



The market value for product attribute improvements under price personalization[☆]



Garrett P. Sonnier

University of Texas at Austin, 1 University Station, Austin, TX 78712, United States

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ABSTRACT

Personalization of the marketing mix is a topic of much interest to marketing academics and practitioners. Using discrete choice demand theory, we investigate the aggregate market value for product attribute improvements when firms are engaged in personalized pricing. Our results provide a theoretically grounded rule for how to aggregate consumer valuations to assess the overall profitability of attribute improvements under price personalization. Under common pricing, each consumer contributes the same margin. Profitability of an attribute improvement is thus driven by inducing more consumers to buy. Consumers with high choice probabilities are given less weight in the market valuation under common pricing as they are less responsive to attribute improvements. Under personalized pricing, profitability of an attribute improvement is driven by extraction of consumer surplus from high valuation consumers. Consumers with higher valuations, and consequently higher choice probabilities, are given more weight in the market valuation under personalized pricing. Since individual consumers play a more central role in the market valuation under personalized pricing, estimation of consumer-level valuations is of increased importance. Under common pricing, the market valuation for an attribute improvement is robust to extreme estimates of the consumer-level valuations. Through our theoretical and empirical analyses, we demonstrate that this robustness does not hold under personalized pricing.

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1. Introduction

New product development is crucial to sustained firm performance. Companies that fail to develop new products risk being supplanted by more nimble competitors responding to shifts in consumer demand. While new companies often focus on creating disruptive technologies that alter the competitive landscape, most new product development activity focuses on incremental innovation devoted to improving existing products. For example, at Sony, over three quarters of new product activity is dedicated to improving existing products (Kotler & Keller, 2006). Bayus (1994) notes the existence of a similar pattern across a range of industries (Abernathy & Utterback, 1978) as well as evidence that incremental innovation is more crucial to profitability than breakthrough technology (Gomory, 1989). While new product development is undeniably important, it is also risky. Some studies suggest a failure rate of 95% in the U.S. (Kotler & Keller, 2006). To improve the odds of success, product managers must carefully assess how consumers value product attribute improvements and, importantly, how to aggregate consumer valuations into a market-level valuation useful for product planning decisions.

From the perspective of an individual consumer, the value for a product attribute improvement is typically defined as the change in price that would keep consumer utility constant given the attribute improvement (Train, 2003). Appealing to discrete-choice theory of

consumer and firm behavior, Ofek and Srinivasan (2002) derive a market-level analog to this consumer-level valuation termed the market value for an attribute improvement (MVAI). MVAI can be compared to the marginal cost of the attribute improvement, providing product managers with guidance in assessing the overall profitability of the improvement. However, the Ofek and Srinivasan (2002) derivation of MVAI assumes that firms charges a common price to all consumers. In contrast to a homogenous pricing policy, the notion of personalized pricing is of great appeal to both marketing academics and managers (Fay, Mitra, & Wang, 2009). A stream of research in the marketing literature has considered the personalization of the marketing mix from both an empirical and theoretical perspective (Chen & Iyer, 2002; Choudhary, Ghose, Mukhopadhyay, & Rajan, 2005; Heilman, Kaefer, & Ramenofsky, 2003; Khan, Lewis, & Singh, 2009; Knox & Eliashberg, 2009; Liu & Zhang, 2006; Rossi, McCulloch, & Allenby, 1996; Shaffer & Zhang, 2002). Firms from the apparel, airline, bank issued credit-card, and enterprise software industries have engaged in personalized pricing (Choudhary et al., 2005; Montgomery & Smith, 2009; Shaffer & Zhang, 2002). In light of academic and practitioner attention to the topic of personalized pricing, it is interesting to consider whether and how price personalization affects the market value for product attribute improvements.¹

¹ Rather than focusing on the normative question of whether or not firms should engage in price personalization, we adopt a positive point of view to understand the implications of engaging in one-to-one price personalization for estimates of the market value for a product attribute improvement.

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The main contribution of this paper is to derive the market value for product attribute improvements when firms are engaged in price personalization. Our results generalize the MVAI measure for common pricing and provide managerial guidance on product planning decisions under personalized pricing. Similar to Ofek and Srinivasan's (2002) analysis of MVAI under common pricing, we obtain closed form expressions for MVAI under personalized pricing in the context of the widely used multinomial logit demand model. However, two important differences in MVAI under common versus personalized pricing emerge from our analysis. First, under common pricing, every consumer contributes the same margin. Incremental profitability from an attribute improvement is thus driven by inducing more consumers to purchase. Consumers with extreme choice probabilities are given less weight in the aggregate market valuation as these consumers are less responsive to attribute changes. In contrast, under personalized pricing, the profitability of an attribute improvement is driven by the extraction of surplus from consumers with higher valuations and, consequently, higher choice probabilities. Under personalized pricing, consumers with high choice probabilities are given greater weight in the market valuation. The first difference between market-level valuations under common and personalized pricing (i.e., which consumers matter more for the aggregate market valuation) relates to the second difference. As individual consumers matter more under personalized pricing, extreme consumer-level valuations have a greater impact in this setting. Unlike the case of common pricing, computing MVAI under personalized pricing requires more careful attention to the estimation of the consumer-level valuations, a point underscored by the results of our empirical application.

Choice models specified with additive linear utility imply that the consumer-level valuation for an attribute improvement is identified as the ratio of the estimated attribute and price coefficients (Train, 2003). With a heterogeneous model, the distribution of consumer-level valuations is specified indirectly as a ratio of random coefficients. Such an identification strategy may yield distributions of the valuations that lack finite moments (Daly, Hess, & Train, 2012). Even if finite moments are assured, the distribution may be prone to yield extreme estimates (Meijer & Rouwendal, 2006; Ofek & Srinivasan, 2002). Alternatively, the valuations can be directly identified in the choice model likelihood which avoids ratio estimation and its associated problems (Cameron & James, 1987; Jedidi, Jagpal, & Manchanda, 2003; Sonnier, Ainslie, & Otter, 2007). An interesting and important property of MVAI under common pricing is its robustness to extreme consumer valuations (Ofek & Srinivasan, 2002) which renders the estimation of the consumer-level valuations less important. Our results demonstrate that robustness to outliers is not a general property of the MVAI measure and does not hold under personalized pricing. Using Ofek and Srinivasan's (2002) data set on stated preferences for portable camera mounts we empirically investigate the MVAI under personalized pricing. Computing MVAI under personalized pricing with ratio estimates of the consumer-level valuations suggests that nearly every attribute improvement is profitable for any product. In contrast, using consumer-level valuations that are directly identified and less prone to extreme estimates to compute MVAI under personalized pricing yields estimates that are smaller in magnitude and suggest a smaller subset of profitable attribute improvements.

