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Bundle promotions—the practice of granting consumers a discount when they buy a certain number of units from a designated range of stockkeeping units—have gained popularity among manufacturers and retailers. In this research, the authors investigate the purchase effects of bundle promotions for a category of packaged goods. Contrary to intuition, they find that promotional bundles are far more effective at inducing switching than at boosting category sales. The strong switching effects result from two mechanisms: (1) Stockkeeping units that are part of a bundle promotion appear to reinforce each other's choice probability, and (2) the bundle discount tends to attract consumers even if they do not buy enough to qualify for the price reduction. The weak category effects follow from the notion that the purchase quantity requirement is often too stringent to make consumers buy earlier and/or more in the category. The authors develop incidence, quantity, and choice models that incorporate the intricate bundle mechanisms, and they use simulations to contrast the sales impact of bundle and traditional per-unit promotions. On the basis of the model estimates, they present managerial implications and tentative guidelines for optimal bundle design.

Shopper Response to Bundle Promotions for Packaged Goods

Ongoing consolidations in the packaged goods industry and the category management paradigm in retailing have created a need for an integrated approach to the promotion of product assortments. Manufacturers and retailers increasingly have begun to adopt promotional tools that tout multiple products simultaneously (e.g., *Brandweek* 2002). One such technique is promotional bundling, or the practice of temporarily selling a bundle of different items at a discounted price. For example, a yogurt brand could offer a discount if the consumer buys three units from a range of flavors. Although promotional bundling has gained wide acceptance in retailing, its impact on consumers' purchase decisions has not been sufficiently addressed in marketing academia.

Extant price promotion literature focuses exclusively on the effects of traditional per-unit discounts and has not studied bundle offers as a distinct type of price promotion (e.g., Bell, Chiang, and Padmanabhan 1999; Pauwels, Hanssens, and Siddarth 2002). However, bundle promotions differ significantly from per-unit discounts in that a bundle requires that consumers buy a specific number of units from a range of items. Although bundling (e.g., Bakos and Brynjolfsson 2000; Chung and Rao 2003; Stremersch and Tellis 2002) and multiunit packaging/quantity discount strategies (e.g., Allenby et al. 2004; Gerstner and Hess 1987; Wilcox et al. 1987) have been studied, in general, they have been considered regular pricing issues rather than promotional devices. Moreover, most bundling research is constrained to the context of durables and services, areas in which consumers usually are interested in only one unit of each item. The literature on multiunit packaging releases this constraint but introduces another by exclusively addressing packages of a single item (e.g., a six-pack of one brand of beer).

In this study, we empirically investigate the purchase effects of bundle promotions in a category of consumer packaged goods. We address settings in which both the bundles and the separate items (at their regular prices) are for

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sale (“mixed bundling”; Adams and Yellen 1976) and consumers themselves determine the composition of the bundle. Thus, we investigate promotions of the type “Pick 2, get $.50 off” or “Buy one, get one free.” We describe a bundle promotion in terms of three characteristics: discount, range (i.e., the designated set of items to which the promotion applies), and quantity requirement (i.e., the number of units that must be purchased).

The purpose of this research is twofold. First, we shed light on the mechanisms that affect purchase decisions in the context of bundle promotions. We find that bundle promotions trigger several mechanisms that induce pronounced switching behavior. However, a bundle promotion’s potential to make consumers buy earlier and/or more in the category turns out to be surprisingly limited. Second, we determine the net effect of these mechanisms by evaluating a bundle’s impact on the unit sales of an individual stockkeeping unit (SKU), a brand line, and the whole category. We clarify the role of the bundle characteristics and compare the impact of bundle promotions with that of traditional per-unit discounts. Among other things, the results indicate that bundle promotions tend to be more effective than per-unit promotions if the goal is to increase item or brand line sales, but they are less effective in terms of category sales. This research comes at a time when the practice of promotional bundling is pervasive enough to allow empirical analysis but is still novel enough to benefit from a better understanding of its effects.

To achieve our objectives, we calibrate choice, quantity, and incidence models on consumer panel data in the snack chip category. At various points in the decision process, the intrinsic characteristics of bundling require a different modeling approach than that demanded by per-unit promotions. Therefore, in addition to a substantive contribution, we propose adapted statistical models that accommodate promotional bundles for consumer packaged goods.

We organize the remainder of this article as follows: In the next section, we discuss the effects of promotional bundling on consumers’ purchase decisions. We then present choice, quantity, and incidence models that account for the effects of the different bundle characteristics and calibrate the models with data from the snack chip category. Next, we simulate different bundle scenarios to evaluate the impact of bundles on sales, both overall and in comparison with per-unit promotions. Finally, we conclude with some managerial implications and directions for further research.

THE EFFECTS OF BUNDLE PROMOTIONS

A vast body of research documents the effects of price promotions on consumers’ purchase behavior and distinguishes between choice effects (what to buy) and incidence/quantity effects (whether and how much to buy in the category). Price promotions induce consumers to switch items and buy more and earlier in the category, otherwise known as the acceleration effect (e.g., Ailawadi and Neslin 1998; Bell, Chiang, and Padmanabhan 1999; Neslin 2002). In a bundle context, the choice effects cannot be studied independently of the quantity effects. For example, consider a bundle promotion that grants a discount of $.40 on the purchase of two bags of Lay’s chips. For a consumer who usually buys one bag of Kettle chips, switching to Lay’s pays off only if he or she is prepared to increase purchase volume in the category. These interdependencies must be accounted for in our exposition of the expected bundle effects and subsequent models. We first address the choice effects and then discuss the incidence and quantity effects.

Choice Effects

In the context of bundle promotions, the quantity decision influences the choice decision; therefore, we conceptualize consumers’ choices given their category purchase quantities.[1] Specifically, we distinguish between two cases in which the consumer’s total purchase quantity (1) equals or exceeds the bundle quantity requirement or (2) is lower than the bundle quantity requirement.

In the first case, consumers have a clear economic motive to switch. Allocating a large enough share of their total purchase quantity in the category to one or more bundle-promoted items enables them to take advantage of the bundle discount. Thus:

H_1: When a consumer’s total purchase quantity in the category equals or exceeds the bundle quantity requirement, the bundle discount has a positive impact on a bundle item’s choice probability.

Because a bundle promotion involves a range of items, consumers may consider switching to several bundle items simultaneously. However, the decision to switch to one bundle item is not made independently of the decision to switch to another. Buying one bundle item may enhance the likelihood that the consumer will also switch to another bundle item in an attempt to meet the bundle quantity requirement.[2] In other words, when the utility of one bundle item rises, a consumer’s willingness to allocate the required purchase quantity to the bundle range will increase, thus leveraging the choice probabilities of all bundle items compared with those of nonbundle items. Inspired by the industrial organization literature on bundling (e.g., Martin 1999; Whinston 1990),[3] we refer to this phenomenon as the “leverage effect.”

From a behavioral perspective, this leverage effect bears some resemblance to the “cluster effect,” a context effect in which adding an item to a choice set helps similar items in the choice set (Sivakumar 1995). In contrast to the cluster effect, however, the bundle-promotion leverage effect does not stem from the items’ similarity but rather from the consumer’s understanding that constraining his or her selection of items to the limited bundle set will lead to a monetary benefit. Thus:

H_2: When a consumer’s total purchase quantity in the category equals or exceeds the bundle quantity requirement, the bundle items leverage each other’s choice probability.

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[1]Other authors have also adopted this quantity-then-choice sequence; it is the most obvious approach to tackle multi-item purchases (e.g., Bucklin, Gupta, and Siddarth 1998; Dillon and Gupta 1996; Harlam and Lodish 1995).

[2]In the current context, a bundle promotion does not force consumers to accept different items; they may also purchase several units of the same item. However, probabilistically, the bundle’s pressure works in both directions. Thus, at the choice level, we discuss the bundle’s ability to force consumers to accept multiple units of different items.

[3]This research stream demonstrates that a seller can extend its market power by bundling its product with some other good that is produced in a more competitive market.

In the second case, when the total purchase quantity is lower than the bundle quantity requirement, a rational consumer might be expected to refrain from any promotional reaction because the bundle discount is out of reach. However, we believe that consumers may still respond to the bundle discount as a result of both positive and negative psychological effects. On the positive side, consumers may process the promotional information only partially and notice the discount but ignore the quantity requirement. Previous research has demonstrated that consumers do not always engage in detailed information processing when confronted with price promotions (Inman, McAlister, and Hoyer 1990). Consequently, the bundle discount may be able to entice even those consumers who do not actually benefit from the promotion. We call this phenomenon the "discount communication effect."

On the negative side, if consumers process all bundle information and thus realize that they do not qualify for the discount, they may switch away from the bundle-promoted items. Feinberg, Krishna, and Zhang (2002) find evidence of a betrayal effect, by which consumers switch to another brand if they become aware that their favorite brand offers deals to other select consumers. Their research is grounded in relative deprivation and perceived fairness theories. Another explanation for potential negative switching effects emerges from the reference price literature (Kopalle and Lindsey-Mullikin 2003; Mayhew and Winer 1992). By offering a bundle at a reduced price, the seller provides an external reference price, which may reduce the consumer's willingness to purchase the items at the regular price.[4] In any case, according to both the betrayal and the reference price rationales, a bundle discount may induce negative switching behavior among consumers who do not qualify for the bundle promotion.

