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Producers of consumer packaged goods often offer several package sizes of the same product and charge a lower unit price for a larger size. In this article, the authors investigate the "quantity-discount effect," or the phenomenon that consumers derive transaction utility from the unit price difference between a small and a large package size of the same product. The authors propose a modeling framework composed of a demand-side model and a supply-side model. The empirical results suggest that quantity-discount-induced gains or losses have a significant impact on consumer buying behavior. The authors also find a substantial amount of structural heterogeneity; that is, some consumers perceive quantity discounts as gains, whereas others perceive quantity discounts as losses. Conversely, the supply-side analysis suggests that manufacturers in the empirical application do not consider quantity-discount effects when setting prices. Through a series of policy experiments, the authors show that by accounting for quantity-discount-dependent consumer preferences, manufacturers can design more effective nonlinear pricing schemes and obtain greater profits.

Keywords: quantity-discount effects, perceived gains, perceived losses, nonlinear pricing, transaction utility

Quantity-Discount-Dependent Consumer Preferences and Competitive Nonlinear Pricing

Producers of consumer packaged goods, such as detergents, beers, and paper towels, often offer several package sizes of the same product and charge a lower unit price for a larger package. Such a nonlinear pricing schedule is commonly viewed as a price discrimination tool (e.g., Spence 1980). In this article, we investigate the "quantity-discount effect" induced by nonlinear pricing, or the phenomenon that consumers derive transaction utility (Thaler 1985) from the unit price difference between a small and a large package size of the same product. This transaction utility may arise in the form of perceived gains from purchasing the large package, derived from consumers' belief that they would need to spend more if they were paying the unit price of the small package, or this transaction utility may arise as perceived losses from purchasing the small package, derived from consumers' belief that they would have saved some money if they were paying the unit price of the large package.

To investigate this phenomenon of quantity-discount effects, we propose a model framework composed of a demand-side model and a supply-side model. On the demand side, consumers choose to buy one of the available product items or choose not to buy. Consumer utility from buying a product item includes acquisition utility and transaction utility. The acquisition utility depends on the brand, package size, price, feature, display, and state dependence. The transaction utility is derived from the quantity-discount effect. Consumers may perceive quantity discounts as gains from buying larger packages instead of smaller ones or as

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ISSN: 0022-2437 (print), 1547-7193 (electronic)

losses from buying smaller packages instead of larger ones. A unique aspect of our proposed demand model is that we incorporate structural heterogeneity; that is, we allow consumers to perceive quantity discounts as gains or losses with certain probabilities. This structural heterogeneity captures differences in consumer decision mechanisms while forming external reference prices. On the supply side, we model profit-maximizing decisions of both manufacturers and retailers. We infer channel members' interaction relationships and their pricing strategies by estimating and comparing a menu of supply-side specifications.

We apply the model to a household-level data set of canned light beer purchases. Our empirical results suggest that quantity-discount-induced gains or losses have a significant impact on consumer purchases. We also find a substantial amount of structural heterogeneity; that is, some consumers perceive quantity discounts as gains, whereas others perceive quantity discounts as losses. We find a greater impact of quantity-discount-induced losses than of quantity-discount-induced gains, consistent with the implications of prospect theory. Finally, we find that demand price elasticity driven by quantity-discount effects may be positive within brand and negative across brands, whereas demand price elasticity driven by price coefficients is always negative within brand and positive across brands. This result suggests that the presence of quantity-discount effects can mitigate interbrand price competition.

Despite the strong impact of quantity-discount effects on consumer buying behavior, our supply-side analysis suggests that manufacturers do not consider quantity-discount effects when setting prices. Such a discrepancy implies that current nonlinear pricing schemes are suboptimal, and manufacturers can potentially enhance their market performance by incorporating quantity-discount effects in pricing decisions. We explore this insight through a series of policy experiments. First, we find that manufacturers enjoy greater profits by considering quantity-discount effects in pricing. When both competitive manufacturers consider quantity-discount effects, both obtain greater profits. Second, we find that consumer quantity discount preferences (context effects) and consumer size preferences (self-selection effects) have different strategic implications for manufacturers. In particular, the presence of quantity-discount effects (context effects) hurts the profitability of naive manufacturers that ignore such effects in setting prices but can enhance profitability of strategic manufacturers that consider such effects. Conversely, an increased difference between consumers' preferences for the small and the large package sizes (self-selection effects) that hurts the profitability of naive manufacturers also hurts strategic manufacturers. Finally, we find that a stronger quantity-discount effect motivates a strategic manufacturer to set a smaller quantity discount. This finding suggests that the quantity discount tends to be larger than optimal in a nonlinear pricing system in which quantity-discount effects are ignored.

Collectively, our study makes three contributions. First, we develop a model framework to capture quantity-discount effects. On the demand side, we develop a choice model that simultaneously incorporates the impact of quantity-discount-induced gains and the impact of quantity-discount-induced losses through structural heterogeneity. We also develop a flexible supply-side model that allows for a variety of channel interaction relationships and channel pricing strategies. Second, we apply our model to scanner panel data of beers. We empirically demonstrate that with a nonlinear pricing scheme, quantity-discount-induced gains or losses significantly affect consumer purchases. We also reveal heterogeneity in consumer tendencies to perceive quantity discounts as gains or losses. Third, we empirically demonstrate that manufacturers in the beer industry ignore consumers' quantity-discount-dependent preferences and can benefit from incorporating such preferences in designing nonlinear pricing schemes. Our study furthers the understanding of consumer decision making in a nonlinear pricing setting, and our findings generate important insights that can help marketing managers design more effective nonlinear pricing schemes.

We organize the rest of the article as follows: We first provide a literature review and discuss how our study is related to and extends the literature. Next, we present our modeling framework. Then, we apply the proposed model to a scanner panel data set of light beer purchases and investigate the strategic implications of the quantity-discount effect for competitive nonlinear pricing. In the final section, we conclude with a discussion of the limitations of the research and possibilities for further research.

LITERATURE REVIEW

A vast amount of economics and marketing literature examines how nonlinear pricing can be designed as a price discrimination tool. On the theoretical side, product line models (Gerstner and Hess 1987; Spence 1980) assume that a monopolist offers an optimal set of package sizes and prices to sort self-selecting consumers in the most profitable way. Product line models then explain differences in package sizes and prices with consumer heterogeneity in consumption rates, storage costs, and transaction costs. Bundling models (Adams and Yellen 1976; Schmalensee 1982) view firms' offering multiple sizes of the same product as a mixed bundling strategy and show that this strategy can effectively sort consumers into groups, allowing a monopolist to profitably price discriminate. In related work, Salop (1977) argues that consumers are different in their searching efficiencies or costs in finding the best deal, and so a "noisy" monopolist will use a temporary price change to separate consumers of different "searching efficiencies" into different groups to permit price discrimination.

Many empirical studies also exist on nonlinear pricing. Cohen (2002) examines nonlinear pricing by manufacturers in the paper towel industry and finds that a substantial portion of the variation in unit prices across package sizes can be attributed to price discrimination. Complementing Cohen's work, our study suggests that the quantity-discount effect can be another driving force for manufacturers' nonlinear pricing practices. Allenby and colleagues (2004) propose a demand-side model to incorporate consumer choices of package sizes. However, their model does not take into account quantity-discount-induced transaction utility or market competition. Iyengar (2004) examines how the nonlinear pricing structure of a monopolistic wireless service provider affects consumer choices of calling plans. Lambrecht, Seim, and Skiera (2007) study how consumers' demand uncertainty for cell phone usage drives their choices among different nonlinear pricing plans. Different from these two articles, we study how quantity-discount-induced gains or losses influence consumer choices among nonlinearly priced packaged goods. Khan and Jain (2005) examine the over-the-counter analgesic category and find that a retailer can achieve greater profitability by combining two price discrimination tools, nonlinear pricing and store-level pricing. While Khan and Jain examine a monopolistic retailer's nonlinear pricing incentive, we focus on manufacturers' nonlinear pricing incentive in a competitive market.

Our work is also related to the vast literature on reference price, especially the external reference price (for a comprehensive review, see Mazumdar, Raj, and Sinha 2005). Using data from the yogurt category, Mayhew and Winer (1992) demonstrate that consumers use both internal reference points ("memory-resident" prices of the product) and external reference points (regular prices of the product) to evaluate prices when making decisions. Using data from the refrigerated orange juice category, Hardie, Johnson, and Fader (1993) demonstrate that losses relative to the reference brand have a greater impact than gains. Rajendran and Tellis (1994) examine scanner panel data of saltines and conclude that consumers use the lowest price in the category as an external reference price. In addition, some research shows that consumers can be further segmented into an internal reference price segment and an external reference price segment (e.g., Kumar, Karande, and Reinartz 1998; Mazumdar and Papatla 1995; Moon, Russell, and Duvvuri 2006). Researchers have also found heterogeneity in consumer tendencies to perceive gains or losses with respect to the reference price (e.g., Arora, Kopalle, and Kannan 2001; Erdem, Mayhew, and Sun 2001). Our study is different from this stream of literature in two important ways. First, we examine the reference price effect in the context of quantity discounts and nonlinear pricing. Second, we investigate strategic implications of the quantity-discount effect for manufacturers' nonlinear pricing practices.

