphasize top tier SKUs in large stores and large categories with low private label share. In contrast, they tend to emphasize private label in smaller stores closer to the entry, and in categories where private label share is high. Consistent with our previous findings, EDLP stores try to differentiate themselves by emphasizing top tier SKUs but not private label. Drug stores are likely to increase top tier SKUs at the expense of private label in large and high penetration categories. In contrast, they tend to reduce top tier SKUs in categories that are of low margin, promotion intensive, or highly concentrated, where price sensitivity and competitiveness may make such SKUs less viable.

Third-Stage Analysis: Linking Reactions to Sales Outcomes

In Table 9, we report the parameter estimates of Equation 2 as well as results of likelihood ratio tests for the significance of several blocks of variables.[5] All blocks of variables tested, except “other category characteristics”, are statistically significant.

<*Insert Table 9 About Here*>

Effects of store and category characteristics. Our hypotheses about the effects of incumbent store characteristics on incumbents’ sales outcomes are largely supported by those parameter estimates that are significant. As expected, proximity increases the negative sales impact. The further away the store is from the entry the smaller the sales loss. Stores that face a Wal-Mart store in their vicinity for the first time suffer a greater sales loss than those with prior exposure. As indicated by the coefficients of retail format dummy variables, mass stores suffer the greatest sales loss while drug stores suffer the least. Interestingly, incumbent store size as measured by weekly revenue does not appear to have a significant effect.

Several category characteristics also exhibit significant effects. As we expected, widely distributed and highly concentrated categories suffer greater sales loss, because these categories face greater competitive pressure from Wal-Mart. In contrast, large and promotion elastic categories suffer smaller sales loss. As we expected, staple categories, which tend to have shorter purchase cycles, suffer more severe sales losses. This should be alarming news to retailers. On the positive side, they can take some comfort in knowing that their cash generator categories (those with high sales revenue) are hit less hard, and that categories where consumers are more responsive to promotions are losing out less to Wal-Mart's everyday low prices.

Effects of marketing mix reactions. Many of the marketing mix reactions have significant effects, indicating that a retailer's reactions to a Wal-Mart entry do influence its sales outcome. This implies that retailers can proactively adjust their marketing mix to mitigate the negative impact of the entry on their sales. The pattern of these effects varies substantially across retail formats, indicating that sensible reaction strategies need to consider the retail format. We highlight below the key insights for each retail format.

Supermarkets. Supermarkets appear to be able to counter a Wal-Mart entry with multiple marketing mix actions. Regular price reaction has a positive effect on sales outcomes, implying that reducing regular price does not boost sales *volume* enough to offset the drop in unit price, and on the flip side, raising regular prices does not lead to substantial volume losses. Thus, increasing regular price can increase sales *revenue*. Reaction in promotion depth also has a positive effect. While assortment size does not have a significant effect, assortment composition reactions do matter. Increasing the percentage of top-tier SKUs and the percentage of private labels increases sales revenue. And increasing the percentage of bottom-tier SKUs also has a marginally significant positive effect. These effects imply some separation of segments between Wal-Mart and supermarkets. Consistent with Cleeren et al. (2008) and Zhu, Singh, and Dukes (2006), as price sensitive consumers and categories are drawn away to Wal-Mart, supermarkets may be able to maintain prices for the other segments that stay with them. Similarly, since Wal-Mart tends to carry large-market-share mid-tier national brands, emphasis on other brands can help mitigate the negative impact of Wal-Mart entry.

The implication is that supermarkets should pursue a differentiation strategy against Wal-Mart. As seen in Table 2, this format is more competitive on prices and assortment size than the other two formats. Instead of further lowering regular prices or increasing assortment size, they should offer deeper promotions. They should also increase the percentage of top-tier national brands at one end and bottom-tier national brands and private labels at the other end of their assortment to further differentiate from Wal-Mart. From a cost viewpoint, this is good news – supermarkets can shift resources from regular price to promotion depth and can trim assortment size, in particular by cutting mid-tier SKUs that overlap with Wal-Mart's assortment.

Drug stores. Our analysis points to a somewhat different set of recommendations for drug stores. Like for supermarkets, the coefficient of regular price reaction is positive here. But the other marketing mix reactions differ in their significance. Promotion breadth and assortment size reactions have positive effects. Therefore, drug stores too should refrain from cutting regular prices and in fact can benefit from modestly increasing regular prices, and they should step up promotions to counter the impact of Wal-Mart entry. The promotion budgets, however, should be focused on expanding promotions to a broad range of products instead of increasing promotion depth. The positive effect of reduction in assortment size indicates that drug stores can mitigate sales losses by increasing their assortment sizes, especially given the fact that they have the smallest assortment size on average across the three formats (see Table 2).

The finding that regular price and promotion breadth reactions have positive effects on sale revenues for this format may be explained by the fact that drug stores are not a primary choice for weekly grocery shopping of many consumers. Lowering regular prices in these secondary outlets is unlikely to induce consumers to change their store choice behavior, and increasing regular prices may not lead to substantial switching away. In contrast, indirect store switching is more likely in response to *promotions* (Bucklin and Lattin 1992), and consumers may simply buy more products while they are in the drug store for their secondary shopping if there are a large number of products on promotion.

Mass stores. Dealing with Wal-Mart is most challenging for mass stores. As described earlier, these stores suffer the greatest sales loss amongst the three formats. Table 9 shows that they also have fewer strategic options to combat the sales loss compared to the other two formats. Regular price reaction has a negative effect and assortment size reaction has a positive effect but the remaining marketing mix reactions do not affect sales outcomes significantly. The negative effect of regular price reaction means that, to prevent severe losses in sales revenue, mass stores are left with little choice but to follow Wal-Mart's everyday low prices by further slashing their own regular prices and thus reducing profit margins. Offsetting these costs with a reduction in assortment size does not appear to be a viable cost-cutting option for this format, even though it was the most common reaction among mass stores (see Tables 4 and 5).

