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USING BIG DATA TO PREDICT CONSUMER RESPONSES TO PROMOTIONAL DISCOUNTS AS PART OF SALES & OPERATIONS PLANNING

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ABSTRACT

Price promotions (discounts) are a well-known means by which a supply chain can stimulate demand for a product. These promotions could affect demand for a product in three ways by: 1) increasing the overall market growth, 2) stealing market share from competitors, and/or 3) increasing the amount of consumer forward buying. Supply chain members must be able to estimate these effects on demand and the corresponding effects on both revenues and costs when conducting sales and operations planning. We analyzed the effects on demand using a big data approach on promotional data made publicly available by Grupo Bimbo (a multinational bakery product manufacturing company headquartered in Mexico City). This company offered promotional coupons to customers for particular items. Bimbo captured sales history for each customer on how often they shopped, what they bought, and the amount that they spent. Bimbo then tracked how many times during the next year that customers returned to buy the promoted items at full price. Using this data set, we assessed which types of offers were more effective at achieving the goal of increasing repeat purchases at full price. Whether the offer was for a weekend or weekday had no significant effect. However, we found that a larger discount percent was associated with fewer repeat purchases at full price. Further, customers who tended to spend more, on average, per trip had a higher number of repeat purchases for an item.

JEL: C33, C35, M110

KEYWORDS: Big Data, Data Analytics, Multiple Regression, Promotions, Sales and Operations Planning

INTRODUCTION

When performing sales and operations planning for a supply chain, the manufacturer must be able to understand and anticipate the effects on demand, revenue, and costs that result from offering a discount on a product. The starting point for this planning is to estimate how and why demand will change over the planning horizon when a discount (sales promotion) is offered to customers. Grocery retailers have been applying advanced analytic tools to customer data to tailor promotional offers to customers based on their shopping history. For example, one study noted that Kroger tailored coupons to regular customers and increased customer coupon redemption rates to nearly 50% compared to an industry average of 1 to 3% (Manthan). Kroger employs more than 100 analysts to sift through hundreds of terabytes of shoppers data (McClean, 2015). Additionally, companies are using data analytics for purposes beyond collecting and analyzing sales data. For example, Grupo Bimbo has used Brandwatch Analytics to track customers' online conversations, trends, and ranks to determine the viability of new product launches (Dua, 2017). We present the results of an analysis of a big data set related to incentives (coupons) that Grupo Bimbo offered to customers and customer responses (number of repeat purchases) to those offers.

Using this data set, we assessed which types of customers and offers were associated with increased repeat purchases at full price. Whether the offer was for a weekend or weekday had no significant effect on repeat trips. However, we found that larger discounts spurred fewer repeat purchases of a promoted item, and customers who tended to spend more on average per trip had a higher number of repeat purchases for a promoted item. The remainder of this paper is organized as follows. The next section focuses on literature relevant to the anticipated effects of price promotions. Next, we discuss the data and methodology used in the current study. In the following section, we present the results and a discussion of those results. The paper closes with some concluding comments.

LITERATURE REVIEW

This section summarizes the literature on price promotions and the effects expected from those price promotions. In a seminal article, Neslin and Shoemaker (1983) criticized managers for evaluating coupon promotions on surrogate measures (e.g., redemption rates, market share, and the direct costs of the coupon promotion) instead of estimated net profitability. Chopra and Meindl (2016, p. 234) argued that when a firm offers a promotion, that period's demand for an item tends to increase based on three factors: market growth, stealing share, and forward buying. Market growth corresponds to an increase in consumption of a product by new or existing customers. Stealing share refers to customers substituting the firm's product for a competitor's product. Forward buying refers to customers moving up future purchases to the present. Estimating item demand for the promotion period and future periods enables a manufacturer to determine when to offer a discount and the size of the discount to offer. Therefore, the manufacturer must estimate these three effects before conducting sales and operations planning. To estimate these effects, a planner must have a deep understanding of the effects of coupon promotions on demand.

DelVecchio, Henard, and Freling (2006) argued that despite the long-run use of sales promotions, brand managers and marketing scholars still lacked a clear understanding of the effects of sales promotions on post-promotion brand preference. Although they argued in their meta-analysis that sales promotions do not affect post-promotion brand preference (on average), they went on to analyze individual effects on post-promotion brand preference. For example, they argued that post-promotion brand preference was more favorable when the sales promotion was a coupon or premium and that large promotion (> 20% of a product's value) had a detrimental effect on brand preference. Zeelenberg and van Putten (2005) proposed that a sales dip after a product has been promoted might result from forward buying/stockpiling by customers taking the discount and/or by customers who missed a large discount for their regular brand being more likely to switch to another brand of that product.

