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An Assessment of When, Where and Under What Conditions In-Store Sampling is Most Effective

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Abstract

In-store product sampling is a commonly used promotional technique designed to give prospective consumers an opportunity to experience a product prior to purchase. While prior research has documented a positive relationship between short-term sales and perceptual measures of the customer shopping experience, little is known about the long-term impact of sampling or factors that moderate its success. In this paper, we develop an empirical approach that allows us to study the short-term and long-term effects of in-store sampling on both own and competitive products. We apply our approach to six store-level scanner data sets across four different product categories and show that in-store sampling has both an immediate (short-term) and sustained (long-term) impact on sales. We also show that the impact of sampling on sales is moderated by the characteristics of the store conducting the event, and that repeated sampling for a single product leads to a multiplicative increase in its long-term sales performance. We find that, unlike many types of in-store promotion, sampling results in a category expansion effect as opposed to a pure substitution effect. We contrast the immediate and long-term sales patterns for in-store sampling to those of product displays and discuss managerially relevant differences. Finally, we demonstrate incremental profit implications and store selection scenarios for different incremental costs of conducting the in-store events using constrained optimizations.

Keywords: In-store sampling; Marketing mix modeling; Retail strategy

Introduction

Manufacturers regularly engage in in-store promotions that involve the distribution of free product samples. This is a common practice in the grocery industry where manufacturers seek to distinguish their products from a myriad of competitors. According to a VSS Communications Industry Forecast, marketers spent $2.21 billion dollars on product sampling in 2009. In February 2009, Walmart launched a weekly program called “Bright Ideas” that aims to make product sampling and demonstrations an integral part of a customer’s in-store experience (Industry Insights 2009). Furthermore, a recent article describes how food product sampling is again on the rise with companies taking advantage of options like SamplingLab (Heneghan 2015). These announcements have generated significant interest among both manufacturers and retailers alike in determining how to optimally execute and measure the success of these events.

Sampling provides consumers with an evocative, visceral experience that allows them to touch, taste and smell the product, thus appealing to both hedonic and utilitarian values. As a result, the impact of product sampling on sales has been shown to be larger than that of other forms of marketing activity like advertising Mcguinness et al. 1992(Mcguinness, Gendall, and Mathew 1992). Manufacturers prefer in-store sampling events to price-based promotions like couponing, temporary price reductions (TPR) or rebates, as they add value to a product by encouraging trial without reducing margins or altering consumer expectations of price (Simpson 2006). Retailers also benefit from the use of in-store sampling as it enhances the consumer shopping experience, thus encouraging both increased sales and store loyalty (Dong-Mo 2003; Sprott and Shimp 2004)

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In contrast to at-home sampling promotions where free samples are delivered to consumer households, in-store sampling promotions occur at point-of-purchase and have unique characteristics that require studies of their own (Heilman, Lakishyk, and Radas 2011). Past research on product trial has primarily focused on at-home sampling (Bawa and Shoemaker 2004; Gadenk and Neslin 1999; Rothschild and Gaidis 1981). Research on in-store sampling is more limited (Heilman et al. 2011; Lammers 1991). Although it has been demonstrated that in-store sampling has a positive impact on short-term sales, it is unclear how this effect will evolve over time. In addition, research is needed that addresses several critical aspects of in-store sampling promotions.

First, in-store sampling events can be conducted a single time to introduce consumers to a product, or they can be run repeatedly for the same product to reinforce perceptions of the positive benefits of the product. As such, it is important to understand the impact (both immediate and carryover) of sampling and how this effect differs for events that are run once versus multiple times. Second, manufacturers and retailers use other types of promotions like in-store displays that are similar in nature, that is, products placed at a secondary location in addition to their primary location. Unlike in-store sampling events, in-store displays do not provide shoppers with the opportunity to 'experience' the product. It would be of interest to both manufacturers and retailers to understand how sampling events compare to other forms of non-price promotions like in-store display. Specifically, it would be useful to know if in-store sampling produces a bigger immediate lift in sales than in-store displays, and how the carryover effects differ for the two types of promotion. Further, it would be useful to know how these effects differ for events that are run once versus multiple times.

Finally, a common goal of in-store sampling is to encourage trial of a new or existing product with the intent of converting the consumer to the product, thus leading to repurchase in the future. Ideally, retailers would like to see repeat purchases in the same store, thus allowing them to grow the category sales. Although manufacturers benefit from sales of their products irrespective of outlet, in the case of new products their interests are also closely aligned with those of the retailers. They would like to establish the prominence of a particular SKU in a given retail location. This is the direct result of current category management practice where assortment decisions are largely based upon sales rankings for both own and competitive stores. If the manufacturer can demonstrate that a product is successful in Retailer A it will increase the probability of Retailer B adopting the product into its assortment, thus increasing its sales potential. Thus, it is imperative to understand the store characteristics and the competitive structure that are conducive to the success of an in-store sampling event.

We approach these research questions by developing a model that allows us to capture both the short-term and carryover impact of in-store sampling. Specifically, we build a sales-response model that (i) incorporates non-geometric decay in carryover effects through the use of a gamma distribution. This allows us to study not just the immediate effect of in-store sampling but also the shape of its carryover effect; (ii) explicitly accounts for potential endogenous store selection for in-store sampling events; (iii) incorporates the impact of conducting single versus multiple events; (iv) accounts for serial autocorrelation and incorporates store characteristics to learn about competitive and environmental effects that moderate the effect of sampling.

We apply our model to six different data sets containing products from four distinct product categories. We use the results of our model to empirically contrast the effects of in-store sampling to an empirical generalization of the effect of in-store displays. This latter effect is constructed using our model specification (to facilitate an apples-to-apples comparison of effect sizes) and scanner data for similar types of products. We also demonstrate the differences in effect size and decay for products with single versus multiple in-store sampling events.

Our study provides insight about the short-term and long-term impact of in-store sampling events on sales. We find that in-store sampling events have both an immediate (short-term) and carryover (long-term) effect. This is true in all six of our data sets, thus increasing our confidence in the generalizability of this finding. As expected, the magnitude of the short-term effect is larger than that of the long-term effect. We also find that the short-term effect of in-store sampling vary for different types of products. The effects of sampling are also heterogeneously distributed across stores of varying characteristics. For example, we find that the impact of in-store sampling is more localized and stores with smaller assortment of products have more to gain than stores with larger assortments. In terms of the benefit of conducting a single versus multiple events, we find that the immediate effect of repeated sampling is lower, but that the effect lasts for a much longer period of time. Furthermore, our comparison of in-store sampling events with in-store displays provides important implications for the retailer in terms of the magnitude and decay of sampling effects compared to display effects. Finally, we demonstrate using constrained optimizations that incremental profits can be increased when selecting a subset of the stores compared to a given benchmark scenario. We also find the incremental cost threshold at which sampling event will not be profitable for the manufacturer. Additionally, we also show that if manufacturers have a predetermined incremental profit goal it can be achieved by conducting the sampling event at a much smaller set of stores based on variations in incremental costs.

The remainder of this paper is organized as follows: We begin by reviewing the literature on product sampling and identify key features of the process that should be formally included in our model. We use this theory to develop a general model of in-store sampling and discuss our approach to estimation and inference. We then describe the data used for our empirical application. Results obtained from this analysis are then discussed. We conclude the paper with a discussion of the key managerial implications of our research, as well as limitations and potential extensions.

Theoretical Motivation

As a result of an increasingly competitive operating environment, manufacturers must expend considerable effort to add value to the consumer shopping experience in order to increase sales and differentiate themselves from their competition. In-store product sampling has emerged as an effective marketing vehicle that manufacturers can use to introduce their products to consumers in an efficient (utilitarian) and enjoyable (hedonic) way (Peattie and Peattie 1993). Prior research has demonstrated that in-store sampling events lead to an increase in short-term sales (Lammers 1991; Shi, Cheung, and Prendergast 2005), where the increase can result from brand switching, product trial, purchase acceleration or stockpiling (Houben 2007). In this paper we do not investigate the different routes through which sales increase, but rather treat any increase in product sales (through in-store sampling) as the manufacturer's motivational driver for conducting these events. Similarly, a retailer's motivation for in-store sampling could be one of increasing either the entire category sales or increasing store traffic.

