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The Effectiveness of Customized Promotions in Online and Offline Stores

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With recent innovations in both online and brick-and-mortar stores, marketers now face the choice of how to allocate promotion budgets between the online and offline channels, and at what level of granularity (mass-market, segment-based, or personalized) to customize promotions. In this study, we intend to provide insights that may help to address these issues by empirically examining the profit potential of various customized price promotion programs. Our analyses are based on a joint model of purchase incidence, choice, and quantity, and a subsequent optimization procedure that derives the profit-maximizing price promotions using household purchase data collected from a matched sample of stores from these two channels. We compare the expected profit of various promotions across a factorial combination consisting of over 800 conditions, and find 1) that it is more profitable to offer loyalty promotions in online stores and more profitable to offer competitive promotions in offline stores, and 2) that the onl ne shopping environment is a more profitable venue for offering customized promotions at individual-household level.

LEADING IN THOUGHT AND ACTION

The Effectiveness of Customized Promotions in Online and Offline Stores

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and

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“The Effectiveness of Customized Promotions
in Online and Offline Stores”

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INTRODUCTION

In recent decades, marketing companies have not only steadily increased their promotion expenditures, but have explored innovative ways to improve promotion effectiveness. In brick-and-mortar retailing, in-store promotion programs designed to target certain consumers have begun to gain popularity. Catalina Marketing Corporation's flagship in-store coupon distribution service Checkout Coupon® is such an example. It relies on a computer system connected to a store's cash registries to generate coupons of a particular manufacturer's product(s) at the check-out counter based on what products a customer has purchased at the shopping trip. The growth of the Internet as a distribution channel has brought even more new promotion opportunities. In addition to offering traditional mass-market promotions, online retailers have begun to experiment with customized promotion programs to target certain customers for selected corporate sponsors (*e.g.*, Peapod Inc. and NetGrocer[1]). The evolution from mass-market promotion strategies to targeted strategies appears to be a general trend (*Global Cosmetic Industry* December 2001). This trend is driven by the fact that many companies have come to realize that, although they may not be able to afford the substantial investment to produce products fine-tuned to the needs of heterogeneous segments, they can design other components of the marketing mix, such as sales promotions, to better serve different customers in the market. New information technology has facilitated the development of such customized approaches to promoting to heterogeneous customers at more granular levels (Wedel and Kamakura 2002).

In industry practice, a company targets promotions in online and offline stores mainly by selecting a certain segment of customers as the target. The depth of promotions is typically not tailored to individual households nor updated when new information on their purchase behavior becomes available. The interactive nature of the Internet, however, does offer the ability to

[1] See company web sites: www.peapod.com , www.nexpansion.com

target individual consumers and personalize the depth of a promotion based on their brand preference, price/promotion sensitivity and other aspects of purchase behavior. Such customized promotions have not yet been exploited in practice, but could present new opportunities for online retailers and manufacturers. In addition, recent technological development makes it possible to implement such personalized promotions in brick-and-mortar stores. For example, Klever Marketing, Inc. has developed an electronic device place on shopping carts for in-store interactive advertising and promotions,[2] which has the potential to implement personalized promotions.

The growth of the online shopping channel and the development of innovative promotion methods have brought unprecedented opportunities for retailers and manufacturers to improve promotion effectiveness, but have also increased the complexity of their decision tasks. Manufacturers (with a presence in either or both of the online and offline channels) need to figure out what promotion programs to engage in and how to allocate promotion budgets to achieve greater profits. Online retailers need to know the incremental profit potential of offering customized promotions to their manufacturer clients in order to determine how much to charge for such services. Brick-and-mortar retailers are faced with the questions of how to take advantage of their strengths in the physical stores, whether to go online, and what types of promotion programs to provide in either or both channels. They too need to know how much profit can be obtained from different types of promotions in the online and offline channels. As yet, little is known about the relative profitability of promotional programs in online and offline stores, what types of promotional programs these venues are best suited for, and what level of customization is most desirable. Our study intends to provide insights that address these issues. We detail the intended contributions in next section.

[2] The reader is referred to www.kleverkart.com for details.

RESEARCH PROBLEM AND INTENDED CONTRIBUTIONS

Previous research has looked at differences in consumer purchase behavior in online stores and traditional supermarkets (e.g., Degeratu, Rangaswamy and Wu 2000; Danaher, Wilson, and Davis 2003). Little is known, however, about differences in the profit potential of promotions between the two venues. Zhang and Krishnamurthi (2003) showed increased profitability of personalized promotions in online stores over current practice, but they did not compare online and brick-and-mortar stores, nor did they compare the effectiveness of promotion programs at various levels of customization (mass-market, segment-level, personalized).

The main objective of our study is to examine the profit potential of customized price promotions at different levels of granularity in online and offline stores. Promotion is one of the marketing mix components that eminently lend itself to customization, especially in the online shopping environment. We focus on price promotion since it is arguably the most important form of sales promotions, although our framework can be applied to the study of other forms of promotions as well. We compare the profit potentials of different promotion programs based on the profit maximizing promotion plans derived from a joint model of purchase incidence, choice, and quantity.

We compare three distinctive types of price promotions that we call: "mass promotion", "targeted promotion", and "personalized promotion". A *mass promotion* is defined as one where the same amount of price discount is offered to all customers (or to a vast majority of customers as in a frequent-shopper program). It is still the most widely used promotion in practice. In this study, we will derive the *optimal* mass-market level promotions, which may improve over the type of mass promotions used in the current practice. A *targeted promotion* is defined as one in which a certain segment of customers is selected for a given price promotion, but the amount of price discount is not tailored toward individual households within the segment. This type of promotion represents the recent trend in the retail industry. A *personalized promotion* is defined as one that is tailored toward each household and adjusted on each individual shopping trip. This type of promotion represents customer-centric marketing at the most granular level and has the potential to achieve greater profitability than the first two types of promotions. For each of the three promotion types, we will derive the optimal amount of price promotion which yields the maximum profit. As a result, each of these three types of promotion may improve over the current practice of implementing promotions which we will include in our comparisons.

We further categorize promotions into the following two types according to their strategic orientations: 1) "competitive promotions" are aimed at those consumers who did not purchase the target brand on the previous purchase occasion; 2) "loyalty promotions" are aimed at those consumers who purchased the target brand on the previous purchase occasion. This categorization is consistent with, for example, Catalina Marketing Corporation's definition of competitive coupons and loyalty coupons, and the way (last purchase) loyalty is commonly operationalized in consumer choice models.