Because the existing literature does not provide any indication about which effect will prevail—the positive discount communication or the negative betrayal/reference effect—we leave this point as an empirical question and hypothesize the following:

H_3: Even when a consumer's total purchase quantity in the category is lower than the bundle quantity requirement, the bundle discount affects the bundle items' choice probabilities.

Incidence/Quantity Effects

Similar to per-unit promotions, bundle offers that involve deeper discounts or apply to a wider range of items should enhance consumers' category purchase quantities and incidences. However, unlike per-unit promotions, bundle promotions do not allow consumers to accelerate (i.e., buy more and/or earlier) as they see fit; rather, consumers must respect the bundle's quantity requirement. Therefore, the bundle's impact at the incidence and quantity level is not the mere result of the bundle's discount or range but also includes mechanisms triggered by the quantity requirement.

With regard to a consumer's quantity decision, we argue that the quantity requirement works in opposite ways. On the one hand, a higher quantity requirement pushes the consumer to buy more. The higher the quantity requirement, the more consumers must buy to receive the discount. In addition, Wansink, Kent, and Hoch (1998) demonstrate that even in the absence of price discounts, suggested purchase quantities could lead consumers to accelerate. That is, the bundle's quantity requirement may serve as a benchmark on which consumers anchor their quantity decision, thus leading to higher purchase quantities.[5]

On the other hand, an increasing quantity requirement drives up the consumer's burden in terms of transaction and inventory costs (see Gerstner and Hess 1987). Consequently, if the quantity requirement becomes too high, the consumer will be more reluctant to accept the bundle promotion. From that point on, the quantity requirement lowers the impact of the bundle promotion.

H_4: All else being equal, as long as a bundle's quantity requirement does not exceed some critical point, it increases the impact of the bundle promotion on the consumer's purchase quantity. Beyond that point, it decreases the bundle's impact.

At the incidence level, when the consumer weighs purchasing in the category against the no-purchase option, we theorize that the quantity requirement will only reduce the bundle's impact; that is, when the quantity requirement increases, so do the efforts required from the consumer. As a result, the bundle will become less attractive and less effective in stimulating purchase incidence.

H_5: All else being equal, the quantity requirement negatively affects a bundle promotion's impact on a consumer's purchase incidence.

MODELING APPROACH

To assess the effects of bundle promotions, we build response models at the level of the individual consumer. In particular, we model the probability that a consumer h buys the quantities (q_{h1t}, q_{h2t}, …, q_{hIt}) of the I items in the product category on shopping trip t. This probability, denoted as $P_{ht}(q_{h1t}, q_{h2t}, \ldots, q_{hIt})$, can be broken up into three component probabilities:

$$(1) \qquad P_{ht}\left(q_{h1t}, q_{h2t}, \ldots, q_{hIt}\right) = P_{ht}\left(\text{purchase}\right) \times P_{ht}\left(Q_{ht}\middle|\text{purchase}\right) \times P_{ht}\left(q_{h1t}, q_{h2t}, \ldots, q_{hIt}\middle|Q_{ht}\right),$$

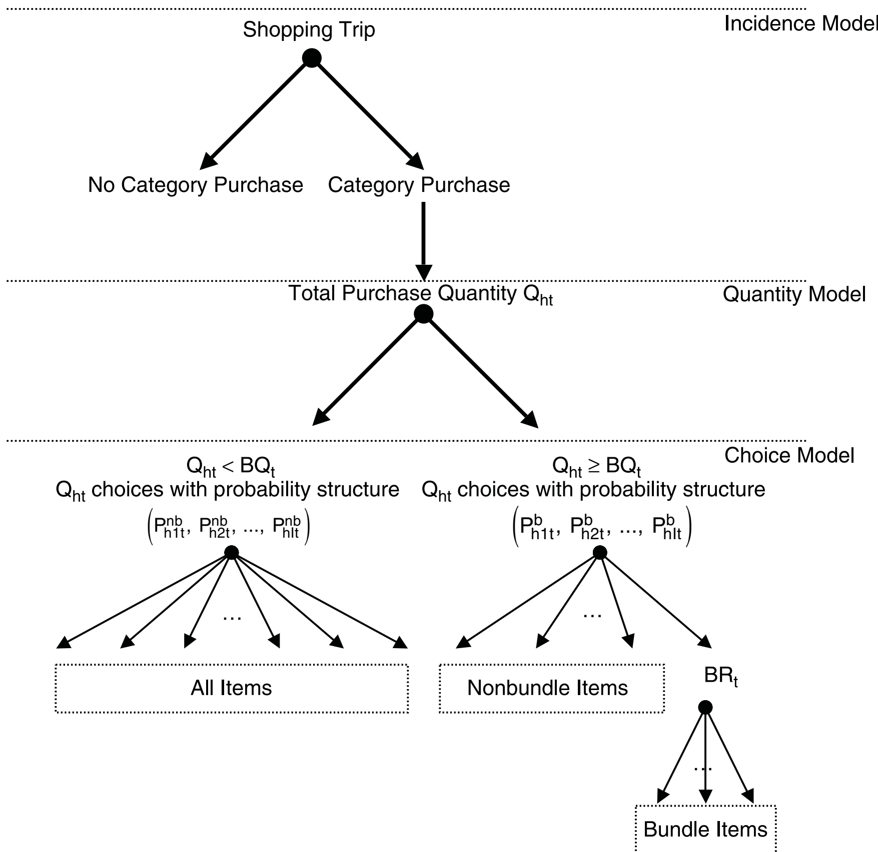
where P_{ht}(purchase) is the probability that consumer h decides to buy in the category (incidence decision); $P_{ht}(Q_{ht}|\text{purchase})$ refers to the probability that consumer h purchases a total quantity of Q_{ht} units, given a category purchase (quantity decision); and $P_{ht}(q_{h1t}, q_{h2t}, \ldots, q_{hIt}|Q_{ht})$ is the probability of a specific allocation of Q_{ht} across items, such that $Q_{ht} = \Sigma_i q_{hit}$ (choice decision). Figure 1 depicts these three consumer decisions in the face of a bundle promotion.

In the following discussion, we first present the choice model and then address quantity and incidence. We charac-

[4]Note that this scenario does not describe a traditional case of comparative pricing, in which the regular price provides an external cue that determines the attractiveness of the deal price. Here, we argue that the promotional bundle price may influence the evaluation of the regular per-unit price.

[5]We thank an anonymous reviewer for pointing this out.

Figure 1
CONSUMERS' PURCHASE DECISIONS IN THE FACE OF A BUNDLE PROMOTION



terize bundle promotions by their bundle discount BD_t (expressed per weight unit), range of bundle items BR_t, and quantity requirement BQ_t (Table 1 summarizes these and other symbols).

Choice Model

Because choice is preceded by the quantity decision, we can treat the total purchase quantity Q_{ht} as a given. Similar to Dillon and Gupta (1996) and Bucklin, Gupta, and Siddarth (1998), we assume that a consumer allocates this total quantity across the items in the product category by making Q_{ht} individual choices. As a result, $(q_{h1t}, q_{h2t}, \ldots, q_{hIt})$ follows a multinomial distribution:

$$P_{ht}\left(q_{h1t}, q_{h2t}, \ldots, q_{hIt} \middle| Q_{ht}\right) = \frac{Q_{ht}!}{\prod_{i=1}^{I} q_{hit}!} \prod_{i=1}^{I} \left(P_{hit}\right)^{q_{hit}}, \quad (2)$$

where P_{hit} is the probability that consumer h buys item i on shopping trip t. In the absence of bundle promotions, P_{hit} takes a classic multinomial logit (MNL) form (Dillon and Gupta 1996). However, when consumers are confronted with promotional bundles, the specification becomes complicated by the dependence of the choice effects on total purchase quantity. To account for this quantity–choice relationship, we introduce two choice probability structures. The validity of one or the other depends on whether the consumer qualifies for the bundle discount (see Figure 1). Thus, we allow for two regimes with different choice response patterns, in which the prevailing regime is the outcome of another stochastic process, namely, the quantity decision. Our use of a two-regime model is similar to that of Vakratsas and colleagues (2004).

When a consumer does not buy enough in the category to qualify for the bundle discount (i.e., $Q_{ht} < BQ_t$), the choice probabilities maintain a classic MNL form. We refer to this probability structure as $(P^{nb}_{h1t}, P^{nb}_{h2t}, \ldots, P^{nb}_{hIt})$ and write the items' deterministic utility U^{nb}_{hit} as

$$U^{nb}_{hit} = Y'_{hit}\gamma^{y} + \gamma^{nb} \times BD_{it}, \quad (3)$$

where γ^y is a parameter vector and Y_{hit} is a vector of consumer-, time-, and item-specific variables. Furthermore, although the consumer does not qualify for the bundle promotion, we include BD_{it} because the featured bundle discount may still affect the appeal of the bundle items. Thus, parameter γ^{nb} enables us to test H_3, and its sign will reveal the existence of positive discount communication effects or negative betrayal/reference price effects.