The remainder of the paper is organized as follows. We begin with a discussion of personalized pricing to motivate the study of product planning decisions under one-to-one pricing. We then review the derivation of the market valuation for an attribute improvement under common pricing and extend the derivation to the case of one-to-one price personalization. In doing so, we also consider the intermediate case of a discrete segment-based price discrimination strategy. We then discuss discrete choice demand models and the specification of consumer-level valuations used to compute the market-level valuation under personalized pricing. Our empirical application follows. The final section summarizes and concludes.

2. Personalized pricing in marketing

The marketing literature has discussed numerous examples of personalized marketing in both consumer and business-to-business markets. Choudhary et al. (2005) discuss examples of firms in the enterprise software industry, such as IBM, Hewlett-Packard, and Sun Microsystems, that use personalized pricing discounts for products of the same quality. In consumer markets, information technology has enabled firms to develop rich databases of consumer information giving firms the ability to reach individual consumers and personalize the marketing mix. Direct marketing firms such as Land's End and L.L. Bean use promotional discounts to tailor prices to individual households (Shaffer & Zhang, 2002). Firms in the bank issued credit card industry, such as Wells Fargo, engage in price personalization through personalized discounts on card fees (Choudhary et al., 2005). The consulting firm Accenture offers clients a personalized pricing tool to assist in implementing a one-to-one price promotion program.² A CNN.com report details price variation across consumers for the same product in a variety of online product categories, including airline tickets, digital cameras, and personal computers.³ The online data provision company Lexis-Nexis sells to different consumers at different prices (Ghose & Huang, 2009). Even when met initially with consumer resistance, firms such as Amazon continue to find innovative ways to implement personalized pricing, such as the Gold Box (Choudhary et al., 2005).

A challenge in implementing a personalized pricing strategy is that firms must obtain consumer willingness-to-pay for the products in the competitive set. Fay et al. (2009) consider conditions under which firms invest in technology to solicit preferences from consumers at the point of purchase versus technology that allows the firm to infer preferences based on past observations. Wertenbroch and Skiera (2002) discuss different methods for determining consumer valuations, or willingness-to-pay, in market research. These methods include Vickrey auctions, the Becker-DeGroot-Marshak (BDM) elicitation procedure, and discrete choice models applied to either stated preference data or market transaction data. Cameron and James (1987), Jedidi et al. (2003), and Ofek and Srinivasan (2002) use discrete choice models to estimate consumer valuations for product attributes. Most empirical applications of personalized marketing also utilize discrete choice models (Ansari & Mela, 2003; Khan et al., 2009; Knox & Eliashberg, 2009; Rossi et al., 1996; Zhang & Krishnamurthi, 2004; Zhang & Wedel, 2009). An advantage of using discrete choice models is that with an attribute based utility function (Fader & Hardie, 1996), the valuation for the product can easily be decomposed into the valuations for the product attributes. Furthermore, if the valuations can be linked to consumer characteristics, such as demographics or purchase history, the model can be used to impute the valuations for new consumers conditional on the characteristics enhancing the firm's ability to implement a personalized pricing strategy (Rossi et al., 1996).

In considering the question of whether and how the firm's pricing strategy affects the market value for product attribute improvements it is natural to address the problem from the perspective of firms selling direct to consumers. Shaffer and Zhang (2002) study one-to-one promotions among competing direct marketing firms. Chen and Iyer (2002) study competition among firms that offer personalized prices assuming that firms have an imperfect ability to reach consumers. Choudhary et al. (2005) consider how price personalization in a duopoly impacts firm choices over product quality. It is important to note, though, that selling through a retailer does not preclude the

² Accenture.com, http://www.accenture.com/NR/rdonlyres/6E9FD307-3CBE-40AE-B1929F7FAD5776/0/personalized_pricing_tool.pdf, retrieved on Dec 12, 2009.

³ CNN.com, <http://www.cnn.com/2005/LAW/06/24/ramasastry.website.prices/>, retrieved on Dec 12, 2009.

manufacturer from engaging in personalized pricing. Gerstner, Hess, and Holthausen (1994) analyze a manufacturer targeting pull discounts in the form of coupons or rebates to price sensitive consumers purchasing through a retailer. Liu and Zhang (2006) study personalized pricing in a channel where both the manufacturer and the retailer can personalize price and the manufacturer can open a direct to consumer channel. Silva-Risso and Ionova, (2008) study customized manufacturer incentives in the automotive industry, where manufacturers spend approximately \$45 billion per year on sales incentives directed at consumers.

3. Theoretical analysis

3.1. The market value for an attribute improvement under pricing common to all consumers

We begin by reviewing the derivation of the market value for an attribute improvement (MVAI) under common pricing (Ofek & Srinivasan, 2002). Assume a market consisting of $i = 1, \dots, I$ consumers choosing amongst a set of $m = 0, \dots, M$ products (where 0 denotes the “outside” alternative). Let product m be defined by a vector of continuously differentiable product attributes, x_m , and a common price, p_m .⁴ The share of consumers predicted to choose product m

from the competitive set is $S_m = \frac{1}{I} \sum_{i=1}^I \Pr[y_{im} = 1]$ where $y_{im} = 1$ denotes the choice of product m and $\Pr[y_{im} = 1]$ is the choice probability. Assume that competing firms sell only one product (such that m also indexes firms) and that fixed costs are zero. The profits from product m , π_m ,

are given by $\pi_m = \sum_{i=1}^I \Pr_{im}[p_m - c_m] = I \times S_m[p_m - c_m]$ where c_m is the variable cost. Note that the aggregation of the choice probabilities into market shares prior to multiplication with the margin is possible in this setting because the prices are common across all consumers. The firm's first order condition for the pricing decision is

$\frac{\partial \pi_m}{\partial p_m} = S_m + \frac{\partial S_m}{\partial p_m}[p_m - c_m] = 0$. Now consider the total change in profitability of product m triggered by a change in the k^{th} product attribute, x_m^k . The total derivative of profits with respect to a change in x_m^k is $\frac{d\pi_m}{dx_m^k} = I \left[\frac{\partial S_m}{\partial x_m^k}[p_m - c_m] - S_m \frac{\partial c_m}{\partial x_m^k} \right]$. After substitution of the pricing

first order condition, the total derivative of profits with respect to the attribute change is given by $\frac{d\pi_m}{dx_m^k} = IS_m \left[-\frac{\left[\frac{\partial S_m}{\partial x_m^k} \right]}{\left[\frac{\partial S_m}{\partial p_m} \right]} - \frac{\partial c_m}{\partial x_m^k} \right]$.