We compare the expected payoff of these six classes of promotions (three types × two orientations) between online and brick-and-mortar stores. This will provide insights to help retailers and manufacturers choose a suitable promotion program, to allocate promotion budgets between online and offline channels, and to price/compensate specialized promotion services. Specifically, we intend to contribute towards answering the following questions:

1. For online retailers, what is the potential of utilizing its one-on-one and interactive nature and offer targeted or personalized promotions, in terms of the incremental profit? Is it worthwhile to invest/participate in a targeted promotion program or a personalized promotion program?
2. For brick-and-mortar retailers, what is the incremental profit to be expected from personalized promotions over targeted promotions over mass promotions? Is it worthwhile

to invest in technological innovations which bring personalized promotions to brick-and-mortar stores?

3. For manufacturers, which channel offers the most effective way to promote a product? Through what type of promotion program? Does it depend on the promotion orientation?

Alba and colleagues (1997) postulate that online consumers may be more or less price sensitive depending on the accessibility of information on price and non-price attributes on the Internet. Degeratu et al. (2000) suggest that online consumers have higher opportunity costs of time and therefore are likely to be more sensitive to convenience and less to price. In an extensive study across many product categories, Danaher et al. (2003) report that brand loyalty is substantially higher in online stores than in offline stores. Note that these studies investigated online and offline consumer behavior, but not the optimal marketing decisions derived from that. Although targeted promotions have the potential to be more profitable than mass promotions, and customized promotions have the potential to be more profitable than targeted promotions, the exact nature of the differences between these promotion strategies in the two channels is unknown without careful empirical examination. This is a focus of our study.

ESTIMATION AND OPTIMIZATION PROCEDURES

Model of Purchase Incidence, Choice, and Quantity

Our model is a joint model of purchase incidence, brand choice, and purchase quantity decisions, fitting in the stream of studies by Hanemann (1984), Chiang (1991), Chintagunta (1993), Bell, Chiang and Padmanabhan (1999), and Zhang and Krishnamurthi (2003). It is based upon the latter model and modified to better suit the purposes of this research. The model structure is outlined below and described in more detail in the Appendix. The interdependence of the purchase incidence, brand choice, and purchase quantity decisions are accommodated in the model. To capture heterogeneity, we employ a latent class formulation (cf. Kamakura and Russell 1989), in which all parameters are segment-specific. The discrete latent-class specification has been shown to be empirically equivalent to continuous approaches to represent heterogeneity, such as the hierarchical Bayes' formulations (Andrews, Ansari, and Currim 2002).

We assume that, at each shopping trip, a household makes a category purchase if and only if the utility of at least one brand in the category exceeds a threshold, leading to a conditional logit formulation for the joint probability of brand choice and purchase incidence. We further assume that the threshold for making a category purchase is affected by a household's purchase frequency, obtained from an initialization period, and the household's (mean-centered) last purchase quantity before the shopping trip. Purchase frequency is hypothesized to have a positive effect on purchase incidence since it captures the intent to buy from the category, which means its effect on the threshold is negative. Last purchase volume is hypothesized to increase the threshold due to inventory effects, and thus negatively affects purchase incidence.

Brand choice is modeled using a multinomial logit formulation, in which the probability that a brand is chosen is assumed to be affected by the intrinsic brand preference (brand constant), the regular price and price cut of the brand, and display or feature ad (the latter two are only available offline). We expect the effects of regular price to be negative and those of price cuts to be positive. In addition, there may be variety seeking/inertia tendencies, modeled through the inclusion of a last purchase indicator variable, and an additional parameter capturing a possible modifying effect of whether or not the purchase was made on promotion on variety seeking/inertia. We expect that there is positive purchase event feedback, and that this effect is reduced if the previous purchase was made on a price promotion (see Gedenk and Neslin 1999).

Finally, we model purchase quantities as a function of regular prices and price cuts, and use the household's average purchase quantity in an initialization period as a control variable. We hypothesize a negative effect of regular price on purchase quantity, a positive effect of a price cut, and a positive effect of the household's average purchase volume. Assumptions on the error terms in the brand utility equations and the quantity equations allows for a parsimonious representation of the correlation between quantity and choice and leads to a closed-form expression of the joint probability of purchase incidence, choice, and quantity (see Zhang and Krishnamurthi 2003 for details).

Implementing Customized Promotions

We adopt the concept of a sole manufacturer sponsor mechanism to implement customized promotions (Zhang and Krishnamurthi 2003). In this arrangement, a retailer can offer customized promotion services to its corporate (manufacturer) clients. There is only one client, i.e., a sponsor, for this service for a given product category. The retailer is free to accept other regular trade promotions. The customized promotions are sponsored by the manufacturer and implemented by the retailer. The retailer is compensated for administering the promotions and also gets a share of the incremental profits generated by the service. The retailer essentially works as the manufacturer's agent and they have a common profit objective. This sole manufacturer sponsor model has been used in practice by for example, Catalina Marketing Corporation's in-store coupon distribution service Checkout Coupon® , which offers one manufacturer the right to be the sponsor of a product category for competitive coupons. The sole manufacturer sponsor arrangement minimizes competition among manufacturers within a category. It increases the retailer's incentive to carefully monitor the implementation process, since the profit is to be shared by the manufacturer and the retailer.

We derive the optimal price discounts that maximize the gross profit of a brand for each promotion plan. Deriving the profit maximizing promotions enables us to compare the maximum potential for each of the promotion programs in the online and offline venues, as describe before. We extend the method by Zhang and Krishnamurthi (2003) for that purpose. The approach is based on first obtaining the estimates of the model by maximizing the likelihood function, then forecasting incidence, choice, and quantity in the hold-out period to compute the expected profit, and finally deriving the profit maximizing price discounts accordingly. Note that the objective function is computed independently of the likelihood specification itself, as advocated by Allenby et al. (2002), because the likelihood function reflects consumer behavior while the profit function reflects the companies' objective for decision making.

The expected profit is maximized over a sequence of time points with regard to the price promotion variables at those times to get the optimal promotion scheme. This operation reflects the notion that current promotions may affect future purchase outcome. For mass-market promotions, the promotions that are derived are the same for all households in a given week. For segment-level targeted promotions, the optimization is performed for each segment separately, and the optimal promotions are the same for households within a segment, but are different across segments in a given week. For individual-level customized promotions, the optimization derives a promotion for each household on each shopping trip, and thus the promotions are completely household-specific.

In actual business practice, the manufacturer's regular profit margin for each brand is known to the manufacturer, as well as to the retailer per their cooperation in a customized promotion program. In the application section, since the actual margins are unavailable in our data, we assume a range of values for the wholesale and retailer margins in the optimizations, which provides greater generality to our results. We express the manufacturer's profit margin as a percentage of the regular retail price of its brand, where the percentage is a function of the wholesale and retail percentage margins. We vary that percentage profit margin from 0.1 to 0.4 in steps of 0.05, which provides much generality, since the results are not dependent on the specific current margins. A more detailed description of the model formulation and optimization procedure is presented in the Appendix.