When the consumer qualifies for the bundle discount (i.e., $Q_{ht} \geq BQ_t$), the probability structure becomes $(P^{b}_{h1t}, P^{b}_{h2t}, \ldots, P^{b}_{hIt})$, and the bundle items' utility function takes the following form:

Table 1
SYMBOLS

Symbol	Description
UD_t	Per-unit discount (if any) on shopping trip t.
BD_t	Bundle discount (if any) on shopping trip t.
BQ_t	Bundle quantity requirement (if any) on shopping trip t.
BR_t	Bundle range (if any) on shopping trip t.
q_{hit}	Purchase quantity of item i for consumer h on shopping trip t.
Q_{ht}	Total purchase quantity in the category for consumer h on shopping trip t.
P_{hit}	Probability that consumer h chooses item i on shopping trip t, in the absence of bundle promotions.
P^{nb}_{hit}	Probability that consumer h chooses item i on shopping trip t, given that $Q_{ht} < BQ_t$.
P^{b}_{hit}	Probability that consumer h chooses item i on shopping trip t, given that $Q_{ht} \geq BQ_t$.
CUD_{ht}	Per-unit discount at category level for consumer h on shopping trip t.
CBD_{ht}	Bundle discount at category level for consumer h on shopping trip t.
QP_{ht}	Quantity pressure for consumer h on shopping trip t; see Equation 9.

$$(4) \qquad U^b_{hit} = Y'_{hit}\gamma^y + \gamma^b \times BD_{it},$$

where γ^b gauges the mere impact of the bundle discount. We expect γ^b to differ from γ^{nb} in Equation 3 because the appeal of the bundle discount in this case is based on other (more rational) arguments. Given that $Q_{ht} \geq BQ_t$, the bundle discount is now within the consumer's reach and therefore is likely to increase the bundle items' utilities (see H_1).[6] However, the bundle promotion may not only affect utilities as such but also create interrelationships among the bundle items as a result of the leverage effect (H_2). Indeed, consumers attracted by one bundle item may also select other bundle items to meet the bundle quantity requirement. Consequently, if a bundle-promoted item gains attractiveness, this will be more detrimental to items outside the bundle range than to the other items within the bundle range. Train, Ben-Akiva, and Atherton (1989) and Lee (1999) use a nested MNL model with a scale parameter greater than 1 to model such response patterns, in which consumers are more likely to switch to or away from a set of items than among the items within that set. Accordingly, we accommodate the interrelationships among the bundle items using a nested MNL model, in which the nest consists of the bundle-promoted items (see Figure 1), and we expect a scale parameter greater than 1. Thus, a bundle item's choice probability can be expressed as (see McFadden 1981)

[6]We recognize that a consumer may switch to the bundle items and buy only a fraction of the bundle quantity requirement. However, this is not a major concern in our data set because in 91.9% of the occasions for which $Q_{ht} \geq BQ_t$, the purchase quantity for the bundle items corresponds to an integer multiple of the quantity requirement.

$$(5) \qquad P^b_{hit} = \exp\left[\frac{U^b_{hit}}{\mu} + (\mu - 1) \times INC_{hBRt}\right] \Bigg/ \left\{\sum_{j \in BR_t} \exp\left[\frac{U^b_{hjt}}{\mu} + (\mu - 1) \times INC_{hBRt}\right] + \sum_{j \notin BR_t} \exp(U_{hjt})\right\},$$

and the choice probability of a nonbundle item k is as follows:

$$(6) \qquad P^b_{hkt} = \exp(U_{hkt}) \Bigg/ \left\{\sum_{j \in BR_t} \exp\left[\frac{U^b_{hjt}}{\mu} + (\mu - 1) \times INC_{hBRt}\right] + \sum_{j \notin BR_t} \exp(U_{hjt})\right\},$$

where

$$INC_{hBRt} = \ln\left[\sum_{j \in BR_t} \exp\left(\frac{U^b_{hjt}}{\mu}\right)\right]$$

refers to the inclusive value of the nested items and μ is the scale parameter of the nested logit model (Ben-Akiva and Lerman 1985). Again, to find evidence of the leverage effect, μ should exceed 1.[7] To understand this, we must analyze the ratio between the choice probability of a bundle item $i \in BR_t$ and that of a nonbundle item $k \notin BR_t$, given that $Q_{ht} \geq BQ_t$. We can verify that

$$(7) \qquad \frac{P^b_{hit}}{P^b_{hkt}} = \exp(\gamma^b \times BD_{it}) \times \left(\frac{P^b_{hit}}{\sum_{j \in BR_t} P^b_{hjt}}\right)^{1-\mu} \times \frac{P_{hit}}{P_{hkt}},$$

where $P_{hit}(P^b_{hit})$ and $P_{hkt}(P^b_{hkt})$ refer to the choice probabilities in the absence (presence) of bundle promotions. Thus, Equation 7 shows how the choice probability of a bundle item i, compared with that of a nonbundle item k, is affected in the shift from a nonbundling to a bundling situation. The first factor on the right-hand side represents the mere discount effect and exceeds 1 if γ^b is positive. The second factor is greater than 1 if $\mu > 1$ (the term in parentheses is item i's share within the bundle), in which case it represents the leverage effect. Note that for a given $\mu > 1$, the leverage effect gains strength when the other bundle items' choice probabilities increase. However, the leverage effect collapses when i is the only item in the bundle.

Total Quantity and Incidence Model

The quantity decision (conditional on incidence) is modeled by means of a zero-truncated Poisson regression in which the consumer's average purchase rate λ_{ht} is an exponential function of several explanatory variables. The incidence decision is specified as a binomial logit model in which the category attractiveness V_{ht} is a linear function of the same variables (e.g., Dillon and Gupta 1996; Silva-

[7]Subsequently, we argue that though $\mu > 1$, our model remains consistent with random utility theory within the data range.

Risso, Bucklin, and Morrisson 1999). We propose the following expressions:

$$(8)\quad \lambda_{ht} = \exp\big(X'_{ht}\beta^{x} + \beta^{cbd} \times CBD_{ht} + \beta^{qp} \times QP_{ht} + \beta^{qp2} \times QP_{ht}{}^{2}\big)$$

$$V_{ht} = X'_{ht}\alpha^{x} + \alpha^{cbd} \times CBD_{ht} + \alpha^{qp} \times QP_{ht} + \alpha^{qp2} \times QP_{ht}{}^{2},$$

where β^x and α^x are parameter vectors and X_{ht} is a vector consisting of a constant and consumer- and time-specific variables. The variable CBD_{ht} refers to the category-level bundle discount and is computed as the weighted average of BD_{it} across the SKUs in the category, in which the weights reflect a consumer's SKU preferences. In particular, these weights are based on attribute-specific loyalties computed over an initialization period (see the Appendix). As such, CBD_{ht} captures both the bundle promotion's discount depth and the bundle range. Furthermore, we account for the impact of the quantity requirement BQ_t. Because the stringency of the quantity requirement is consumer specific—for example, a bundle of three units is more of an imposition for a consumer who usually buys one unit than for a consumer who usually buys two—we normalize BQ_t by dividing it by the consumer's average purchase quantity. We refer to this consumer-specific version of BQ_t as the bundle's quantity pressure QP_{ht}:

$$(9)\qquad QP_{ht} = BQ_t/AVQ_h,$$

where AVQ_h refers to consumer h's average purchase quantity in the category across purchase occasions during an initialization period. We use a quadratic polynomial to model the impact of QP_{ht} at the quantity and incidence levels. At the quantity level, this functional form accommodates the inverted U-shaped effect we proposed in H_4; that is, for a given consumer, increasing the quantity requirement is rewarding up to some point but counterproductive thereafter. At the incidence level, H_5 requires the polynomial to decrease monotonically in QP_{ht}, such that for a given consumer, raising the quantity requirement lowers the incidence probability. In the first two columns of Table 2, we summarize the proposed mechanisms at the different decision levels and the corresponding model parameters.

APPLICATION

We calibrate our models with consumer panel data from the snack chip category. In the following sections, we briefly describe the characteristics of our data and then discuss the estimation, results, and validation of our models.

Data

We apply our models to countrywide consumer panel data provided by GfK. The data set covers the years 1999–2000. All 1181 panelists in our sample made at least 10 purchases in the chip category during those two years. We distinguish among 220 different SKUs, which account for 96.9% of category unit sales.[8] These SKUs are distinct types (e.g., corn, potato, extruded), flavors, and sizes of 17 different chip brands. Altogether, the panelists made 116,885 shopping trips and 31,745 SKU purchases in eight different store chains. We combine the GfK data with Publi Info promotional information, which provides rich and detailed descriptions of promotions at the store-chain and SKU levels.

In Table 3, we summarize the main characteristics of the bundle promotions in our data set. During all shopping trips, consumers were confronted with 19,949 bundle promotions, which typically involved several SKUs. Bundle promotions, similar to per-unit promotions, occurred for virtually all chip types, flavors, and package sizes but were offered by only a limited number of brands. Still, these brands include both national and private labels and represent both low- and high-end brands. Furthermore, 11% of the bundle promotions occurred across type categories (i.e., the bundled SKUs belong to different types), and 87% occurred across flavors. However, a given bundle always contained SKUs of the same brand and similar size. Finally, 93% of the bundle promotions in our data set were framed

Table 2
HYPOTHESES, CORRESPONDING MODEL PARAMETERS, AND EMPIRICAL SUPPORT

Hypothesis	*Relevant Model Parameters/Test*	*Empirical Support*
Choice Model		
H_1. If $Q_{ht} \geq BQ_t$, the bundle discount has a positive impact on the bundle item's choice probability (mere discount effect).	$\gamma^b > 0$	√
H_2. If $Q_{ht} \geq BQ_t$, the bundle items leverage up each other's choice probability (leverage effect).	$\mu > 1$	√
H_3. If $Q_{ht} < BQ_t$, the bundle discount still affects the bundle item's choice probability.	$\gamma^{nb} \neq 0$	√ ($\gamma^{nb} > 0$)
Incidence/Quantity Model		
H_4. At quantity level, the quantity requirement first enhances and then decreases the impact of bundle promotion.	$\exp(\beta^{qp}QP_{ht} + \beta^{qp2}QP_{ht}{}^2)$ inverted U-shaped over positive QP_{ht} values	√
H_5. At incidence level, the quantity requirement negatively affects the impact of bundle promotion.	$\beta^{qp}QP_{ht} + \beta^{qp2}QP_{ht}{}^2$ decreasing over positive QP_{ht} values	√

Table 3
PROMOTION DESCRIPTIVES

	M	*SD*
Per-Unit Promotions		
Price discount (cents/ounces)	3.30	1.88
Bundle Promotions		
Price discount (cents/ounces)	4.18	1.63
Quantity requirement	3.70	.77
Range (number of bundle items)	4.78	3.55

[8]This does not mean that consumers chose from 220 different SKUs on a given shopping trip; the actual assortments varied across store chains and over time.

as "Pick Y units for only \$X," as opposed to "Pick Y units, get \$X off."