Our study is also related to research on product line management (Draganska and Jain 2006; Kivetz, Netzer, and Srinivasan 2004). Our study complements this research stream by focusing on product lines composed of different package sizes and on manufacturer strategies in pricing such product lines.

Finally, our study is related to the literature on context-dependent consumer preferences (Huber, Payne, and Puto 1982; Simonson 1989; Simonson and Tversky 1992; Tversky and Simonson 1993). While this stream of research is typically conducted in a laboratory setting, we use scanner panel data collected in the real grocery environment.

MODEL DEVELOPMENT

We develop a model framework composed of a demand-side model and a supply-side model to investigate the quantity-discount effect. We discuss each in turn.

Demand-Side Model

We develop a choice model to capture the quantity-discount effect, controlling for consumer structural heterogeneity, consumer preference heterogeneity, and unobserved demand shocks. Following Guadagni and Little (1983) and Fader and Hardie (1996), we treat the same product in different package sizes as different alternatives. Consumers choose either one of the inside options (a set of closely related product items) that provides the highest utility or the outside good option (no purchase).

We specify the utility function of household h (h = 1, ..., H) for alternative j (j = 1, ..., J) with brand b_j and package size z_j at week t (t = 1, ..., T) as follows:

$$U_{hjt} = X_{jt}'\beta_h + \alpha_h p_{jt} + \Delta_{jt}'\gamma_h + \xi_{jt} + \varepsilon_{hjt}. \quad (1a)$$

We specify the outside option (J + 1)'s utility as follows:

$$U_{h,j+1,t} = \varepsilon_{h,j+1,t}. \quad (1b)$$

In Equation 1a, x_{jt} contains observed characteristics of the product item, including brand dummies, package size dummies, feature, display, brand-specific state dependence (whether the same brand was purchased in the most recent purchase), and size-specific state dependence (whether the same package size was purchased in the most recent purchase); p_{jt} denotes the product's shelf price (the unit price times the total units in the package); and β_h and α_h are the corresponding coefficients. In Equation 1a, we can interpret $x_{jt}'\beta_h + \alpha_h p_{jt}$ as consumer h's acquisition utility from purchasing product item j at time t.

We capture the consumer's transaction utility with $\Delta_{jt}'\gamma_h$, where $\Delta_{jt} = (\delta_{jt}^1 z_j, ..., \delta_{jt}^d z_j)'$ is a vector of consumers' perceived gains (or losses) derived from quantity discounts for buying alternative j at time t; γ_h is the vector of corresponding coefficients of quantity-discount-induced gains or losses; and d is the number of quantity-discount effects, or the number of cross-size price comparisons consumers can potentially make within a brand. In particular, when there are Z different package sizes within each brand, $d = C_Z^2$, where C_Z^2 denotes the total number of combinations of choosing two of Z objects. For example, if there are Z = 3 different package sizes—small, medium, and large—consumers can have $d = C_3^2$ different perceived quantity discounts: (1) between the small and the medium size, (2) between the medium and the large size, and (3) between the small and the large size. We then have $\gamma_h = (\gamma_h^1, \gamma_h^2, \gamma_h^3)$, where γ_h^1, γ_h^2, γ_h^3 represents the coefficients of quantity-discount effects defined in points 1–3, respectively.

Consumers may perceive quantity discounts as gains from buying larger packages instead of smaller ones or as losses from buying smaller packages instead of larger ones. To model quantity-discount effects as perceived gains, we define δ_{jt}^m as the unit price difference in pair m (m = 1, ..., d) of same-brand products, if item j is of the larger size identified in the paired comparison. Otherwise, $\delta_{jt}^m = 0$. Thus, $\Delta_{jt} = (\delta_{jt}^1 z_j, ..., \delta_{jt}^d z_j)'$ is a vector of a consumer's perceived gains from buying product alternative j over various smaller packages of the same brand. For example, consider a brand product with three package sizes, z_{small}, z_{medium}, and z_{large}, priced at $p_{small,t}$, $p_{medium,t}$, and $p_{large,t}$, respectively. We let m = 1 denote the pair of the brand's small and medium sizes, m = 2 denote the pair of its medium and large sizes, and m = 3 denote the pair of its small and the large sizes. We write δ_{jt}^m for the three package sizes of the brand product, modeled as quantity-discount-induced gains, as follows:

$$\delta_{small,t}^1 = \delta_{small,t}^2 = \delta_{small,t}^3 = 0, \quad (2a)$$

(2b) $$\delta^1_{\text{medium},t} = \frac{p_{\text{small},t}}{z_{\text{small}}} - \frac{p_{\text{medium},t}}{z_{\text{medium}}};$$

$$\delta^2_{\text{medium},t} = \delta^3_{\text{medium},t} = 0, \text{ and}$$

(2c) $$\delta^1_{\text{large},t} = 0; \delta^2_{\text{large},t} = \frac{p_{\text{medium},t}}{z_{\text{medium}}} - \frac{p_{\text{large},t}}{z_{\text{large}}};$$

$$\delta^3_{\text{large},t} = \frac{p_{\text{small},t}}{z_{\text{small}}} - \frac{p_{\text{large},t}}{z_{\text{large}}}.$$

Conversely, to model quantity-discount effects as perceived losses, we define δ^m_{jt} as the unit price difference in pair m (m = 1, …, d) of same-brand products, if item j is of the smaller size identified in the paired comparison. Otherwise, $\delta^m_{jt} = 0$. Thus, $\Delta_{jt} = (\delta^1_{jt}z_j, \ldots, \delta^d_{jt}z_j)'$ is a vector of a consumer's total perceived losses from buying product alternative j over various larger packages of the same brand. In the previous example, δ^m_{jt} for the three package sizes, modeled as quantity-discount-induced losses, are as follows:

(3a) $$\delta^1_{\text{small},t} = \frac{p_{\text{small},t}}{z_{\text{small}}} - \frac{p_{\text{medium},t}}{z_{\text{medium}}}; \delta^2_{\text{small},t} = 0;$$

(3b) $$\delta^1_{\text{medium},t} = 0; \delta^2_{\text{medium},t} = \frac{p_{\text{medium},t}}{z_{\text{medium}}} - \frac{p_{\text{large},t}}{z_{\text{large}}}; \delta^3_{\text{medium},t} = 0, \text{ and}$$

(3c) $$\delta^1_{\text{large},t} = \delta^2_{\text{large},t} = \delta^3_{\text{large},t} = 0.$$

Previous literature has suggested that some consumers tend to focus more on gains, whereas others tend to focus more on losses (Arora, Kopalle, and Kannan 2001; Erdem, Mayhew, and Sun 2001). To capture this phenomenon, we integrate the gain-focused model and the loss-focused model through structural heterogeneity (Kamakura, Kim, and Lee 1996) as follows:

(4) $$l_h(\theta^G_h, \theta^L_h \mid Y_{h1}, \ldots, Y_{hT}) = \varphi \prod_{t=1}^{T} \text{pr}(Y_{ht} \mid \text{gains}, \theta^G_h) + (1-\varphi)\prod_{t=1}^{T} \text{pr}(Y_{ht} \mid \text{losses}, \theta^L_h).$$

In Equation 4, l_h stands for the likelihood of household h's observed purchase history, denoted by Y_{h1}, …, Y_{hT}. Here, Y_{ht} is a J + 1 vector of dummies indicating which product item household h purchased at time t, in which the first J dummies indicate the household's purchase on the J inside options and the (J + 1)th dummy indicates the household's purchase on the outside option. Equation 4 suggests that household h has a probability Φ of being a gain-focused consumer and a probability $1 - \Phi$ of being a loss-focused consumer; $\text{pr}(Y_{ht} \mid \text{gains}, \theta^G_h)$ denotes the choice probability of household h's purchase at time t if it is gain focused; and $\text{pr}(Y_{ht} \mid \text{gains}, \theta^L_h)$ denotes the choice probability of household h's purchase at time t if it is loss focused. Furthermore, we model heterogeneous consumer preferences by adopting the random coefficient specification. We add a normal prior distribution on θ^G_h and θ^L_h:

(5a) $$\theta^G_h \sim \text{MVN}(\overline{\theta^G}, D^G), \text{ and}$$

(5b) $$\theta^L_h \sim \text{MVN}(\overline{\theta^L}, D^L),$$

where $\overline{\theta^G}$ ($\overline{\theta^L}$) are the average preference parameters for gain-focused (loss-focused) consumers, and D^G (D^L) is the heterogeneity variance–covariance matrix for gain-focused (loss-focused) consumers. Note that we model individual consumers' tendencies (or probabilities) to perceive quantity discounts as either gains or losses. This means that in a single choice context, a consumer perceives quantity discounts as either gains or losses but not both at the same time. For this reason, we are able to identify gains and losses separately in our proposed model.