EMPIRICAL ANALYSES

Data Description

We use household purchase data provided by a leading Internet grocery retailer, and Information Resources, Inc. (IRI) to calibrate the model for online and brick-and-mortar stores, respectively. The data are from the same market and cover the same time period (about two years between 1977 and 1999). In this market, the Internet retailer procured its products through a brick-and-mortar retail chain during the time period of data collection. To minimize the differences in pricing and merchandising between the two venues, we use the brick-and-mortar data containing only purchases made in this particular retail chain that is cooperating with the Internet retailer in the same market[3]. We calibrate the model using two product categories on which data from both venues were available: stick butter and liquid detergent. To control for differences in product assortment between the online and offline stores, we chose to analyze the best selling brands that are common across the two channels. This procedure yields the top four brands in each category. These brands accounted for 99.4% of total category purchases for stick

[3] Our data indeed show almost identical regular prices and similar price discounts for each brand in the online and brick-and-mortar samples.

butter and 62.2% of total category purchases for liquid detergent in the brick-and-mortar chain, and 95.3% and 74.5% respectively, in the online store. For the brick-and-mortar data, households that have made at least 90% of their category purchases from the chain are included in the sample: the resulting sample size was 115 households for stick butter and 105 households for liquid detergent. The sample sizes for the online stick butter and liquid detergent data are 129 households and 108 households, respectively. For reasons of confidentiality, we cannot disclose the names of the retailers.

The data are divided into an estimation period and a holdout validation period. Parameter estimates are obtained from the estimation data, while profit comparisons are conducted on the holdout data for each brand in the two categories. The estimation and holdout data for the online and offline samples cover exactly the same time period: 48 weeks for estimation and 40 weeks for profit optimization.

Estimation Results

The BIC statistics (Schwartz 1978) point to a two segment solution for both categories online and offline. A fairly small number of segments seem to describe the heterogeneity of subjects well, which may in part be caused by the modest sample size that resulted from the need to properly match the online and offline samples.

Table 1 displays the estimation results for the butter category. We summarize the main findings. The correlation between brand choice probability and purchase quantity was mildly positive, about 0.2-0.3 for the different segments and categories. The signs of all the significant coefficients are as expected. For example, regular price affects both brand choice and purchase quantity negatively. These price effects are significant in only one of the two segments in both the online and offline data. Price cuts have positive effects on both brand choice and purchase quantity. The effect on brand choice is significant for both segments, and the effect on quantity is significant in one segment, in both the online and offline data. Display and feature advertising are available in offline stores, and their effects on brand choice are positive. Whereas in offline stores both segments display a similar degree of choice inertia, one segment (segment 1) is clearly much more inertial than the other one in the online store. In addition, the more inertial segment is larger in the online store, but it is smaller in offline stores. The online segments differ substantially in size, the smallest segment being 28.4%, while the offline segments are more similar in size (59.6% and 40.4%, respectively).

The general patterns are similar for the liquid detergent category, as shown in Table 2. All significant coefficients are also of the expected signs. In both the online and the offline data, only one segment's choice behavior is fairly sensitive to regular price. Price cut has positive effects on choice and quantity, and its effects on quantity are especially strong in one of the segments, which is the case for both the online (segment 2) and offline (segment 1) data. (Note that the price coefficients for quantity are large because of the units of measurement). The segment sizes have about a 65/35 ratio, both online and offline.

Profit Optimization Results

We derive the optimal price cuts and profits numerically for seven profit margin scenarios, at three levels of aggregation (mass-market, segment, individual), for two promotion orientations (competitive promotions versus loyalty promotions), in the online and offline venues, for four brands in each of the two product categories. We also compute the expected profit of the current allocation of price promotions as reflected in the data, for each of the above cases. Thus, across all factorial combinations of the seven factors: Venue (Online/Offline), Aggregation Level (Current/Mass/Segment/Individual), Promotion Orientation (Competitive/Loyalty), Category (Butter, Detergents), Brand (1,…,4), Profit Margin (0.1,0.15,…,0.4), we ran the optimization routines 896 times, using the parameter estimates of the model as input. We then analyze the expected optimal profits from these analyses with fixed effects factorial ANOVA, including all 1st order interactions[4] (the effect of Brand is nested within Categories).

The results are shown in Table 3. All main effects and first order interactions are highly significant, which testifies to the importance of effects of the factors in our design on expected profit. The table shows that "Category" and "Brand" are the main sources of differences in profitability, explaining over 30% of the sums of squares (SS). "Promotion Orientation" and "Profit Margin" obviously are also important factors, explaining close to 10% of the SS each. In addition, "Venue" and its interactions with the other factors explain close to 10%, "Aggregation Level" and its interactions with the other factors explain around 6%. In Table 4, we present detailed results for the optimal price cuts and profits for three representative profit margin scenarios ranging from the low end to the high end (0.2, 0.3, 0.4). The price cut and profit figures are averaged cross brands for each category, because the patterns across brands are very similar and we are not primarily interested in the differences between brands. To account for (minor) sample size differences, we convert profits to US$ per brand for 100 households in 40 weeks. We describe the results for all seven profit scenarios in more detail next.

[TABLES 3 AND 4 ABOUT HERE]

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[4] An ANOVA that also includes the 2nd order interactions reveals that most of those are significant as well, with the exception of all three-factor interactions that include Margin and Level. Most of the higher order interactions involving online/offline are of the non-cross over type.

The optimal allocation of promotions at each level of aggregation yields substantially higher profit than current practice. On average, the expected incremental profit over current practice is $100.78 for the mass market level optimization, $102.01 for the segment level optimization, and $103.32 for the individual level optimization. Our analysis indicates that the average optimal price cut is usually much lower than the average actual price cut, suggesting that the increase in profitability is brought about to a large degree by reducing promotional spending. Across brands, categories, orientations, and profit scenarios, the average current promotion depth in the holdout period is $0.53, while the average optimal price cut is $0.09 at the individual level, and around $0.07 at the mass and segment levels (note that this is averaged across different profit margins). It seems that companies operating in the categories investigated in this study are over-promoting currently, both in the online and offline stores, if the margins included in this study reflect the profit margins in practice. It is worth pointing out that the optimal price cut is zero under some low profit margin scenarios (10-25% of the regular retailer price) for both product categories. An important implication of our analysis results is that manufacturers should be very prudent with implementing deep price promotions especially at low profit margins, regardless of the shopping venue.