Anderson and Simester (2004) conducted three field studies of promotions for durable goods and concluded that with respect to repeat purchase rates, increasing the amount of a price promotion had a positive long-run effect among prospective customers (due to favorable expectations about future price and/or quality levels) and a negative long-run effect on established customers. In summary, the previous literature on the size of discounts suggests that companies could see increases in demand and brand preference by limiting the use of large price promotions to <u>new</u> customers only. Mouland (1998) reported on a study of the relationship between coupon usage and consumer spending and concluded that coupon redeemers were heavier buyers of a brand than non-coupon buyers were. In addition, repeat purchase rates for couponed brands were higher among coupon redeemers than non-redeemers. Mouland noted that this finding on repeat purchase rates contrasted to a general perception that coupon redeemers have low rates of repeat purchase. Similarly, Arce-Urriza and Cebollada (2017) found results that showed that frequent customers were more influenced by promotions than infrequent customers were. Lal and Bell (2003) studied the use of a promotional coupon offered to customers in a frequent shopper program at a U.S. grocery retailer and found that a ham promotion coupon had the biggest effect (% increase in overall spending) on the worst customers (low spenders). In another study, Thach and Olsen (2015) analyzed the amount spent by customers on wine. They observed that low spenders were more likely to use wine apps to find coupons for grocery stores, while moderate and high spenders were more likely to use social media instead to search for product information. In summary, the relationship between the amount of consumer spending, repeat purchases and coupons appears to be mixed.

DATA AND METHODOLOGY

We obtained data that Bimbo Group (headquartered in Mexico City) made publicly available (Acquire Valued Shoppers Challenge). Bimbo made these data publicly available in large relational files and included a warning on the web site that the four decompressed files required about 22 GB of space. To ensure confidentiality, Bimbo scrubbed the data to anonymize customer and sales information. The web site included another warning that the specific meanings of fields would not be provided and that viewers should not ask about the meanings. Therefore, we needed to observe the data and apply some judgment regarding the meaning of some fields. In addition, as advised by Bradlow et al. (2017), we used data based on promotional theory in our models, rather than relying entirely on a data driven, data mining approach, for which we indiscriminately would have included all variables provided in the Bimbo data set. The three of the four files that we used contained the following information:

trainHistory.csv : Includes incentives offered to each customer and information about each customer's response to the offer (a coupon) for a specific product. Our analysis of the data indicated that coupons were sent to customers March – April of 2013. Each record contained the following data: customer identifier, an identifier for the offer, the geographical market area in which the item was sold, the number of times that the customer made a repeat purchase of the item, and the date that the customer received the offer. Note: This file included the number of repeat purchases post-offer only—it did not include information on the exact period over which those repeat purchases were tracked.

transactions.csv : Includes transaction history for all Bimbo customers and all products that they purchased (not just items for which an incentive was offered) for at least 1 year prior to the customer's offered incentive. Note: Our analysis of the data indicated that transaction data were recorded for March 2012 – July 2013. Each record contained the following data: customer identifier, store number where the Bimbo item was purchased, the product category to which the item belonged, the retail company that sold the item, the Bimbo brand to which the item belonged, the date of the customer purchase, and the quantity and the dollar amount for the item purchased by the customer.

offers.csv: Includes information about the offers. As previously stated, we analyzed offers made between March–April 2013. Each record contained the following data: an identifier for the offer, the product category to which the item belonged, the number of units that a customer needed to purchase to receive the discount on the item, the retail company that sold the item, the dollar value of the offer, and the Bimbo brand to which the item belonged. Note: Percent discount for an offer was not provided in this file. First, we estimated unit price by dividing the dollar amount of each purchase by the purchase quantity. Second, we divided the dollar value of the offer by unit price of an item to determine percent discount. We merged the files along key fields, e.g., customer id, and then calculated intermediate variables of interest, such as mean dollar spent and number of trips by customer and company.