Consumer preferences may depend on unobserved product characteristics, or common demand shocks that cause changes in tastes across all consumers but are not observed by the researcher (Villas-Boas and Winer 1999). Examples of common demand shocks include certain aspects of products that are difficult to quantify, such as prestige and reputation (Berry, Levinsohn, and Pakes 1995); consumer taste changes induced by other marketing-mix variables, such as in-store effects, advertising, or coupon availability (Besanko, Gupta, and Jain 1998); and seasonal effects. In our proposed model, the unobserved demand shock is captured by ξ_{jt}, the product-and-time-specific effect on utility that affects all households but is unobserved by the researcher. We allow ξ_{jt} to be correlated across product alternatives.

Assuming that ε_{hjt} is distributed i.i.d. with Type II extreme value probability density, we can write the choice probability q. If household h is gain focused, we have the following:

(6a) $$q_{hjt} = \frac{\exp(x_{hjt}'\beta^G_h + \alpha^G_h p_{jt} + \Delta^G_{jt}{}'\gamma^G_h + \xi_{jt})}{1 + \sum_{l=1}^{J} \exp(x_{hlt}'\beta^G_h + \alpha^G_h p_{lt} + \Delta^G_{lt}{}'\gamma^G_h + \xi_{lt})},$$

for j = 1, ..., J and

(6b) $$q_{hjt} = \frac{1}{1 + \sum_{l=1}^{J} \exp(x_{hlt}'\beta^G_h + \alpha^G_h p_{lt} + \Delta^G_{lt}{}'\gamma^G_h + \xi_{lt})},$$

for j = J + 1.

If household h is loss focused, we have the following:

(6c) $$q_{hjt} = \frac{\exp(x_{hjt}'\beta^L_h + \alpha^L_h p_{jt} + \Delta^L_{jt}{}'\gamma^L_h + \xi_{jt})}{1 + \sum_{l=1}^{J} \exp(x_{hlt}'\beta^L_h + \alpha^L_h p_{lt} + \Delta^L_{lt}{}'\gamma^L_h + \xi_{lt})},$$

for j = 1, ..., J, and

(6d) $$q_{hjt} = \frac{1}{1 + \sum_{l=1}^{J} \exp(x_{hlt}'\beta^L_h + \alpha^L_h p_{lt} + \Delta^L_{lt}{}'\gamma^L_h + \xi_{lt})},$$

for j = J + 1.

We adopt a flexible covariance structure across choice alternatives to remove IIA (independence from irrelevant alternatives) concerns in a standard logit model. First, we allow unobserved demand shocks to be correlated across alternatives at time t. Second, we allow preferences for choice alternatives to be correlated for household h, by allowing brand and package coefficients to be all correlated. Taking these two specifications together, we obtain a flexible correlation structure across choice alternatives for each individual at each period (similar to a probit specification), thus eliminating the potential IIA concerns.

Supply-Side Model

We develop a supply-side model in which manufacturers set wholesale prices and retailers set retail prices, taking into account current demand and cost conditions. Theoretical literature on nonlinear pricing examines firms' simultaneous decisions of package sizes and prices (e.g., Spence 1980). In business practice, however, package size changes are much less frequent than price changes, possibly because package size changes are associated with costly and complex changes in production processes. In this study, we model channel members' optimal pricing decisions, taking package sizes as given.

We empirically infer the nature of channel interactions and channel members' pricing strategies by comparing a menu of supply-side specifications and picking the best-fitting model. We consider supply-side models with different types of channel interaction relationships. For the horizontal interaction between manufacturers, we consider Bertrand competition and tacit collusion. For the vertical interaction between manufacturers and retailers, we test vertical Nash and manufacturer Stackelberg. We also consider various possible channel pricing strategies. For the consideration of quantity-discount-dependent consumer preferences, we test channel pricing schemes with and without incorporating quantity-discount effects. For the consideration of state-dependent consumer preferences, we examine channel pricing strategies with and without incorporating state dependence. In total, we compare 2 (manufacturer interactions) × 2 (manufacturer–retailer interactions) × 2 (quantity-discount effect considerations) × 2 (state dependence considerations) = 16 different specifications of the supply-side model.

We model retailers as local monopolists, following Besanko, Gupta, and Jain (1998) and Sudhir (2001). Each retailer decides optimal retail prices to maximize its category profit. At time t, a retailer R carrying J product items chooses the optimal retail prices $p_t = (p_{1t}, ..., p_{Jt})$ to maximize its category profit:

$$\text{(7)} \qquad \underset{p_t}{\text{Max}}\, \pi_t^R = \sum_{j=1}^{J} (p_{jt} - w_{jt} - rc_{jt}) s_{jt}(p_t) M^R,$$

where M^R is the size of retailer R's local market, w_{jt} is the wholesale price of product j set by its manufacturer, rc_{jt} is the retailer's marginal cost for selling product j, and $s_{jt}(p_t)$ is the market share of product j at prices p_t. We can then obtain the retailer's profit margin $p_t - w_t - rc_t$ by empirically solving first-order conditions of its profit maximization problem (Equation 7).

The J product items the retailer carries come from F different manufacturers, with manufacturer f (f = 1, ..., F) producing J_f different sizes of its product, $\Sigma_{f=1}^{F} J_f = J$. Manufacturer f sets wholesale prices $w_t^f = (w_{gt})_{g \in \{1, 2, ..., J_f\}}$ to maximize its product line profit π_t^f:

$$\text{(8)} \qquad \underset{w_t^f}{\text{Max}}\, \pi_t^f = \sum_{g=1}^{J_f} (w_{gt} - mc_{gt}) s_{gt}(p_{gt}) M^R, \forall f \in \{1, ..., F\},$$

where mc_{gt} is the marginal production cost of product item g (g = 1, …, J_f). Manufacturer margin $w_t - mc_t$ can then be obtained by empirically solving the first-order conditions of the manufacturer profit maximization problem (Equation 8).

We formulate the retail prices p_t as containing three components: (1) marginal production and selling costs, $mc_t + rc_t$; (2) retailer margins, $p_t - w_t - rc_t$; and (3) manufacturer margins, $w_t - mc_t$. We provide a detailed derivation of the price equation in the Appendix.

AN EMPIRICAL APPLICATION

We apply our proposed model to a data set of light beer purchases collected from five retail stores in Eau Claire, Wis., by Information Resources Inc. (Bronnenberg, Kruger, and Mela 2008). We focus on six items whose purchase frequency accounts for 85% of total canned beer purchases in this market: Miller Lite 144 ounce (oz.), 216 oz., and 288 oz. and Bud Light 144 oz., 216 oz., and 288 oz. In this case, the quantity-discount effect may exist for each brand (1) between the 144 oz. pack and the 216 oz. pack, (2) between the 216 oz. pack and the 288 oz. pack, and (3) between the 144 oz. pack and the 288 oz. pack. Our panel data cover 104 consecutive weeks in 2004 and 2005. We select 168 panelists who made a total of 4702 purchases during the study period, among which 2420 purchases are on the six product items in which we are interested. Table 1 summarizes the promotion frequency and choice shares of the six items.

Before proceeding with model estimation, we run linear regressions to check the associations between unit sales and quantity discounts from the store-level aggregate data. As Table 2, Panel A, shows, the unit sales of a small package (Bud Light 144 oz.) is significantly negatively ($p < .001$) associated with the magnitude of the quantity discount between the small and the large packages of the same brand (between Bud Light 144 oz. and 216 oz.). Conversely, as Table 2, Panel B, shows, the unit sales of a large package (Bud Light 216 oz.) is significantly positively ($p < .001$) associated with the magnitude of the quantity discount (between Bud Light 144 oz. and 216 oz.). These data patterns are consistent with the notion of quantity-discount effects.

We employ a two-stage estimation approach, following Che, Sudhir, and Seetharaman (2007) and Pancras and Sudhir (2007). First, we estimate the demand-side model using the Bayesian approach, correcting for potential price endogeneity. Conditional on the demand estimates, we compute

Table 1
DATA DESCRIPTION

Item	*Price Per Ounce (Cents)*	*Feature Frequency (%)*	*Display Frequency (%)*	*Choice Share (%)*
Bud Light 144 oz.	5.80	1.15	1.54	1.72
Bud Light 216 oz.	5.17	15.19	23.27	5.56
Bud Light 288 oz.	4.96	25.38	55.19	9.76
Miller Lite 144 oz.	5.65	6.92	10.96	4.99
Miller Lite 216 oz.	5.18	13.65	23.85	10.08
Miller Lite 288 oz.	4.96	25.58	52.88	19.35

Table 2

REGRESSION RESULTS FROM THE AGGREGATE DATA

A: Dependent Variable: Total Units of Bud Light 144 oz. Sold				
	Coefficients	*SE*	*t-Statistic*	p-*Value*
Intercept	10.201	.272	37.463	.000
Price difference between Bud Light 144 oz. and 216 oz. (cents per ounce)	–2.864	.351	–8.153	.000
R^2 = 11.5%				

B: Dependent Variable: Total Units of Bud Light 216 oz. Sold				
	Coefficients	*SE*	*t-Statistic*	p-*Value*
Intercept	8.540	.794	10.755	.000
Price difference between Bud Light 144 oz. and 216 oz. (cents per ounce)	12.077	1.024	11.791	.000
R^2 = 21.3%				

Notes: The regression checks how the unit sale of Bud Light 144 oz. (Panel A) and Bud Light 216 oz. (Panel B) is associated with the quantity discount between Bud Light 144 oz. and Bud Light 216 oz.

manufacturer and retailer margins and estimate cost equations under alternative supply-side specifications. Second, we choose the best-fitting supply-side model.