In general, the incremental benefits of the various optimal promotion programs over current practice appear to be higher for the butter category than the liquid detergent category, which is likely caused by the fact that consumer behavior with respect to butter is more sensitive to promotions. Across the profit margin scenarios, optimal price cut and expected profit increase with the manufacturer's regular profit margin (as a percentage of the regular retailer price which is explained previously). On average, expected profit increases $13.21 per percentage point for each butter brand and $3.89 per percentage point for each detergent brand. Across all conditions, the attainable profits are higher when promotions are offered to consumers who purchased the target brand on the previous purchase occasion, i.e., "loyalty promotions", than when promotions are offered to consumers who purchased competitors' brands on the previous purchase occasion, i.e., “competitive promotions” (expected profit per brand is $443.52 versus $159.15 for butter, and $155.76 versus $35.21 for liquid detergent, on average). This is consistent with the common knowledge that it is more profitable to serve existing customers than to acquire new customers.

The comparison of online and offline stores reveals quite interesting patterns. The differences between optimal promotions at the three levels of granularity as well as their differences with current practice are greater in online stores than in offline stores. In both venues the optimal approaches yield much higher profit than current practice, but the profit gains over the current practice are much more pronounced online, both in an absolute and relative sense. Clearly, there seems to a large untapped profit potential in the online channel. The differences among the optimal promotion programs in offline stores are much smaller, especially between the segment and individual levels, as shown below.

Level:	**Current**	**Mass**	**Segment**	**Individual**
Online Profit	$ 82.82	$212.95	$215.17	$217.49
Offline profit	$109.52	$180.95	$181.18	$181.50

These patterns suggest that customizing promotions at the individual level, if it is to be pursued, is more suitable for implementation in online stores than in brick-and-mortar stores. In addition, promotions targeted at the segment level may already provide enough granularity in online stores. The very small differences between the three aggregation levels in offline stores in this study may indicate that a mass-market level promotion optimization program would be sufficient for this shopping venue. In addition, while the operation costs of implementing promotion programs at different levels of granularity are likely to be similar for online stores, they are likely to increase substantially when moving to finer level of granularity for offline stores[5]. This suggests much greater economies of scale of offering the same promotions to large

[5] The three promotion programs all involve installing a decision support system with the same hardware and software, estimating the model and updating the promotion decisions every week using every household’s purchase history data up to the most recent week, and delivering the promotions to the mass market/segment/individual accordingly. In an online store, the last step means modifying the online menu in a certain manner, and personalized modifications can be administered by a software program without much incremental costs. In contrast, in a brick-

groups in brick-and-mortar stores, which could mean even higher net profitability of mass market level over segment level optimization, and segment level over individual level optimization for the offline shopping venue.

Our results further reveal that the expected profit of competitive promotions is higher in brick-and-mortar stores, and the expected profit of loyalty promotions is higher in online stores. One can see that by comparing the average on- and offline expected profits for these two strategic orientations, as provided in the columns of the table below.

Orientation:	**Competitive Promotions**	**Loyalty Promotions**
Online Profit	$ 41.99	$322.22
Offline Profit	$125.25	$201.32

The results are shown in more detail in Table 4 and further illustrated in Figures 1 and 2, in which the optimal individual level price cuts and profits are plotted against the percentage profit margin, for each of the two promotion orientations. The figures show that, for competitive promotions the optimal expected profit is lower and the optimal price discount is higher in online stores than in brick-and-mortar stores. The reverse holds for loyalty promotions. The figures also show that the optimal depth of price promotion is close to zero for low profit margins, regardless of the venue and promotion orientation. Deep discounts, however, are required at higher profit margins for competitive promotions in the online channel, while profit increases resulting from these promotions are small. The optimal promotions aimed at previous period buyers in brick-and-mortar stores are also deeper at higher profit margins, but much less so than for competitive promotions in online stores. Note from Table 4 that the results are very consistent across categories, brands, and levels of aggregation. These findings suggest that brick-and-mortar and online shopping venues each have their unique advantages in terms of promotion effectiveness. Online stores are a more appealing channel for retaining a brand's existing customers, while the

and-mortar store, the cost difference in the last step is much greater because it requires additional (and substantially more expensive) technology to deliver customized promotions at segment and individual levels.

traditional brick-and-mortar stores present a better channel for acquiring new customers of a brand.

DISCUSSION

Managerial Implications

In this study we evaluate the relative effectiveness and profit potential of various promotion strategies in online and brick-and-mortar stores. The advantage of using a modeling framework to support promotion decisions is evident: our analyses suggest that profits may as much as double over current practice when implementing the promotions suggested by our approach. Note that a common feature of the promotion programs examined in this study is that they all involve optimizing promotion offerings every week using each individual household's purchase history data up to the most recent week. The results thus speak to the power of utilizing individual household purchase information and optimization methods in designing promotion-decision support systems, for both online and brick-and-mortar stores.

One key finding of our study is that the benefit of offering customized promotions at more granular levels differs between online and brick-and-mortar stores. There appear to be very little differences in the expected profit between optimal promotions at the mass market level, segment level, and individual level in brick-and-mortar stores. On the contrary, although modest in magnitude -which we think is mainly caused by the modest sample sizes-, the differences between the three levels in online stores are meaningful, and here there are clear benefits from customizing promotions at the segment and individual levels. In general, regardless of the level of granularity, there seems to be a larger untapped profit potential in online as compared to offline stores as it comes to the optimal allocation of promotions. Note that our optimization is based on gross profit, because the fixed costs of implementing those promotion programs are unknown. As discussed in the previous section, these costs are likely to increase substantially for implementing more granular promotions in brick-and-mortar stores, while the corresponding cost structures in the online shopping environment are similar. Therefore, one can expect a greater percentage increase in the net profit when customizing promotions at the segment or individual household level in online stores, whereas the net profit of a mass market or segment level optimal promotion program could well exceed that at the individual level in brick-and-mortar stores. This finding is very relevant for evaluating the current development in the retail industry to explore innovative ways to customize promotions in both online and offline channels. Our results suggest that it would not be worthwhile to invest in personalized *price* promotions in brick-and-mortar stores, at least for the product categories studied here. It is not surprising that most customization initiatives are implemented in the Internet shopping environment in practice so far. Our study confirms that online stores are a substantially more appealing venue to implement personalized price promotions.