Under common pricing, incremental profitability hinges on the changes in market share in response to the attribute improvement and price. As each consumer contributes the same margin, the profitability of an attribute improvement will ultimately depend on inducing more consumers to purchase the product. For the attribute change to be profitable to the firm, the ratio of market share changes with respect to the attribute and price must exceed the marginal cost of the attribute change. Ofek and Srinivasan (2002) term this ratio of

⁴ As with Ofek and Srinivasan's (2002) derivation of MVAI under common pricing, our conceptual analysis considers continuously differentiable product attributes, such as fuel economy for automobiles or processor speed for personal computers. Some product attributes are, of course, discrete. For the case of discrete product attributes, simulation techniques would be required to assess the profitability of an attribute improvement. For example, in the multinomial logit model, there is a closed form expression for the derivative of the choice probability with respect to a change in a continuous product attribute. For a change in a discrete product attribute, the effect on the choice probability is computed as the difference in choice probabilities with the new and original level of the product attribute.

market shares, $-\frac{\frac{\partial S_m}{\partial x_m^k}}{\frac{\partial S_m}{\partial p_m}}$, the market value for an attribute improvement (MVAI).⁵

3.2. The market value for an attribute improvement and market share simulators

Managers often use the parameter estimates from a discrete choice model to build a market share simulator. The simulator can be used to assess the sensitivity of market share to changes in price and product attributes. Under common pricing, simulation techniques can also be used to compute the price increase given an attribute improvement that leaves aggregate market share constant. The manager first improves the level of the product attribute then searches for the price change that would leave market share unchanged. Ofek and Srinivasan (2002) show that for common pricing this approach coincides with the MVAI. The total differential of market share with respect to the k^{th} product attribute

and price is $dS_m = \frac{\partial S_m}{\partial x_m^k} dx_m^k + \frac{\partial S_m}{\partial p_m} dp_m$. The price change that satisfies $dS_m = 0$, which is the price change given an attribute change that holds

market share constant, is $\frac{dp_m}{dx_m^k} = -\frac{\frac{\partial S_m}{\partial x_m^k}}{\frac{\partial S_m}{\partial p_m}}$ which is exactly the MVAI under common pricing.

Consider now the case of personalized pricing. Rather than finding the incremental change in the common price that equalizes market share before and after the attribute improvement, the manager seeks the incremental change in the personalized price that leaves the individual's choice probability unchanged. This consumer specific price change can also be approximated via simulation. The manager changes the product attribute then searches for the personalized price change that would leave the individual choice probability unchanged. However, at the end of this exercise the manager is left with a set of consumer-level quantities approximate to the consumer-level valuations from the choice model. The question of how to aggregate these quantities into a market-level value to assess the profitability of the attribute improvement remains. Intuitively, the attribute change will be profitable to the firm if the sum of the expected incremental prices that can be captured from consumers exceeds the sum of the expected costs of the improvement.

3.3. The market value for an attribute improvement under price personalization

Before addressing one-to-one personalized pricing, it is useful to dwell on whether and how MVAI under common pricing would differ if the firm engaged in a more discrete price discrimination strategy. Under such a strategy, the firm might offer product m at different prices to discrete segments of consumers. Assume there are $d = 1, \dots, D$ segments of consumers each of size I^d and each of which receive a price of p_m^d . Let S_m^d represent the share of product m in segment d . The profits from product

m would then be $\pi_m = \sum_{d=1}^D \left[\sum_{i=1}^{I^d} \Pr_{im}^d [p_m^d - c_m] \right] = \sum_{d=1}^D [I^d \times S_m^d [p_m^d - c_m]]$.

The derivative of the profit function is obtained by summing the segment specific derivatives. After substitution of the pricing first order condition, the total derivative of profits with respect to the

attribute change is given by $\frac{d\pi_m}{dx_m^k} = I \left[\frac{1}{I} \sum_{d=1}^D \left[I^d S_m^d \left[-\frac{\left[\frac{\partial S_m^d}{\partial x_m^k} \right]}{\left[\frac{\partial S_m^d}{\partial p_m^d} \right]} - \frac{\partial c_m}{\partial x_m^k} \right] \right] \right]$.

Thus, the MVAI under a discrete price discrimination strategy is given

⁵ See Ofek and Srinivasan (2002) for a more complete discussion of MVAI under common pricing.

by $\frac{1}{I} \left[\sum_{d=1}^D \left[I^d S_m^d \left[-\frac{\partial S_m^d}{\partial x_m^k} \right] \right] \right]$. Each segment MVAI is computed exactly the

same as MVAI under common pricing (i.e., as the ratio of market share derivatives) and is weighted by the segment size and market share within the segment.

Consider now the profits from product m under personalized pricing, $\pi_m = \sum_{i=1}^I \pi_{im} = \sum_{i=1}^I \text{Pr}_{im} [p_{im} - c_m]$.⁶ Unlike common pricing or segment pricing, under price personalization the choice probabilities cannot be aggregated into market shares prior to multiplication with the margin. Profits are obtained in this case by summing over the product of each individual consumer's purchase probability and the consumer specific contribution margin. Thus, we may view segment or common pricing as special cases of the more general case of personalized pricing, where analysis of the two former situations is simplified by the ability to aggregate the choice probabilities into shares prior to multiplication with the common or segment margins. For each consumer, the firm's first order condition for the pricing decision under personalization is

$$\frac{\partial \pi_{im}}{\partial p_{im}} = \text{Pr}_{im} + \frac{\partial \text{Pr}_{im}}{\partial p_{im}} [p_{im} - c_m] = 0. \quad (1)$$

The total derivative of profits with respect to the attribute change is

$$\frac{d\pi_m}{dx_m^k} = \frac{\partial \pi_m}{\partial x_m^k} + \sum_{i=1}^I \frac{\partial \pi_{im}}{\partial p_{im}} \frac{dp_{im}}{dx_m^k}. \quad (2)$$

Since $\pi_m = \sum_{i=1}^I \pi_{im}$, the second term in this equation becomes

$\sum_{i=1}^I \frac{\partial \pi_{im}}{\partial p_{im}} \frac{dp_{im}}{dx_m^k}$ which is zero by the first order condition. Thus, $\frac{d\pi_m}{dx_m^k} = \sum_{i=1}^I \left[\frac{\partial \text{Pr}_{im}}{\partial x_m^k} [p_{im} - c_m] - \text{Pr}_{im} \frac{\partial c_m}{\partial x_m^k} \right]$. Plugging in the expression for $[p_{im} - c_m]$ from the first order condition and rearranging terms yields the following condition

$$\frac{d\pi_m}{dx_m^k} = I \left[\frac{1}{I} \sum_{i=1}^I \text{Pr}_{im} \left[-\frac{\frac{\partial \text{Pr}_{im}}{\partial x_m^k}}{\frac{\partial \text{Pr}_{im}}{\partial p_{im}}} - S_m \left[\frac{\partial c_m}{\partial x_m^k} \right] \right] \right]. \quad (3)$$