To give a first impression of consumers' reaction patterns, we provide several tentative response indicators in Table 4. Of all the shopping trips that did not involve a price promotion, 12.2% led to a purchase in the category (i.e., a purchase occasion). This incidence percentage was 18.5% for shopping trips on which consumers were confronted with per-unit promotions and 13.8% for shopping trips with bundle promotions. On purchase occasions without price promotions, consumers, on average, bought 2.20 units in the category. This average purchase quantity increased to 2.81 in the presence of per-unit promotions and 2.41 in the presence of bundle promotions. We further find that the average choice share was 1.6% for nonpromoted SKUs, 2.9% for per-unit promoted SKUs, and 3.1% for bundle-promoted SKUs.[9] Finally, across purchase occasions, the uptake was 4.7% for per-unit promoted SKUs and 5.0% for bundle-promoted SKUs. Evidently, we must exercise caution when interpreting these figures because they depend on current promotion practices and may not reveal potential promotion effectiveness.

Estimation

Because we plan to compare bundle offers with traditional per-unit promotions, we include per-unit discount variables in our choice, quantity, and incidence models. At the incidence and quantity levels, we compute the per-unit discount variable CUD_{ht} similarly to CBD_{ht}—namely, as a weighted average of all per-unit discounts in the category.

Furthermore, at the choice level, we add attribute-level intercepts, loyalty indexes, and attribute-specific purchase-feedback dummies. In the incidence and quantity models, we include intercepts, consumption rate, inventory, and the inclusive value INC_{ht}, which is based on the choice-level parameters and captures the expected maximum utility of buying in the category (Grover and Srinivasan 1992). We compute INC_{ht} as if there were no promotions in the category to ensure that CUD_{ht} and CBD_{ht} capture the full discount effect.[10] In other words, we allow assortment characteristics and consumers' SKU preferences on a given shopping trip to affect consumers' incidence and quantity decisions (through INC_{ht}), and we separately model the impact of price promotions. In the Appendix, we describe the included variables precisely.

To accommodate unobserved consumer heterogeneity, we model all promotion parameters (as well as other parameters; see the Appendix) as normally distributed random coefficients. We calibrate our models through simulated maximum likelihood (Train 2002). We first estimate the choice model, then use household-specific choice parameters to compute INC_{ht}, and finally estimate the incidence/quantity model.[11] Because some variables need to be initialized, we designate the first 15% of each consumer's purchase history (with a minimum of four purchase occasions) as the warm-up period.

Results

Choice model. In Table 5, we summarize the estimation results of the choice model. In the interest of space, we do not report the attribute-level constants. As is indicated by the coefficients of the loyalty indexes and the mean purchase-feedback effects, in general, households are most loyal to the brand and least loyal to the type of chips. Although all mean feedback effects are positive and significant, this does not mean that variety seeking does not take place at all. For example, the relatively large variance in the type feedback parameter implies that though 79% of the households have a positive feedback parameter, 21% tend to switch over time between different chip types (e.g., corn, potato). Moreover, households with positive feedback parameters may still exhibit "within-trip" variety seeking and repeat-purchase the same, though varied, set of items.

The population mean of the per-unit discount coefficient (.10) is positive and significant ($p < .001$). For the discussion of the bundle-related coefficients, we distinguish between the two choice regimes. When $Q_{ht} \geq BQ_t$, the bundle discount parameter γ^b and the scale parameter μ are the relevant bundle coefficients (see Table 2). The estimated mean for γ^b (.17) is positive and significant ($p < .001$), which confirms that the mere bundle discount increases the bundle items' choice probabilities (H_1). We also note that this mean is significantly higher ($p < .05$) than the mean per-unit discount effect. Furthermore, the estimated mean for the scale parameter μ (1.33) is significantly higher than 1 ($p < .001$), which corroborates H_2 that when $Q_{ht} \geq BQ_t$, the bundle items leverage each other's choice probability.[12]

[9]To enhance comparability, we computed these average shares only for the SKUs that had been promoted both on a per-unit basis and as part of a bundle during the observation period.

[10]Our decision to neutralize all promotional effects in INC_{ht} and incorporate CUD_{ht} and CBD_{ht} is driven by the need to test and compare the impact of per-unit and bundle promotions on incidence and quantity. Still, we also tested two models in which INC_{ht} included promotion effects (see Grover and Srinivasan 1992). In the first model, the promotion effects could manifest themselves only through INC_{ht}; in the second model, we also included CUD_{ht} and CBD_{ht}. Both models performed worse than our approach in terms of within-sample and out-of-sample fit. We are grateful to an anonymous reviewer for suggesting these extra tests.

[11]Because our data are at the SKU level and pertain to eight different store chains, our "joint" data set contains more than 7 million records. Combined with the many nonlinearities in the likelihood function, this makes simultaneous estimation of all three levels (choice, quantity, and incidence) intractable (for similar observations, see Ailawadi and Neslin 1998; Jedidi, Mela, and Gupta 1999).

[12]Note that with a scale parameter greater than 1, the model is not globally consistent with random utility maximization (Train 2002). Several other researchers have found similar and much higher scale parameters, albeit in different contexts (see, e.g., Lee [1999], who finds a scale parameter equal to 2.67; Train, Ben-Akiva, and Atherton [1989], who find a scale parameter equal to 1.19; and Train, McFadden, and Ben-Akiva [1987],

Table 4

TENTATIVE PROMOTION RESPONSE INDICATORS

	No Promotion	*Per-Unit Promotion*	*Bundle Promotion*
Purchase incidence	12.2%	18.5%	13.8%
Average purchase quantity	2.20	2.81	2.41
Average choice share	1.6%	2.9%	3.1%

Table 5

ESTIMATION RESULTS FOR CHOICE MODEL

Parameter	Population Mean	SD
Loyalty Measures	*Estimates (SE)*	
γ^{tloy} (type loyalty)	.81 (.027)	
γ^{bloy} (brand loyalty)	1.95 (.027)	
γ^{floy} (flavor loyalty)	1.73 (.026)	
γ^{sloy} (size loyalty)	1.24 (.023)	
Purchase Feedback		
γ^{lt} (last type purchased)	.42 (.022)	.69 (.023)
γ^{lb} (last brand purchased)	.98 (.026)	1.05 (.026)
γ^{lf} (last flavor purchased)	.89 (.019)	.71 (.019)
γ^{ls} (last size purchased)	.48 (.022)	.91 (.022)
Promotion Effects		
γ^{ud} (per-unit discount)	.10 (.007)	.25 (.009)
γ^{nb} (bundle discount, $Q_{ht} < BQ_t$)	.07 (.027)	.20 (.034)
γ^{b} (bundle discount, $Q_{ht} \geq BQ_t$)	.17 (.035)	.69 (.052)
μ (inclusive value bundle nest)	1.33 (.072)	.82 (.050)
Log-likelihood[a]	–680.45	
AIC[a]	1470.90	
BIC[a]	1920.69	

[a]Based on a rescaled likelihood function.

Notes: AIC = Akaike information criterion, and BIC = Bayesian information criterion.

Table 6

ESTIMATION RESULTS FOR INCIDENCE/QUANTITY MODEL

Parameter	Estimates (SE) Population Mean	SD
Incidence		
α^{cud} (category per-unit discount)	.44 (.03)	.43 (.05)
α^{cbd} (category bundle discount)	–.06 (.09)	.15 (.11)
α^{qp} (quantity pressure)	–.09 (.05)	.10 (.03)
α^{qp2} (quantity pressure^2)	.01 (.02)	.01 (.01)
Quantity		
$\exp(\beta^{cud} \times \overline{CUD})$	1.06 (.01)	.06 (.01)
$\exp(\beta^{cbd} \times \overline{CBD})$	1.005 (.02)	.11 (.03)
$\exp(\beta^{qp} \times \overline{QP})$	1.25 (.11)	.20 (.06)
$\exp(\beta^{qp2} \times \overline{QP^2})$	.82 (.06)	.05 (.03)
Log-likelihood[a]	–966.24	
AIC[a]	1986.47	
BIC[a]	2240.39	

[a]Based on a rescaled likelihood function.

Notes: AIC = Akaike information criterion, and BIC = Bayesian information criterion.

When $Q_{ht} < BQ_t$, the parameter of interest is γ^{nb}, which captures any remaining switching behavior. In support of H_3, we find that the estimated population mean for γ^{nb} (.07) is significantly different from 0 ($p < .01$). The positive sign indicates that the average consumer, even when he or she does not qualify for the bundle discount, switches to the promoted items. This finding reveals that the mere communication of the bundle discount attracts consumers to the promoted items.