DISCUSSION

In this study, we have conducted a systematic examination of incumbent retailers' reactions to entry of Wal-Mart in their local markets. Our analyses include seven Wal-Mart supercenter entries and are carried out using detailed store movement data for 46 product categories from a large number of supermarket, drug, and mass stores. We have examined these incumbents' reactions not just on price, but also on a variety of other marketing mix variables. More importantly, we link incumbent reactions to Wal-Mart's impact on their sales. In addition, we explore the factors that may explain differences in reactions and sales outcomes across retail formats, stores, and categories. In this section, we summarize the key substantive findings and their implications for retailers and researchers.

Wal-Mart entry has a significant and predictable effect on incumbents' sales. In the year following entry, mass stores suffer a median sales decline of 40% and supermarkets suffer a median sales decline of 17%, while drug stores experience a much smaller median decline of 6%. This magnitude of sales impact is broadly consistent with prior research (e.g., Stone 1995; Singh, Hansen, and Blattberg 2006). There is, however, substantial variation across stores and categories within each retail format. For instance, even within mass stores, which are the most vulnerable, 35% of the cases show no significant sales decline.

Variations in sales outcomes can be explained by incumbent store and category characteristics. We confirm, at the individual store level, the firm-level findings of Gielens et al. (2008) that incumbents who have greater proximity or assortment overlap with Wal-Mart suffer more. We also find significant association of sales outcomes with category characteristics such as category size, purchase cycle, distribution, manufacturer concentration, and promotion sensitivity. Therefore, the constructs in our framework are useful for researchers and retailers to predict the impact of entries by Wal-Mart and other big-box retailers.

No reaction is a common reaction. Despite an entry of Wal-Mart's magnitude, incumbents show little reaction in many stores and categories and the magnitude of reaction is fairly small in general. Infrequent reactions have been reported in prior research. For example, Steenkamp et al. (2005) find that the most frequent competitive reaction in ongoing price, promotion and advertising activity is "no reaction". Still, it is quite surprising that no reactions are so frequent when it comes to entry of a major player like Wal-Mart. This finding cannot be attributed to lack of statistical power in our analyses, because we do find strong impact on incumbents' sales using the same method and samples of experimental and control stores. The significant sales impact also indicates that lack of reaction is not because incumbents are unaffected by the entry. Perhaps they feel incapable of effectively reacting to a behemoth like Wal-Mart. Future research should examine whether reactions to other entrants are different.

There are substantial differences in reactions across retail formats and marketing mix instruments. Mass stores react more frequently than supermarkets and drug stores, likely because they are most vulnerable to Wal-Mart entry. No reactions are most common in promotion breadth and depth (about 70-80%) while most reactions occur in assortment size and composition with about 50-70% of the cases showing significant reactions. This is consistent with the degree of flexibility individual stores have over their marketing mix instruments.

Our study only covers chain retailers. An important extension is to study small independent retailers. On one hand, they may be more vulnerable and are likely to have less financial resources to retaliate, but on the other, they may be more flexible in adjusting their merchandising decisions. Thus their reactions and outcomes may be quite different.

It is difficult to explain variation in reactions, especially across categories. When reactions do occur, there is substantial variation in the direction of reaction. But factors identified based on prior research, especially category characteristics, have limited ability in explaining the variation. These characteristics predict sales outcomes well but not reactions, which suggests that retailers are not localizing and fine-tuning their reactions as much as they should.

There are also some other plausible reasons for the overall low explanatory power of these factors in explaining incumbent reactions. As Table 3 shows, some factors may have opposing associations with an incumbent's vulnerability to the entry versus how effectively it can react. Also, as we noted previously, retailers may balance sales, profit, and other objectives unobserved by researchers. Our outcome measure, sales revenue, is very important for retailers, but future research should also examine profit impact. Retailers may also be constrained by their overall positioning or simply by the logistics of execution. Qualitative research focused on understanding incumbents' motivations, objectives, and decision making processes would be very helpful.

Reactions do matter – they significantly influence sales outcomes of incumbents. Therefore, incumbents can proactively adjust their marketing mix activities to mitigate the negative impact of entry by Wal-Mart and possibly other large discount retailers. Effective reaction strategy, however, varies substantially across retail formats. Overall, differentiation is a sound strategy for supermarkets and drug stores, while mass stores have few options. Supermarkets and drug stores both should refrain from cutting regular price and can benefit from modest regular price increases, and they should step up promotion depth and breadth, respectively. Supermarkets should differentiate their already large assortment by reducing composition overlap with Wal-Mart and increasing the percentages of top-tier national brands and private labels. Drug stores, whose assortment overlap with Wal-Mart is lower than other formats, should focus on increasing their assortment size. Mass stores are in a difficult situation. They have to reduce regular prices, but reducing assortment size hurts them so they cannot resort to it as a cost-cutting strategy.

In our analysis, we assume a linear relationship between reactions and sales outcomes. It is possible that reactions in at least some of the marketing mix instruments may have asymmetric effects on sales outcomes. We leave it to future research to examine how the impact may differ when an incumbent increases versus decreases a particular marketing mix variable.

Also, we have focused on studying the intermediate term (within one year) effect of Wal-Mart entry. Both retailer reactions and sales outcomes may vary over time. Our preliminary analysis of the first versus second six months after entry indicates that this is the case. Therefore, an important direction for future research is to examine dynamics in reactions and outcomes. This includes potential reactions in anticipation of the actual entry as well as explicit analysis of feedback effects from incumbents' sales outcomes and other competitors' reactions to subsequent adjustments in reactions.

In conclusion, we have conducted a systematic examination of incumbent retailers' reactions to Wal-Mart entry into their local markets. Our study reveals substantial variations in reactions and sales outcomes across formats, stores, and categories. Most importantly, we find that the sales impact for a retailer is significantly affected by the way in which it reacts to the entry, and retailers can proactively adjust their marketing mix to mitigate the negative impact of the entry. Through three stages of analyses, we provide valuable insights for retailers across the supermarket, drug, and mass formats in their continuing combat with a formidable competitor.