Since each consumer has a unique contribution margin under price personalization, the firm cares much more about which consumers are induced to purchase. High valuation consumers are more likely to tolerate higher prices and yield higher margins. Thus, incremental profits depend not solely on attracting more customers (as is the case under common pricing) but more on the extraction of consumer surplus from buyers with larger valuations for the attribute improvement. Under personalized pricing the ratio of consumer choice probability derivatives with respect to the attribute and price determines the MVAI. More specifically, the attribute improvement will be profitable if the weighted average of these ratios exceeds the marginal cost weighted by the product's market share. Specifically, MVAI under personalized pricing is

$$\text{MVAI}^{\text{per}} = \frac{1}{I} \sum_{i=1}^I \text{Pr}_{im} \left[-\frac{\frac{\partial \text{Pr}_{im}}{\partial x_m^k}}{\frac{\partial \text{Pr}_{im}}{\partial p_{im}}} \right]. \quad (4)$$

⁶ We will return to the question of how the firm implements personalized pricing in our empirical application.

3.4. MVAI under personalized pricing and the multinomial logit (MNL) model

We now discuss expressions for MVAI under personalized pricing implied by the widely used multinomial logit model. Suppose we observe the choices of the $i = 1, \dots, I$ consumers on a set of $t = 1, \dots, T$ choice occasions. Assume a linear indirect utility function, $V_{imt} = x'_{imt} \phi - \alpha^* p_{imt} + \varepsilon_{imt}^*$, with error term $\varepsilon_{imt}^* \sim EV(0, \mu^*)$. It is well known that the utility function can be multiplied by a constant without changing the consumer's utility maximizing choice. This scale identification problem is typically addressed by estimating the parameters $\phi = \frac{\phi^*}{\mu^*}$ and $\alpha = \frac{\alpha^*}{\mu^*}$, normalizing utility by the scale parameter of the error distribution (Swait & Louviere, 1993; Train, 2003). The choice probabilities are

$$\text{Pr}[y_{imt} = 1] = \frac{\exp[x'_{imt} \phi - \alpha p_{imt}]}{1 + \sum_{l=1}^M \exp[x'_{ilt} \phi - \alpha p_{ilt}]}. \quad (5)$$

Parametric distributions of heterogeneity are easily incorporated into the analysis. For example, one could specify $\theta_i \sim MVN(\bar{\theta}, \Sigma_\theta)$ where $\theta_i = [\phi_i \ln(\alpha_i)]$. Following Eq. (4), with heterogeneous θ the MVAI for the k th product attribute under personalized pricing is given by

$$\text{MVAI}_\theta^{\text{per}} = \frac{1}{I} \sum_{i=1}^I \text{Pr}_{im} \left[\frac{\phi_i^k}{\alpha_i} \right]. \quad (6)$$

Under personalized pricing the MVAI is the average of the consumer-level valuations weighted by the choice probabilities.⁷ In this specification the distribution of the consumer-level valuations is identified indirectly as the ratio of the random attribute and price coefficients, $\frac{\phi_i}{\alpha_i}$ (Train, 2003). While commonly employed, unfortunately not much can be said in favor of such an identification strategy in the context of MVAI under personalized pricing. The heterogeneity distribution for the attribute and price coefficients implies a distribution for the ratio which will generally be different from that specified for the coefficients. For example, a normal distribution on the coefficients does not imply a normal distribution on the ratio. The implied heterogeneity distribution may reflect a prior belief that the researcher has no intention of expressing. Since ratios of random variables are generally heavy tailed, the researcher using indirect identification is implicitly (and perhaps unwittingly) imparting a prior belief that the distribution of consumer-level valuations is heavy tailed. Furthermore, it is not at all clear that the implied distribution possesses finite moments (Daly et al., 2012). Even if the heterogeneity distribution does possess finite moments, it is clear that consumers with estimates of α_i tending towards zero will be problematic in this setting as their valuations will tend to be very large. Such consumers will inflate the market value for the product attribute improvement. Indeed, only a handful of such consumer-level valuations would likely result in the MVAI exceeding the share weighted marginal cost, suggesting a profitable attribute improvement.

Given the significance of the consumer-level valuations in the MVAI under personalized pricing, it seems advantageous to parameterize the model to directly identify the valuations.⁸ We can estimate $\beta = \frac{\phi}{\alpha}$ and $\mu = \frac{\mu^*}{\alpha^*}$, normalizing by the price coefficient and directly identifying

⁷ Interestingly, the weighted average approach has been suggested as an ad-hoc aggregation rule for consumer-level valuations (Ofek & Srinivasan, 2002).

⁸ The interested reader is directed to Sonnier et al. (2007) for a more detailed discussion of direct and indirect estimation of consumer-level valuations.

the consumer-level valuation via β (Cameron & James, 1987; Sonnier et al., 2007). The choice probabilities are

$$\Pr[y_{imt} = 1] = \frac{\exp\left[\frac{x'_{imt}\beta - p_{imt}}{\mu}\right]}{1 + \sum_{l=1}^M \exp\left[\frac{x'_{ilt}\beta - p_{ilt}}{\mu}\right]} \quad (7)$$

An advantage of direct identification is that the heterogeneity distribution is specified directly on the consumer-level valuations. For example, one could specify normally distributed valuations via $\lambda_i \sim MVN(\bar{\lambda}, \Sigma_{\lambda})$ where $\lambda_i = [\beta'_i \quad \ln(\mu_i)]$. This would place less prior mass in the tails of the distribution of the valuations tamping down on outlier valuations. Alternatively, if the researcher believes the distribution of valuations is in fact thick-tailed, a heterogeneity distribution that reflects this belief, such as the t -distribution, may be utilized. The valuations may also be modeled as a function of demographics or other consumer-level covariates, allowing for the prediction of valuations for future consumers conditional on this information.

For heterogeneous λ , the market value for an improvement in the k th product attribute under one-to-one price personalization is computed as

$$MVAI_{\lambda}^{per} = \frac{1}{I} \sum_{i=1}^I \Pr_{im}[\beta_i^k] \quad (8)$$

The expression for MVAI in Eq. (8) makes use of the directly identified consumer valuations and avoids potential problems associated with ratio estimates of the valuations. From Eqs. (7) and (8) we see that for MVAI under personalized pricing the scale of error variance, captured by the parameter μ , plays a role similar to that in the case of common pricing. As the effect of the error variance increases, the ability of the valuations to explain consumer choices diminishes. In the extreme, as $\mu \rightarrow \infty$ the value of \Pr_{im} approaches $\frac{1}{1+M}$. As the effect of the error variance decreases, the probability of choosing the alternative with the highest valuation increases. Under common pricing, MVAI gives smaller weight to such high value, high probability consumers since the weight $\Pr_{im}[1 - \Pr_{im}]$ reaches its maximum value at $\Pr_{im} = 0.5$ (Ofek & Srinivasan, 2002). Under common pricing consumers very likely to buy product m are given a smaller weight in the market valuation for an attribute improvement compared with consumers who are indifferent between product m and the composition of all other products. Under personalized pricing, the consumer-level valuations are weighted by the choice probabilities, \Pr_{im} . Consumers very likely to buy product m are given a larger weight in the market valuation.