Another key insight provided by our study is that, for competitive promotions which are aimed at consumers who did not buy the target brand on the previous purchase occasion, the average optimal price discount is lower and the expected profit is higher in brick-and-mortar stores than in online stores. On the contrary, for loyalty promotions which are aimed at previous-period buyers of the target brand, the average optimal price discount is lower and the expected profit is higher in online stores than in brick-and-mortar stores. This pattern is likely to be driven by differences in purchase behavior between online and offline consumers. Based on our model estimation results, online consumers seem to be more inertial and less promotion-sensitive than their offline counterparts[6]. This finding challenges the conventional wisdom that consumers are

[6] As a technical note, the parameter estimates on brand choice are not directly comparable between two samples, because they are identifiable only up to a scale factor (Swait and Louviere 1993). The ratio of two parameters,

more price-sensitive in online stores, but is consistent with prior studies in the literature. Alba et al. (1997) postulate that online consumers may be more or less price sensitive, depending on the accessibility of information on price and non-price attributes on the Internet. Degeratu, et al. (2000) suggest that online consumers have higher opportunity costs of time and therefore are likely to be more sensitive to convenience and less to price. We believe that both factors are at work: online consumers are inherently different from offline consumers, and could be more affluent or time-constrained for example; in addition, features available in online stores (e.g., personal shopping lists, previous purchase lists) could also make consumers more inertial and less price/promotion sensitive. Given the fact that many other online merchants offer features comparable to those appearing in the online shopping environment we have investigated, the conventional wisdom is likely to err for a substantial number of online businesses. Interestingly, Lal and Sarvary (1999) have demonstrated that the Internet can reduce price competition under certain circumstances, and suggested that brick-and-mortar stores are important for customer acquisition while the Internet can help leverage the acquired customer base. Our study provides empirical support to their conjectures, and offers a rationale from the perspective of promotion effectiveness. Our results corroborate the conventional wisdom that it is more profitable to serve existing customers than to acquire new customers and point to the strategic role of the online channel for accomplishing that.

Given the fact that a large brand in a category is more likely to be purchased on any given previous purchase occasions and thus in the position to consider "loyalty promotions", while a small brand is less likely to be purchased on any given previous purchase occasions and thus more likely to consider "competitive promotions", the above finding implies that the Internet may be a preferred venue for large brands to deliver promotional effectiveness, while brick-and-

however, is identifiable and can be compared across data sets. Our inference is based on comparisons of the average ratios of regular price and price promotion parameters to the inertia/variety seeking parameter.

mortar stores are a better venue for smaller brands. An advantage that large brands enjoy on the Internet is the lower required promotion budgets and higher profitability compared to that in brick-and-mortar stores. At the mean time, the Internet is likely to present a hurdle for small brands by requiring larger promotion budgets and achieving lower profits than in brick-and-mortar stores. Interestingly, Danaher et al. (2003) have shown that large share brands enjoy greater than expected brand loyalty in online shopping environment, while this does not hold in the traditional shopping environment. Our study reveals the additional advantage for large brands on the Internet of using optimal allocation of promotions for purposes of customer retention. It also demonstrates that brick-and-mortar stores are likely to remain a more favorable channel to place small brands[7].

Limitations and Future Research

Our analyses are not without caveats. One limitation is that our study has focused on examining gross profits of the various promotion programs. Fixed costs of these promotions have been omitted, because we have neither exact data nor reasonable estimates of them. Nonetheless, we have some conjectures on how they may affect our results. Within each channel, the main costs would arise from building the infrastructure of computer systems that enable model calibration and customization. As discussed in the previous section, the differences in costs between mass-market level promotions and promotions at the segment and individual levels are likely to be very small in the online environment, while being much more substantial in brick-and-mortar stores. This implies that the differences in promotion effectiveness of targeted segment-level or personalized promotions between online and offline venues would be even greater when the differences in fixed costs are considered. It is worth pointing out that, in

[7] This discussion is based on the assumption that the costs of placing a product in both channels are the same. The implication may be modified if one considers the possible differences in placement costs.

actual practice, costs of infrastructure are shared by all product categories and will drop drastically as the number of categories engaging in a particular form of promotions increases. We believe evaluation of the gross profit, as we have done, has substantive implications for both manufacturers and retailers. It enables us to assess and compare unit margins for each type of promotion. These results may provide a direct basis for firms to conduct a break-even analysis based on their own fixed costs, and estimate the net profit given knowledge of the marketplace, the size of customer base, the number of categories involved, etc.

A concern that marketers need to address when implementing customized (segment or individual level) promotions is that some consumers may be offended if they get less price discounts than other consumers (see Feinberg, Krishna, and Zhang, 2002). This problem could be serious if the same consumers consistently receive less price promotions than others across categories, but it is less likely to be an issue if different consumers get discounts in different product categories. An implication of this is that marketers need to think about what are the proper ways to reward "good customers". We believe that the virtue of customized promotions is to deliver promotions when and only when a consumer values them. It does not mean that marketers should ignore its less price sensitive/more loyal customers. Rather, they should think of better ways to reward them. Although it is beyond the scope of this study, we suggest that managers conduct follow-up studies on the amount of promotions received by individual consumers across a broad array of categories and identify those who have had received substantially less promotions than others. These consumers should be provided rewards that are mutually beneficial for the consumers and marketer, such as free samples of product categories that they are interested in, discounts based on the total expenditure of the shopping trip, speedy check-out line in brick-and-mortar stores, and free delivery to online store customers.

We have analyzed the profitability of promotional strategies of all brands in two categories, which lends greater credibility to the generality of our findings. Nonetheless, our findings primarily pertain to packaged consumer goods. More research is needed to examine the generalizability of our findings for other types of products. We have focused on price promotion decisions in this research. The general approach adopted here can be extended to studying other forms of promotions as well, such as the differential effects of in-store displays versus online displays of special promotions. An interesting extension of the current research would be to examine the spill-over effects of promotions in one type of shopping venue (online or offline) on purchase behavior in the other shopping venue, for which panel data on customers visiting both venues would be required.

In summary, our study sheds light on threats and opportunities facing online and traditional retailers. Online retailers have the opportunity to offer personalized promotion services to their corporate clients. Such promotion services would be especially attractive to manufacturers with large brands that are disposed toward offering loyalty promotions. On the other hand, brick-and-mortar stores are likely to be a more suitable channel for acquiring new customers through promotions, due to the lower required promotion costs and higher potential profit. Given the differences in promotion efficiencies between online and brick-and-mortar stores, we conjecture that traditional retailers may benefit from opening their own Internet stores. A dual channel strategy enables traditional retailers to enjoy the benefits of both worlds and offer "one-stop promotion services" to manufacturers who carry multiple brands in many product categories. Retailers that already have a presence in both channels need to decide on how to choose the appropriate promotion programs in their brick-and-mortar and online branches, and how to place products and allocate promotion budgets in each channel. Our results may provide useful input for these retailers as well.