Incidence/quantity model. To save space, we report only the results for the promotion parameters (see Table 6; the other parameters are significant and in the expected direction). For the mixed truncated Poisson model, it is important to stress that neither the size nor the sign of the estimated population means can be readily interpreted. The reason is that the purchase rate λ_{ht} is an exponential and, thus, highly asymmetric ad hoc transformation of the random coefficients (e.g., Aitchison and Ho 1989; Chib, Greenberg, and Winkelmann 1998). As a result, it is much more instructive to write λ_{ht} as a product of the form $\exp(\beta_1 \times x_1) \times \exp(\beta_2 \times x_2) \times \ldots$ and study the mean and standard deviation of the individual factors (see Goldberger 1968).[13] The estimation results for the quantity model in Table 6 pertain to these converted factors and should be evaluated relative to 1. That is, a factor greater than 1 indicates that, on average, the corresponding variable positively affects λ_{ht}, whereas a factor lower than 1 reveals the opposite. (The original parameter estimates are available on request.)

For per-unit promotions, we find that, on average, the discount variable has a positive impact on category utility and purchase quantity. At the incidence level, the population mean for α^{cud} (.44) is significantly greater than 0 ($p <$ .001), and at the quantity level, the population mean (1.06) for the factor $\exp(\beta^{cud} \times \overline{CUD})$ is significantly greater than 1 ($p < .001$).

For bundle promotions, on average, the discount variable does not significantly affect either incidence or purchase quantity.[14] However, because a bundle discount does not operate independently of the quantity requirement, a more accurate assessment of the bundle impact would evaluate $\alpha_h^{cbd} \times CBD + \alpha_h^{qp} \times QP + \alpha_h^{qp2} \times QP^2$ at the incidence level and $\exp(\beta_h^{cbd} \times \overline{CBD} + \beta_h^{qp} \times QP + \beta_h^{qp2} \times QP^2)$ at the quantity level. To study the role of the quantity requirement and, thus, QP in this overall bundle impact (see H_4 and H_5), we keep CBD constant at its average value and vary the value of QP. In Figure 2, Panels A and B, we plot the population means of these expressions as a function of QP.

In support of H_5, we find in Figure 2, Panel A, that increasing the quantity requirement and, thus, QP negatively affects the bundle's mean impact on incidence. Surprisingly, however, even for small QP values, the total bundle effect on incidence does not exceed zero. Apparently, any quantity requirement (i.e., at least two units) is too stringent to convert nonbuyers into buyers. Worse still,

who even report a value of 4.18). Typically, these authors interpret the parameters in a purely statistical sense, such that the size of the scale parameter simply captures the degree of substitutability between alternatives. Most important, however, a scale parameter greater than 1 does not necessarily keep a model from being locally consistent with random utility maximization (i.e., consistent within the range of sensible data points). To check for local consistency, we use the procedure that Herriges and Kling (1996) and Kling and Herriges (1995) describe, which involves testing two necessary conditions. We find that within the range of observed data points, our model is locally compatible with utility maximization. Details are available on request.

[13]Given that the random coefficients follow a normal distribution, the factors $\exp(\beta_k \times x_k)$ are log-normally distributed with mean m = $\exp[\bar{\beta}_k \times x_k + (x_k \times \sigma_{\beta k})^2/2]$ and standard deviation s = m × $\{\exp[(x_k \times \sigma_{\beta k})^2] - 1\}^{.5}$. Because these measures depend on x_k, we evaluate them for the mean value of x_k. The reported standard errors of m and s are based on simulation.

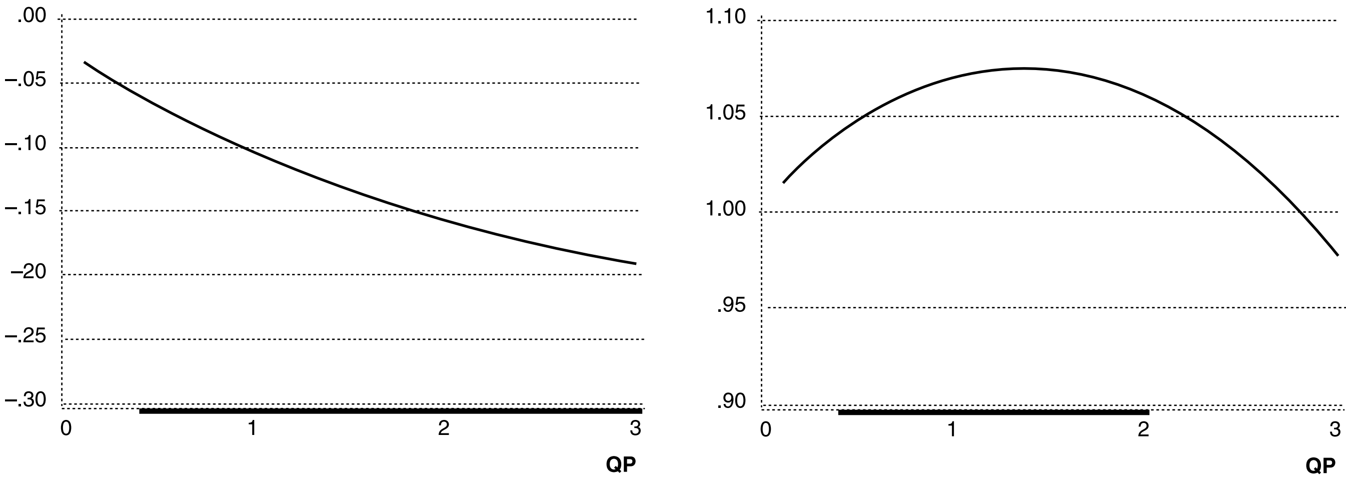
[14]At the quantity level, the impact is computed for the average value of CBD, the category-level bundle discount. However, even for very high values, the discount impact remains nonsignificant.

Figure 2

IMPACT OF QUANTITY PRESSURE ON INCIDENCE AND QUANTITY

A: Incidence Level (Population mean for $\alpha^{cbd} \times \overline{CBD} + \alpha^{qp} \times QP + \alpha^{qp2} \times QP^2$ as a function of QP)

B: Quantity Level (Population mean for $\exp(\beta^{cbd} \times \overline{CBD} + \beta^{qp} \times QP + \beta^{qp2} \times QP^2)$ as a function of QP)



Notes: In Panel A, the bold line on the QP axis marks the zone where the curve is significantly lower than 0 ($p < .05$). In Panel B, the bold line on the QP axis marks the zone in which the curve is significantly higher than 1 ($p < .05$).

when the quantity requirement rises and QP exceeds .4, the mean bundle impact becomes significantly negative ($p <$ .05). Even if we compute household-specific coefficients, we find that for almost all panelists, bundling tends to affect incidence negatively, especially when QP becomes large. We can interpret this finding by referring to the same principles that we used to explain potential negative switching effects at the choice level. That is, consumers who consider the quantity requirement too stringent may deem it to be unfair that the promoted brand offers price reductions only to consumers who meet the quantity requirement and therefore may cancel the category purchase altogether (see Feinberg, Krishna, and Zhang 2002). A slightly different argument is that these consumers use the bundle price as an external reference price (see Kopalle and Lindsey-Mullikin 2003), which may reduce their willingness to pay the regular price. The higher QP, the more likely the consumer feels forced to turn to the regularly priced unbundled items and therefore engages in adverse purchase reactions.

In turn, we use Figure 2, Panel B, to confirm the inverted U-shaped effect predicted in H_4. For the average consumer, increasing the quantity requirement (and, thus, QP) enhances the bundle's impact on purchase quantity up to some point but tempers the impact after that point. Only for a select range of QP values does the average bundle impact approximate a per-unit promotion's average impact (1.06). For relatively high QP values, the plotted curve drops below 1, which implies that for those QP values, the bundle promotion lowers consumers' purchase quantities on average. However, this effect becomes significant only when QP exceeds 5, which is outside the range of actually observed QP values.

Validation

To assess the impact of bundle promotions, we developed and estimated modified incidence, quantity, and choice models. In this section, we report additional checks on whether the proposed models actually gauge the phenomena of interest and accommodate the bundle mechanisms better than more naive specifications. Subsequently, we report the relative performance of several benchmark models and discuss the validity of the scale parameter of the nested logit model as a measure of the leverage effect.

Benchmark models. First, we compare our proposed choice and incidence/quantity models with traditional MNL and truncated Poisson models that ignore the peculiarities of the bundle promotion and assume an equivalent discount on a per-unit basis. This is how existing models would accommodate bundle promotions. In Table 7, CHOICE1 and INCIQUAN1 refer to these more naive benchmark models. Second, we estimate a choice model (CHOICE2) that corresponds to our proposed choice model but lacks the bundle nest and thus ignores the interdependencies among bundle items. We (re)estimate all the models, including our full models, for a subsample of the original data set to permit out-of-sample model evaluation. The holdout sample comprises the last four months of the observation period. As we portray in Table 7, the results indicate that our full models outperform simpler benchmark models in terms of both within-sample fit (log-likelihood, Akaike information criterion, and Bayesian information criterion) and out-of-sample predictive power (we compute the log-likelihood on the observations in the holdout sample). Given the relatively limited number of bundle observations that benefit from a more sophisticated model structure, we assert that the improvements in model performance are substantial.