Since the choice probability increases in the valuations, consumers with higher valuations for the attributes of product m are also more likely to be consumers with higher choice probabilities for product m . Under common pricing, the firm can raise the price of a product subsequent to an attribute improvement to capture surplus from higher value consumers, but does so at the risk of losing consumers with lower attribute valuations and choice probabilities. By the nature of the S-shaped logit probability response curve, consumers with choice probabilities away from zero or one will exert most of the influence on the changes in market share with respect to the attribute and price, which ultimately determines MVAI under common pricing. MVAI under common pricing reflects the importance of these consumers by giving them higher weights. However, one-to-one price personalization allows the firm to capture surplus from higher valuation, higher probability consumers without driving lower valuation, lower probability consumers away from the product. Thus, consumers with higher valuations, and consequently higher choice probabilities, are given more weight in the market valuation under one-to-one price personalization as incremental

profitability from an attribute improvement is driven by the extraction of surplus from these consumers.

4. Empirical application

Using a data set on consumer stated preferences for camera mounts we explore estimates of MVAI under personalized pricing.⁹ A complete description of the data and a thorough treatment of MVAI under common pricing can be found in Ofek and Srinivasan (2002). A total of 302 respondents each rank 18 profiles. Each profile is described by 5 attributes and a price. In addition, respondents completed a holdout ranking task with 4 profiles. We begin by considering heterogeneity distributions for the directly identified valuations, β_i . We consider normal and t heterogeneity distributions for valuations. A normal heterogeneity distribution, $\beta_i \sim N(\bar{\beta}, \Sigma_{\beta})$, places small prior mass on outlier consumer valuations. In contrast to a normal heterogeneity distribution for the valuations, a t distribution of heterogeneity, $\beta_i \sim t_{\nu}(\bar{\beta}, \Sigma_{\beta})$, permits more prior mass in the tails. For both cases, we use a log-normal heterogeneity distribution for μ_i . For the t -distribution, the degree of freedom parameter ν must lie on the range $(0, \infty)$. We specify a log-normal prior for ν and treat it as an unknown parameter to be estimated. We estimate the normal and t models with standard Markov–Chain Monte Carlo methods, running the sampler for a total of 15,000 iterations, keeping the last 5000 for inference. Time series plots of the model log-likelihoods indicate that this is sufficient for convergence. In-sample fit measured by the Deviance Information Criteria (DIC) (Spiegelhalter, Best, Carlin, & van der Linde, 2004) and holdout fit measured by the log predictive density (LPD) suggest that the model based on a t -distribution of heterogeneity outperforms the model based on normal heterogeneity (DIC of 15,994 vs. 16,689 and LPD of -689 vs. -691 for the t vs. normal model, respectively).

Table 1 presents the attributes and levels of the five products used in our MVAI analyses along with the marginal costs of improvement for each attribute. An issue to consider is how the firms might implement personalized pricing in practice. An approach widely discussed in the literature is to offer a personalized discount, via a coupon or rebate, off of a regular common price (Rossi et al., 1996; Shaffer & Zhang, 2002). However, in a personalized marketing environment, firms could forgo regular price altogether. Regular prices place an upper bound on the price a consumer pays which limits the ability of the firm to extract surplus from high value customers. Of course, this issue could be resolved by simply charging a high regular common price, at or above the maximum suggested consumer-level price, and offering discounts accordingly. Shaffer and Zhang (2002) show that in a competitive environment lower regular prices perform the important function of limiting competitive poaching of a firm's high value customers. From a practical vantage point, a regular common price coupled with a personalized discount may also be a more feasible strategy for firms to implement. In light of these issues, we consider a personalized price discount, denoted by z_{im} , off of the common prices used in Ofek and Srinivasan (2002) and reported in Table 1.¹⁰ We show in Appendix A that the MVAI under a personalized discount is equivalent to the expression shown in Eq. (4). To find the optimal personalized price discounts, we compute for each consumer the vector of discounts that satisfies the first order condition with respect to z_{im} by finding the consumer-specific discount vector that minimizes $\sum_{m=1}^M \left[\left([p_m - z_{im} - c_m] - \frac{\Pr_{im}}{\partial \Pr_{im} / \partial z_{im}} \right)^2 \right]$. As in Rossi et al. (1996), we allow for the possibility that the optimal discount may be zero. Once the optimal discounts are obtained, we compute MVAI accordingly.

⁹ While our empirical application makes use of stated preference data, computation of MVAI is not limited to stated preference data. MVAI can also be computed from a choice model calibrated on revealed preference data.

¹⁰ This can be viewed as an approximation to a two stage game where competing firms choose a regular price in the first stage then price discounts in the second stage.

Table 1

Marginal costs, attribute levels, and common prices for camera mount product simulations.

Attribute	Marginal cost of attribute improvement ^a	UltraPod	Q-Pod	Gorilla Pod	Camera Critter	Half Dome
Weight (tens of oz.)	\$4.90	0.20	0.35	0.46	0.17	0.57
Size ^b	\$0.23	0.98	0.84	1.27	0.80	1.20
Set up time (min.)	\$1.41	0.98	0.84	0.50	0.62	0.42
Stability ^c	\$0.31	1.80	2.50	2.30	2.50	3.00
Flexibility ^d	\$0.26	1.96	2.17	2.84	1.80	2.33
Common prices for competitive set ^e						
Three products		\$8.84	\$9.89	\$9.53		
Four products		\$7.72	\$9.22	\$8.50	\$8.22	
Five products		\$7.15	\$8.53	\$7.75	\$7.49	\$10.39

^a Marginal cost of weight in dollars to reflect coding of weight in tens of ounces. All other marginal cost data are in tens of dollars.

^b Where 1 represents a camera mount that fits into a standard pocket and 3 in a standard book bag.

^c Where 1 means stable enough under light-medium wind conditions for a small camera with a built-in lens and 3 for a full-size camera with a large lens.

^d Where 1 is low flexibility and 3 is high flexibility. Flexibility is the degree to which the camera mount can be adapted to various terrains and adjusted for height and angle.

^e Prices in tens of dollars, as reported in Ofek and Srinivasan (2002).