APPENDIX

Description of the Model Formulation and Optimization Procedure

Model Formulation

We have $g = 1, \ldots, G$ segments with sizes π_g. Let: $I_{i,t}$ = 1 if household *i* makes a category purchase at shopping trip *t*, 0 otherwise; $y_{i,k,t}$ = 1 if household *i* purchases brand *k* at shopping trip *t*, 0 otherwise; $Q_{i,k,t}$ = household *i*'s purchase quantity of brand *k* at shopping trip *t* (in ounces). The utility of brand *k* at shopping trip *t* for household *i* is given by:

(A1) $$U_{i,k,t} = \beta_{0,k,g} + X'_{i,k,t}\beta_{1,g} + \beta_{2,g}\, y_{i,k,t-1} + \beta_{3,g} y_{i,k,t-1} z_{i,k,t-1} - \beta_{4,g}\Delta_{k,j(t-1)} + \varepsilon_{i,k,t}\,,$$

where $X'_{i,k,t}$ is a vector of marketing mix variables (regular price and price cut for the online data, and these plus feature advertising and display for the offline data); $y_{i,k,t-1}$ equals 1 if brand *k* was chosen by household *i* on the last purchase occasion and 0 otherwise; $z_{i,k,t-1}$ equals 1 if brand *k* was on price promotion on household *i*'s last purchase occasion and 0 otherwise; $\Delta_{k,j(t-1)}$ is a measure of distance between brand *k* and the brand chosen by household *i* on the previous purchase occasion, *j*(*t*-1), and is derived from a survey. Note that $\Delta_{k,k} = 0$ by definition. In (A1), $\beta_{0,k,g}$ are the brand specific constants, $\beta_{1,g}$ are coefficients of marketing mix variables, $\beta_{2,g}$ captures a household's inertia/variety seeking tendency, and $\beta_{3,g}$ captures the moderating effect of promotion on inertia/variety seeking. Purchase incidence is modeled by assuming that a consumer makes a category purchase at *t* if and only if the utilities of the brands exceed a threshold defined by:

(A2) $$U_{i,0,t} = \theta_{0,g} + \theta_{1,g} R_i + \theta_{2,g}\tilde{Q}_{i,t-1} + \varepsilon_{i,0,t}\,,$$

where $\theta_{0,g}$ is a constant, R_i is household *i*'s purchase frequency in the initialization period, and $\widetilde{Q}_{i,t-1}$ is household *i*'s mean-centered last purchase quantity. Finally, to model purchase quantities, let observed purchase quantity $Q_{i,k,t} = Q^*_{i,k,t}$ if $I_{i,t} = 1$ and $y_{i,k,t} = 1$, and $Q_{i,k,t} = 0$ otherwise, where $Q^*_{i,k,t}$ is a latent variable obtained as:

(A3) $$Q^*_{i,k,t} = \phi_{0,g} + \phi_{1,g}\overline{Q}_i + X'_{k,t}\phi_{2,g} + \xi_{i,k,t},$$

where $\overline{Q}_i$ is household *i*'s average purchase quantity in the initialization period, $X'_{i,k,t}$ includes brand *k*'s regular price and price cut. We assume a bivariate logistic distribution for the joint distribution of $\varepsilon_{i,k,t}$, k = 0, 1, 2, …, the error terms in equations (A1) and (A2), and $\xi_{i,k,t}$, the error term in equation (A3). The bivariate logistic distribution involves a parameter that reflects the correlation between choice and quantity. This assumption on the error terms leads to a closed-form expression of the joint probability of purchase incidence, choice, and quantity, and enables estimation of the model by a standard maximum likelihood method (see Zhang and Krishnamurthi 2003 for details).

Optimization Procedure

Let brand *k* be the target brand. The manufacturer's expected gross profit of brand *k* from household *i* during a certain time period *T* is given by:

(A4) $$\Pi_i = \sum_{t_i=1}^{T_i} \hat{P}(I_{i,t_i} = 1, y_{i,k,t} = 1)E[Q_{i,k,t} \mid I_{i,t_i} = 1, y_{i,k,t} = 1](M_{k,t_i} - PC_{k,t_i}),$$

where $\hat{P}(I_{i,t_i} = 1, y_{i,k,t_i} = 1)$ = the expected probability of household *i* buying brand *k* on shopping trip t_i; $E(Q_{ik,t_i} \mid I_{i,t_i} = 1, B_{ik,t_i} = 1)$ = the expected purchase quantity of *k* given that *k* is chosen by household *i* on shopping trip t_i; M_{k,t_i} = the manufacturer's regular profit margin of brand *k* without a promotion at t_i; and PC_{k,t_i} = amount of brand k's price cut at t_i. The purchase and incidence probabilities at the future time points are obtained by a conditional branching process. We numerically maximize a profit function with respect to the price promotion at a sequence of T time points to get the optimal promotion scheme. For mass-market promotions, profit function $\Pi = \sum_{i=1}^{N} \Pi_i$ is maximized with respect to $\{PC_{k,t}, PC_{k,t+1}, ..., PC_{k,T}\}$, a common set of price promotions for all households in the sample, to get the optimal price promotions. For segment-level targeted promotions, profit function $\Pi_g = \sum_{i=1}^{N_g} \Pi_i$ is maximized with respect to $\{PC_{g,k,t}, PC_{g,k,t+1}, ..., PC_{g,k,T}\}$, a set of price promotions common for households in segment g, to get the optimal price promotions. For individual-level personalized promotions, the profit function as shown in equation (A4) is maximized with respect to $\{PC_{k,t_i}, PC_{k,t_i+1}, ..., PC_{k,T_i}\}$ for each household i to get the optimal price promotions at individual household level. We assume values for the wholesale and retailer margins, denoted by m_m and m_r respectively, to derive $M_{k,t}$ from regular price $RP_{k,t}$. We vary the levels of $m_m(1 - m_r) = \frac{M_{k,t}}{RP_{k,t}}$, which is called the "percentage profit margin" in this paper.