This limited information approach has two advantages. First, this approach enables us to obtain consistent demand estimates without making assumptions about the supply-side model. This feature is particularly helpful when we have 16 supply-side specifications to test. In contrast, in a full information approach, any misspecification on the supply side will bias demand estimates (Yang, Chen, and Allenby 2003). Second, because of the complexity of our proposed demand-side model, simultaneously estimating demand and supply will lead to intractable solutions.

Demand-Side Model Estimation and Results

Profit-maximizing firms take into account the unobserved demand shock ξ_{jt} while setting prices, which causes the price endogeneity problem. Not controlling for such price endogeneity will lead to biased estimates. Following Villas-Boas and Winer (1999), we denote p^f_{jt} as price instruments and write the observed price as a function of price instruments:

$$p_{jt} = \lambda_{j0} + \lambda_{j1} p^s_{jt} + \eta_{jt}. \quad (9)$$

We use lagged prices as instruments (Villas-Boas and Winer 1999; Yang, Chen, and Allenby 2003) because they are often highly correlated with the current-period price and weakly correlated with the current-period demand shock. For robustness testing, we also used as instruments current-period prices from a different market (Che, Sudhir, and Seetharaman 2007) and recovered the same estimates. To capture potential price endogeneity, we allow demand shock ξ_{jt} to be correlated with supply-side error η_{jt}:

$$(\xi_{1t}, ..., \xi_{Jt}, \eta_{1t}, ..., \eta_{Jt})' \sim \text{MVN}(0, \Sigma). \quad (10)$$

Given the complexity of the demand-side model, we adopt the Bayesian estimation approach. Compared with the classical estimation approach, the Bayesian estimation approach has advantages, such as results being insensitive to choice of starting values; ability of facilitating exact, finite-sample inferences and not relying on asymptotic results, and easy computation for complicated models (Rossi and Allenby 2003).

We compare four demand-side model specifications, including our proposed model and three benchmark models. In Model 1, we model preference heterogeneity and control for price endogeneity, but we do not model the quantity-discount effect. In Model 2, we extend Model 1 by modeling quantity-discount-induced gains. In Model 3, we extend Model 1 by modeling quantity-discount-induced losses. Finally, in Model 4, our proposed model, we extend the three benchmark models by modeling consumer structural heterogeneity in perceiving quantity-discount effects; that is, each household has certain probabilities of perceiving quantity discounts as gains versus as losses. We report the model fit of the four models measured in the log-marginal density in Table 3. As Table 3 shows, the proposed model (Model 4) outperforms the other three benchmark models. This finding highlights the importance of modeling quantity-discount effects and consumer heterogeneity in perceiving quantity discounts as gains or losses.

Because our proposed model outperforms the benchmark models, we discuss only the estimation results based on this model. Five sets of findings emerge from our analysis. First, we find significant quantity-discount effects, as Table 4 shows. For gain-focused consumers, we find a significant, positive quantity-discount effect on the pair of the 216 oz. pack and the 288 oz. pack; for loss-focused consumers, we find significant, negative quantity-discount effects on all three size pairs. In addition, the impact of quantity-discount-induced losses is greater than that of quantity-discount-induced gains, consistent with the implications of the prospect theory (Hardie, Johnson, and Fader 1993).

Second, we find similarities and differences in consumer preferences between the gain-focused group and the loss-focused group. As Table 4 shows, on average, consumers in both groups prefer Miller Lite to Bud Light. On package size, gain-focused consumers tend to have stronger preferences for large packages (the 216 oz. pack and the 288 oz. pack) than loss-focused consumers. On marketing variables, gain-focused consumers are more price sensitive and more responsive to feature than loss-focused consumers. For both groups, we find significant, positive state dependence

Table 3

DEMAND-SIDE MODEL COMPARISON

Model Specification	*Model 1*	*Model 2*	*Model 3*	*Model 4 (Proposed Model)*
Preference heterogeneity	x	x	x	x
Price endogeneity	x	x	x	x
Quantity-discount-induced gains		x		
Quantity-discount-induced losses			x	
Structural heterogeneity (both gains and losses)				x
Log-marginal (Bayesian information criterion)	–5839.15	–5769.32	–5778.46	–5592.48

Table 4

MEAN LEVEL PREFERENCE PARAMETER ESTIMATES ($\bar{\beta}$) FROM PROPOSED DEMAND-SIDE MODEL

	Gain-Focused Consumers		*Loss-Focused Consumers*	
	Posterior Mean	*Posterior Standard Deviation*	*Posterior Mean*	*Posterior Standard Deviation*
Bud Light	**–1.259**	.356	**–1.807**	.376
Miller Lite	–.208	.372	.015	.275
144 oz.	**–3.095**	.214	**–3.339**	.207
216 oz.	–.166	.153	**–1.032**	.262
288 oz.	**2.356**	.211	**1.105**	.327
Price	**–.532**	.037	**–.430**	.034
Feature	**.283**	.134	.098	.122
Display	**.235**	.125	**.237**	.117
Gain/loss 144 oz.–216 oz.	–.078	.096	**–.584**	.182
Gain/loss 216 oz.–288 oz.	**.175**	.063	**–.271**	.109
Gain/loss 144 oz.–288 oz.	–.041	.086	**–.572**	.197
Brand-specific state dependence	**3.382**	.311	**3.361**	.283
Size-specific state dependence	**.667**	.249	**.536**	.222

Notes: Bold indicates a statistically significant result.

effects with respect to brands and with respect to sizes. In addition, the coefficient of brand-specific state dependence is six times as large as that of the size-specific state dependence, suggesting stronger consumer inertia in brands than in sizes.

Third, we find significant structural heterogeneity in consumers' quantity-discount-dependent preferences. Our results suggest that close to 48% of the sample are gain-focused consumers, and the remaining 52% are loss-focused. We also find substantial consumer preference heterogeneity, as we report in Table 5.

Fourth, we find significant unobserved demand shocks. Table 6 reports our estimated variance–covariance matrix of demand shocks. As Table 6 shows, all diagonal elements and many off-diagonal elements are significant. This finding indicates the importance of modeling the covariance of demand shocks across choice alternatives.

Table 5

ESTIMATES FOR UNOBSERVED CONSUMER PREFERENCE HETEROGENEITY (D) FROM PROPOSED DEMAND-SIDE MODEL

	Gain-Focused Consumers		*Loss-Focused Consumers*	
	Posterior Mean	*Posterior Standard Deviation*	*Posterior Mean*	*Posterior Standard Deviation*
Bud Light	**4.869**	1.023	**5.231**	1.085
Miller Lite	**6.296**	1.709	**3.775**	1.011
144 oz.	**1.626**	.554	**1.517**	.339
216 oz.	**.839**	.219	**.617**	.171
288 oz.	**1.396**	.344	**2.101**	.536
Price	**.126**	.025	**.117**	.022
Feature	**.721**	.174	**.532**	.120
Display	**.601**	.164	**.538**	.121
Gain/loss 144 oz.–216 oz.	**.344**	.079	**.857**	.263
Gain/loss 216 oz.–288 oz.	**.324**	.071	**.473**	.102
Gain/loss 144 oz.–288 oz.	**.308**	.061	**1.574**	.409
Brand-specific state dependence	**4.812**	1.017	**3.940**	.805
Size-specific state dependence	**2.718**	.671	**2.147**	.518

Notes: Bold indicates a statistically significant result.

Table 6

DEMAND SHOCK VARIANCE–COVARIANCE MATRIX ESTIMATE

	Bud Light			*Miller Lite*		
	144 oz.	*216 oz.*	*288 oz.*	*144 oz.*	*216 oz.*	*288 oz.*
Bud Light						
144 oz.	**.877**	.062	**.153**	**.164**	.033	.076
	(.253)	(.157)	**(.039)**	**(.048)**	(.131)	(.096)
216 oz.		**.623**	.067	.027	**.137**	–.010
		(.139)	(.071)	(.116)	**(.048)**	(.078)
288 oz.			**.366**	**.098**	.040	.040
			(.081)	**(.024)**	(.083)	(.054)
Miller Lite						
144 oz.				**.639**	**.107**	–.005
				(.189)	**(.045)**	(.083)
216 oz.					**.645**	.013
					(.130)	(.071)
288 oz.						**.364**
						(.075)

Notes: Bold indicates a statistically significant result.