From a theoretical perspective, in-store sampling of new products is considered to be more effective than other promotional tools in building brand awareness, loyalty, expanding category participation and encouraging brand switching (Jain, Mahajan, and Muller 1995). One of the primary theoretical explanations for its effectiveness is that it provides consumers with direct product experience. Prior research has demonstrated that experience is a highly engaging mode of learning because it is both vivid and intentional (Fazio and Zanna 1978; Hoch 2002). Direct product experience is self-selected and self-generated and can therefore have a lasting advantage in terms of recall (Hoch 2002), as contrasted to learning that occurs without experience. Product knowledge gained through experiential modes of learning like product trial lead to the development of strongly held brand beliefs and attitudes that will have a stronger correlation with future product usage (Fazio and Zanna 1978; Smith and Swinyard 1988).

In addition to experiencing the product, most sampling events involve direct contact with a sales person that can provide additional information about the product (i.e., calorie content, complimentary products, price differences relative to competitors). This, in combination with the information obtained from product experience, results in less uncertainty about product quality which aids in the formation of consumer preferences (Levin and Gaeth 1988) and has greater influence on subsequent attitudes and behavior as compared to advertising and other promotions (Kempf and Smith 1998). For example, Wright and Lynch (1995) demonstrate that attention paid to experiential attributes is higher during product trial than when the same information is provided through an advertising message.

The theoretical appeal of experiential promotional activities like in-store sampling has been bolstered by a rapidly expanding literature on sensory marketing. Research in this area has shown that odor related memory is more emotionally effective than cues presented visually or verbally (Herz and Schooler 2002) and persists over long periods of time (Engen, Kusima, and Eimas 1973; Zucco 2003). Krishna (2012) shows that engaging consumers through subconscious triggers that appeal to the basic senses is more effective than traditional advertising messages. Elder and Krishna (2010) demonstrate that sensory simulation that emphasizes multiple sensations (i.e., taste, smell and touch) results in better perceptions of taste than simply emphasizing taste in isolation. Taken collectively, this research is highly relevant to in-store sampling as it provides consumers with a multi-sensory experience that evokes multiple modes of learning.

In addition to its sensory and experiential aspects, product sampling is also attractive from the perspective of reciprocity (Gouldner 1960). It is well known that upon receipt of a gift or unrequested service consumers feel socially obliged to respond in kind. In the context of sampling, this suggests that consumers may feel indebted to the store or sponsoring company when they accept a free trial (Laochumnanvanit and Bednall 2005). This could lead to a variety of positive outcomes, including immediate purchase, repeat purchase, and increased loyalty to the brand or store or both.

Finally, research on advertising has extensively discussed the issue of single versus multiple exposures to advertising messages. The common logic suggesting that single exposure could create awareness whereas real effectiveness requires consumers to be exposed to the ad multiple times (Vakratsas and Ambler 1999). Given the aforementioned benefits of in-store sampling, the common dilemma faced by manufacturers and retailers alike is understanding the benefits of single versus multiple product sampling. Does a single in-store sampling event create enough awareness and are there benefits to conducting the event multiple times? Additionally, how do the immediate and long-term effects differ for single versus multiple events?

In sum, these theories strongly suggest that in-store sampling should have both a short-term and carryover impact on consumer purchase behavior. While the sensory aspect of in-store sampling likely gives consumers immediate hedonic benefits, the information obtained at the event and from experiential learning provides utilitarian benefits that can influence not only current but future product purchase (Jones, Arnold, and Reynolds 2006). In this paper we show empirical evidence that in-store sampling indeed provides short-term lift that is larger than in-store product display (i.e., placing the product in a second position in the store) and is also more effective than display when conducted multiple times. In addition, we find substantive differences between various products in terms of the relative importance of short-term and carryover effects. Further, we demonstrate the cumulative impact and benefit of conducting these events multiple times.

Our study focuses on three unique and important aspects for understanding in-store sampling events. First, we investigate both the short-term and carryover effects of in-store sampling. While manufacturers and retailers are particularly interested in understanding if in-store sampling events can provide sustained sales lift and thus be more than just a short-term tactic, there has been little research on the carryover and dissipation of the impact of non-price promotions such as in-store sampling events. This is in contrast to price promotions, where there has been abundant research on both the short and long-term impacts (e.g., Blattberg and Neslin 1989; Gupta 1988; Lewis

2004; Mela, Gupta, and Lehmann 1997; Pauwels, Hanssens, and Siddarth 2001; Raghubir, Inman, and Grande 2004; Van Heerde, Gupta, and Wittink 2003). Given the need for and lack of research on in-store sampling we aim to provide a framework to better understand the sales-sampling event relationship. Second, across various data sets for different products and different categories, we demonstrate the impact of in-store sampling from both the manufacturer and retailer standpoint. Finally, we compare and contrast the impact of single and multiple in-store sampling events with single and multiple in-store displays.

Model Development

We propose a general model that captures the impact of in-store sampling on sales, while accounting for the potential endogenous selection of stores where the in-store sampling events are conducted. We also account for possible inter-temporal and cross-brand dependencies. This model assumes that we observe repeated (over-time) observations of store-level sales for a collection of one or more products, where at least one product was promoted through the use of in-store sampling. The proposed model uses a flexible specification that captures the cumulative impact of repeated sampling events, the decay of sampling effects over time and potential spill-over effects of own-brand sampling to competitive brands.

Specifically, we model sales, y_{jst} for product j in store s at time-period t as:

$$y_{jst} = x_{jst}\eta_{js} + \sum_{m}\tau_{mjs}\lambda_{mjst}I_{mjst} + \varepsilon_{jst} \tag{1}$$

where x_{jst} denotes a vector with 1 in the first element and a collection of control variables that can influence sales such as price, seasonality, trend, and so forth. Due to the discrete nature of in-store sampling, we follow Aribarg and Arora (2008) and capture the effect of the mth in-store sampling event through $\tau_{mjs}\lambda_{mjst}I_{mjst}$.

The parameter τ_{mjs} captures the magnitude of sales increase due to the in-store sampling event and the parameter λ_{mjst} allows this effect to change over time. I_{mjst} is an indicator variable that denotes the presence of an in-store sampling event. It assumes the value of 1 on the week of the sampling event and retains that value throughout the following 52 weeks. This allows the sales lift from in-store sampling to last beyond a single week but not beyond one year after the event. The shape of the carryover effect is modeled through a flexible gamma density distribution, that is, λ_{mjst} is expressed as:

$$\lambda_{mjst} = \frac{\iota_{mjst}^{\kappa_j-1} e^{-\iota_{mjst}\beta_j^{-1}}}{\Gamma(\kappa_j)\beta_j^{\kappa_j}} \tag{2}$$

where ι_{mjst} is an index that is equal to 1 during the week of the in-store sampling event, 2 during the week following the event, and so on. The gamma density distribution accommodates many different shapes of carryover effects, including the monotonically decreasing exponential decay function when the κ parameter equals 1 and the more flexible Erlang-2 decay function that allows for both a monotonic or non-monotonic shape. For model sparsity, Aribarg and Arora (2008) recommended setting κ parameter equal to 2 and estimating the β parameter of the gamma function.