After calculating our variables at the aggregate customer level, we removed detailed data to reduce the data set size to include only those records and variables needed for our analysis. We included control variables to remove spurious effects, e.g., perhaps customers who shop on weekdays work part-time and thus might not buy items at full prices after receiving an offer, or any other confounding effects outside of the main independent variables that we studied. To avoid presenting results influenced by outliers, after calculating the variables of interest, we Winsorized our data set at the 1% level to account for outliers that appeared to have resulted from data recording errors. Our final data set sample consisted of 160,057 customers, with 37 unique offers given to them on 12 specific Bimbo brands, for a total 349,655,789 records. Because consumers, their preferences, and their buying patterns are motivated by many unknown factors, coupled with the anonymized sample data provided by Bimbo, we did not expect our multiple regression model to identify all factors that would predict consumer purchase responses. The R-squared of a model tells how much of the variability in the dependent variable is predicted by the variance in the control and independent variables. We did not anticipate a large R-squared value in our model, but we did expect that the factors we were able to test would be statistically significant in predicting increased (decreased) customer repeat purchases at full price after an offer is given. A description of the variables follows.

Variables

Dependent Variable

Repeat Trips: number of times that a customer made a repeat purchase of a particular Bimbo item after redeeming a coupon for that item
Control variables:

Weekend : a dummy variable based on the date that a customer received the offer (coupon) from Bimbo
Company 1 … Company 10 – dummy variables used to code ten of the eleven retail companies selling Bimbo items. Note: When all ten values equaled zero, this corresponded to the 11th store, which was used as the reference case.

Independent Variables

Mean Spent per Trip ($) : the mean amount spent (converted from pesos to dollars) on a particular Bimbo item per customer per shopping trip in the training data

Number of Trips : the mean number of trips for which a customer bought a particular Bimbo item (determined based on historical transaction data from at least one year prior to an offer on an item)

Offer Percent :the percent discount off the regular retail price of an item Using these data, we first ran a multiple regression using Stata 14 by specifying *Repeat Trips* as the dependent variable, *Mean Spent per Trip ($)* and *Number of Trips* as independent variables, and control variables for *Weekend* and *Company*. The first hypotheses that we tested were:

Hypotheses

As mentioned above, Mouland (1998) concluded that coupon redeemers were heavier buyers of a brand (i.e., spent more) than non-coupon buyers. Even though the relationship between the amounts of consumer spending, repeat purchases and coupons appears to be mixed, we assumed that customers who spend more on Bimbo items or are in the store more frequently to purchase Bimbo items are more likely to purchase repeats of a given item that they tried through coupon shopping. Our regression equation is:

$$RepeatTrips = \beta_0 + \beta_1(Company_1) + \beta_2(Company_2) + \beta_3(Company_3) + \beta_4(Company_4) + \beta_5(Company_5) + \beta_6(Company_6) + \beta_7(Company_7) + \beta_8(Company_8) + \beta_9(Company_9) + \beta_{10}(Company_{10}) + \beta_{11}(Mean) + \beta_{12}(Offer) + \beta_{13}(NumberTrips) + \varepsilon_{it}$$

Given these relationships, we propose the following two hypotheses:

> *H1: Customers with a higher mean spent per shopping trip will be positively associated with more repeat trips post-offer to buy the item at full price.*

H2: Customers who shop more frequently will be positively associated with more repeat trips post-offer to buy the item at full price.

Next, we added *Offer Percent* into the regression model. Anderson and Simester (2004) noted that large discounts should be offered to new customers only. Given that the data that we studied were captured for existing Bimbo customers only, we tested the following hypothesis:

H3: A higher percent offer will be negatively correlated with repeat trips to buy the item at full price.

After that, we tested for interaction effects in the second regression model based on the following reasons: Expanding on hypothesis three, we theorized that the higher the discount percent, the more likely customers would be to stockpile an item. Therefore, we expected to observe a moderating relationship of offer percent on the number of repeat trips for higher mean spent per trip and higher frequency of shopping trips. Those who spend more are less likely to repeat purchase if a higher discount percent is offered because they have the disposable income to buy large quantities of an item when a discount is offered compared to customers who cannot afford to buy extra items. In addition, the greater the percent of the discount, the more likely a customer who regularly purchases a product will be to stockpile that highly discounted product. Moreover, those who shop more frequently are less likely to repeat purchase if a higher discount percent is offered because they also are able to stockpile, and then on subsequent trips, they will not need to purchase the previously discounted item. Therefore, we tested the following hypotheses by adding on *Offer Percent* as a moderator:

H4: The offer percent moderates the relationship between higher mean spent and repeat trips, such that higher offer percent decreases repeat trips.

H5: The offer percent moderates the relationship between frequency of shopping and repeat trips, such that higher offer percent decreases repeat trips.