Fifth, we find significant price endogeneity. Table 7 shows our estimates for the covariance between demand shocks and price regression error terms, which are significant for all six product items, except for Bud Light 144 oz.. This finding is consistent with the literature (Villas-Boas and Winer 1999; Villas-Boas and Zhao 2005).

In our proposed model, we adopt a flexible variance–covariance specification similar to a probit model to remove possible IIA concerns. To obtain further confidence in our findings of quantity-discount effects, we also test the nested logit specification as an alternative way to account for IIA. Specifically, we test two nested structures with different consumer decision sequences, incidence–brand–size and incidence–size–brand, and find that our proposed model outperforms both.

Note that the presence of quantity-discount effects changes the substitution pattern between product alternatives. Without quantity-discount effects, a product item with an increased price will lose demand to other package sizes and other brands. With quantity-discount effects, however, the lost demand is more likely to shift to other package sizes of the same brand. To understand this insight, we decompose price elasticity with respect to each brand's market share into two components, one driven by price coefficients

Table 7

COVARIANCE ESTIMATE OF THE DEMAND SHOCKS AND SUPPLY EQUATION ERRORS (BY ITEMS)

	Posterior Mean	*Posterior Standard Deviation*
Bud Light		
144 oz.	.047	.038
216 oz.	**.116**	.041
288 oz.	**.108**	.035
Miller Lite		
144 oz.	**.132**	.049
216 oz.	**.154**	.057
288 oz.	**.153**	.059

Notes: Bold indicates a statistically significant result.

and one driven by quantity-discount effects. As Table 8, Panel A, shows, demand-price elasticity driven by price coefficients is always negative within brand and positive across brands. Notably, demand-price elasticity driven by quantity-discount effects can be positive within brand and negative across brands. In other words, the presence of quantity-discount effects can mitigate interbrand price competition. We also decompose price elasticity with respect to package sizes in Table 8, Panel B. The result shows that demand price elasticity induced by both price coefficients and quantity-discount effects is negative within the same size and positive across different sizes.

Supply-Side Model Estimation and Results

On the basis of the demand-side estimates, we proceed to compute manufacturer and retailer margins and estimate the cost equation. Our demand-side estimation using the Bayesian approach generates coefficient estimates for each individual household, which we use to simulate the aggregate market demand (Dubé et al. 2008). We empirically solve for the marginal production and selling costs for product j in store R at period t. We assume that the marginal production and selling costs for a product item j is composed of store-specific costs, brand-specific costs, size-specific costs, and other production costs. We then formulate the cost equation as follows:

$$(11) \qquad mc^{f}_{jt} + rc^{R}_{jt} = c_R STORE_{jt} + c_f BRAND_{jt} + c_z SIZE_{jt} + \sum c_k INPUT^{k}_{jt} + \vartheta_{jt},\ j = 1, ..., J$$

In Equation 11, $STORE_{jt}$, $BRAND_{jt}$, and $SIZE_{jt}$ are dummy variables; $INPUT_{jt}^{k}$ is the input price of ingredient k; and c_R, c_f, c_z, and c_k are cost coefficients to be estimated.

Table 8

ESTIMATED DEMAND PRICE ELASTICITY

	Total Elasticity		*From Price Coefficient*		*From Quantity-Discount Effect 144 oz.–216 oz.*		*From Quantity-Discount Effect 216 oz.–288 oz.*		*From Quantity-Discount Effect 144 oz.–288 oz.*	
	Estimate	*SE*	*Estimate*	*SE*	*Estimate*	*SE*	*Estimate*	*SE*	*Estimate*	*SE*
A: Own-Brand Elasticity										
Bud Light										
144 oz.	**–4.946**	.018	**–3.982**	.006	**–.661**	.016			**–.306**	.007
216 oz.	**–1.716**	.039	**–4.060**	.028	**.616**	.015	**1.733**	.045		
288 oz.	**–5.985**	.029	**–4.673**	.017			**–1.586**	.043	**.265**	.008
Miller Lite										
144 oz.	**–6.909**	.064	**–3.899**	.013	**–1.729**	.045			**–1.278**	.036
216 oz.	**–2.768**	.054	**–4.341**	.015	**1.684**	.054	**–.101**	.029		
288 oz.	**–3.120**	.035	**–4.442**	.021			**.146**	.030	**1.172**	.039
B: Across-Brand Elasticity										
Bud Light										
144 oz.	**.008**	.000	**.006**	.000	**.001**	.000			**.0004**	.0000
216 oz.	**.030**	.002	**.059**	.001	**–.001**	.000	**–.028**	.001		
288 oz.	**.122**	.002	**.097**	.001			**.026**	.001	**–.0004**	.0000
Miller Lite										
144 oz.	**.023**	.001	**.018**	.000	**.003**	.000			**.002**	.000
216 oz.	**.046**	.006	**.112**	.002	**–.003**	.000	**–.063**	.005		
288 oz.	**.258**	.006	**.207**	.004			**.053**	.002	**–.002**	.000
C: Same-Size Elasticity										
Bud Light										
144 oz.	**–4.978**	.018	**–4.013**	.006	**–.661**	.015			**–.306**	.008
216 oz.	**–5.380**	.015	**–4.371**	.017	**–.001**	.000	**–1.013**	.014		
288 oz.	**–7.935**	.020	**–5.279**	.009			**–2.647**	.027	**–.0004**	.0000
Miller Lite										
144 oz.	**–6.987**	.067	**–3.932**	.012	**–1.757**	.041			**–1.300**	.042
216 oz.	**–5.917**	.008	**–4.516**	.012	**–.019**	.002	**–1.385**	.011		
288 oz.	**–6.213**	.021	**–5.024**	.018			**–1.178**	.011	**–.007**	.001
D: Cross-Size Elasticity										
Bud Light										
144 oz.	**.041**	.000	**.038**	.000	**.002**	.000			**.001**	.000
216 oz.	**3.684**	.047	**.369**	.005	**.618**	.017	**2.713**	.036		
288 oz.	**2.068**	.013	**.706**	.011			**1.095**	.016	**.266**	.008
Miller Lite										
144 oz.	**.100**	.005	**.054**	.001	**.027**	.002			**.020**	.002
216 oz.	**3.205**	.064	**.286**	.005	**1.689**	.043	**1.221**	.015		
288 oz.	**3.339**	.036	**.790**	.010			**1.375**	.014	**1.178**	.042

Notes: The empty cells are not applicable. Price elasticity with respect to each brand's market share is decomposed into what is driven by price coefficients and what is driven by quantity-discount effects. Standard errors are obtained through bootstrapping. Standard errors are obtained through bootstrapping. Bold indicates a statistically significant result.

For cost shifters, we collect monthly Producer Price Index for barley from the U.S. Bureau of Labor Statistics. We then smooth the monthly data to obtain weekly cost data. The term ϑ_{jt} is the random error distributed normally with zero mean and a full covariance matrix V_{ϑ}. We estimate cost equations through iterated feasible generalized least squares to obtain maximum likelihood estimates (Greene 2008).

We estimate and compare a menu of demand–supply systems to infer channel members' interaction relationships and pricing strategies. We estimate two types of horizontal games between manufacturers, Betrand competition and tacit collusion, and two types of vertical games between manufacturers and retailers, vertical Nash and manufacturer Stackelberg. We estimate channel pricing strategies incorporating and not incorporating quantity-discount effects and pricing strategies incorporating and not incorporating consumer state dependence. In total, we estimate 16 supply-side specifications, and each generates different predicted values of manufacturer margins, retailer margins, and marginal cost estimates. Table 9 shows the maximized log-likelihood values associated with alternative model specifications. We construct Vuong test statistics for nonnested models with respect to the best-fitting model with the highest log-likelihood. As we demonstrate in Table 9, the model with (1) Bertrand competition between manufacturers, (2) vertical Nash between manufacturers and retailers, (3) no quantity-discount effect considerations in setting prices, and (4) no state dependence considerations in setting prices significantly outperforms the others. Table 10 presents the cost coefficient estimates of the best-fitting supply-side model.[1]

[1]To demonstrate that the limited information approach can produce consistent price estimates as in a full information approach, we estimate the demand-side model (no quantity discount, no state dependence) and supply-side model (vertical Nash, Bertrand competition) simultaneously (i.e., the full information approach). We also estimate the demand-side model (no quantity discount, no state dependence) using instruments to account for price endogeneity (the limited information approach). Our estimation results from the two approaches are highly consistent. The price coefficient estimate is –.39 based on the full information approach and –.40 based on the limited information approach. The t-test shows that the price coefficients estimated under the two different approaches are not significantly different from each other. In addition, the supply-side model presumes that the price parameters and covariance between equations are invariant to the policy simulations.