Note that with the gamma density specification of λ_{mjst}, we have $\int_{\iota}\lambda_{mjst}d\iota = 1$, and thus the parameter τ_{mjs} in Eq. (1) can be interpreted as the total sales increase of product j in store s due to this mth sampling event. To examine how the sales increase is affected by the presence of previous sampling events and time lapsed between the events, τ_{mjs} can be further modeled as

$$\tau_{mjs} = \tau_{0js} + C_{mjs}\gamma \tag{3}$$

where C_{mjs} include variables such as whether there was at least one previous in-store sampling event and the number of weeks since the last event, and γ is the vector of parameters that capture the effects of the these variables. Note that γ can only be identified if there are multiple sampling events and there are enough variations in the C_{mjs} variables. In the case of one single sampling event or when there are not enough variations in C_{mjs} (for example, all stores had previous sampling events), we set τ_{mjs}=τ_{0js}.

To account for the potential endogenous selection of stores where in-store sampling events are conducted, we model the probability that in-store sampling occurs in store s as a logit function of the expected magnitude of sales lift from the event. That is,

$$Prob(\max_t I_{mjst} = 1) = \frac{\exp(\alpha_{1j} + \alpha_{2j} * \tau_{0js})}{1 + \exp(\alpha_{1j} + \alpha_{2j} * \tau_{0js})} \tag{4}$$

For a given product j, if $\alpha_2 > 0$, then there is endogenous store selection where those stores with higher expected sales lift tend to be selected for in-store sampling promotions. On the other hand, if $\alpha_2 = 0$, then all stores have equal chances of getting in-store sampling promotions and thus there is no endogenous store selection.

Next, to account for heterogeneity of effects across stores, we complete the hierarchy in the model by allowing the store-specific parameters η_s and τ_{0s} to vary by covariates Z_s such as store characteristics, that is, let $\eta_s^* = (\eta_s, \tau_{0s}) = (\eta_1 s, \ldots, \eta_J s, \tau_{01s}, \ldots, \tau_{0Js})$, and

$$\eta_s^* \sim \text{Multivariate Normal}(Z_s\delta, D_{\eta^*}). \tag{5}$$

Finally, we account for inter-temporal dependence and across-brand dependence through the following specification of the unobserved errors ε_{jt} for each store s in Eq. (1):

$$\varepsilon_{jt} = \phi_j\varepsilon_{jt-1} + \nu_{jt}. \tag{6}$$

The cross-brand dependence is captured through the covariance matrix Σ where vector $\nu_t = (\nu_{1t}, \ldots, \nu_{Jt}) \sim$ Multivariate Normal(0, Σ). The inter-temporal dependence is modeled by the stationary VAR(1) process (Chib and Greenberg 1995) where the vector ϕ_j captures serial correlations between brand j at time t and all brands at time t-1. The matrix $\Phi = (\phi_1, \ldots, \phi_J)$ is a positive definite $J \times J$ matrix with characteristic roots inside the unit circle.

In summary, the model provides a flexible specification that captures not only the overall effect of sampling events on sales,

Table 1
Descriptive statistics – manufacturer (univariate) data.

	Data set 1 Mean (std. dev.)	Data set 2 Mean (std. dev.)	Data set 3 Mean (std. dev.)	Data set 4 Mean (std. dev.)	Data set 5 Mean (std. dev.)
Avg. unit sales	10.83	3.41	3.66	8.46	8.05
	(7.88)	(4.00)	(3.80)	(6.46)	(5.89)
Avg. price	3.88	3.20	3.19	3.65	3.69
	(1.01)	(0.16)	(0.16)	(0.35)	(0.34)
ACV (in 1,000,000s)	33.83	24.70	24.70	19.02	20.30
	(8.96)	(8.88)	(8.88)	(5.06)	(6.51)
# Competitors	6.89	9.43	9.43	9.26	13.55
	(3.29)	(4.69)	(4.69)	(5.91)	(5.78)
# Weeks before sampling	15	8	8	21	21
# Weeks after sampling	13	10	10	31	31
# Total stores	39	83	83	157	223
# Stores – sampling	23	83	83	157	223

but also the shape and decay of the effect of sampling over time. Additionally, it captures spill-over effects of own-brand sampling to competitive brands and accounts for the possibility of temporal dependence and endogenous selection of stores for sampling events. We estimate the model using hierarchical Bayesian methods. A variety of simulations studies were conducted to validate the efficacy of this approach. Full details of the estimation routine appear in the appendix.

Data Description

In this section, we describe in detail the various data sets that we use. As a general note, we found that it was very difficult to get access to this type of data as it requires a fusion of scanner data from IRI or Nielsen and data on sampling events that must be provided by a retailer or third-party provider. When data are collected from the manufacturer's standpoint, it does not usually have information on competitor sales or pricing, which makes it difficult to investigate competition effects. On the other hand, data collected for the retailer does, but retailers are reluctant to divulge this information.

For this project, we were able to obtain six different scanner data sets to demonstrate the consistency and robustness of our findings. The six data sets include four different product categories. Five of these data sets were provided by manufacturers (referred to hereafter as the manufacturer or univariate data) and an additional data set was provided by a retailer (referred to hereafter as the retailer or multivariate data). The manufacturer (univariate) data each contain only one instance of an in-store sampling event during the observed time series, while in the retailer (multivariate) data we observe multiple in-store sampling events. The primary reason for using multiple data sets is to demonstrate the generalizability of our findings across different products and categories. Multiple data sets also allow us to examine how the effect of sampling across brands and product categories differs for multiple and single sampling events, and how these effects are attenuated by store characteristics. Details of each of these data sets and corresponding summary statistics and time series plots appear below.

Manufacturer (Univariate) Data

A total of five data sets were obtained from manufacturers and contain data with varied lengths of post-sampling observations (from 9 to 31 weeks) for five different products and three different product categories. The number of stores conducting the events also varied from 23 to 223. The data sets that we use to test our model come from scanner data for different products during 2009 and 2010. No promotional activity (i.e., feature or display) was conducted for these SKUs during the observed time period. This helps us investigate the true impact of in-store sampling and is an inherent advantage of the different data sets that we use.

Data set 1: The product for data set 1 is a single SKU in the Diet/Health snacks category. Although this product was released by a well known national brand, it is not a simple line extension and is therefore new to the market. As it is a consumable, shelf-stable snack product, it is ideal for use in in-store sampling demonstrations. Collectively, our data include information for 28 weeks about the number of units sold, price of each unit (which incorporates price discounts) and store characteristics (ACV and number of competitors for each store). The store characteristics were provided by a national syndicated data source provider that is widely used in the grocery industry. We also have information about the exact day of the in-store sampling event at each store. The first column in Table 1 provides the descriptive statistics for the data set. Table 2 provides the correlation matrix and Fig. 1 provides the plot for the average sales across all stores. The manufacturer conducted the in-store sampling event in 23 of the total 39 stores.

Data sets 2 and 3: The products for data sets 2 and 3 are two different SKUs in the frozen snacks categories. Unlike data

Table 2
Correlation matrix – dataset 1.