RESULTS AND DISCUSSIONS

The models in this study were analyzed using Stata 14 to perform the two regressions shown below. Both models used Repeat Trips as the dependent variable. Column 1 of Table 1 shows the ANOVA results for the first model with the control variables and the three independent variables (Mean Spent per Trip ($), Offer Percent, and Number of Trips). Column 2 shows the ANOVA results from taking the first regression model and adding in the moderation effects of Offer Percent. Adding in moderation effects did increase the explanatory power of Model 2 over Model 1 (R-squared). In addition, the second model does point to statistically significant aspects that lead to more (fewer) repeat purchases at full price post-offer.

Hypothesis Results

H1: Customers with a higher mean spent per shopping trip will be positively associated with more repeat trips post-offer to buy the item at full price. This hypothesis was supported.

H2: Customers who shop more frequently will be positively associated with more repeat trips post-offer to buy the item at full price. This hypothesis was supported. There was mixed information in the literature about consumer spending, repeat purchases, and coupons. Our findings indicate that the more a customer spends per trip and the more frequently a customer shops, the more likely a customer is to make repeat purchases of a discounted item.

H3: A higher percent offer will be negatively correlated with repeat trips to buy the item at full price. This hypothesis was supported.

We also found that a greater percent discount did not lead to more repeat purchases at full price. Customers will stockpile items that they regularly buy when they have the disposable income to do so. The greater the percent of the discount, the more likely a customer who regularly purchases a product will be to stockpile that highly discounted product. A customer who shops frequently will notice a highly discounted product and will be more prone to stockpile that item. If the discount percent is high, a customer is more likely to stockpile the item. This logic brings us to hypotheses four and five.

Table 1: Multiple Regression Results for Models 1 & 2

	(1)		(2)	
VARIABLES	**Repeat Trips**		**Repeat Trips**	
	Coeff.	**P>|t|**	**Coeff.**	**P>|t|**
Weekend Dummy	-0.0017	0.970	-0.0063	0.887
Company 1 Dummy	0.5868***	0.000	0.6789***	0.000
Company 2 Dummy	-0.2472	0.108	-0.3983***	0.009
Company 3 Dummy	-0.5319***	0.002	-0.1119	0.508
Company 4 Dummy	0.1758	0.296	0.5035***	0.003
Company 5 Dummy	0.1072	0.622	0.3990*	0.066
Company 6 Dummy	1.9640***	0.000	1.9283***	0.000
Company 7 Dummy	-0.1510	0.346	-0.0571	0.720
Company 8 Dummy	1.8955***	0.000	1.8966***	0.000
Company 9 Dummy	0.8830***	0.000	1.0055***	0.000
Company 10 Dummy	3.1128***	0.000	3.3459***	0.000
Mean Spent per Trip ($)	0.0948***	0.000	0.2321***	0.000
Offer Percent	-1.6611***	0.000	1.0887***	0.000
Number of Trips	0.1009***	0.000	0.2709***	0.000
Mean Spent per Trip ($) x Offer Percent	---		-0.3631***	0.000
Number of Trips x Offer Percent	---		-0.3752***	0.000
Constant	0.2304	0.203	-1.0321***	0.000
Observations	40,063		40,063	
R-squared	0.0821		0.0924	
F	255.93***		255.91***	

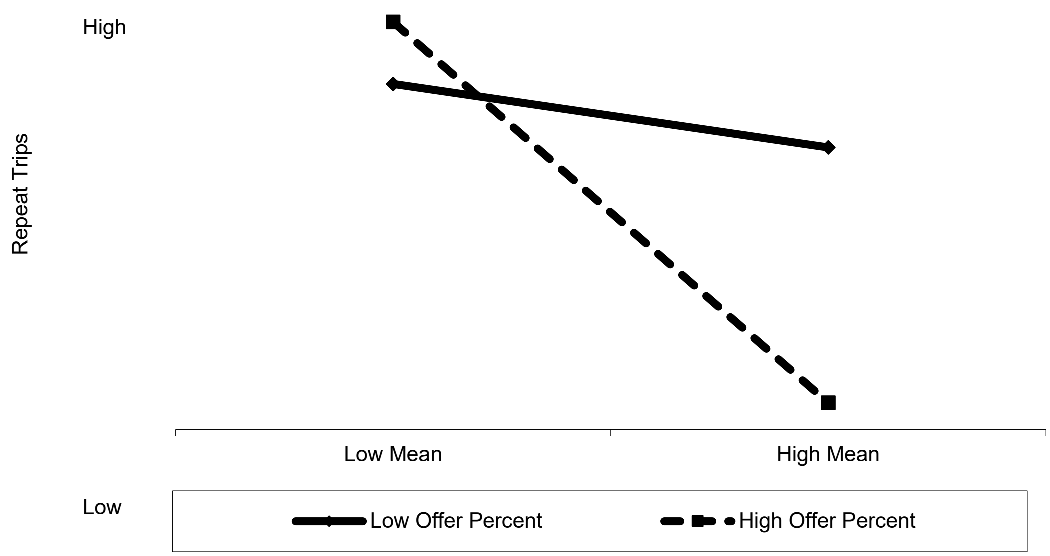
*This table shows the results of both regressions. ***, **, and * indicate significance at the 1, 5, and 10 percent levels, respectively. Both regression models were statistically significant. In Model 1, Mean Spent per Trip, Offer Percent, and Number of Trips were statistically significant predictors of Repeat Trips. In Model 2, Mean Spent per Trip, Offer Percent, and Number of Trips were statistically significant predictors of Repeat Trips. However, the slope for the Offer Percent variable switched from negative to positive. All interaction effects were statistically significant as well.*