Our results suggest that manufacturers do not incorporate quantity-discount effects into their nonlinear pricing decisions. This finding is consistent with existing literature, which views nonlinear pricing solely as a price discrimination tool (Spence 1980). Importantly, this finding suggests that current pricing strategies are suboptimal, and manufacturers can design a more profitable nonlinear pricing scheme by taking advantage of quantity-discount-dependent consumer preferences. We explore this insight in the next section through policy experiments.

POLICY EXPERIMENTS

Our demand-side analysis demonstrates significant quantity-discount-dependent consumer preferences, whereas the supply-side analysis suggests that market players do not consider such quantity-discount effects in setting prices. This discrepancy motivates us to conduct policy experi-

Table 10

COST ESTIMATES FROM THE BEST-FITTING SUPPLY-SIDE MODEL

	Estimate	*SE*
Store dummies		
Store 1	**1.366**	.018
Store 2	**1.184**	.018
Store 3	**.929**	.018
Store 4	**1.192**	.018
Store 5	**1.088**	.018
Manufacturer dummies		
Bud Light	**3.004**	.009
Miller Lite	**2.753**	.018
Package size dummies		
144 oz.	**–1.038**	.014
216 oz.	**1.890**	.027
288 oz.	**4.906**	.018
Cost		
Barley price	**.002**	.0004
Number of observations	3120	
Number of parameters	11	

Notes: In the best-fitting supply model, manufacturers play Bertrand competition with each other and play vertical Nash games with the retailer. Manufacturers and retailers do not consider quantity-discount effects or state dependence in setting prices. Bold indicates a statistically significant result.

Table 9

SUPPLY-SIDE MODEL COMPARISON

Channel Interaction		*Log-Likelihoods (Vuong Test Statistic) Channel Pricing Strategies*			
		Not Incorporating Quantity-Discount Effects		*Incorporating Quantity-Discount Effects*	
Manufacturer–Retailer Interaction	*Manufacturer Interaction*	*Not Incorporating State Dependence*	*Incorporating State Dependence*	*Not Incorporating State Dependence*	*Incorporating State Dependence*
Vertical Nash	Bertrand competition	**–2,573.84** (___)	–3,945.00 (–8.28*)	–3,915.52 (–20.46*)	–6,133.92 (–18.30*)
	Tacit collusion	–2,673.02 (–5.41*)	–4,250.83 (–10.23*)	–3,913.20 (–20.40*)	–6,043.43 (–18.37*)
Manufacturer Stackelberg	Bertrand competition	–2,823.46 (–9.55*)	–5,657.08 (–18.25*)	–3,721.78 (–6.77*)	–6,035.07 (–8.28*)
	Tacit collusion	–3,026.94 (–9.59*)	–5,857.52 (–20.01*)	–3,709.33 (–6.76*)	–6,289.28 (–20.33*)

Notes: The Vuong test statistic pertains to the best-fitting model (with the highest log-likelihood). Bold indicates a statistically significant result.
*$p < .01$.

ments to explore how incorporating quantity-discount effects influences manufacturers' nonlinear pricing schemes and their market performance. We conduct three policy experiments. Experiment 1 examines how much manufacturers can benefit from incorporating quantity-discount effects into nonlinear pricing decisions. Experiment 2 compares the strategic implications of consumers' quantity-discount-dependent preferences (context effects) and size preferences (self-selection effects). Experiment 3 examines how the strength of quantity-discount effects influences nonlinear pricing. In all three experiments, we assume that manufacturers play Bertrand competition with each other and play vertical Nash with retailers, as we infer in our supply-side analysis. We assume that retailers do not consider quantity-discount effects to focus on manufacturers' pricing strategies. Each experiment contains a set of simulations. In each simulation, we set up manufacturers' price decision rules (e.g., considering quantity-discount effects or not) and solve for equilibrium retail prices and total manufacturer profits for 52 periods. In each period, we simulate consumer choices using demand coefficient estimates. Using cost estimates from the best-fitting supply-side model, we solve for the equilibrium retail and wholesale prices of all available product alternatives that maximize the retailer's assortment profit as well as each manufacturer's product line profit. We use Store 1 for demonstration.

Policy Experiment 1

We designed Experiment 1 to investigate how much manufacturers can benefit from incorporating quantity-discount effects into their pricing decisions. We consider two manufacturers, Bud Light and Miller Lite, each selling three package sizes, the 144 oz. pack, the 216 oz. pack, and the 288 oz. pack. Each manufacturer can choose to consider quantity-discount effects or not. This leads to a 2×2 design of the experiment, including four simulations. In Simulation 1, neither Budweiser nor Miller considers quantity-discount effects in setting prices; in Simulation 2, only Budweiser considers quantity-discount effects; in Simulation 3, only Miller considers quantity-discount effects; and in Simulation 4, both Budweiser and Miller consider quantity-discount effects. Table 11 reports the six product items' equilibrium retail prices and total manufacturer profits in all four simulations; we compare the results from the four conditions.

Comparing Simulations 2 and 3 with Simulation 1, we find that a manufacturer that considers consumer quantity-discount effects charges a lower price ($p < .01$) and enjoys a greater profit ($p < .01$). Comparing Simulation 4 with Simulations 2 and 3, we find that when competitive manufacturers both consider quantity-discount effects, each obtains a greater profit ($p < .01$). This finding suggests that incorporating quantity-discount effects in nonlinear pricing can effectively enhance manufacturer performance in a competitive market.

Our simulations focus on manufacturers and assume that retailers do not consider quantity-discount effects. Intuitively, retailers would also benefit from considering quantity-discount effects in setting retail prices. Retailers' knowledge about quantity-discount effects would also strengthen their competition power in the vertical Nash game with manufacturers. As a result, manufacturers may have no incentive to inform retailers about quantity-discount effects. We conducted simulations and obtained results consistent with this intuition.

Table 11

SIMULATION RESULTS FROM POLICY EXPERIMENT 1

	M	*SD*	*Mean Difference from Simulation 1*	*Standard Error of Mean Difference*
A: Simulation 1: Neither Bud nor Miller Consider Quantity-Discount Effects				
Equilibrium retail price (cents/oz.)				
Bud 144 oz.	5.980	.019		
Bud 216 oz.	4.998	.313		
Bud 288 oz.	4.971	.113		
Miller 144 oz.	5.780	.281		
Miller 216 oz.	5.028	.219		
Miller 288 oz.	4.996	.120		
Total profit (cents)				
Bud	5.030	.840		
Miller	8.610	1.140		
B: Simulation 2: Only Bud Considers Quantity-Discount Effects				
Equilibrium retail price (cents/oz.)				
Bud 144 oz.	5.126	.471	**–.854**	.065
Bud 216 oz.	4.743	.134	**–.254**	.047
Bud 288 oz.	4.824	.130	**–.146**	.024
Miller 144 oz.	5.781	.278	.001	.054
Miller 216 oz.	4.996	.219	–.032	.043
Miller 288 oz.	5.027	.121	.031	.023
Total profit (cents)				
Bud	7.200	2.080	**2.170**	.308
Miller	8.600	1.150	–.010	.222
C: Simulation 3: Only Miller Considers Quantity-Discount Effects				
Equilibrium retail price (cents/oz.)				
Bud 144 oz.	5.975	.020	–.005	.004
Bud 216 oz.	4.997	.314	–.001	.061
Bud 288 oz.	4.967	.116	–.003	.022
Miller 144 oz.	4.824	.381	**–.957**	.065
Miller 216 oz.	4.773	.111	**–.255**	.034
Miller 288 oz.	4.753	.158	**–.243**	.027
Total profit (cents)				
Bud	5.020	.840	–.010	.163
Miller	14.570	3.200	**5.960**	.467
D: Simulation 4: Both Bud and Miller Consider Quantity-Discount Effects				
Equilibrium retail price (cents/oz.)				
Bud 144 oz.	5.044	.387	**–.936**	.053
Bud 216 oz.	4.814	.150	**–.184**	.048
Bud 288 oz.	4.999	.359	**.028**	.052
Miller 144 oz.	4.763	.157	**–1.018**	.044
Miller 216 oz.	4.625	.618	**–.403**	.090
Miller 288 oz.	4.669	.531	**–.327**	.075
Total profit (cents)				
Bud	6.730	2.310	**1.700**	.338
Miller	14.120	3.420	**5.510**	.495

Notes: The experiment demonstrates the benefits for manufacturers (Bud and Miller) to consider quantity-discount effects in setting prices. The mean and standard deviation of retail prices and manufacturer total profits are obtained from simulation results for 52 weeks in Store 1. Bold indicates a statistically significant result.