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FOOTNOTES

1. Note that it is possible for an incumbent store within a 15-mile radius of an entry to have another Wal-Mart within a 15-mile radius although none of the Wal-Mart entries themselves have another Wal-Mart within a 15-mile radius.
2. Of course, mass stores have the same format as Wal-Mart, so they may be more vulnerable in categories where the mass format has a large share.
3. Since the composition of a category can change over time, the change in category price may be due to actual price changes or due to a shift in composition towards less or more expensive brands. We repeated our analysis with only a "common subset" of brands that remained in the assortment throughout and found similar results. We do not report results based on the "common subset" because that subset tends to be quite small.
4. A small number of outliers were deleted in the second and third stage analyses. Allowing for error terms to be correlated across categories within a store did not improve model fit (AIC and BIC) for any of the reactions. Importantly, it also did not make any substantive difference in coefficient estimates and their significance. Details are available upon request.
5. There are no straightforward goodness-of-fit measures of the model that we estimate here. We computed two "pseudo" measures instead. One is similar to R^2 for OLS regressions where we use the mean of the dependent variable for each store and category as the observed variable, and it equals .231. The other is computed in the same way as ρ^2 for discrete choice models ($\rho^2 = 1-L(\beta)/L(0)$, where $L(\beta)$ = log-likelihood of the model, $L(0)$ = log-likelihood with only the intercept), and it equals .530.

TABLE 1
THE EFFECT OF WAL-MART ON RETAILERS: HIGHLIGHTS OF PRIOR RESEARCH

Study	Type of Data	Key Findings
Retail Prices:		
Basker (2005b)	Average retail prices for 10 products in 165 cities over 20 years. From quarterly survey of retailers conducted by American Chamber of Commerce Research Association. Longitudinal analysis including variable for Wal-Mart entry. Instrumental variable for endogeneity of Wal-Mart entry timing.	Price decline of 1.5%-3% immediately after entry in four of ten products. Becomes four times in long-term through auto-regression.
Hausman and Leibtag (2007)	Average price paid for 20 food products for 4 years. From AC Nielsen Homescan consumer panel. Longitudinal analysis monthly market level data including a variable for % of expenditure in SMCs (supercenters, mass merchants, and club stores). Instrumental variable for endogeneity of SMC expenditure.	Average prices paid by consumers fall by 3% over four years or .75% per year as shopping shifts to the lower-priced SMCs. Average price decrease in traditional outlets is smaller.
Noel and Basker (2007)	Retail prices for 24 grocery items in 175 markets for four years. From annual survey of retailers by American Chamber of Commerce Research Association. Model of price as a function of Number of Wal-Mart supercenters in the market and other product and market variables.	Prices are lower by about 1.2% on average when a Wal-Mart supercenter is present in the market. For large supermarket chains, prices are lower by a smaller amount -- .45%.
Retailer Performance:		
Stone (1995)	Retail sales data for Iowa communities in Wal-Mart towns and non-Wal-Mart towns from 1983 to 1993. Overall sales and sales for various retail classes. From Iowa Retail Sales and Use Tax Reports.	5-6% increase in retail sales in Wal-Mart towns (including Wal-Mart sales). Significant sales loss for incumbent retailers, from 5% for supermarkets to 13% for building material stores. Largest decrease for mass merchants. Home furnishings and eating stores gain 2-3%.

Singh, Hansen, and Blattberg (2006)	Purchases by top 10,000 loyalty program customers of a supermarket store. 20 months spanning period before and after Wal-Mart entry. Analysis of pre- versus post-entry store visits and expenditure per visit, allowing for heterogeneity in reaction across consumers.	Monthly store sales volume decreases by an average of 18% from fewer store visits per month and smaller basket size per visit. Heterogeneity in reaction across consumers with 20% of consumers accounting for 70% of lost revenue. More likely to be large basket, weekend and heavy store brand buyers.
Basker (2005a)	County level data on population, employment, number of retail establishments over 23 years. From Census Bureau. Longitudinal analysis including variable for number of Wal-Mart openings. Instrumental variable for endogeneity of Wal-Mart entry timing.	Very small decline in number of large retail establishments within a year after Wal-Mart entry. Decline of 0.7 medium establishments within two years, and decline of 3 small establishments within two years after entry.
Jia (2005)	Number, location, and size of discount chain stores over 10 years by county. From Chain Store Guide and County Business Patterns. Empirical estimation of three-stage game with (1) pre-chain competition between small establishments, (2) chain (Wal-Mart and Kmart) entry decision, and (3) post-entry decisions of small establishments.	Approximately 40% of the reduction in small discount stores is explained by Wal-Mart's expansion in the country. 2-3 fewer small discount stores as a result of entry.
Gielens et al. (2008)	Stock prices for 98 incumbent retailers before, during, and after Wal-Mart's take-over of Asda to enter the U.K. Retailers identified from Thompson Analytics and stock prices from Datastream. Event study to quantify effect of entry on each retailer's expected performance (as measured by cumulative abnormal return, CAR) and subsequent regression to explain variations in CAR across retailers.	Expected performance is more negative for retailers whose assortment and positioning overlap more with Wal-Mart. It is also more negative for small, less financially healthy firms. It is less negative for retailers with experience in competitive countries with a strong price focus.

TABLE 2
MEAN VALUES OF VARIABLES IN THE THREE FORMATS

Variable	Supermarkets		Drug stores		Mass stores	
	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.
Regular price	.94[a]	.16	1.13	.19	.96	.19
Assortment size	1.20	.45	.53	.47	1.17	.73
% SKUs bottom tier	1.11	.61	.78	.52	1.11	.92
% SKUs top tier	1.02	.50	.94	.55	1.04	.58
% SKUs PL	1.16	.92	.89	1.18	.66	.60
Promotion breadth	.94	.47	1.09	.53	1.02	.40
Promotion depth	.99	.29	1.06	.32	.93	.22
Sales revenue	1.27	.58	.19	.26	1.56	1.38

Note: All variables are first indexed to the within-category average across all stores and formats.
[a] Read as: Regular price relative to the average price of the category across all stores, averaged across all categories in supermarket stores is .94.