Leverage effect. Although the comparison of CHOICE2 with our full choice model offers an initial indication of the importance of modeling item interdependencies, we carry out three additional validity checks. First, we test for departures from the independence of irrelevant alternatives (IIA) property after we remove all purchase occasions in which

Table 7

FIT MEASURES FOR FULL AND BENCHMARK MODELS

Model	Description	Number of Parameters	Within-Sample Fit Log-Likelihood[a]	AIC[a]	BIC[a]	Out-of-Sample Fit Log-Likelihood[a]
Choice Level						
CHOICE1	No separate bundle effect	49	–644.77	1387.53	1778.52	–505.64
CHOICE2	Full model without bundle nest	53	–569.04	1244.07	1666.98	–476.77
CHOICE3	Full model	55	–542.10	1194.20	1633.06	–470.48
Incidence/Quantity Level						
INCIQUAN1	No separate bundle effect	15	–455.19	940.39	1078.04	–397.91
INCIQUAN2	Full model	27	–312.32	678.64	926.40	–380.78

[a]Based on a rescaled likelihood function.

Notes: AIC = Akaike information criterion, and BIC = Bayesian information criterion.

consumers qualified for the bundle discount. If the choice asymmetries captured by our parameter μ are only the result of the leverage effect, we may expect such asymmetries to be absent when consumers do not qualify for a bundle discount. On the basis of a series of IIA tests (see McFadden, Train, and Tye 1976), we find that the IIA assumption holds for choice situations in which consumers are not eligible for a bundle discount. (Test results are available on request.) This finding rules out the possibility that μ captures intrinsic item interactions, such as complementarities due to variety seeking.

Second, we estimate a model with a bundle nest for each choice regime (in lieu of for $Q_{ht} \geq BQ_t$ only) but with different scale parameters. When $Q_{ht} \geq BQ_t$, the population mean for μ is virtually identical to that which we report in Table 5. For $Q_{ht} < BQ_t$, however, we find a value of 1.02, which is not significantly different from 1 ($p > .4$). This is in line with our hypotheses. When consumers do not qualify for the bundle discount, there is no reason to expect a leverage effect.

Third, because the leverage effect has implications for the distribution of market shares across the bundle items, we verify whether our full model is better able to predict choice shares within the bundle than a model without bundle nesting (CHOICE2). This analysis includes purchase occasions on which consumers qualify for the discount because the leverage effect is active only in those instances. When we compare actual and estimated within-bundle choice shares, we obtain a mean absolute deviation of .130 and a mean square error of .044 for CHOICE2. In our full model, mean absolute deviation and mean square error drop to .121 and .040, respectively, thus underscoring the importance of accommodating the leverage effect.[15]

EVALUATING A BUNDLE PROMOTION'S EFFECTS

In the previous sections, we shed light on the incidence, quantity, and choice effects triggered by a bundle promotion. At this point, we use the estimated models to simulate a bundle promotion's net impact on unit sales. We take the perspective of both the brand manager, who focuses on the sales of his or her SKUs, and the retailer, which is mainly interested in the sales of the whole product category. We illuminate the role of the bundle characteristics and pit the bundle's impact against that of per-unit discounts.

In our simulation, we use consumer-specific coefficients, which are computed as the means of the consumer-specific posterior parameter distributions (Train 2002). Time-variant variables take on average values, and stores' assortments reflect actual assortment compositions.

A Bundle Promotion's Sales Implications for Brand Managers

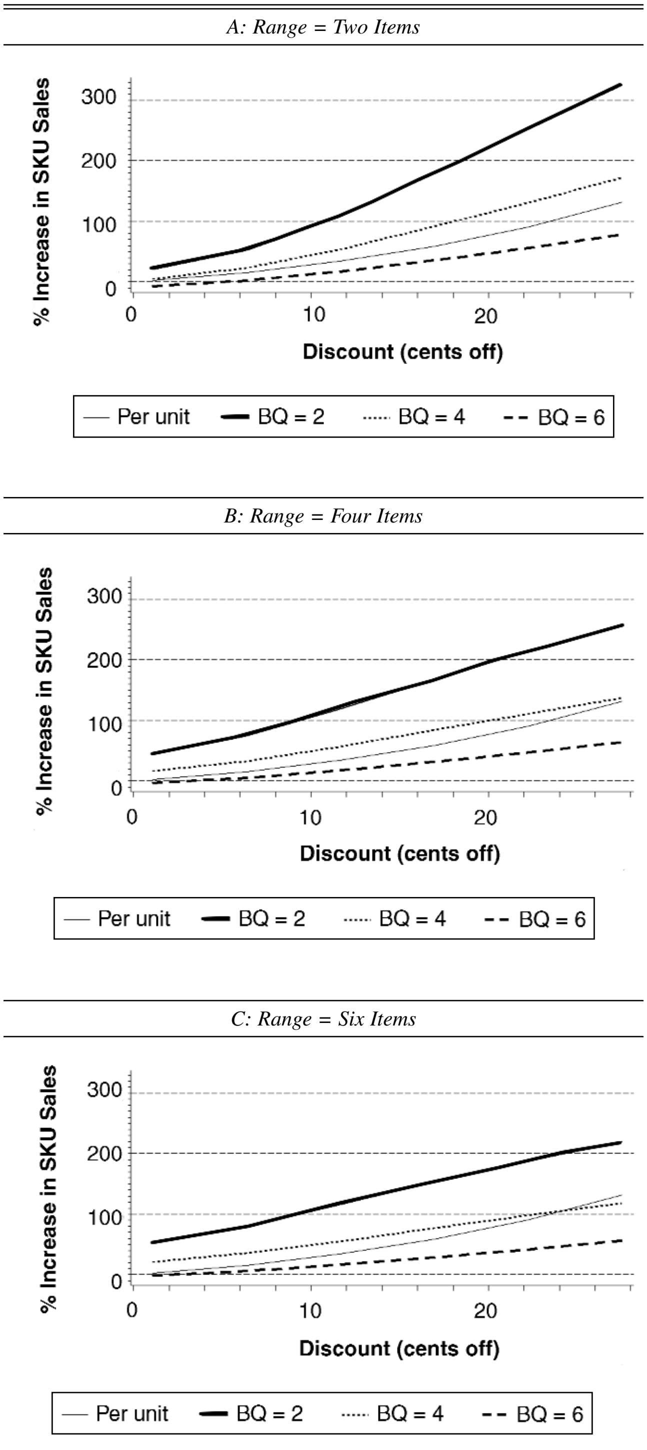
To evaluate the effects of bundling from a brand manager's perspective, we simulate alternative promotions in the Lay's brand line of 5-ounce bags of regular potato chips, which consists of seven distinct SKUs. Simulations for another major snack chip brand (consisting of six distinct SKUs) led to similar results. For each promotion alternative, we compute the percentage change in the expected unit sales for (1) a single SKU (Lay's Classic, 5 ounces) that is part of the promotion and (2) the complete Lay's brand line. In the Web Appendix (see http://www.marketingpower.com/content84060.php), we derive an expression for expected unit sales.

In Figure 3, Panels A–C, we depict the percentage change in the sales for the single SKU (Lay's Classic, 5 ounces) as a function of the promotional discount. The discount ranges from \$.01 to \$.28 per unit, with the highest value being equal to approximately 35% of the regular price. Each graph corresponds to a specific bundle range (two, four, and six items) and portrays the effect for three quantity requirements (BQ = two, four, and six units). Because our focus is on optimizing the sales of a particular SKU, we compare the bundle promotions with a per-unit promotion that applies only to that focal SKU. Several striking observations emerge.

First, bundle promotions considerably increase the sales of the focal SKU overall. For example, for a range of four items (Figure 3, Panel B), when BQ is 2 and the discount is \$.15, the promotion increases the sales of Lay's Classic by approximately 150%. The outspokenly positive effects at the choice level (mere discount, leverage, and discount communication effects) compensate for the modestly positive or even negative effects at the incidence and quantity level.

[15]We thank an anonymous reviewer for suggesting this test.

Figure 3
BUNDLE PROMOTION IMPACT ON SKU SALES



Notes: Per-unit promotions apply only to the focal SKU.

Second, raising the bundle quantity requirement decreases the bundle effect on the focal SKU's sales. As we show in Figure 3, Panel B, imposing a quantity requirement of four instead of two units reduces the previous sales increase from approximately 150% to approximately 80%. This is the result of three effects: (1) All else being equal, an increasing BQ makes the choice regime for Q ≥ BQ with its leverage and strong mere-discount effect less likely to be valid, (2) a higher BQ may induce a negative bundle impact at the incidence level, and (3) increasing BQ beyond a certain point reduces the bundle impact at the quantity level.

Third, extending the bundle range lifts up the bundle's initial impact on Lay's Classic's sales. In the switch from a two-item (Figure 3, Panel A) to a four-item (Figure 3, Panel B) bundle, the response curves' intercepts shift upward. That is, as the bundle range increases, the focal SKU benefits more from the leverage effect. At the same time, the response curves become flatter; that is, when the bundle range increases, the focal SKU must share the promotion effect with more items (cannibalization), such that its sales become less discount elastic. For higher discounts, this cannibalization outweighs the leverage effect, and the focal SKU's sales decrease.

Fourth, the marginal contribution of the leverage effect decreases as the bundle range extends. A comparison of Panels B and C in Figure 3 indicates that adding another two items to a four-item bundle does not lead to any noticeable upward shift of the response curves. Whereas expanding a narrow range triggers leverage, any further range expansions contribute little to the leverage effect. Instead, any incremental leverage effect is almost immediately nullified by a further loss of discount elasticity.