TABLE 1
Estimation Results for Stick Butter

Variables/Parameter	Online Segment 1	Online Segment 2	Offline Segment 1	Offline Segment 2
Brand Choice				
LOL salted	0.083	2.400 ***	2.879 ***	-2.377 ***
LOL unsalted	-0.012	1.950 **	-0.052	-0.923 *
Store brand salted	-0.093	3.267 ***	3.425 ***	-0.087
(Store brand unsalted)	(0)	(0)	(0)	(0)
Regular price	-0.166 ***	-0.089	-0.147 **	-0.002
Price cut	0.566 ***	1.386 **	0.292 **	0.759 ***
Display			0.439 ***	0.946 ***
Feature ad			0.755 ***	0.728 ***
Inertia/ variety seeking	2.178 ***	0.876 ***	0.395 ***	0.451 ***
Price cut on inertia/v.s.	0.110	-0.326 **	-0.080	0.035
Category Incidence				
Constant	3.518 ***	4.392 ***	7.268 ***	5.205 ***
Purchase frequency	-5.126 ***	-1.860 **	-8.335 ***	-8.812 ***
Last purchase volume	-0.048	4.339 **	2.064 **	0.015
Purchase Quantity				
Constant	-0.458	-0.100	-0.596 **	-0.700 **
Regular price	-0.393	-1.188 **	-0.188 **	-0.089
Price cut	0.596	1.616 **	0.364 *	0.223
Average purchase volume	1.185 ***	0.370	1.011 ***	1.443 ***
Segment Size	71.6%	28.4%	59.6%	40.4%

*** P-value < 0.01. ** P-value < 0.05. * P-value < 0.10.

TABLE 2
Estimation Results for Liquid Detergent

Variables/Parameter	Online Segment 1	Online Segment 2	Offline Segment 1	Offline Segment 2
Brand Choice				
Wisk	-0.123	1.815 **	0.633 **	0.076
All	-0.291	-0.924 *	-0.223	-1.966 ***
Tide	0.525	2.357 **	0.854 ***	0.025
(Cheer)	(0)	(0)	(0)	(0)
Regular price	-0.092	-0.966 ***	-0.206	-0.707 **
Price cut	0.292	0.214 ***	0.264 **	0.341 *
Display or Feature Ad			1.924 ***	1.194 ***
Inertia/variety seeking	1.773 ***	1.706 ***	0.309 ***	2.552 ***
Price cut on inertia/v.s.	-0.325 ***	0.074	0.126	-0.121 *
Category Incidence				
Constant	2.485 ***	-1.889 **	5.243 ***	1.810 *
Purchase frequency	-2.069 ***	-2.890 ***	-13.564 ***	-10.762 ***
Last purchase volume	0.058	0.031 ***	0.008	0.071 ***
Purchase Quantity				
Constant	5.999 ***	21.980***	11.846 ***	1.441 *
Regular price	-0.957	-25.644***	-5.236 ***	-0.179
Price cut	-0.047	2.119 **	9.482 ***	0.113
Average purchase volume	0.457 ***	0.922 ***	0.188 ***	0.870 ***
Segment Size	65.9%	34.1%	62.6%	37.4%

*** P-value < 0.01. ** P-value < 0.05. * P-value < 0.10.

TABLE 3
ANOVA Results for Expected Optimal Profit

Source		SS	%SS	F	P
Category	1	6038690	8.45	671.39	0.0000
Venue	1	79332	0.11	8.82	0.0031
Orientation	1	7109032	9.95	790.40	0.0000
Level	3	1749901	2.45	64.85	0.0000
Margin	1	6550635	9.17	728.31	0.0000
Category/Brand	6	16319220	22.84	302.40	0.0000
Category:Venue	1	588161	0.82	65.39	0.0000
Category:Orientation	1	923348	1.29	102.66	0.0000
Category:Level	3	1144362	1.60	42.41	0.0000
Category:Margin	1	1944447	2.72	216.19	0.0000
Venue:Orientation	1	2334251	3.27	259.53	0.0000
Venue:Level	3	155194	0.22	5.75	0.0007
Venue:Margin	1	75737	0.11	8.42	0.0038
Orientation:Level	3	384152	0.54	14.24	0.0000
Orientation:Margin	1	1516611	2.12	168.62	0.0000
Level:Margin	3	82407	0.12	3.05	0.0278
Category/Brand:Venue	6	4011854	5.61	74.34	0.0000
Category/Brand:Orientation	6	8533613	11.94	158.13	0.0000
Category/Brand:Level	18	908945	1.27	5.61	0.0000
Category/Brand:Margin	6	3556830	4.98	65.91	0.0000
Residuals	828	7447256			
Total	895	71453978			

TABLE 4
Summary of Optimal Price Cuts and Profits

Category	Orientation	Source	Margin	Mass Price Cut	Mass Profit	Segment Price Cut	Segment Profit	Individual Price Cut	Individual Profit	Current practice Price Cut	Current practice Profit
Butter	Competitive	Online	0.20	0.03	52.68	0.04	54.50	0.05	56.81	0.60	-34.39
			0.30	0.34	84.27	0.15	90.34	0.28	94.37	0.60	28.17
			0.40	0.77	132.46	0.54	141.83	0.79	150.25	0.60	90.72
		Offline	0.20	0.00	192.71	0.00	192.71	0.00	193.00	0.39	54.32
			0.30	0.00	288.44	0.02	288.83	0.02	289.60	0.39	180.00
			0.40	0.14	386.15	0.15	388.54	0.16	390.55	0.39	305.67
	Loyalty	Online	0.20	0.00	408.93	0.01	409.94	0.01	412.65	0.57	-8.22
			0.30	0.00	614.14	0.04	617.43	0.05	622.76	0.57	273.35
			0.40	0.02	818.99	0.08	834.59	0.09	842.16	0.57	554.93
		Offline	0.20	0.00	295.45	0.00	295.45	0.00	295.45	0.39	132.07
			0.30	0.01	442.65	0.02	442.76	0.02	443.18	0.39	305.71
			0.40	0.15	589.98	0.16	591.15	0.19	592.47	0.39	479.36
Detergents	Competitive	Online	0.20	0.00	22.65	0.00	22.65	0.00	22.65	0.50	14.75
			0.30	0.00	34.38	0.01	34.52	0.12	34.99	0.50	28.75
			0.40	0.30	46.54	0.30	47.32	0.71	49.29	0.50	42.75
		Offline	0.20	0.00	33.13	0.00	33.13	0.00	33.13	0.23	26.75
			0.30	0.00	49.70	0.03	49.70	0.01	49.73	0.23	45.32
			0.40	0.16	66.40	0.32	66.61	0.22	67.33	0.23	63.89
	Loyalty	Online	0.20	0.00	192.61	0.00	192.61	0.00	192.61	0.50	125.54
			0.30	0.00	283.33	0.00	283.38	0.00	284.00	0.50	234.57
			0.40	0.12	375.39	0.13	376.85	0.15	382.32	0.50	343.59
		Offline	0.20	0.00	58.05	0.00	58.05	0.00	58.05	0.23	50.31
			0.30	0.00	87.07	0.00	87.07	0.00	87.07	0.23	81.70
			0.40	0.17	116.56	0.20	116.73	0.25	117.09	0.23	113.09

FIGURE 1
Optimal Individual Level Price Cuts (top) and Profits (bottom) for Stick Butter
(Brands are indicated by different symbols,
the two orientations are indicated in the left and right hand panels.)