TABLE 3
CORRELATES OF INCUMBENT REACTIONS: HYPOTHESES

Correlate	Vulnerability to entry	Importance of market	Ability to react	Likelihood of retaliation
Incumbent Store characteristics				
Weekly sales revenue (Size)	-	+	+	+[a]
ROA (Financial strength)	na	na	+	+
First exposure to Wal-Mart (Proximity)	+	na	?	+
Distance from Wal-Mart (Proximity)	-	na	+	?
EDLP positioning (Proximity)	+	na	?	+
Drug format relative to Mass (Proximity)	-	na	?	-
Supermarket format relative to Mass (Proximity)	-	na	?	-
Category Characteristics				
Weekly US sales revenue (Size)	?	+	+	+
Retail margin (Profitability)	?	+	+	+
Penetration (Staple/Traffic Builder)	+	+	?	+
Purchase cycle (Staple/Traffic Builder)	-	-	?	-
Distribution ACV (Competitive Pressure)	+	na	-	?
Manufacturer concentration (Compet. Pressure)	+	na	-	?
Manufacturer advertising (Compet. Pressure)	+	na	-	?
Private label share (Compet. Pressure)	?	+	+	+
Promotion intensity (Sensitivity to Entrant Positioning)	?	na	+	+
Promotion elasticity (Sensitivity to Entrant Positioning)	?	na	+	+
% US sales in incumbent's format (Incumbent Strength)	-	+	+	+

[a]Read as: Weekly sales revenue of an incumbent store is expected to be positively associated with retaliation, i.e., with a decrease in regular price, and an increase in promotion breadth, depth, and assortment size.

TABLE 4
DIRECTION OF INCUMBENT RETAILER REACTIONS AND OUTCOMES

Variable	% of Effects in Supermarket Format				% of Effects in Drug Format				% of Effects in Mass Format			
	Sig. +	Insig.	Sig. -	MetaZ	Sig. +	Insig.	Sig. -	MetaZ	Sig. +	Insig.	Sig. -	MetaZ
Incumbent Retailer Reactions												
Regular Price	14.3[a]	57.5[b]	28.2[c]	-16.0[d]	13.2	70.8	16.0	-3.8	17.1	44.9	38.0	-10.9
Promotion Breadth	4.9	78.7	16.4	-11.4	12.5	80.4	7.1	2.1	22.4	60.7	16.9	7.9
Promotion Depth	9.7	83.5	6.8	3.6	11.1	80.0	8.9	2.4	13.1	76.0	10.9	.3
Assortment Size	18.5	47.9	33.6	-37.2	22.2	44.5	33.3	-12.2	14.9	30.0	55.1	-44.6
% SKUs bottom tier	27.4	50.8	21.9	2.5	31.1	40.3	28.6	2.8	28.7	39.7	31.6	-.1
% SKUs top tier	18.8	45.8	35.4	-26.6	25.1	44.8	30.1	-5.1	30.1	33.0	36.9	-4.8
% SKUs PL	26.9	52.3	20.8	16.2	27.2	38.1	34.7	-2.8	37.4	38.1	24.5	5.3
Incumbent Retailer Outcomes												
Sales Revenue	6.2	41.7	52.1	-58.7	10.7	75.1	14.2	-2.6	3.2	31.0	65.8	-44.3

[a]Read as: Regular price increased significantly in reaction to Wal-Mart entry in 14.3% of all categories in supermarkets.
[b]Read as: There was no significant change in regular price in reaction to Wal-Mart entry in 57.5% of all categories in supermarkets.
[c]Read as: Regular price decreased significantly in reaction to Wal-Mart entry in 28.2% of all categories in supermarkets.
[d]Read as: Across all supermarket categories in supermarkets, regular price decreased significantly, with a meta-analytic Z-statistic of -16.0.

TABLE 5
MAGNITUDE OF INCUMBENT RETAILER REACTIONS AND OUTCOMES

Variable	Median % Effect in Supermarket Format			Median % Effect in Drug Format			Median % Effect in Mass Format		
	Overall	Sig. +	Sig. -	Overall	Sig. +	Sig. -	Overall	Sig. +	Sig. -
Incumbent Retailer Reactions									
Regular Price	-.4[a]	3.9[b]	-5.1[c]	-.1	8.1	-10.5	-2.0	16.5	-6.4
Promotion Breadth	-6.7	46.3	-25.9	-.5	45.5	-28.1	-1.0	142.0	-32.0
Promotion Depth	1.2	28.1	-20.2	2.1	39.2	-32.3	-1.0	52.2	-31.2
Assortment Size	-1.2	5.8	-13.8	-2.6	20.7	-15.3	-6.0	9.8	-13.7
% SKUs bottom tier	.4	8.9	-8.5	-.5	22.2	-22.6	-.3	15.0	-12.6
% SKUs top tier	-1.3	8.3	-10.0	-.8	17.0	-18.7	-1.5	15.7	-10.4
% SKUs PL	.1	13.5	-8.2	-1.6	19.7	-17.6	1.6	17.2	-17.2
Incumbent Retailer Outcomes									
Sales Revenue	-17.3	20.4	-27.2	-5.8	60.2	-29.3	-40.4	65.4	-46.2

[a]Read as: Overall, the median change in regular price was -0.4% in reaction to Wal-Mart entry in supermarkets.
[b]Read as: When regular price increased significantly in reaction to Wal-Mart entry, the median increase was 3.9% in supermarkets.
[c]Read as: When regular price decreased significantly in reaction to Wal-Mart entry, the median decrease was -5.1% in supermarkets.