	Units	Price	ACV
Units			
Price	−0.14		
ACV	0.31	0.03	
# Competitors	0.02	0.00	−0.03

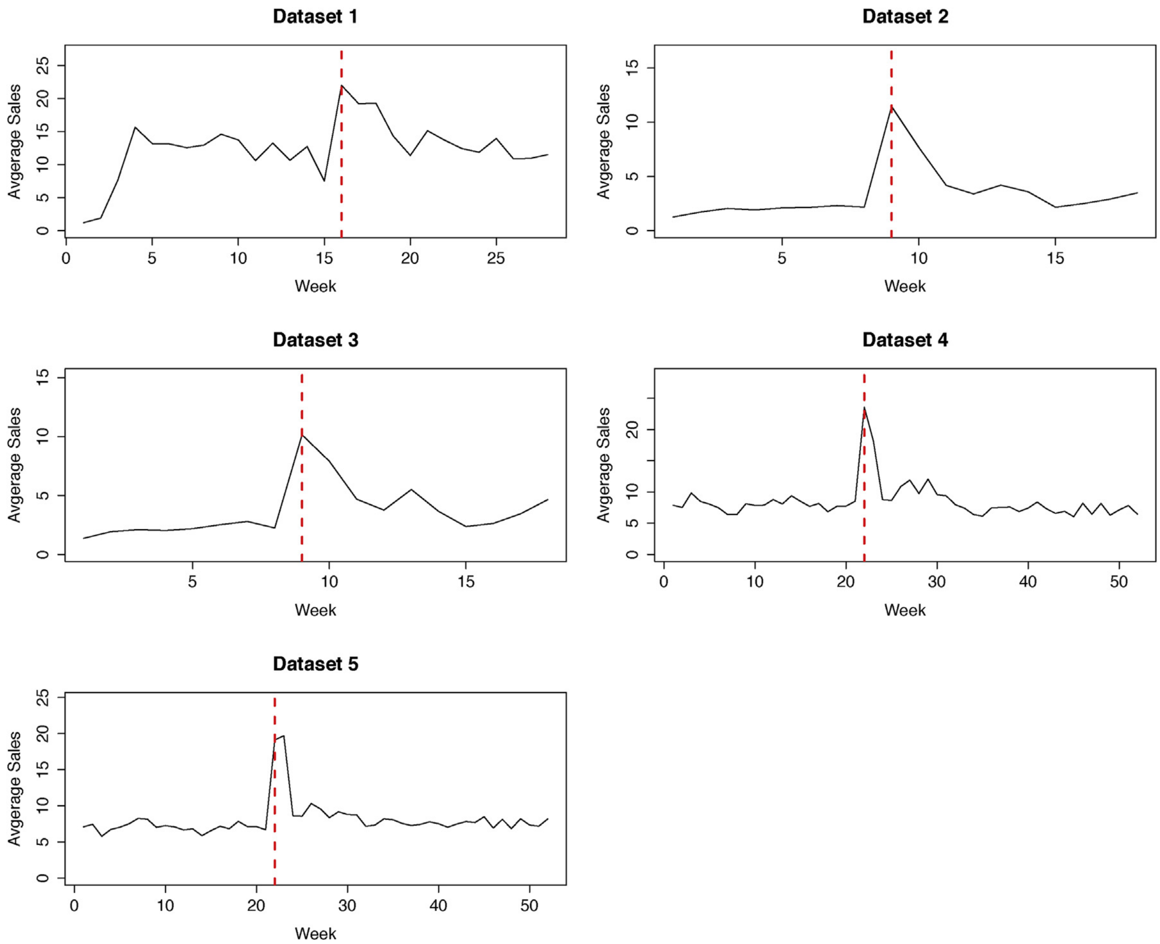

Fig. 1. Average weekly sales for the univariate datasets.

Table 3
Correlation matrix – dataset 2.

	Units	Price	ACV
Units			
Price	−0.29		
ACV	0.17	−0.03	
# Competitors	0.04	−0.05	0.12

Table 4
Correlation matrix – dataset 3.

	Units	Price	ACV
Units			
Price	−0.30		
ACV	0.14	−0.04	
# Competitors	0.01	−0.08	0.12

set 1, which involves a new product introduction, products in data sets 2 and 3, released by a well-known national brand, are existing products and are therefore not new to the market. This data includes information for 18 weeks about the number of units sold, price of each unit (which incorporates price discounts) and store characteristics (ACV and number of competitors for each store). The second and third columns in Table 1 provide the descriptive statistics for the data sets. Tables 3 and 4 provide the correlation matrices, and the middle two charts in Fig. 1 provides the plot of average sales across all stores for the two products. We find that the manufacturer conducted the in-store sampling event in all of the 83 stores.

Data sets 4 and 5: The products for data sets 4 and 5 are two different SKUs in the snacks categories in a large coffee shop chain while data sets 1, 2 and 3 are from two different large grocery retailer chains. Unlike products in data sets 1 through 3 (which are shelf stable products), the products in data sets 4 and 5 are consumable frozen novelty products. Collectively, this data include information for 52 weeks about the number of units sold, price of each unit (which incorporates price discounts) and store characteristics (ACV and number of competitors for each store). The fourth and fifth columns in Table 1 provide the descriptive statistics for these data sets. Tables 5 and 6 provide

Table 5
Correlation matrix – dataset 4.

	Units	Price	ACV
Units			
Price	−0.17		
ACV	0.33	−0.01	
# Competitors	0.16	−0.04	−0.01

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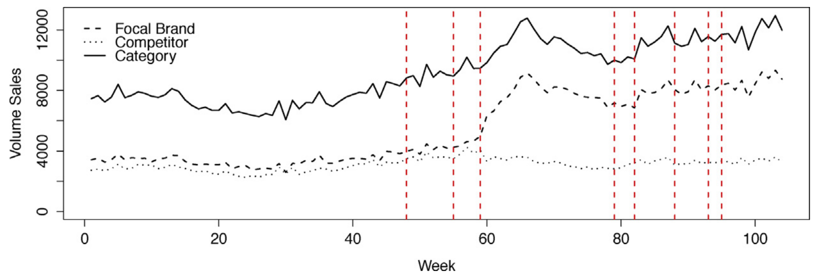

Fig. 2. Plot of retailer (multivariate) data.

Table 6
Correlation matrix – dataset 5.

	Units	Price	ACV
Units			
Price	−0.15		
ACV	0.31	−0.02	
# Competitors	0.08	−0.02	−0.03

the correlation matrices, and the last two charts in Fig. 1 provide the plot for the average sales across all stores. We find that the manufacturer conducted the in-store sampling event in all of the 157 and 223 stores for data set 4 and 5, respectively.

Retailer (Multivariate) Data

We obtained one data set from a large grocery chain store in the eastern United States. The product category includes only two major brands. We obtained the scanner data for sales, price and promotion information for both brands in the category to understand the total category-level impact of in-store sampling of one of the brands during 2013 and 2014. No promotional activity (i.e., feature or display) was conducted for these SKUs during the period we observe in our data. Again, this helps us investigate the true impact of in-store sampling and is an inherent advantage of this data set.

Only one of the brands (focal brand) conducted in-store sampling during the two years of data that we obtained, there were 8 sampling events for the same SKU of the focal brand. Collectively, our data include information for 104 weeks about the number of units sold, price of each unit, price discounts and store characteristics (ACV and number of competitors for each store). The store characteristics were provided by a national syndicated data source provider widely used in the grocery industry. We also have information about the exact days of all the in-store sampling events at each store. Table 7 provides the descriptive statistics for this data set. Table 8 provides the correlation matrix (with prefix C. and F. referring to competitor and focal brand respectively) and Fig. 2 provides the plot for the average sales for both the focal and competitor brand (and the category) across all stores. We find that the in-store sampling events were conducted in all of the 73 stores.

Table 7
Descriptive statistics - retailer (multivariate) data.

Variable	Mean	Std. dev.
Competitor brand		
Avg. sales (oz)	3,182.56	2,196.87
Avg price (per oz)	0.33	0.01
Avg discount (per oz)	0.007	0.002
Focal brand		
Avg. sales (oz)	5,568.13	3,746.52
Avg price (per oz)	0.23	0.02
Avg discount (per oz)	0.001	0.004
Store characteristics		
ACV	2,373.34	289.85
Number of competitors	1.45	0.28
# Total stores	73	–
# Stores – sampling	73	–
Data characteristics		
# Weeks before first sampling event	47	–
# Weeks after first sampling event	57	–
# Weeks after last sampling event	11	–

Results

For ease of comparison across different data sets, we used standardized log sales for the dependent variable in the model. Similarly, we used standardized log price for the control variable and standardized ACV and number of competitors for the store characteristics. Table 9 provides the posterior estimates and the 95% credible intervals (in parenthesis) for all five manufacturer (univariate) data sets. To ensure convergence we ran our estimation routine for 100,000 draws, keeping every 100th draw and using the last 750 draws to compute the posterior estimates.