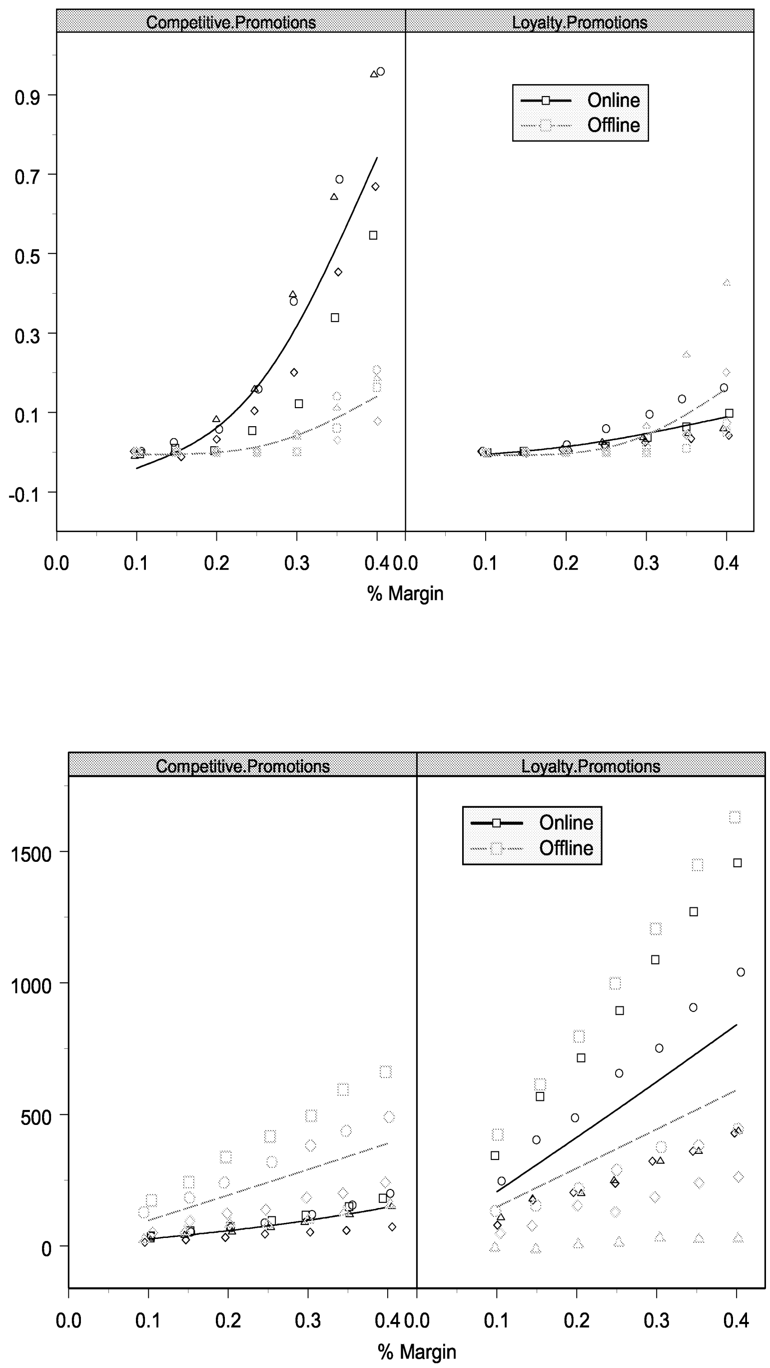
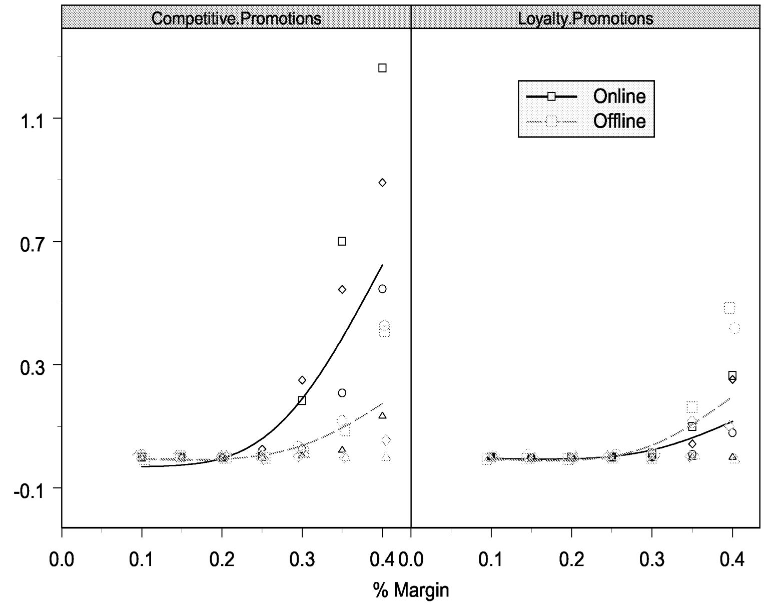
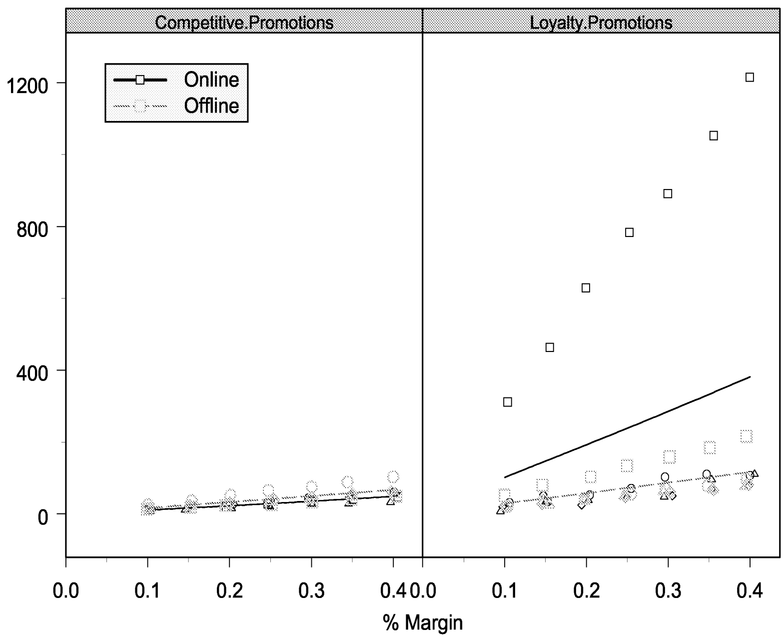


FIGURE 2
Optimal Individual Level Price Cuts (top) and Profits (bottom) for Liquid Detergent
(Brands are indicated by different symbols,
the two orientations are indicated in the left and right hand panels.)





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