Policy Experiment 2

Because the literature (e.g., Spence 1980) explains nonlinear pricing mainly as a price discrimination tool, we design Experiment 2 to examine how consumers' quantity-discount-dependent preferences (context effects) and their size preferences (self-selection effects) influence manufacturer performance differently. We conduct the experiment on two competitive brands, Bud Light and Miller Lite, with each selling two package sizes, the 144 oz. pack and the 216 oz. pack. Note that our demand-side estimation suggests that overall quantity-discount effects cause more losses than gains in consumer utility. In particular, on the size pair of 144 oz. and 216 oz., gain-focused consumers perceive no quantity-discount effect, and loss-focused consumers perceive a quantity-discount-induced disutility for purchasing the small package size. Recall that the utility of the outside good is normalized to zero. Thus, this impact of the quantity-discount effect is similar to a self-selection effect that lowers the utility for the small package size. In this experiment, we consider two levels of the context effect: (1) no context effect, in which consumers have no quantity-discount-dependent preferences, and (2) with context effect, in which consumers have quantity-discount-dependent preferences. We consider two levels of the self-selection effect: (1) current level, in which consumers' size utilities for the 144 oz. and 216 oz. sizes are both set as what we estimated from the demand model, and (2) increased level, in which consumers' size utilities for the 216 oz. size are set as what we estimated from the demand model while their size utilities for the 144 oz. size are lowered to increase the utility differences between the two sizes. We chose the degree of self-selection effect such that for naive manufacturers that do not consider context effects or increased selection effects, the context effect and the increased selection effect lead to profit losses with roughly the same magnitude. We then have a 2×2 design of the experiment with four simulations. In Simulation 1, consumers have no context effects or increased selection effects; in Simulation 2, consumers have only increased selection effects but no context effects; in Simulation 3, consumers have only context effects but no increased selection effects; and in Simulation 4, consumers have both context effects and increased selection effects.

Strategic manufacturers adjust their nonlinear pricing schemes according to the increased selection effect (in Simulation 2), the context effect (in Simulation 3), or both (in Simulation 4). Table 12 summarizes the equilibrium prices of available product items and total profits for strategic manufacturers in all four simulations. The result shows that strategic manufacturers encountering quantity-discount effects (in Simulation 3) end up obtaining a greater profit ($p < .01$) than they do without such effects (in Simulation 1). In contrast, strategic manufacturers encountering increased selection effects (in Simulation 2) still earn less profit ($p < .01$) than they do without such effects (in Simulation 1). This disappointing outcome of incorporating self-selection effects into pricing results from the lowered consumer size utilities for the small package, which can hardly be compensated despite manufacturers' efforts. Conversely, as we discussed previously, quantity-discount effects can have the benefit of mitigating interbrand price competition, which may enhance manufacturer profitability if incorporated in pricing.

Table 12

SIMULATION RESULTS FROM POLICY EXPERIMENT 2

	M	*SD*	*Mean Difference from Simulation 1*	*Standard Error of Mean Difference*
A: Simulation 1: No Quantity-Discount Effect/Current Self-Selection Effect				
Equilibrium retail price (cents/oz.)				
Bud 144 oz.	5.522	.034		
Bud 216 oz.	5.014	.316		
Miller 144 oz.	5.129	.300		
Miller 216 oz.	4.844	.247		
Quantity discount (cents/oz.)				
Bud	.508	.282		
Miller	.285	.053		
Total profit (cents)				
Bud	1.690	.390		
Miller	3.390	.610		
B: No Quantity-Discount Effect/Increased Self-Selection Effect				
Equilibrium retail price (cents/oz.)				
Bud 144 oz.	5.496	.035	**–.026**	.007
Bud 216 oz.	5.001	.313	–.013	.061
Miller 144 oz.	5.072	.311	–.056	.059
Miller 216 oz.	4.812	.247	–.032	.048
Quantity discount (cents/oz.)				
Bud	.495	.278	–.013	.054
Miller	.260	.065	**–.025**	.012
Total profit (cents)				
Bud	1.520	.400	**–.170**	.077
Miller	2.810	.610	**–.580**	.118
C: Simulation 3: With Quantity-Discount Effect/ Current Self-Selection Effect				
Equilibrium retail price (cents/oz.)				
Bud 144 oz.	4.818	.365	**–.704**	.050
Bud 216 oz.	4.511	.045	**–.503**	.044
Miller 144 oz.	4.405	.325	**–.724**	.061
Miller 216 oz.	4.347	.127	**–.497**	.038
Quantity discount (cents/oz.)				
Bud	.307	.320	**–.201**	.059
Miller	.058	.198	**–.227**	.028
Total profit (cents)				
Bud	2.070	.060	**.380**	.054
Miller	3.860	.440	**.470**	.103
D: Simulation 4: With Quantity-Discount Effect/ Increased Self-Selection Effect				
Equilibrium retail price (cents/oz.)				
Bud 144 oz.	4.799	.368	**–.723**	.051
Bud 216 oz.	4.485	.053	**–.529**	.044
Miller 144 oz.	4.103	.378	**–1.025**	.066
Miller 216 oz.	4.043	.142	**–.801**	.039
Quantity discount (cents/oz.)				
Bud	.313	.314	**–.195**	.058
Miller	.060	.236	**–.225**	.033
Total profit (cents)				
Bud	1.870	.070	**.180**	.054
Miller	6.120	.550	**.720**	.134

Notes: The experiment demonstrates how self-selection effect and quantity-discount effect differ in influencing market payoffs of strategic manufacturers that take these effects into consideration in setting prices. The mean and standard deviation of retail prices and manufacturer total profits are obtained from simulation results for 52 weeks in Store 1. Bold indicates a statistically significant result.

Policy Experiment 3

The results from Experiments 1 and 2 suggest that a manufacturer that considers quantity-discount effects implements a smaller quantity discount than if the manufacturer does not. In Experiment 3, we further explore this finding. Similar to Experiment 2, we conduct Experiment 3 on Bud Light and Miller Lite, each selling two package sizes, the 144 oz. pack and the 216 oz. pack. We assume that both

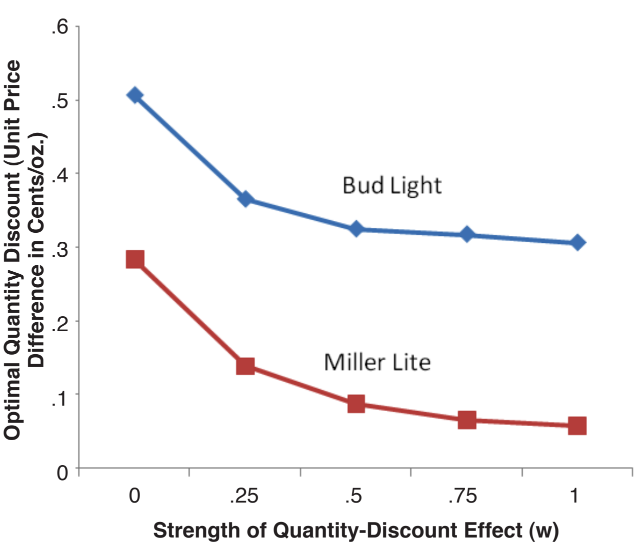
Budweiser and Miller consider quantity-discount effects. We conduct five simulations, each with a different strength of quantity-discount effects: w = 0, .25, .5, .75, and 1. In each simulation, we multiply the strength parameter w with individual consumers' estimated coefficients for the quantity-discount effect between the 144 oz. pack and the 216 oz. pack. Thus, a larger w generates stronger quantity-discount-dependent consumer preferences. In each of the five simulations, we calculate the equilibrium quantity discount between the 144 oz. pack and the 216 oz. pack (unit price difference in cents per ounce) for Bud Light and Miller Lite, respectively, and plot the results in Figure 1. As Figure 1 shows, a stronger quantity-discount effect leads to a smaller quantity discount in equilibrium for both manufacturers. The intuition behind this result pertains to the notion that, overall, quantity-discount effects cause more losses in consumer utility for the small package size than gains in utility for the large package size. Although the quantity-discount effect increases demand for the large package size, it also lowers the overall attraction of the brand compared with the outside product (with constant zero utility). Therefore, when the quantity-discount effect becomes stronger, a firm has incentive to implement a smaller quantity discount to reduce this negative impact. Our findings also suggest that ignoring quantity-discount effects will result in a larger quantity discount than optimal.

CONCLUSION

In this article, we investigate the quantity-discount effect, a type of transaction utility consumers derive from the unit price difference between a small and a large package size of the same product in a nonlinear pricing environment. Consumers may perceive quantity discounts as gains obtained from purchasing larger package sizes with lower unit prices or as losses resulting from purchasing smaller package sizes with higher unit prices. In addition, consumers may differ in their tendencies to perceive quantity discounts as gains or losses.

Figure 1

SIMULATION RESULTS FROM POLICY EXPERIMENT 3



Notes: The experiment demonstrates how the optimal quantity discount between a small (the 144 oz.) and a large (the 216 oz.) package varies by the strength of quantity-discount effect.