We find a consistent pattern in the results across the different data sets. We find that the immediate impact of sampling is positive and significant, while the magnitude of the impact differs across various products. We also find that, as expected, price has a negative and significant impact on unit sales. We find that store ACV has a negative and significant interaction effect with sampling (−0.91) for data set 5, indicating that smaller stores probably benefit more from sampling than larger stores (i.e., stores with a smaller assortment of products have more to gain from in-store sampling than stores with a larger assortment of products). This is an interesting finding and we observe this to be the case with the retailer (multivariate) data as well.

In terms of sampling endogeneity we find that it is not significant (α_2) for data set 1, which is the only data set where

Table 8
Correlation matrix – retailer (multivariate) data.

	C. Units	F. Units	C. Price	F. Price	C. Disc	F. Disc.	ACV
C. Units							
F. Units	0.66						
C. Price	−0.38	−0.41					
F. Price	−0.04	0.42	−0.31				
C. Disc	−0.12	−0.20	0.16	−0.12			
F. Disc.	−0.10	−0.01	0.05	0.27	0.45		
ACV	0.67	0.51	−0.21	−0.03	−0.10	−0.10	
# Competitors	−0.27	−0.20	0.08	0.01	0.07	0.06	−0.36

Table 9
Manufacturer (univariate) data results.

	Data set 1 Estimates	Data set 2 Estimates	Data set 3 Estimates	Data set 4 Estimates	Data set 5 Estimates
Intercept	−0.15	**−0.36**	**−0.41**	**0.12**	0.001
	[−0.4,0.01]	[−0.5,0.23]	[−0.55,−0.28]	[0.01,0.24]	[−0.09,0.08]
Time trend	0.02	0.02	0.03	−0.01	−0.001
	[−0.1,0.1]	[−0.03,0.07]	[−0.03,0.08]	[−0.03,0.02]	[−0.02,0.02]
Price	**−0.28**	**−0.34**	**−0.38**	**−0.15**	**−0.13**
	[−0.43,−0.13]	[−0.42,−0.26]	[−0.46,−0.30]	[−0.19,−0.12]	[−0.16,−0.10]
Sampling	**2.61**	**4.66**	**4.43**	**7.89**	**16.31**
	[1.58,4.0]	[4.32,4.99]	[4.06,4.79]	[5.23,18.7]	[8.73,29.16]
Sampling interactions					
ACV	0.1	−0.22	0.19	−0.19	**−0.91**
	[−0.9,1.0]	[−0.55,0.12]	[−0.11,0.53]	[−0.89,0.20]	[−2.21,−0.21]
# Competitors	0.14	0.11	0.28	−0.27	−0.34
	[−0.74,0.98]	[−0.22,0.44]	[−0.03,0.62]	[−1.01,0.14]	[−1.32,0.29]
Sampling endogeneity					
α_1	**−3.18**	–	–	–	–
	[−5.47,−1.64]	–	–	–	–
α_2	−1.31	–	–	–	–
	[−3.92,0.32]	–	–	–	–
Gamma decay					
β	**0.95**	**0.58**	**0.65**	**0.24**	**0.18**
	[0.58,1.47]	[0.52,0.64]	[0.58,0.72]	[0.18,0.30]	[0.16,0.23]
Error autocorrelation					
ϕ	**0.37**	**0.08**	**0.13**	**0.12**	**0.11**
	[0.31,0.43]	[0.01,0.15]	[0.05,0.20]	[0.10,0.15]	[0.09,0.13]

sampling was conducted in a subset of the stores. In all other data sets, sampling was conducted in all stores. All the β shape parameters in Table 9 are less than one, indicating that the peak effect is attained during the first week and the joint impact of the shape and lift indicate the dissipation occurs fairly quickly across all data sets. Fig. 3 provides the lift and shape variation for each of the data sets.

We find that the dissipation of the sampling effect lasts anywhere from 2 weeks to 8 weeks across the different data sets. This is similar to the pattern for feature advertising observed by Aribarg and Arora (2008). We also find that the number of competitors does not have a significant interaction effect with in-store sampling. This indicates the localized impact of in-store sampling (i.e., since sampling is usually conducted inside a store with customers from competing stores having very little knowledge of these events), it is possible that in-store sampling is not impacted by the number of competitor stores in the vicinity. We find a significant positive serial correlation between the sales at time t and sales at time $t-1$ (ϕ parameter in Table 9).

Table 10 provides the parameter estimates for the model estimated using the retailer (multivariate) data. We observe that, across the two brands, in-store sampling for the focal brand has a large significant positive impact on unit sales and a small positive impact on the competitor brand (0.32). This demonstrates the category benefits of in-store sampling (i.e., in-store sampling has a positive spillover effect on competitor brand in the category). This is especially useful for retail managers because, unlike price promotions that lead to brand switching, sampling events could be considered as quality events that lead to category expansion. With regard to the interaction of in-store sampling and store characteristics, using Table 11, we find that store ACV has a negative (−1.96) and significant interaction effect with sampling, indicating that smaller stores probably benefit more from sampling than larger stores (i.e., stores with a smaller

Table 10
Retailer (multivariate) data results.

	Competitor brand	Focal brand
Intercept	−0.15	**−0.53**
	[−0.35,0.03]	[−0.70,−0.37]
Trend (weeks 59–104)	−0.03	**0.26**
	[−0.13,0.07]	[0.15,0.39]
Price own	**−0.08**	0.001
	[−0.16,−0.01]	[−0.10,0.10]
Price cross	**−0.11**	−0.007
	[−0.19,−0.02]	[−0.07,0.06]
Discount	0.02	0.02
	[−0.07,0.10]	[−0.04,0.07]
Sampling	**0.32**	**16.22**
	[0.23,0.40]	[14.86,17.39]

Table 11
Additional sampling model parameter estimates.

Sampling interactions	
ACV	**−1.96**
	[−3.0,−0.93]
# Competitors	−0.45
	[−1.45,0.58]
Gamma decay	
β	**12.40**
	[11.77,12.97]
Error autocorrelation	
ϕ_{11}	**0.28**
	[0.11,0.44]
ϕ_{22}	**0.27**
	[0.10,0.43]

assortment of products have more to gain from in-store sampling than stores with a larger assortment of products). Given the presence of multiple in-store sampling events we find that the focal brand reaches its peak (β = 12.40) and the dissipation takes much longer (i.e., more than 45 weeks), unlike single sampling events where the dissipation is quick. Thus, one of the benefits of conducting the sampling event multiple times is a sustained lift that dissipates slowly.

Fig. 3 provides the lift and shape variation patterns for both single and multiple event data (i.e., univariate and multivariate data). These plots were created using the estimated β parameters for the Gamma decay function for each data set in conjunction with the estimated τ parameters that capture the magnitude of the sampling effect. For single events, the results show that the peak impact of in-store sampling is observed in the week of the sampling and then dissipates over time, ranging from 2 weeks to 8 weeks after the sampling event. We do find that there is some heterogeneity for the different products in terms of the dissipation time and the peak (or lift). We find that data set 2 has the greatest immediate lift in sales, while data set 1 has the longest carryover effect.

For multiple events, we find that the there is a sustained lift followed by a gradual dissipation that lasts much longer (in the vicinity of 48 weeks). It is evident from Fig. 3, that there is considerable difference in the impact of single and multiple sampling events. We further investigate these differences and compare it with another extensively used promotion in retail industry (i.e., in-store displays) in the following section.