Table 2 reports the estimates of MVAI under personalized pricing implied by the model that directly identifies the valuations with a *t*-distribution of heterogeneity. The estimates are reported for the three product market in Ofek and Srinivasan (2002). Under common pricing, Ofek and Srinivasan (2002) find that improvements in weight, size, stability and flexibility are profitable for all three products. Improvements in set up time are not profitable for any of the three products. When firms are engaged in price personalization, MVAI estimates suggest a smaller set of profitable attribute improvements. As with common pricing, improvements in size and flexibility are profitable for all three products. However, improvements in weight fail to generate incremental profits for any of the products. Similarly, improvements in stability are profitable only for *Q-Pod* and *Gorilla Pod*. Interestingly, under personalized pricing improvement in set up time is profitable for *Gorilla Pod*. These results reflect two effects at play when firms move from common to personalized pricing. On the one hand, personalization allows firms to capture more consumer surplus versus common pricing. This implies that finding incremental profitability from attribute improvements may be more difficult under price personalization as firms are already wringing much of the surplus from the market. On the other hand, moving to price personalization may render some attributes that are unprofitable to improve under common pricing profitable. This is due to the fact that profitability under personalization is driven by capturing surplus from high value

Table 2

Market value for attribute improvements under price personalization: direct identification of consumer-level valuations.

Attribute	UltraPod	Q-Pod	Gorilla Pod
Weight	1.70 (0.10)	1.04 (0.06)	0.94 (0.05)
Size	0.55^a (0.04)	0.63 (0.09)	0.39 (0.03)
Set up time	0.36 (0.03)	0.44 (0.04)	1.26 (0.13)
Stability	−0.31 (0.28)	1.09 (0.14)	0.79 (0.08)
Flexibility	0.48 (0.03)	0.57 (0.04)	1.18 (0.11)

Table cells report the posterior mean (in tens of dollars) and posterior standard error (in parenthesis).

^a Bold indicates that 95% of the distribution of the difference between the valuation and the share weighted marginal costs is positive.

Table 3

Market value for attribute improvements under segment pricing: direct identification of consumer-level valuations.

Attribute	UltraPod	Q-Pod	Gorilla Pod
Weight	1.16 (0.08)	0.82 (0.05)	0.87 (0.07)
Size	0.50^a (0.04)	0.40 (0.03)	0.34 (0.03)
Set up time	0.34 (0.02)	0.31 (0.03)	0.51 (0.06)
Stability	0.10 (0.03)	0.54 (0.10)	0.83 (0.22)
Flexibility	0.40 (0.02)	0.41 (0.03)	0.70 (0.08)

Table cells report the posterior mean (in tens of dollars) and posterior standard error (in parenthesis).

^a Bold indicates that 95% of the distribution of the difference between the valuation and the share weighted marginal costs is positive.

consumers. Under common pricing, firms are unable to capture this value without driving down share. Price personalization frees the firm from this constraint. As noted, we see both of these effects in our results.

It is interesting to compare the estimates of MVAI under personalized pricing with those under segment pricing. The segments may be determined according to any of a number of bases (e.g., demographics, brand loyalty, or usage). For our illustration, we perform a two-step cluster analysis on the posterior means of the attribute valuations. This cluster analysis results in two segments. The first segment is comprised of 87% of the respondents while the second segment is comprised of 13% of the respondents. The mean attribute valuations in the second segment are all higher than the mean valuations in the first segment. We compute the optimal segment-specific price discounts and then compute the MVAI under segment pricing. The results appear in Table 3. The results under segment pricing suggest largely the same smaller set of profitable attribute improvements as the results under personalized pricing. The exception is that improvements in set up time are not profitable for *Gorilla Pod* under segment pricing. In addition, the MVAI estimates under segment pricing are, for the most part, smaller in magnitude.

While an indirect identification strategy on the valuations raises a number of concerns, it is nonetheless instructive to dwell on such a strategy. Normal heterogeneity distributions are often used by academics and practitioners alike.¹¹ We may specify $\theta_i \sim MVN(\bar{\theta}, \Sigma_{\theta})$ where $\theta_i = [\phi'_i \ln(\alpha_i)]$. The log-normal distribution for α_i ensures that the consumer-valuations are well-defined (Daly et al., 2012). However, the valuations are distributed as the ratio of normal and log-normal random variables and are likely to be heavy tailed. This specification is thus analogous to using the thick tailed *t*-distribution in the case of direct identification. An important difference though is that under indirect identification, small price coefficients will lead to valuations tending towards infinity. While such valuations have smaller prior probability under direct identification, this is not necessarily so under indirect identification. A draconian fix to this problem is to restrict the price coefficient to be homogeneous across consumers. The implied valuations are then identified as the normally distributed attribute coefficients scaled by the homogeneous price coefficient. This is analogous to the direct model using a normal heterogeneity distribution on the valuations. However, such an approach cannot be recommended as the price of normality in this case is the more restrictive homogeneous specification on price responsiveness. While degradation of model fit is a concern, a larger concern is bias in the estimates of the price coefficient and hence the attribute valuations (Chintagunta, Jain, & Vilcassim, 1991; Daly et al., 2012).

¹¹ For example, Sawtooth Software's Hierarchical Bayes module for choice based conjoint analysis uses normal heterogeneity distributions.

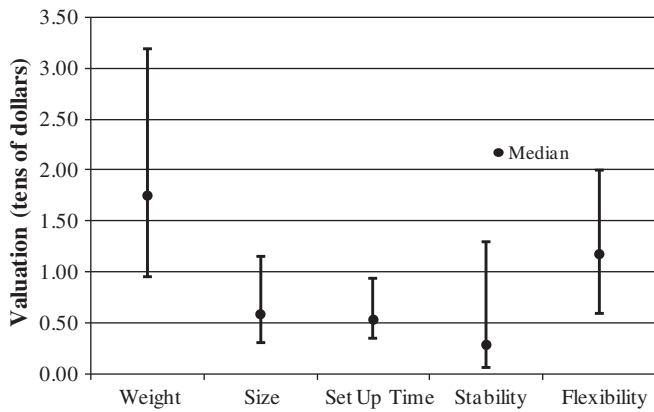


Fig. 1. Inter-quartile range of consumer-level attribute valuations based on β_i .