H4: The offer percent moderates the relationship between higher mean spent and repeat trips, such that higher offer percent decreases repeat trips. This hypothesis was supported.

H5: The offer percent moderates the relationship between frequency of shopping and repeat trips, such that higher offer percent decreases repeat trips. This hypothesis was supported.

Although heavy shoppers (higher mean spent per trip) seem the most likely to make a repeat purchase of an item at full price post-offer, this was not the case when we accounted for the effects of percent discount. A heavy shopper responds better to a lower discount percent coupon. A shopper who spends less (lower spend per trip) is more likely to continue to buy an item for which they redeemed a high discount percent coupon (see Figure 1 below). This again could be explained by customer stockpiling as the customer who stockpiles would display a higher amount spent per trip than the customer who is purchasing an item for that single promotion.In addition, those customers who shop more often are less likely to repeat purchase at full price after buying an item at a large percent discount. For infrequent (low number of trips) shoppers, the opposite is true—they perhaps will try an item with a heavily discounted offer and come back and buy that item at full price more often than they would purchase an item with a lower percent offer item (see Figure 2 below). We assumed that this relationship would hold because the more frequent customers will be in the store more. Thus, the size of a promotion would favor the low discount percent because more frequent shoppers would be less likely to stockpile the product. After analyzing the data, we recognized that there is a possibility that high percentage promotions lead to forward buys for customers who spend a large amount (high spend) and shop more frequently (high number of trips). Those who spend less (low spend per trip) and shop less frequently (low number of trips) could be first time users of a product. Therefore, the high percent promotions could be reaching the intended customers for repeat purchasing.

Figure 1: Mean Spent Per Trip X Offer Percent Interaction



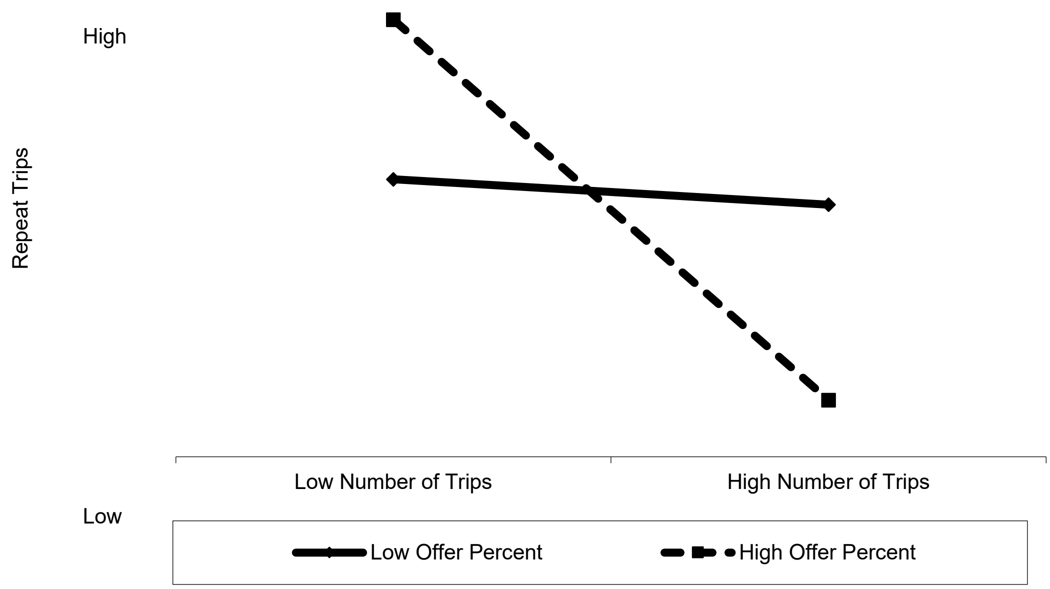
This figure shows the relationship of repeat trips to customers with low mean purchases versus high mean purchases on the x-axis. The moderating effect of low versus high offer percent is indicated by the solid versus dashed line. There is no single offer percentage that fits all customers. However, higher offer percentages work better on Low Mean customers, while lower offer percentages work better on High Mean customers.