Discussion and Conclusion

Comparing the Effects of Sampling Versus In-Store Display

To help frame the effects described above, Fig. 4 provides a comparison of the estimated decay curves for the sampling events observed in our data (for both single and multiple sampling events) and an empirical generalization of the effect of in-store display. When a product is on “display” it is stocked in a secondary location in the grocery store, in addition to its primary location on the shelf in its category. Common types of displays include end-caps, free-standing displays, and clip-strips. Display is used frequently as a form of promotion and is commonly included as a variable provided in IRI and Nielsen’s scanner data sets. We chose display as a point of contrast to sampling as in-store sampling can be viewed as a form of display as the product being sampled is given a secondary location in the store on the day of the sampling event.

We contrast the results of our model to the average effect of display by constructing an empirical generalization of display effects. This is accomplished by fitting our proposed model to scanner data where we substitute display for sampling. Specifically, we used data from six categories in the academic IRI data set (Bronnenberg, Kruger, and Mela 2008), including Spaghetti Sauce, Frozen Pizza, Mayonnaise, Salty Snacks, Sugar Substitutes, Peanut Butter and Hot Dogs. We selected a collection of shelf-stable, frozen and refrigerated products to enhance the generalizability of this result and ensure that it is similar to the categories of in-store sampling products used.

In order to facilitate as fair a comparison as possible, we use the following procedure. We begin by first importing 52 weeks

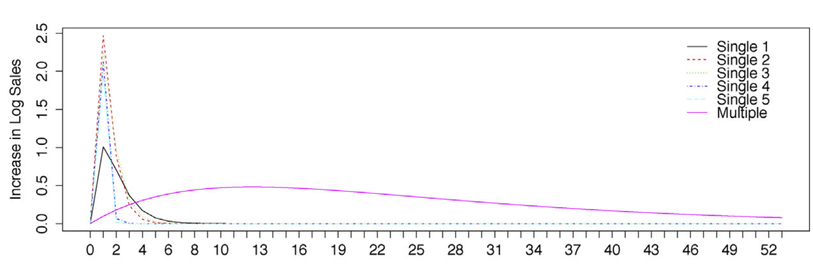

Fig. 3. Estimated shape of the decay curve for stores with single versus multiple sampling events.

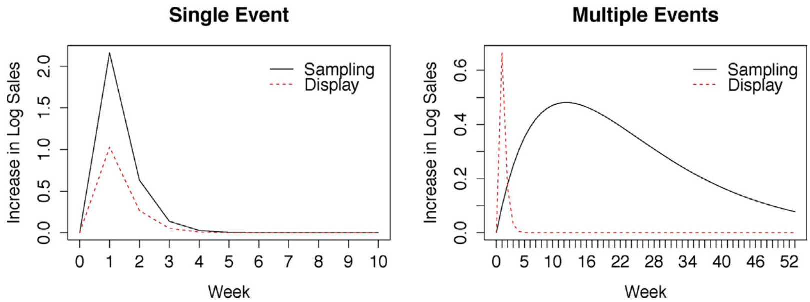

Fig. 4. A comparison of sampling versus display decay curves.

of data for a given category. We then select a single SKU (starting with the top-selling item in the category) and search over all stores in the data to identify the subset of stores that only conducted one display during the 52 week time period in question. We then clean the data so the structure was identical to that of our proposed model (i.e., standardized log sales, standardized log price, time trend, etc.) and estimate the model saving the coefficients of interest. This process is then repeated for the 10 SKUs in the category and for each of the categories listed above. We compute a representative display effect by taking a weighted (by observations) average of the parameters of interest. This process is repeated for stores with multiple display events to build an empirical generalization of display effects for multiple events. The results of this analysis appear in Fig. 4. The left panel shows the average decay curve for sampling events versus display for a single event/display. The right panel shows the same decay curves for stores with multiple events/displays.

For stores with single events, there are a couple of features of the curve that are worth noting. First, the magnitude of the immediate impact of sampling is much larger than that of display. On average, running a sampling event yields an immediate (week-of) increase in log sales of close to 2. For display events this immediate effect is about 1. Second, the carryover effect of in-store sampling is more sustained. Taken collectively, we can infer that the total effect of sampling, as measured by an incremental lift in sales, is much larger than that of in-store display.

The right panel of Fig. 4 shows the decay curves for stores where there were multiple in-store sampling and/or display events executed throughout the year. The decay curve for multiple displays is almost identical to that of stores with a single display. The carryover effect of display dissipates after 2 weeks. The immediate effect of a display in stores with multiple displays is about 0.65 versus 1 for stores with a single display. This suggests that there are diminishing returns to repeated display activity, or that the immediate impact of display decreases as consumers are exposed to a greater number of displays. Further, the pattern of decay is markedly different for sampling versus display. In the case of the former, we observe that the effect of a sampling event is sustained over many weeks. We do recognize that we would need additional data to generalize the impact of multiple sampling events. Nevertheless, it is interesting to find these differences across single and multiple events that can be investigated by future research with the availability of more data.

Optimal Store Selection

In this section, we discuss managerial implications and demonstrate how the findings from our model can help managers make better decisions regarding the selection of stores for an in-store sampling event. Optimal store selection for discrete promotions is a special case of the universal resource allocation problem faced by marketers. As such, it is a topic of high importance as managers are constantly engaged in the process of trying to determine how to best allocate their finite budgets across a multiplicity of potential activities. For the purpose of the analysis, we focus on the first dataset in our study (the only dataset where sampling was conducted in a subset of the stores, i.e., 23 of the 39 stores) and assume that the cost of conducting the in-store sampling event is the same for each store (which is usually true in practice). We also obtained additional information that includes the latitude and longitude for each store and the number of employees in each store (as a proxy for store size). We treat the current store selection scheme as the benchmark, and compare alternative selection schemes to the benchmark. Ideally, managers want to see an increase in incremental profit due to the sampling event. Given the lack of specific cost information for in-store sampling we investigate optimal store selection by: (i) maximizing incremental profit while constraining the number of stores with in-store sampling to be the same as in the benchmark (ii) minimizing the number of stores conducting the sampling event while still maintaining the same incremental profit as in the benchmark scenario. In particular, through this what-if analysis we plan to answer the following questions:

1. Can incremental profits be increased? Given the constraint that only a small number of stores (e.g., 23) can be selected for the in-store sampling event, what is the best set of stores to maximize incremental profit? With the best set of stores at what cost threshold will sampling not be profitable anymore?
2. Can the number of stores conducting the event be minimized? Given the constraint that incremental profit is similar to the current benchmark profit, can the number of stores be fewer than the number of stores in the benchmark scenario? If this can be achieved what is the ideal number of stores for different incremental cost assumptions?

We compute incremental profit as the difference between incremental revenue and incremental cost, where the incremental revenue is calculated as the overall impact of sampling for each store multiplied by the average price of the product at each store. Since we do not have specific information on the incremental cost for in-store sampling, we start by assuming a low cost scenario where the incremental cost is the same as the unit price of the product.

The optimization results show that there is an 8.9% gain in the incremental profit for the lower cost scenario compared to the benchmark (from 940.35 to 1,024.08). To visually investigate the differences in the 23 stores that were selected as part of the incremental profit maximization, we plot in Fig. 5 the set of stores based on the latitude and longitude of the stores. Additionally, the size of each circle in the figure represents the store size (number of employees). As can be seen there are clear differences in the various stores that are selected under the goal of profit maximization as compared to the benchmark. We also find that, with the same set of stores obtained by profit maximization (bottom panel Fig. 5), if the incremental cost of sampling event exceeded fifteen times the unit price of the product then the sampling event would not be profitable anymore for the manufacturer. We obtain this estimate by increasing the assumed cost of in-store sampling in the what-if analysis and finding the break-even point beyond which the sampling event would not be profitable. Thus, our proposed methodology helps manufacturers decide what the optimal stores should be and at what incremental cost threshold does the sampling event stop bringing in additional incremental profits.