Fifth, bundling the focal SKU with other SKUs can be more effective than promoting the SKU on a per-unit basis. For example, in Figure 3, Panel B, a per-unit discount of $.20 increases sales of Lay's Classic by approximately 80%, less than half of the sales increase produced by a bundle promotion with BQ = 2. Thus, a condition for effective bundle promotions appears to be a sufficiently low quantity requirement. For BQ greater than four, the per-unit promotion outperformed the bundle offer. Finally, in general, bundle ranges beyond four SKUs weaken the bundle's position relative to the per-unit promotion because they only trigger cannibalization without further leveraging up the focal SKU's sales.

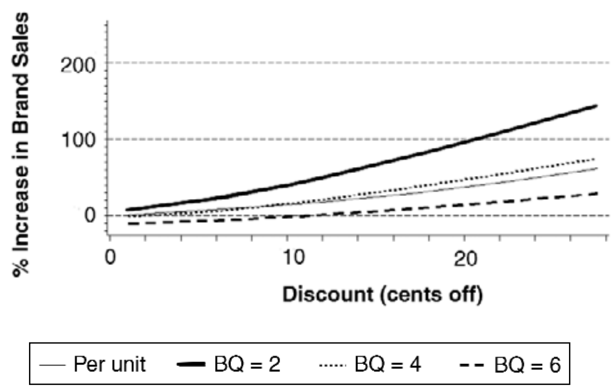
In Figure 4, Panels A–C, we depict the bundle promotions' effects on the sales of the complete Lay's brand line of regular potato chips. Again, we compare bundles with per-unit promotions. However, in this case, per-unit promotions pertain to the same range of items as the corresponding bundle promotions. Although the general response patterns appear to be similar to those in Figure 3, we make two additional observations.

First, the bundle's sales effects at the brand level are not always as spectacular as those at the SKU level, especially for small bundle ranges (Figure 4, Panel A). Because promotional bundles are effective at stimulating switching, they make strong inroads into the sales of other items, including the brand's own nonpromoted SKUs. Still, well-designed bundle promotions can dramatically improve on per-unit promotions (that apply to the same range of items).

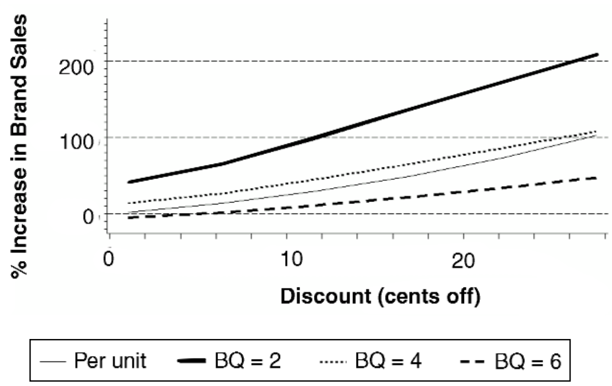
Second, widening the bundle range always increases the bundle's impact on brand sales. Not only a range increase from two to four items (Panels A and B) but also a further extension to six items (Panel C) substantially improves the sales of the Lay's brand line. This trend occurs for two reasons. In terms of a brand line's sales volume, putting more SKUs on deal is always better. Furthermore, broader bundles benefit more from the leverage effect, even if it tapers.

Figure 4
BUNDLE PROMOTION IMPACT ON BRAND SALES

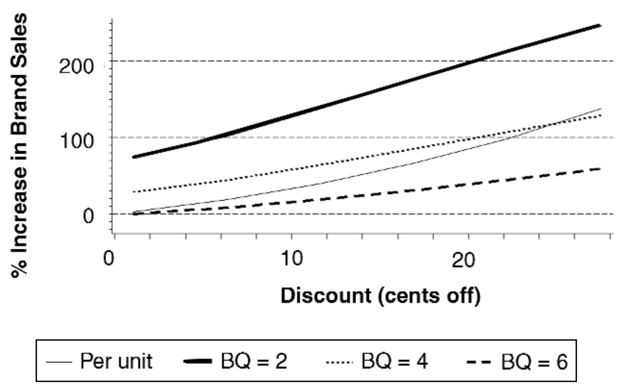
A: Range = Two Items



B: Range = Four Items



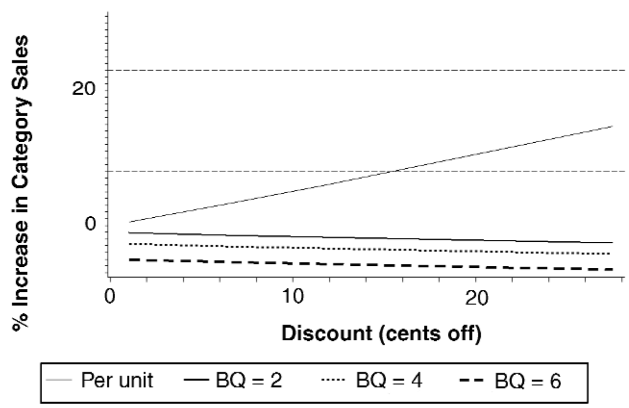
C: Range = Six Items



A Bundle Promotion's Sales Implications for Retailers

Again, we consider various promotions in the Lay's brand line, but now we compute their impact on category sales. Figure 5 presents the results for four-item promotions only, but we found almost identical graphs for two- and six-item promotions (with the per-unit discount curve further tilting upward for larger ranges). The most striking observation is that bundle promotions, in contrast to per-unit discounts, are ineffective at the category level. For small quantity requirements, any positive bundle impact on purchase quantity appears to be nullified by adverse bundle effects at the incidence level. For higher quantity requirements (4 units and higher), the bundle promotion may even lead to a small decrease in category sales. In other words, although bundling tends to increase purchase quantities modestly among consumers who purchase in the category, this effect is at least neutralized by consumers who refrain from purchasing in reaction to an overly restrictive quantity requirement. Finally, the graph shows that the bundle's response curves are discount inelastic; the bundle's performance at the category level is mainly driven by the quantity requirement.

Figure 5
BUNDLE PROMOTION IMPACT ON CATEGORY SALES
(RANGE = FOUR ITEMS)



DISCUSSION

In this study, we investigate the purchase effects of bundle promotions in a category of consumer packaged goods. We calibrate adjusted choice, quantity, and incidence models on consumer panel data in the snack chip category. The estimation results and subsequent simulations provide several insights. This section indicates how our findings contribute to managerial practice, presents tentative guidelines for bundle design, and suggests avenues for further research.

Main Results and Managerial Implications

An important finding of our study is that promotional bundling is particularly effective for stimulating switching behavior but less apt to increase category sales. That is, rather than converting nonusers or light users to heavy users, bundle promotions attract already heavy users from other brands. This result stems from the different bundle mechanisms that govern consumers' purchase decisions.

At the choice level, intense switching behavior occurs mostly among consumers who buy enough in the category to qualify for the bundle discount. For such consumers, bundle items benefit not only from a strong direct discount impact but also from a leverage effect, according to which one bundle item's choice probability is enhanced by the attractiveness of the other bundle items. Surprisingly, even consumers who purchase less than the bundle's quantity requirement and therefore do not qualify for the promotion tend to switch to the bundle items in response to the advertised discount (the discount communication effect).

At the quantity level, a bundle promotion tends to increase a consumer's purchase amount modestly. However, after the quantity requirement exceeds a (consumer-specific) critical point, the bundle's impact shrinks. At the incidence level, bundling does not generate any positive effect. Rather, when the quantity requirement increases, a bundle may reduce the incidence probability.

Taken together, these findings offer some notable implications for brand managers and retailers alike. Because of bundle promotions' pronounced switching effects, a brand manager may find them to be more rewarding than per-unit promotions, especially if the primary objective is to increase a specific item's unit sales. Bundle-promoting that item with other brand items allows the manager to exploit the leverage effect and therefore is more effective than promoting the item on a per-unit basis. For example, to induce trial purchases for a new potato chip flavor, a brand could bundle the new flavor with a few relatively established flavors.

However, retailers aiming to enhance category sales will find little use for promotional bundles. Although bundling is successful at redistributing sales across SKUs, it turns out to be ineffective at the category level. Instead, per-unit promotions substantially increase category sales, such that retailers pursuing category expansion will be better off promoting on a per-unit basis. For similar reasons, a manufacturer that already enjoys a large market share in a product category may benefit more from per-unit promotions. Given their positive impact on category sales, per-unit promotions suffer less from cannibalization.

Designing a Bundle Promotion

Our simulation results underscore the importance of choosing bundle characteristics carefully. Proper selection of the bundle range and the quantity requirement in particular may dramatically improve the bundle promotion's performance.

First, if the quantity requirement is set too high, too many consumers are excluded. These consumers may even react adversely by deliberately canceling their category purchase altogether. In general, for any given product category, the appropriate quantity requirement is expected to depend on the distribution of consumers' regular purchase quantities. For the snack chip category, in which the average purchase quantity is 2.68 units and many consumers stick to one unit per purchase occasion, the recommended quantity requirement is two units.

Second, the appropriate bundle range depends on the marketer's objective. If the focus is on sales of the whole brand line, the company should include all brand items in the bundle. If the marketer aims to increase sales of one specific item, however, it suffices to select only a few attractive items that can increase sales of the focal item through the leverage effect. Including too many items leads to cannibalization of the focal item's sales. In our application, we found that a bundle range of three to four items was most effective, especially for shallow discounts.