TABLE 6

CORRELATIONS BETWEEN MARKETING MIX REACTIONS

Marketing Mix Reaction Pair	Correlation Coefficient in		
	Supermarkets	Drug Stores	Mass Stores
Regular Price – Promotion Breadth	.012	-.019	-.008
Regular Price – Promotion Depth	.016	-.014	.045
Regular Price – Assortment Size	.295***	.021	.117*
Regular Price - % Top Tier SKUs	.337***	.132***	.196***
Regular Price - % Bottom Tier SKUs	-.193***	-.068*	-.267***
Regular Price - % PL SKUs	-.249***	-.025	-.089
Promotion Breadth – Promotion Depth	-.057*	-.019	.137**
Promotion Breadth – Assortment Size	-.018	-.131***	-.388***
Promotion Breadth - % Top Tier SKUs	.021	-.043	.101
Promotion Breadth - % Bottom Tier SKUs	-.033	-.075*	.090
Promotion Breadth - % PL SKUs	-.018	.040	-.062
Promotion Depth – Assortment Size	-.045	-.006	-.113*
Promotion Depth - % Top Tier SKUs	-.031	-.045	-.051
Promotion Depth - % Bottom Tier SKUs	.076**	-.042	-.135**
Promotion Depth - % PL SKUs	-.006	-.038	-.116*
Assortment Size - % Top Tier SKUs	.345***	.106**	.111*
Assortment Size - % Bottom Tier SKUs	-.176***	.031	.068
Assortment Size - % PL SKUs	-.385***	-.220***	-.007
% Top Tier - % Bottom Tier SKUs	-.172***	-.238***	-.340***
% Top Tier - % PL SKUs	-.346***	-.204***	-.222***
% Bottom Tier - % PL SKUs	.025	-.051	.055
Sample size (n)	620	469	159

*** p-value < .01; ** p-value <.05; * p-value <.10.

Note: The correlation coefficients and their p-values are computed using a simulation method to take into account of the uncertainty in parameter estimates of the marketing mix reactions.

TABLE 7
ABILITY OF STORE AND CATEGORY CHARACTERISTICS TO EXPLAIN MARKETING MIX REACTIONS

Independent Variable	**χ^2statistic (df) Supermarket Format**				**χ^2statistic (df) Drugstore Format**				**χ^2statistic (df) Mass Format**			
	RP	**PB**	**PD**	**AS**	**RP**	**PB**	**PD**	**AS**	**RP**	**PB**	**PD**	**AS**
Incumbent Store Characteristics	63.8***[a] (5)	43.3*** (5)	23.8*** (5)	115.3*** (5)	5.5 (4)	8.2* (4)	2.3 (4)	31.3*** (4)	9.0** (3)	116.4*** (3)	21.5*** (3)	93.6*** (3)
Category Characteristics	41.3*** (11)	25.4*** (11)	22.5*** (11)	32.4*** (11)	18.0* (11)	22.0** (11)	7.7 (11)	8.7 (11)	26.3*** (11)	14.3 (11)	11.0 (11)	17.9* (11)
Characteristics related to category role[b]	12.9** (4)	16.3*** (4)	5.1 (4)	7.7 (4)	3.6 (4)	10.6** (4)	0.6 (4)	4.1 (4)	7.5 (4)	6.1 (4)	3.7 (4)	.4 (4)
Characteristics related to compet. pressure[c]	7.2 (4)	7.6 (4)	13.2** (4)	4.4 (4)	6.5 (4)	5.9 (4)	1.5 (4)	4.7 (4)	13.0** (4)	7.4 (4)	6.0 (4)	10.2** (4)
Other category characteristics[d]	23.0*** (3)	4.1 (3)	5.2 (3)	7.4* (3)	7.1* (3)	0.9 (3)	0.7 (3)	1.2 (3)	1.0 (3)	2.2 (3)	2.5 (3)	3.5 (3)
Adjusted R^2	.106***	.051***	.035***	.229***	.025***	.037***	-.013	.036***	.073**	.597***	.140***	.506***
Sample size (n)	704	653	655	696	637	543	537	641	181	178	183	185

RP = Regular Price; PB = Promotion Breadth; PD = Promotion Depth; AS = Assortment Size.
[a]Read as: The joint null hypothesis that the effects of incumbent store characteristics on Regular Price Reaction in supermarkets are all zero is rejected with a χ^2statistic of 63.8 and a p-value<0.01.
[b]Includes weekly revenue, retail margin, penetration, and purchase cycle.
[c]Includes distribution, manufacturer concentration, advertising, and private label share.
[d]Includes promotion intensity, elasticity, and format share.
*** p-value <0.01; ** p-value <0.05; * p-value <0.10