We also conducted a similar constrained optimization exercise as described previously, but, instead of maximizing profit with a constrained number of sampling stores, we minimize the number of stores conducting the sampling event while restricting the incremental profit to be similar to the benchmark scenario. The primary reason for this optimization is to account for unobserved factors that only the manufacturer has information about. For example, if the manufacturer has a predetermined incremental profit as a target, can this be achieved by using a fewer set of stores to conduct the sampling event (which will reduce overhead cost). We find that, as expected, the optimal number of stores to be selected is dependent on the assumed cost of in-store sampling. For higher costs such as when it is ten times the average unit price of the sampling product, we find that the same incremental profit as the benchmark can be obtained using just eleven stores as demonstrated in the top panel of Fig. 6. However, as the cost of sampling lowers to about three times the unit price of the product we find that the minimal number of stores required to obtain the same incremental profit as the benchmark stores is 21 (bottom panel of Fig. 6). This is because as the cost of sampling increases the incremental profit from the benchmark set of stores decreases and vice versa. Thus, as can be expected, the cost of sampling plays an important role in the choice of the store selection if the incremental profit goal is predetermined. This exercise helps manufacturers decide on the optimal number of stores, location and size for conducting the event.

In summary, these findings suggest that our proposed methodology can aid manufacturers in determining the threshold for conducting in-store sampling events and also in the choice of optimal number and location of stores. An interesting avenue for future research would be to obtain more data on additional store characteristics that can aid in store selection for conducting sampling events.

Summary and Conclusion

The results of our analysis yield three key insights that should be of interest to a managerial audience, particularly to category and brand managers. First, in-store sampling is a highly effective form of quality promotion. In-store sampling generates both an immediate increase in sales and a sustained lift in post-promotional sales. In contrast to the traditional price-based promotions that are characterized by an increase in sales during the week of price discount and a sharp decline in sales as price returns to its base level, we can conclude that in-store sampling is an effective tool that managers can use to build long-term sales for a brand. Also, experiential events add value to a product without altering consumers' expectations of price. We recommend that in-store sampling should be used more frequently as brand and category managers seek to expand category penetration and sales.

Second, the relative success of an in-store sampling event is likely influenced by product type. Our research shows that the long-term benefits and subsequently the total impact of a sampling event tend to differ across product types. That said, our results also show that sampling is a more effective form of promotion than other forms of non-price promotion that are currently used in practice, like product display. Given cost information for both sampling and display, it would be useful to contrast the ROI of these types of promotions.

Third, an interesting extension to our proposed modeling approach would be to build a spatial model by obtaining additional information on spatial locations and competitive information for the stores conducting the sampling events. Furthermore, our current approach to address endogeneity only investigates one source that is if stores with higher incremental sales were chosen to run the sampling events. However, future research could investigate another form of endogeneity that involves selection of stores with higher or lower base line sales.

Fourth, analysis of the multivariate data suggests that in-store sampling produces a category expansion effect. That is, execution of a sampling event by one brand leads to an increase in sales for all brands in the category. This should be of interest to category managers who are seeking to find ways to increase total category profitability, and not the individual performance of a single SKU or brand. Price-based promotions are ill-suited to this task as they tend to encourage brand switching and stockpiling behavior. We encourage future research that continues to expand this line of inquiry. Given access to a great number of data sets and cost information, it would be useful to build an

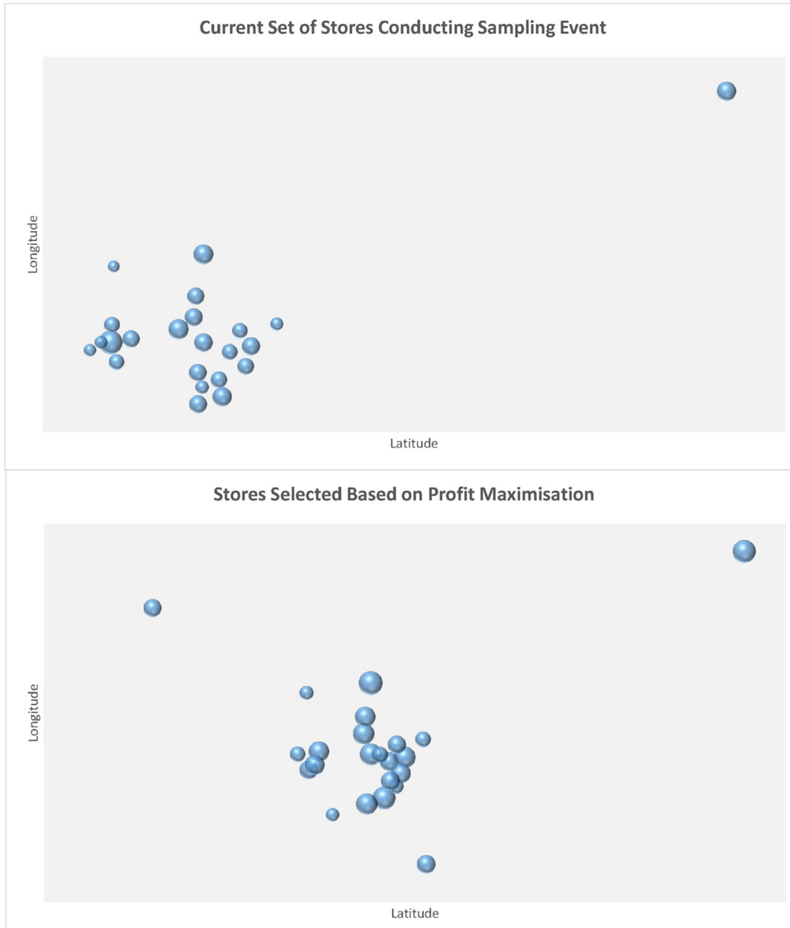

Fig. 5. A comparison of benchmark stores and stores selected by profit maximization.

empirical generalization of the effects of sampling. We view this paper as a first step in that direction. Currently, we only investigate products that are consumed with a subsequent opportunity to purchase. It would also be interesting to understand how this translates to different types of experiential events where there is a product demonstration (e.g., demonstration of the features of a new durable product) without a tasting event followed by an opportunity to buy. This could also be an interesting avenue for future research.

Appendix A. MCMC Algorithm for Model Estimation

The MMC algorithm builds upon that used in Aribarg and Arora (2008). The unique steps are Steps 1 to 3 during which we take into account of the possible endogenous selection of stores where the in-store sampling events are conducted. Specifically, we first let $x^*_{jst} = (x_{jst}, \sum_m \lambda_{mjst} I_{mjst})'$, $x^*_{st} = (x^*_{1st}, \ldots, x^*_{Jst})$, and $W_{jst} = (\sum_m C_{mjs} \lambda_{mjst} I_{mjst})$.

$$X^*_{js} = \begin{pmatrix} x^{*'}_{js2} - x^*_{s1}\phi_j \\ \vdots \\ x^{*'}_{jsT} - x^*_{sT-1}\phi_j \end{pmatrix},$$

$$X^*_s = \begin{pmatrix} X^*_{1s} & & \\ & \ddots & \\ & & X^*_{Js} \end{pmatrix}, \quad Y^*_s = \begin{pmatrix} y^*_{1s2} - y^*_{s1}\phi_1 \\ \vdots \\ y^*_{jst} - y^*_{st-1}\phi_j \\ \vdots \\ y^*_{JsT} - y^*_{sT-1}\phi_J \end{pmatrix},$$

where $y^*_{jst} = y_{jst} - W_{jst}\gamma$, $y^*_{st} = (y^*_{1st}, \ldots, y^*_{Jst})$.