Limitations and Further Research

Because this article is the first study of consumers' reactions to bundle promotions in the context of consumer packaged goods, ample opportunity remains for further research. Most important, for the sake of generalizability, our findings should be verified in other product categories.

Moreover, although the presented model incorporates the essential bundle mechanisms, the hierarchical specification of choice, incidence, and quantity decisions entails some simplifications. First, as is true for most hierarchical models, the inclusive value and weighted aggregate discounts in the incidence/quantity model are based on expected choice behavior and not on the actual choice outcomes. However, the "promotion windfall" may inspire consumers to choose something risky or to indulge in the purchase of an alternative they otherwise would not buy; the impact of such choice behavior is not incorporated in our incidence/quantity model. Second, in the choice model, the bundle discount becomes "active" from the moment the consumer buys enough in the category to qualify for the price reduction. Still, the consumer may buy a quantity of the bundle items that does not suffice to reap the discount. Although this did not turn out to be a major problem in our data set,[16] further research could refine the modeled relation between purchase amounts and the validity of the bundle discount.

In addition, we fail to account for at least two compelling phenomena in our model. First, we ignore the impact of the bundle's price/discount presentation because of the lack of variance in this characteristic. However, an important stream of experimental research (e.g., Yadav and Monroe 1993) documents the existence of semantic price framing effects on bundle perceptions. Second, our model structure does not fully account for the impact of variety seeking on consumers' bundle composition. In our approach, variety seeking within a shopping trip manifests only through the entropy of the baseline (i.e., in the absence of promotions) choice probabilities. Thus, our model predicts that for a given leverage parameter, consumers with equal baseline probabilities for the different bundle items are more likely to compose a diversified bundle than consumers with a high baseline probability for one single bundle item. Even if this makes intuitive sense, it largely ignores the interactions between a consumer's actual choices. That is, we do not allow for changes in a bundle item's marginal utility as a consumer selects units of another bundle item (see Chung and Rao 2003). Accurately modeling these interactions would enrich the analysis, because in addition to the leverage effect, variety seeking may be an important determinant of bundle composition.

Furthermore, the scope of our analysis is limited to the immediate impact on consumer decisions and unit sales. In view of recent academic interest in the impact of promotions over time (e.g., Pauwels, Hanssens, and Siddarth

[16]In 91.9% of the occasions on which a consumer buys enough in the category to qualify for the bundle discount, the purchase quantity for the bundle items corresponds to an integer multiple of the bundle quantity requirement.

2002), further research might assess the adjustment and long-term effects of promotional bundling. To this end, our model could be embedded in a multiple-period framework, in line with the work of Silva-Risso, Bucklin, and Morrisson (1999). Such analysis would also benefit from more refined purchase-feedback effects, which in our model are independent of whether the previous purchase was made under promotional (bundle) conditions or not (Zhang and Krishnamurthi 2004).[17] Future work also could address the impact of promotional bundles on revenue and profit and thus account for the often-cited price discriminatory character of bundling (Adams and Yellen 1976; Bakos and Brynjolfsson 2000).

Finally, our research uncovers bundle responses that require further exploration. Specifically, we observe that a confrontation with (overly stringent) bundle offers may induce consumers to reduce or drop their category purchases altogether. Whether this response is caused by reactance to managers' unreasonable promotion offers or by generalized reference price effects presents yet another worthwhile topic for additional study.

APPENDIX: ESTIMATED EQUATIONS

Choice Model

If $Q_{ht} < BQ_t$ or in the absence of bundle promotions, the choice model takes an MNL form, and the utilities are written as follows:

$$\text{(A1)}\quad U^{nb}_{hit} = u^t_i + u^b_i + u^f_i + u^s_i + \gamma^{tloy} \times TLOY_{hi} + \gamma^{bloy} \times BLOY_{hi} + \gamma^{floy} \times FLOY_{hi} + \gamma^{sloy} \times SLOY_{hi} + \gamma^{lt}_h \times LT_{hit} + \gamma^{lb}_h \times LB_{hit} + \gamma^{lf}_h \times LF_{hit} + \gamma^{ls}_h \times LS_{hit} + \gamma^{ud}_h \times UD_{it} + \gamma^{nb}_h \times BD_{it}.$$

When $Q_{ht} \geq BQ_t$, we use a nested MNL model with scale parameter μ_h and the following utilities:

$$\text{(A2)}\quad U^{b}_{hit} = u^t_i + u^b_i + u^f_i + u^s_i + \gamma^{tloy} \times TLOY_{hi} + \gamma^{bloy} \times BLOY_{hi} + \gamma^{floy} \times FLOY_{hi} + \gamma^{sloy} \times SLOY_{hi} + \gamma^{lt}_h \times LT_{hit} + \gamma^{lb}_h \times LB_{hit} + \gamma^{lf}_h \times LFh_{it} + \gamma^{ls}_h \times LS_{hit} + \gamma^{ud}_h \times UD_{it} + \gamma^{b}_h \times BD_{it},$$

where

$TLOY_{hi}$, $BLOY_{hi}$, $FLOY_{hi}$, $SLOY_{hi}$ = loyalty of consumer h to the type, brand, flavor, or size of item i, computed over the initialization period;

LT_{hit}, LB_{hit}, LF_{hit}, LS_{hit} = 1 if item i was the last type, brand, flavor, or size purchased by household h and 0 if otherwise;

UD_{it} = item i's per-unit discount on shopping trip t (cents/ounce);

BD_{it} = item i's bundle discount on trip t (cents/ounce). The total bundle discount, as recorded in our database, is first divided by BQ_t and then converted into cents/ounce for each bundle item;

$\{u^t_i\}$, $\{u^b_i\}$, $\{u^f_i\}$, $\{u^s_i\}$ = type, brand, flavor, and size intercepts for item i, to be estimated;

γ^{tloy}, γ^{bloy}, γ^{floy}, γ^{sloy} = parameters to be estimated; and

γ^{lt}_h, γ^{lb}_h, γ^{lf}_h, γ^{ls}_h, γ^{ud}_h, γ^{nb}_h, γ^{b}_h, μ_h = independently normally distributed coefficients (means and variances to be estimated).

The use of attribute-specific intercepts is in line with Fader and Hardie's (1996) work. Our approach to loyalty dynamics is consistent with that of Bucklin and Lattin (1991) and Silva-Risso, Bucklin, and Morrisson (1999).

Incidence/Quantity Model

Our purchase incidence and quantity models incorporate the same variables, but with different coefficients. Specifically, we model the purchase rate and category utility for consumer h as follows:

$$\text{(A3)}\quad \ln(\lambda_{ht}) = \beta^{ct}_h + \beta^{inc} \times INC_{ht} + \beta^{cr} \times CR_h + \beta^{inv} \times MCINV_{ht} + \beta^{cud}_h \times CUD_{ht} + \beta^{cbd}_h \times CBD_{ht} + \beta^{qp}_h \times QP_{ht} + \beta^{qp2}_h \times QP_{ht}{}^2, \text{ and}$$

$$\text{(A4)}\quad V_{ht} = \alpha^{ct}_h + \alpha^{inc} \times INC_{ht} + \alpha^{cr} \times CR_h + \alpha^{inv} \times MCINV_{ht} + \alpha^{cud}_h \times CUD_{ht} + \alpha^{cbd}_h \times CBD_{ht} + \alpha^{qp}_h \times QP_{ht} + \alpha^{qp2}_h \times QP_{ht}{}^2,$$

where

INC_{ht} = inclusive value of the whole category for consumer h on shopping trip t, not accounting for any promotional effects. Thus, $INC_{ht} = \ln[\Sigma^I_{i=1} \exp(U^{nb}_{hit})]|_{UD_{it}=0, BD_{it}=0}$;

CR_h = consumption rate for consumer h, computed over the initialization period;

$MCINV_{ht}$ = consumer h's mean-centered inventory on shopping trip t. Following Ailawadi and Neslin (1998) and Silva-Risso, Bucklin, and Morrisson (1999), we allow for flexible consumption in the inventory update equation. Thus, $INV_{ht} = INV_{h(t-1)} + q_{h(t-1)} - INV_{h(t-1)} \times CR_h/[CR_h + (INV_{h(t-1)})^\tau]$, where τ is the consumption flexibility parameter (to be estimated);

CUD_{ht} = the weighted average of all per-unit discounts available on shopping trip t, and $CUD_{ht} = \Sigma_i SKULOY_{hi} \times UD_{it}$, where the SKU loyalties are computed as the sum of attribute-specific loyalties ($TLOY_{hi}$, and so forth; see the choice model discussion) and rescaled to add to 1;

CBD_{ht} = category-level bundle discount, computed similarly to CUD_{ht};

[17]We thank an anonymous reviewer for this insight.

QP_{ht} = a bundle promotion's quantity pressure for consumer h on shopping trip t, $QP_{ht} = BQ_t/AVQ_h$, where AVQ_h is the consumer's average purchase quantity in the initialization period;

β^{inc}, β^{cr}, β^{inv}, α^{inc}, α^{cr}, α^{inv} = parameters to be estimated; and

β_h^{ct}, β_h^{cud}, β_h^{cbd}, β_h^{qp}, β_h^{qp2}, α_h^{ct}, α_h^{cud}, α_h^{cbd}, α_h^{qp}, α_h^{qp2} = independently normally distributed coefficients (means and variances to be estimated).

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