TABLE 8
EXPLAINING MARKETING MIX REACTIONS: REGRESSION COEFFICIENTS

Independent Variable	**Supermarket Format**				**Drugstore Format**				**Mass Format**			
	RP	**PB**	**PD**	**AS**	**RP**	**PB**	**PD**	**AS**	**RP**	**PB**	**PD**	**AS**
Incumbent Store Characteristics												
Weekly revenue	.011***	-.000	-.000	.036***	.032	-.002	-.004	-.053	-.021	-.098***	-.018**	.190***
ROA	.022	-.045***	.026**	.162***	.008	-.013	-.011	.108**	---	---	---	---
First exposure dummy	-.026***	.000	.007**	-.083***	-.027**	-.008*	.002	-.021	-.044	.013	-.015	.066
Distance from entry	.001*	.001***	.001***	.003***	-.001	-.000	.000	.007***	-.002	-.004*	-.005**	.029***
EDLP dummy	.014*	.012***	-.005	.108***	---	---	---	---	---	---	---	---
Category Characteristics												
Weekly revenue	-.035	.047	-.011	.035	-.007	-.007	-.008	.156	.116	.077**	.024	-.025
Retail margin	.051	-.063**	-.006	-.069	.091	-.021	.022	-.067	.209	.056	-.004	-.064
Penetration	-.027	.003	-.002	.025	-.040	-.028**	-.002	.057	-.057	-.010	-.019	-.007
Purchase cycle	-.017***	.011*	.005	-.036**	-.030	.001	-.000	.026	-.045*	.013	.017	-.000
Distribution ACV	.036	.023	-.059**	-.197	.251	.070	-.042	-.472	.300	-.207*	-.147*	.054
Manuf. Concent.	-.010	-.000	-.027	-.037	.054	.003	-.023	-.043	.202	-.040	-.062	.342**
Manuf. advertising	.041**	-.013	.008	-.067*	-.008	-.011	-.016	-.065	-.061	-.031	.017	-.113
Private label share	-.022	.024	.005	-.019	.047	-.048	-.003	.143	.109	.064*	.062	-.012
Promotion intensity	.060	-.063*	-.012	.036	-.365**	.022	-.014	-.145	.021	.085	-.065	-.162
Promotion elasticity	.007***	.001	.001	.010*	.006	.001	-.000	-.002	-.006	-.002	.006	-.009
Format share	-.023	-.003	.018*	-.104*	.025	-.020	.020	-.032	.058	.018	.031	-.123
Intercept	-.076	-.050	.034	.065	-.159	-.030	.051	.345	-.173	.434***	.183***	-.812***

RP = Regular Price; PB = Promotion Breadth; PD = Promotion Depth; AS = Assortment Size.
*** p-value <0.01; ** p-value <0.05; * p-value <0.10