We estimate an indirect model with normal heterogeneity on the attribute coefficients and log-normal heterogeneity on the price coefficient. In-sample fit measured by the DIC is 16,319 while holdout fit measured by the LPD is -713 . Both in-sample and holdout fit is inferior to the direct model with the t -distribution of heterogeneity. As noted, previous research has shown indirect identification of the consumer valuations to be prone to outliers. Figs. 1 and 2, which present the median and inter-quartile ranges of the consumer level valuations implied by the direct and indirect models, respectively, confirm that this is indeed the case for our data. Fig. 1 corresponds to the direct model. The 75th percentile values are in the neighborhood of \$10–\$30. Fig. 2 corresponds to the indirect model. In Fig. 2, the valuations are far more dispersed. The 75th percentile values range from about \$80–\$250. The median valuations are all above the marginal costs reported in Table 1. Table 4 presents the MVAI estimates under personalized pricing for the valuations based on indirect identification. The MVAI estimates imply that improving any of the attributes for nearly all of the products is profitable. The MVAI estimates are also much larger in magnitude compared to those based on the directly identified valuations. Given the distribution of the estimates of the consumer-level valuations under indirect identification, it is not surprising that the MVAI estimates computed with these valuations are large and suggest that nearly any attribute improvement will be profitable. The results demonstrate that extreme consumer valuations have a significant impact on MVAI under personalized pricing.

Table 5 presents the MVAI estimates under segment pricing for the valuations based on indirect identification. As before, we perform a two-step cluster analysis on the posterior means of the attribute valuations which again results in two segments. The first segment is comprised of 87% of the respondents with lower mean valuations

Table 4
Market value for attribute improvements under price personalization: indirect identification of consumer-level valuations.

Attribute	UltraPod	Q-Pod	Gorilla Pod
Weight	6.55^a (2.42)	7.26 (2.20)	8.06 (2.50)
Size	2.72 (1.47)	3.61 (1.85)	2.93 (1.87)
Set up time	1.96 (0.84)	3.01 (1.07)	4.51 (1.73)
Stability	−0.48 (3.35)	4.30 (1.61)	4.04 (2.04)
Flexibility	2.65 (1.15)	4.03 (1.28)	7.60 (2.93)

Table cells report the posterior mean (in tens of dollars) and posterior standard error (in parenthesis).

^a Bold indicates that 95% of the distribution of the difference between the valuation and the share weighted marginal costs is positive.

compared to the smaller second segment comprised of 13% of the respondents. However, the average valuations for both segments are much higher compared to the average valuations for the segments derived from the directly identified valuations. This is to be expected given the distributions shown in Figs. 1 and 2. The more interesting issue is how the MVAI estimates under segment pricing compare to those computed with the directly identified valuations. We compute the optimal segment-specific price discounts and then compute the MVAI under segment pricing. Although the indirectly identified valuations are widely dispersed, as noted in Fig. 2, the MVAI estimates under segment pricing are not impacted to the degree to which the MVAI estimates under personalized pricing are affected. However, under segment pricing, the MVAI estimates computed with the indirectly identified valuations suggest that more attributes can be profitably improved compared to those computed with the directly identified estimates. The estimates imply that improvements in size, stability and flexibility are profitable for all products and improvements in set up time are profitable for *Q-Pod* and *Gorilla Pod*. In addition, the magnitude of the estimates computed with the indirectly identified valuations, although not as explosively large as those under personalized pricing, are generally larger compared to those computed with the directly identified valuations. While the MVAI estimates under segment pricing are more robust compared to those under personalized pricing, it is still the case that the estimates are adversely impacted by the widely dispersed valuations resulting from an indirect identification strategy.

4.1. MVAI and competitive entry

As noted in the conceptual analysis, MVAI under both common and personalized pricing depends upon the consumer choice probabilities,

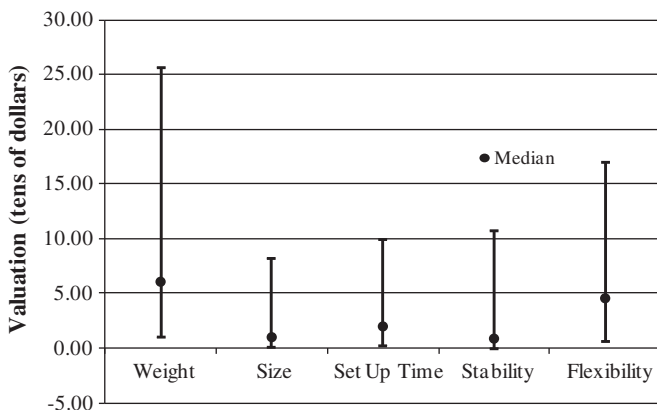


Fig. 2. Inter-quartile range of consumer-level attribute valuations based on $[\phi_i', \alpha_i]$.

Table 5
Market value for attribute improvements under segment pricing: indirect identification of consumer-level valuations.

Attribute	UltraPod	Q-Pod	Gorilla Pod
Weight	1.35 (0.12)	1.35 (0.14)	1.68 (0.19)
Size	0.57^a (0.06)	0.61 (0.07)	0.69 (0.09)
Set up time	0.48 (0.04)	0.56 (0.06)	0.80 (0.10)
Stability	0.18 (0.03)	0.64 (0.07)	0.73 (0.08)
Flexibility	0.66 (0.06)	0.79 (0.09)	1.23 (0.15)

Table cells report the posterior mean (in tens of dollars) and posterior standard error (in parenthesis).

^a Bold indicates that 95% of the distribution of the difference between the valuation and the share weighted marginal costs is positive.

Table 6

The effect of increased product competition on the market value for attribute improvements under price personalization.

Attribute	Three products			Four products				Five products				
	UltraPod	Q-Pod	Gorilla Pod	UltraPod	Q-Pod	Gorilla Pod	Camera Critter	UltraPod	Q-Pod	Gorilla Pod	Camera Critter	Half Dome
Weight	1.70 (0.10)	1.04 (0.06)	0.94 (0.05)	0.70 (0.04)	0.44 (0.03)	0.55 (0.04)	1.99 (0.11)	0.41 (0.03)	0.29 (0.02)	0.40 (0.03)	1.62 (0.09)	0.95 (0.06)
Size	0.55^a (0.04)	0.63 (0.09)	0.39 (0.03)	0.23 (0.02)	0.36 (0.06)	0.23 (0.02)	0.76 (0.07)	0.19 (0.02)	0.30 (0.06)	0.19 (0.02)	0.67 (0.07)	0.24 (0.02)
Set up time	0.36 (0.03)	0.44 (0.04)	1.26 (0.13)	0.16 (0.02)	0.20 (0.02)	0.81 (0.11)	0.88 (0.07)	0.11 (0.01)	0.12 (0.01)	0.52 (0.05)	0.52 (0.04)	0.78 (0.11)
Stability	−0.31 (0.28)	1.09 (0.14)	0.79 (0.08)	−0.38 (0.28)	0.71 (0.08)	0.31 (0.06)	0.94 (0.09)	−0.41 (0.33)	0.19 (0.02)	0.10 (0.04)	0.34 (0.02)	1.37 (0.17)
Flexibility	0.48 (0.03)	0.57 (0.04)	1.18 (0.11)	0.30 (0.02)	0.39 (0.03)	0.94 (0.11)	0.61 (0.03)	0.25 (0.02)	0.22 (0.03)	0.78 (0.09)	0.44 (0.02)	0.55 (0.04)
Market share	36%	30%	34%	17%	16%	20%	47%	13%	11%	15%	39%	21%
Regular price	\$8.84	\$9.89	\$9.53	\$7.72	\$9.22	\$8.50	\$8.22	\$7.15	\$8.53	\$7.75	\$7.49	\$10.39
% receiving discount	54%	54%	41%	43%	56%	33%	59%	37%	51%	34%	53%	62%
Average discounted price	\$7.45	\$8.30	\$8.48	\$6.86	\$7.97	\$7.91	\$6.72	\$6.54	\$7.56	\$7.26	\$6.27	\$8.90

Table cells report the posterior mean (in tens of dollars) and posterior standard error (in parenthesis).