The steps of the MCMC algorithm are as follows

Step 1 Draw vector $\eta^*_s = (\eta_s, \tau_{0s})$ using independent Metropolis–Hastings (M-H) algorithm: draw a new value of η^*_s, that is, η^{*new}_s, from multivariate normal distribution $MVN(a_s,\ A_s)$, where $A_s = [X'^*_s(\Sigma^{-1} \otimes I_T)X^*_s + D^{-1}_{\eta^*}]^{-1}$, and $a_s = A_s[X'^*_s(\Sigma^{-1} \otimes I_T)Y^*_s + D^{-1}_{\eta^*}\bar{\eta}^*]$. Accept the new value with probability that equals $\min(1, \frac{\pi(Y_s|\eta^{*new}_s, else) Prob(\max_t I_{mjst}=1|\eta^{*new}_s)}{\pi(Y_s|\eta^{*old}_s, else) Prob(\max_t I_{mjst}=1|\eta^{*old}_s)})$.

Step 2 Draw $\alpha_j = (\alpha_{1j},\ \alpha_{2j})$ using random-walk M-H algorithm: let $\alpha^{new}_j = \alpha^{old}_j +$ small random normal variates,

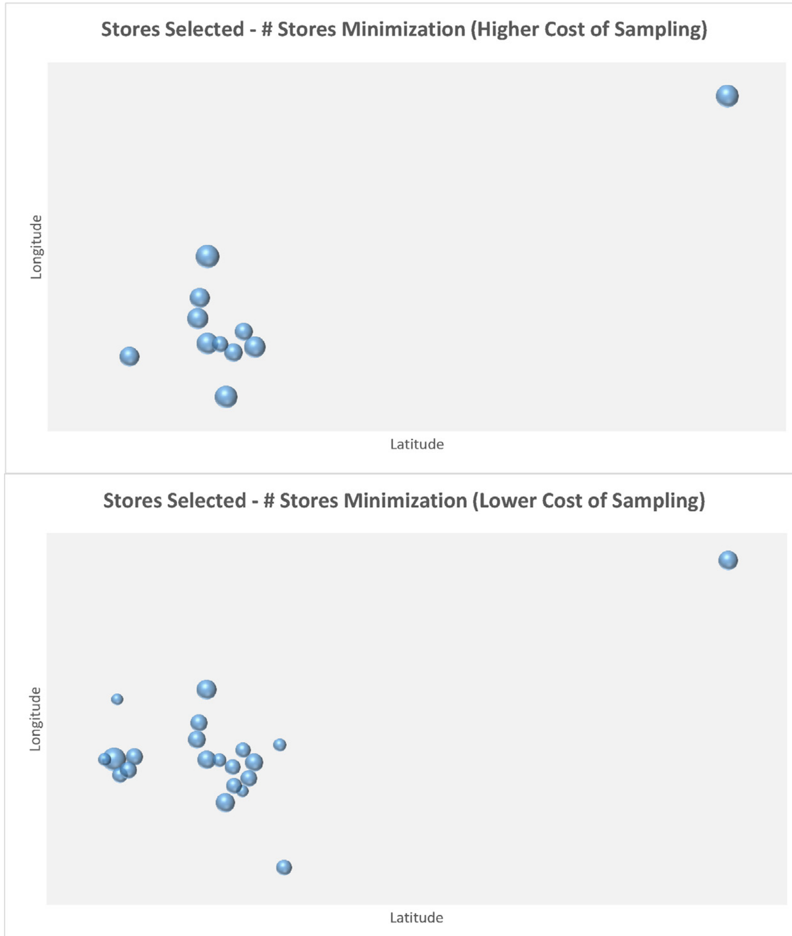

Fig. 6. Comparison for minimizing number of stores for different costs.

and accept the new value with probability that equals $\min(1, \frac{\prod_s Prob(\max_t I_{mjst}=1|\alpha_j^{*new})\pi(\alpha_j^{new})}{\prod_s Prob(\max_t I_{mjst}=1|\alpha_j^{*old})\pi(\alpha_j^{old})})$.

Step 3 Draw β using random-walk M-H algorithm: $\beta^{new}=\beta^{old}+$ small random normal variate, and accept the new value with probability that equals $\min(1, \frac{\prod_s \pi(Y_s|\beta^{new}, else)\pi(\beta^{new})}{\prod_s \pi(Y_s|\beta^{old}, else)\pi(\beta^{old})})$.

Step 4 Generate Σ from Inverted Wishart(n, H) where $n=n_0+T$, and $H^{-1}=H_o^{-1}+(Y^*-X^*\eta^*-W^*\gamma)'(Y^*-X^*\eta^*-W^*\gamma)$, and the prior for Σ is Inverted Wishart(n_0, H_0). Y^*, X^*, and W^* are obtained by stacking up Y_s^*, X_s^*, and W_{jst} respectively.

Step 5 Generate D_{η^*} from Inverted Wishart(g, G) where $g=g_0+S$ and $G^{-1}=G_0^{-1}+\sum_s(\eta_s^*-Z_s\delta)'(\eta_s^*-Z_s\delta)$. The prior for D_{η^*} is Inverted Wishart(g_0, G_0).

Step 6 Let $W_{js}^*=\begin{pmatrix} W_{j12}-W_{11}\phi_j \\ \vdots \\ W_{jst}-W_{st-1}\phi_j \\ \vdots \\ W_{jST}-W_{ST-1}\phi_j \end{pmatrix}$, where $W_{st}=(W_{1st}, \ldots, W_{Jst})$. Stack up W_{js}^* to obtain W_s^*.

$Y_s^{**}=\begin{pmatrix} y_{1s2}^{**}-y_{s1}^{**}\phi_1 \\ \vdots \\ y_{jst}^{**}-y_{st-1}^{**}\phi_j \\ \vdots \\ y_{JsT}^{**}-y_{sT-1}^{**}\phi_J \end{pmatrix}$, where $y_{jst}^{**}=y_{jst}-x_{jst}^{*}\eta_{js}^{*}$.

Draw γ from multivariate Normal distribution $MVN(\bar{\gamma}, \Sigma_\gamma)$, where $\Sigma_\gamma=[\sum_{s=1}^S W_s'^*(\Sigma^{-1}\otimes I_T)W_s^*+D_\gamma^{-1}]^{-1}$, and $\bar{\gamma}=\Sigma_\gamma[\sum_{s=1}^S W_s'^*(\Sigma^{-1}\otimes I_T)Y_s^* * +D_\gamma^{-1}\gamma_0]$. The prior of γ is multivariate Normal (γ_0, D_γ).

Step 7 Generate δ from multivariate Normal distribution: $\delta \sim MVN(\bar{\delta}, \Sigma_\delta)$, where $\Sigma_\delta=[\sum_s Z_s' D_{\eta^*}^{-1} Z_s + D_0^{-1}]^{-1}$, and $\bar{\delta}=\sum_s \Sigma_\delta[Z_s' D_{\eta^*}^{-1}\eta_s^* + D_0^{-1}\bar{\delta}_0]$. The prior of δ is multivariate Normal (δ_0, D_0).

Step 8 Generate Φ – let $e_{jst}=y_{jst}-x_{jst}'^*\eta_{js}^*-w_{jst}'\gamma$, $e_{st}=(e_{1st}, \ldots, e_{Jst})$, $E_s=(e_{s1}, \ldots, e_{sT-1})'$, and stack up E_s to obtain E. Then, following Chib and Greenberg (1995), generate Φ from $\Phi' \sim MATN(\bar{\Phi}', (E'E)^{-1}\otimes\Sigma)\times I(\Phi)$, where $\bar{\Phi}'=(E'E)^{-1}\times(\sum_s\sum_{t=2}^n e_{st-1}e_{st}')$ and $I(\Phi)$ is an indicator function that takes the value of 1 when all roots of Φ lie in the unit circle and 0 otherwise. Specifically, let $\Phi=\bar{\Phi}'+PTQ'$, where P and Q are Choleski decompositions such that $PP' = (E'E)^{-1}$ and $QQ' = \Sigma$, and T is a $k \times k$ matrix that consists of independent standard normal variables. If all the roots of Φ are less than unity (the stationary condition) then Φ is accepted; otherwise another T is drawn and the process repeats.

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