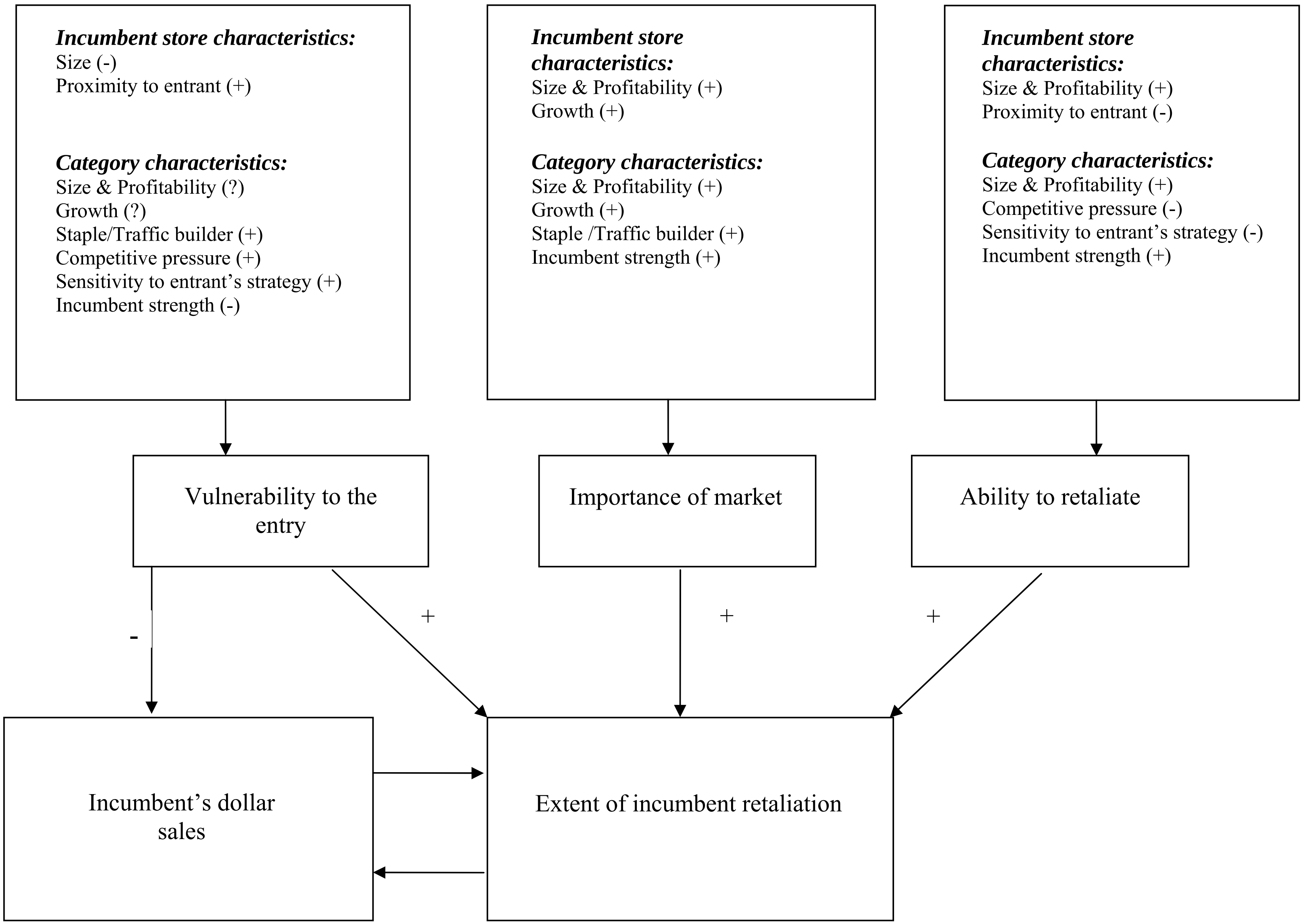
TABLE 9
DRIVERS OF INCUMBENT SALES OUTCOMES

Variable/Parameter	Estimate	t-statistic
Intercept	.616***	5.41
Incumbent Store Characteristics		
Weekly revenue	-.020	-1.38
ROA	-.067	-.78
First exposure dummy	-.101***	-3.42
Distance from entry	.012***	4.98
EDLP dummy	-.019	-.51
Supermarket dummy	.166**	2.05
Drugstore dummy	.231***	3.32
Category Characteristics		
Weekly revenue	.376***	2.80
Retail margin	.154	.67
Penetration	-.087	-1.38
Purchase cycle	.088**	2.46
Distribution ACV	-1.195***	-4.58
Manuf. Concentration	-.334**	-2.22
Manuf. advertising	-.120	-1.53
Private label share	.165	1.53
Promotion intensity	.693	.78
Promotion elasticity	.021*	1.69
Format share	.021	.32
Marketing Mix Reactions		
Δ Regular Price – supermarkets	1.352**	2.57
Δ Promotion Breadth – supermarkets	-.482	-.49
Δ Promotion Depth – supermarkets	2.961**	2.31
Δ Assortment Size – supermarkets	.104	.57
Δ % SKUs Top Tier – supermarkets	2.097***	3.18
Δ % SKUs Bottom Tier – supermarkets	1.904*	1.78
Δ % SKUs Private Labels – supermarkets	6.227***	7.52
Δ Regular Price – drug stores	.326*	1.67
Δ Promotion Breadth – drug stores	2.927***	3.14
Δ Promotion Depth – drug stores	.056	.05
Δ Assortment Size – drug stores	1.001***	6.84
Δ % SKUs Top Tier – drug stores	.756	1.17
Δ % SKUs Bottom Tier – drug stores	-.620	-1.03
Δ % SKUs Private Labels – drug stores	-.442	-.43
Δ Regular Price – mass stores	-1.474***	-2.82

Δ Promotion Breadth – mass stores	.292	.26
Δ Promotion Depth – mass stores	1.090	.48
Δ Assortment Size – mass stores	1.619***	2.88
Δ % SKUs Top Tier – mass stores	-1.482	-.97
Δ % SKUs Bottom Tier – mass stores	-2.586	-1.35
Δ % SKUs Private Labels – mass stores	-.612	-.61
Log-likelihood	-786.62	
Sample size (n)	1249	
Tests of blocks of variables[a]	χ^2-statistic	
All marketing mix reactions (df = 21)	133.34***	
All store characteristics (df = 7)	94.76 ***	
All category characteristics (df = 11)	20.92**	
Characteristics related to category role[b] (df = 4)	12.98**	
Characteristics related to compet. pressure[c] (df = 4)	10.42**	
Other category characteristics[d] (df = 3)	3.14	

[a] Likelihood ratio tests for the significance of each block of variables. The χ^2statistic, degrees of freedom (df), and significance are reported.
[b]Includes weekly revenue, retail margin, penetration, and purchase cycle.
[c]Includes distribution, manufacturer concentration, advertising, and private label share.
[d]Includes promotion intensity, elasticity, and format share.
*** p-value <0.01; ** p-value <0.05; * p-value <0.10

FIGURE 1
CONCEPTUAL FRAMEWORK



APPENDIX
VARIABLE DEFINITIONS

Variable Name	Variable Definition
Incumbents' Marketing Mix Variables	
Regular Price	Average regular price per equivalent volume of the category in the store
Promotion Breadth	% of SKUs in the category that are on price promotion in the store
Promotion Depth	Average % discount when the category is on price promotion in the store
Assortment Size	Number of SKUs in the category in the store (an SKU is inferred not to be in the store if there are no sales of that SKU for a full quarter)
% Top tier SKUs	% of national brand SKUs in the category in the store that are in top price tier
% Bottom tier SKUs	% of national brand SKUs in the category in the store that are in bottom price tier
% Private label SKUs	% of SKUs in the category in the store that are private label
Incumbents' Outcome Variable	
Dollar sales	Dollar sales of the category in the store
Price Tier of National Brands	
Price Tier	Top-, mid-, bottom-tier consists of national brands whose prices are in the top, middle, and bottom third of the category across all stores in the first six months, respectively. (For brands unavailable in the first six months, tier status is computed using their average price in the entire period.)
Store Characteristics	
Weekly Store Revenue	Average weekly sales of the store across the 46 categories in the first six months, in $10,000s
Chain ROA	1999 Company earnings as a % of assets for the experimental store (Compustat, Thompson)
EDLP	Dummy variable =1 if chain has EDLP positioning, 0 otherwise
First Exposure	Dummy variable =1 if this is the first Wal-Mart entry within 15 miles of the experimental store; 0 if there was an existing Wal-Mart within 15 miles though that entry was more than five years ago
Distance to Wal-Mart	Distance from experimental store to Wal-Mart, in miles
Supermarket Dummy	Dummy variable =1 if observation is for a supermarket, 0 otherwise
Drugstore Dummy	Dummy variable =1 if observation is for a drugstore, 0 otherwise

Category Characteristics	
Weekly Revenue	Total sales of the category across all stores in the first six months, in $10,000,000s
Retail Margin	Average % retail margin for the category (P-O-P Data from Supermarket News)
Penetration	% of U.S. households who purchase the category at least once in the year (IRI Marketing Fact Book)
Purchase Cycle	Average inter-purchase time, in months, among US households who buy the category at least once in the year (IRI Marketing Fact Book)
ACV Distribution	All Commodity Volume distribution of the category, i.e., the % of total US volume of all product categories that is sold by stores that carry the category (IRI)
Manufacturer Concentration	Category Herfindahl Index – Sum of squared market shares of all brands in the category, computed using sales of brands across all stores in the first six months
Advertising Expenditure	Total media advertising expenditure by all manufacturers in the category (LNA), in $million
Private Label Share	% Unit share of private label in the category, computed across all stores in the first six months of the data
Promotion Elasticity	Average % increase in category sales with 15% promotional discount (Narasimhan, Neslin, and Sen 1996)
Promotion Intensity	% of US Sales that are made on price promotion (IRI)
Format Share	% of US sales of the category that are made in the incumbent's format (IRI US Panel Data)

Notes:
1) All variables are computed using IRI store level data for the markets in our analysis except when an alternative source is listed.
2) IRI data do not include Wal-Mart.
3) All % numbers are in fractions, e.g., .15, not 15%.