CONCLUSIONS

In the current study, we demonstrated a big data approach to analyzing the effects of a coupon campaign on consumer repeat purchases. We found the following: it is important to control for company because it might be that customers who shop at a "bargain" store might have different price sensitivities to coupons versus customers who shop at "higher end" stores. How much customers spend each shopping trip on Bimbo items brands and how often they go shopping are significant predictors of their likelihood to respond favorably to a coupon. The goal is to offer the right coupon to customers to incent them to return to buy the item many times at full price. The offer percent value has been shown to be significant in prior research, and we found that to be true here as well. Of particular interest in our findings is that a higher discount percentage on the offer works only for some customers (infrequent shoppers and lighter spend shoppers). It is important to vary the coupon discount percent according to customer criteria as we have identified here.Some of the challenges that we faced were that not all of the data that had been collected by Bimbo were made available. A larger and more complete data set would allow other relationships to be tested and would likely have more predictive power of repeat purchases. We posit that the retailer point of sale (POS) data for Bimbo were transmitted to Bimbo. Using all retailer data, we could look for patterns for complementary items and generate better estimates of frequency of shopping and mean spend given that our predictions of repeat purchases were calculated using the available data on purchases of Bimbo products only. In addition, the enormous size of the datasets was right at the limit of a normal desktop PC's capability to handle and analyze. Because the mean and frequency of purchase variables were based on prior purchases, we were not able to analyze offers given to customers for their first time purchases of that item.

More data fields would need to be available because prediction of first time buyers cannot be based on their prior purchase history of that item. Specifically, having demographic data from customers likely would increase the predictive power (R-squared) of the models. Having a loyalty program that asks for data on gender, household income, etc. would produce useful data. Harmon and Hill (2003) noted in their empirical study that men and women do have different purchase patterns. Porter (1993) explored asking for information in exchange for coupons in a case study. We assumed that the coupons were delivered electronically, but if coupons were printed, they could be traded and that would obscure the true demand and repeat purchase pattern (Su et al., 2014). Relatedly, in-store coupons versus discounts advertised on the shelf and given at checkout have different effects on consumers (Dhar and Hoch, 1996). Their work finds nuance in the area of price discriminating consumers, but it would be interesting to compound those discounts (for all) with direct to specific loyal consumer offers (for some) to see the interactions.

Figure 2: Number of Trips x Offer Percent Interaction



This figure shows the relationship of the number of trips a customer made pre-offer to their number of repeat trips post-offer. There is no single coupon strategy that fits this dichotomy of customers. Customers who shop infrequently will respond more to a High Offer Percent discount while a Low Offer Percent works better with customers who shop more frequently.

Suggestions for future research include adding in other customer purchase patterns for commonly paired items or substitute items regardless of manufacturer. For example, a customer who buys peanut butter from a competitor likely would purchase another manufacturer's jelly or bread product. We did not have complete purchase data, only data for Bimbo products. The store point of sales (POS) terminals would collect all data and provide a much richer dataset to explore purchase predictors. Second, it would be important to know which buyers are first-time buyers as opposed to brand-, or product-loyal customers. Knowing the type of customer would allow us to determine if the customers are more likely to stockpile or make forward buys. Third, information on the age of a product would be helpful. We then could examine the benefits of promotions for new versus older items regarding customer repeat purchases. Given that the current data set includes only Bimbo customer data, it is not possible to ascertain whether a product sales increase is due to growth at the expense of a competitor's product or just a general increase in total demand (perhaps the population is growing or a local market recently closed limiting options for buying food). Total sales information by retailer (all products sold, not just Bimbo), and perhaps a cross reference of which products are substitutes, would allow future researchers to enhance our findings by showing that the increases post offer were actually stealing market share from a competitor rather than creating a general growth in the entire retail market.

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