We propose a modeling framework to demonstrate the existence of the quantity-discount effect and to investigate its strategic implications for manufacturers. Our model framework integrates a demand-side model and a supply-side model. On the demand side, we develop a choice model to incorporate the quantity-discount effect, controlling for structural heterogeneity and preference heterogeneity. On the supply side, we model profit-maximizing decisions of both manufacturers and retailers. We infer channel members' interaction relationships and pricing strategies by estimating and comparing a menu of demand–supply systems.

We apply the proposed model to scanner panel data on consumer purchases of two major light beer brands on three package sizes. Our empirical results suggest a significant impact of quantity-discount-related gains or losses on consumer choices. We also find a substantial amount of structural heterogeneity; that is, some consumers perceive quantity discounts as gains, whereas others perceive quantity discounts as losses. Despite the significant impact of quantity-discount effects on consumer buying behavior, we find that the manufacturers we study do not consider quantity-discount effects when setting prices. Through a series of policy experiments, we show that by incorporating quantity-discount effects, manufacturers can develop more effective nonlinear pricing schemes and obtain greater profits. Our findings generate useful insights for marketing managers.

Our study is subject to limitations, suggesting future research directions. First, we do not model product availability. In our application, all six product items are available across five stores for 104 weeks. In reality, however, retailer assortment may vary across stores and/or periods, and it would be worthwhile to extend our model to a more general context. Second, we do not model internal reference prices, which have been found to have a significant impact on consumer choices in reduced-form models (Mayhew and Winer 1992) and in structural models (Erdem, Imai, and Keane 2003; Erdem, Keane, and Sun 2008; Hendel and Nevo 2006) with forward-looking consumers. It would be worthwhile to examine both the quantity-discount effect and the internal reference price effect in the context of forward-looking consumers. Finally, we capture structural heterogeneity across individual consumers. It is possible that whether consumers perceive quantity discounts as gains or losses depends on their most frequently or most recently purchased package size. Modeling this dynamic aspect of the quantity-discount effect could help generate insights for firms' forward-looking nonlinear pricing strategies.

APPENDIX: DERIVATION OF THE PRICE EQUATION IN THE SUPPLY-SIDE MODEL

In line with Besanko, Gupta, and Jain (1998) and Sudhir (2001), we model retailers as local monopolists. Each retailer decides optimal retail prices to maximize its category profit. At time t, a retailer R carrying J product items chooses the optimal retail prices $p_t = (p_{1t}, ..., p_{Jt})$ to maximize its category profit π_t^R:

$$\text{(A1)}\qquad \underset{p_t}{\text{Max}}\ \pi_t^R = \sum_{j=1}^{J}(p_{jt} - w_{jt} - rc_{jt})s_{jt}(p_t)M^R,$$

where M^R is the size of retailer R's local market, w_{jt} is the wholesale price of product j set by its manufacturer, rc_{jt} is the retailer's marginal cost for selling product j, and s_{jt} (p_t) is the market share of product j at prices p_t and is obtained by $s_{jt} + (1/H)\Sigma_{h=1}^{H} q_{hjt}$. If we assume a pure Nash equilibrium, the first-order conditions are as follows:

$$\text{(A2)}\qquad s_{jt} + \sum_{l=1}^{J}(p_{lt} - w_{lt} - rc_{lt})\frac{\partial s_{lt}}{\partial p_{jt}} = 0, \forall j \in \{1, 2, ..., J\}.$$

From Equation A2, we obtain retailer R's implied margins as functions of the demand side for period t:

$$\text{(A3)}\qquad p_t - w_t - rc_t = -(\Omega_t)^{-1}s_t(p_t),$$

where $w_t = (w_{1t}, ..., w_{Jt})$ and $rc_t = (rc_{1t}, ..., rc_{Jt})$ and Ω_t is the retailer's response matrix containing the first-order derivatives of all shares with respect to all retail prices. The (i, j) element of Ω_t is $(\partial s_{jt}/\partial p_{it})$, which we obtain as follows:

$$\text{(A4)}\frac{\partial s_{jt}}{\partial p_{it}} = \frac{1}{H}\sum_{h=1}^{H}\frac{\partial q_{hjt}}{\partial p_{it}} = \frac{1}{H}\sum_{h=1}^{H}[q_{hjt}\frac{\partial U_{hjt}}{\partial p_{it}} - q_{hjt}\sum_{k=1}^{J}(q_{hkt}\frac{\partial U_{hkt}}{\partial p_{it}})].$$

Note that without the quantity-discount effect, $(\partial U_{hjt}/\partial p_{it}) = -\alpha_h$ if i = j and $(\partial U_{hjt}/\partial p_{it}) = 0$ if I ≠ j. With the quantity-discount effect, we have the following:

$$\text{(A5)}\qquad \frac{\partial U_{hjt}}{\partial p_{it}} = \begin{cases} -\alpha_h + \displaystyle\sum_{m=1}^{d}\frac{\partial \delta_{jt}^m}{\partial p_{it}}\gamma_h^m \le -\alpha_h & \text{if} \quad i = j \\ \displaystyle\sum_{m=1}^{d}\frac{\partial \delta_{jt}^m}{\partial p_{it}}\gamma_h^m \ge 0 & \text{if} \quad i \ne j \end{cases}.$$

Equation A5 shows that because of the quantity-discount effect captured by γ_h^m, an increased price leads to a consumer utility drop in addition to that induced by the price coefficient α_h. In addition, the increased price leads to a utility increase for the larger (smaller) package of the same brand for gain-focused (loss-focused) consumers.

The J product items the retailer carries come from F different manufacturers, with manufacturer f (f = 1, ..., F) producing J_f different sizes of its product, $\Sigma_{f=1}^{F} J_f = J$. Manufacturer f sets wholesale prices $w_t^f = (w_{gt})_{g\in\{1, 2, ..., J_f\}}$ to maximize its product line profit π_t^f:

$$\text{(A6)}\qquad \underset{w_t^f}{\text{Max}}\ \pi_t^f = \sum_{g=1}^{J_f}(w_{gt} - mc_{gt})s_{gt}(p_{gt})M^R, \forall f \in \{1, ..., F\},$$

where mc_{gt} is the marginal production cost of product item g (g = 1, …, J_f). Then, the first-order conditions are as follows:

$$\text{(A7)}\qquad s_{gt} + \sum_{l=1}^{J_f}(w_{lt} - mc_{lt})\frac{\partial s_{lt}}{\partial w_{gt}} = 0, \forall g \in \{1, 2, ..., J_f\}.$$

From Equation A7, we obtain the following equation for manufacturers' margins:

$$\text{(A8)}\qquad w_t - mc_t = -[\Theta_t'(T_f \times \Omega_t)]^{-1}s_t(p_t).$$

In Equation A8, T_f is a J × J matrix containing manufacturers' ownership information. In Bertrand competition, T_f (i, j) = 1 if product i and j are produced by the same manufacturer and T_f (i, j) = 0 if otherwise. In tacit collusion, T_f (i, j) = 1 for all i, j = 1, …, J, and "×" denotes element-by-element multiplication of matrices.

Here, Θ_t is a J × J matrix of derivatives of all retail prices with respect to all wholesale prices, whose (i, j) element is $(\partial p_{jt}/\partial w_{it})$. When manufacturers and retailers play a vertical Nash game, Θ_t is a J × J identity matrix. When manufacturers and retailers play a Stackelberg game, we have $\Theta_t = G_t^{-1}\Omega_t$, where

$$\text{(A9)}\qquad G_t(j,i) = \frac{\partial s_{it}}{\partial p_{jt}} + \sum_k(p_{kt} - w_{kt})\frac{\partial s_{kt}^2}{\partial p_{jt}\partial p_{it}} + \frac{\partial s_{jt}}{\partial p_{it}}.$$

In Equation A9, we obtain $\partial s_{kt}^2/(\partial p_{jt}p_{it})$ as follows:

$$\text{(A10)}\qquad \frac{\partial s_{kt}^2}{\partial p_{jt}p_{it}} = \frac{1}{H}\sum_{h=1}^{H}\Bigg[\frac{\partial q_{hkt}}{\partial p_{it}}\frac{\partial U_{hkt}}{\partial p_{jt}} - \frac{\partial q_{hkt}}{\partial p_{it}}\sum_{l=1}^{J}q_{hlt}\frac{\partial U_{hlt}}{\partial p_{jt}} - q_{hkt}\sum_{l=1}^{J}\frac{\partial q_{hlt}}{\partial p_{it}}\frac{\partial U_{hlt}}{\partial p_{jt}}\Bigg].$$

Combining Equation A3 and Equation A8, we obtain the price equation, which contains three components: (1) marginal production and selling costs, (2) retailer margins, and (3) manufacturer margins:

$$\text{(A11)}\qquad p_t = \underbrace{mc_t + rc_t}_{\text{marginal cost}}\ \underbrace{-(\Omega_t)^{-1}s_t}_{\text{retailer margin}}\ \underbrace{-[\Theta_t'(T_f \times \Omega_t)]^{-1}s_t}_{\text{manufacturer margin}}.$$

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