WEB APPENDIX

ESTIMATION DETAILS OF THE THIRD STAGE ANALYSIS

Let i = category i, e = experiment store e, k = retail format k (supermarket, drug, and mass merchandiser), and τ = 1, 2 denoting the first and second six months after entry, respectively. The main model is specified as:

(A1) $$S_{ie}^{\tau=2} = \alpha + X_{ie}^{\tau=2}\gamma_k + Z_{ie}\theta + \varepsilon_{ie}\ ,$$

where $S_{ie}^{\tau=2}$ is the impact on sales in category i and store e during the second six months after entry; $X_{ie}^{\tau=2}$ is a vector of the seven marketing mix reactions in category i and store e during the same time period; and Z_{ie} is a vector of the category and store characteristics. $S_{ie}^{\tau=2}$ and $X_{ie}^{\tau=2}$ are estimated as $\hat{\beta}_{3ie}^{V}$ in Equation (1). The parameter vectors γ_k contain format-specific coefficients of the marketing mix reactions, and θ is the parameter vector of Z_{ie}. The random term ε_{ie} is assumed to follow an i.i.d. normal distribution, $\varepsilon_{ie} \sim N\left(0, \sigma_{\varepsilon}^{2}\right)$. As noted in the main text, sales outcomes and reactions in assortment size and regular price are scaled to make them comparable across categories and stores. The other five reaction variables are measured as percentages and thus do not need to be scaled.

We account for potential endogeneity in $X_{ie}^{\tau=2}$ by using $X_{ie}^{\tau=1}$ as instrumental variables. Following standard procedures, each endogenous explanatory variable is first predicted by the following model:

(A2) $$X_{p,ie}^{\tau=2} = \eta_{p,k} + X_{p,ie}^{\tau=1}\lambda_{p,k} + Z_{ie}\mu_k + \xi_{p,ie}$$

where p denotes the p-th marketing mix reaction variable in $X_{p,ie}^{\tau=2}$ and $X_{p,ie}^{\tau=1}$, the coefficients $\eta_{p,k}$ and $\lambda_{p,k}$ and coefficient vector μ_k are retail format specific, and the random term $\xi_{p,ie}$ follows a

Normal distribution, $\xi_{p,ie} \sim N\left(0, \sigma^2_{p,\xi}\right)$.

To account for estimation uncertainty in $X^{\tau=1}_{p,ie}$ and $X^{\tau=2}_{p,ie}$, we use a simulated maximum likelihood method to estimate Equation (A2). The likelihood function for each marketing mix reaction variable in category i and store e is the probability density function (PDF) of $\xi_{p,ie}$:

$$\text{(A3)} \qquad L_{p,ie} = \frac{1}{\sqrt{2\pi\sigma^2_{p,\xi}}} exp\left\{ -\frac{1}{2\sigma^2_{p,\xi}} [\, X^{\tau=2}_{p,ie} - (\, \eta_{p,k} + X^{\tau=1}_{p,ie}\lambda_{p,k} + Z_{ie}\mu_k \,)]^2 \right\},$$

and the likelihood function of the entire sample is:

$$\text{(A4)} \qquad L_p = \prod_{\forall i,e} L_{p,ie},$$

where the true value of $X^{\tau=1}_{p,ie}$ and $X^{\tau=2}_{p,ie}$ each follows a Normal distribution, $X^{\tau}_{p,ie} \sim N\left(\overline{X}^{\tau}_{p,ie}, \sigma^2_{p,ie\tau}\right)$, τ = 1 or 2, and $\overline{X}^{\tau}_{ie}$ is the parameter estimate and $\sigma_{p,ie\tau}$ is the standard error for each marketing mix reaction variable, obtained from Equation (1). Direct computation of the likelihood function Equation (A4) is intractable because it involves taking integrals over the distributions of $X^{\tau=1}_{p,ie}$ and $X^{\tau=2}_{p,ie}$ for each category i and store e. Instead, we compute L_p based on an unbiased numerical simulator for $L_{p,ie}$ (Lee 1999):

$$\text{(A5)} \qquad \hat{L}_{p,ie} = \frac{1}{M}\sum_{m=1}^{M} L^m_{p,ie}(\, X^{\tau=2}_{p,iem}, X^{\tau=1}_{p,iem}, Z_{ie}, \eta_{p,k}, \lambda_{p,k}, \mu_k, \sigma^2_{p,\xi}\,),$$

where $X^{\tau=2}_{p,iem}$ and $X^{\tau=1}_{p,iem}$ are the m-th draw from the random distributions $X^{\tau}_{p,ie} \sim N\left(\overline{X}^{\tau}_{p,ie}, \sigma^2_{p,ie\tau}\right)$, τ = 1 or 2, and the computation of $L^m_{p,ie}$ follows Equation (A3). We generate M = 500 random draws from each of the distributions. Equation (A2) is estimated by maximizing the simulated log-likelihood function given by:

(A6) $\hat{LL}_p = \sum_{i,e} log(\hat{L}_{p,ie})$.

We then compute the predicted value of each marketing mix reaction, $\hat{X}_{p,ie}^{\tau=2}$, which is uncorrelated with the error term ε_{ie}. The final model to be estimated is:

(A7) $S_{ie}^{\tau=2} = \alpha + \hat{X}_{ie}^{\tau=2}\gamma_k + Z_{ie}\theta + \varepsilon_{ie}$,

where all notations are defined as before. Since $S_{ie}^{\tau=2}$ is also estimated with uncertainty, we estimate Equation (A7) using a simulated maximum likelihood procedure similar to that described above. Through the procedures outlined above, we are able to address the problem of uncertainty in the estimates of the dependent and key independent variables, as well as potential endogeneity of marketing mix reactions, and are able to get consistent estimates of the parameters of interest.

Reference

Lee, Lung-Fei (1999), “Statistical Inference with Simulated Likelihood Functions,” *Econometric Theory*, Vol. 15, No. 3 (June), 337-360.