^a Bold indicates that 95% of the distribution of the difference between the valuation and the share weighted marginal costs is positive.

although in different ways. Dependence on the choice probabilities renders MVAI sensitive to competitive entry. The choice model parameters, of course, do not change. However, competitive entry will alter equilibrium prices, the choice probabilities and hence the MVAI estimates. Under common pricing, the effect of expanding the competitive set on the MVAI of existing products will depend on the choice probabilities through the expression $\Pr_{im}[1 - \Pr_{im}]$. Ofek and Srinivasan (2002) show that under common pricing, MVAI may increase or decrease in response to an expansion of the competitive set. For example, a price cut in response to entry may attract more consumers with lower valuations and lower MVAI while products that can maintain premium pricing in the face of entry may lose some lower valuation consumers while retaining higher valuation consumers thereby increasing the MVAI.

Consider now the effect of expanding the competitive set on MVAI under personalized pricing. Since the consumer-level valuations are directly weighted by the choice probabilities competitive entry will reduce the probability of purchase for incumbent products, entry is likely to reduce the incumbent firms' MVAI estimates. Table 6 presents MVAI under personalized pricing when the choice set expands from three to four products and then four to five products.¹² Also listed in Table 6, for each product, is the market share, the regular price, the percentage of consumers receiving a discount, and the average discounted price. When *Camera Critter* is added to the choice set, it gains a considerable amount of market share at the expense of the three incumbent products. *Camera Critter* is the dominant alternative on weight and size, shares dominance on stability with *Q-Pod*, and engages in personalized discounting with broader scope and scale. As a result, *Camera Critter* obtains a 47% share upon entry. The MVAI estimates for all the incumbent firms decrease. *Gorilla Pod* is the dominant alternative on set up time and flexibility. Consequently, its MVAI for these attributes does not decline as sharply. Indeed, its advantage on flexibility is substantial and the *Gorilla Pod* MVAI for flexibility remains the highest even after *Camera Critter's* entry. *Half Dome* enters with dominance on set-up time and stability. *Camera Critter* retains dominance on weight and size while *Gorilla Pod* retains dominance on flexibility. *Half Dome* has the highest average discounted price but still manages to obtain a 21% share. As expected, share declines bring about declines in MVAI for the incumbent firms. However, *Camera Critter* still has the highest MVAI for size and *Gorilla Pod* the highest MVAI for flexibility.

4.2. MVAI under asymmetric personalization

Personalization of the marketing mix is costly in terms of information, computing, and administration (Rossi et al., 1996). In light of this, firms will likely differ in their willingness and/or ability to implement personalized pricing strategies. In this section, we examine the impact of *asymmetric personalization* on MVAI estimates. We use the term *asymmetric personalization* to refer to the situation where some firms are engaged in personalization while other firms employ common pricing. This is opposed to the case where all firms personalize, which we term *full personalization*. To conduct the analysis, we assume that after setting regular price, *UltraPod* and *Q-Pod* set personalized discounts while *Gorilla Pod* sells at the regular price. We then compute MVAI under personalized pricing for *UltraPod* and *Q-Pod* and MVAI under common pricing for *Gorilla Pod*. The results are presented in Table 7.

Under asymmetric personalization, *UltraPod* and *Q-Pod* offer personalized discounts to over 60% of consumers resulting in an average discounted price of \$7.51 for *UltraPod* and \$8.30 for *Q-Pod*. The average discounted prices are close to those under full personalization and considerably lower than *Gorilla Pod's* regular price of \$9.53. As a result, *Gorilla Pod* share drops to 28% while *UltraPod* and *Q-Pod* shares increase to 37% and 35%, respectively. The MVAI estimates for *UltraPod* and *Q-Pod*

Table 7

Market value for attribute improvements under asymmetric price personalization.

Attribute	UltraPod	Q-Pod	Gorilla Pod
Weight	1.61 (0.10)	1.20 (0.06)	2.77 (0.13)
Size	0.55^a (0.04)	0.67 (0.09)	1.14 (0.07)
Set up time	0.36 (0.03)	0.40 (0.03)	1.58 (0.10)
Stability	−0.29 (0.27)	1.22 (0.14)	2.32 (0.34)
Flexibility	0.52 (0.03)	0.58 (0.04)	2.16 (0.12)
Market share	37%	35%	28%
Regular price	\$8.84	\$9.89	\$9.53
% receiving discount	62%	63%	–
Average discounted price	\$7.51	\$8.30	\$9.53

Table cells report the posterior mean (in tens of dollars) and posterior standard error (in parenthesis). For $m = 1, 2$ MVAI computed under personalized pricing. For $m = 3$ MVAI computed under common pricing.^a Bold indicates that 95% of the distribution of the difference between the valuation and the share weighted marginal costs is positive.¹² For the purposes of this analysis we focus only on the model that directly identifies the consumer-level valuations. See Table 1 for a description of all five products.

(computed via the rule for MVAI under personalized pricing) increase slightly, commensurate with the share increases. Consumers choosing *Gorilla Pod* at the premium price are likely consumers with high valuations for the product. Indeed, *UltraPod* and *Q-Pod* are unable to profitably entice these consumers to switch even with a personalized discount. This intuition is confirmed by the relatively high MVAI's for *Gorilla Pod* (computed via the rule for MVAI under common pricing). Improvements in size, stability, and flexibility are profitable for *Gorilla Pod* under asymmetric personalization.

5. Summary and conclusions

Understanding the market value for product attribute improvements is crucial to successful product planning and new product development. A measure of the consumer's value for an attribute improvement is the increase in price that would leave utility unchanged given the attribute improvement. A discrete choice model calibrated on stated or revealed preference data is a popular method for estimating consumer valuations. With heterogeneous consumers, the issue of how to aggregate the consumer-level valuations into a market-level valuation to assess profitability arises. Ad-hoc methods such as taking the average may yield misleading results and, empirically, may suffer from the effect of extreme valuations. Based on micro-economic theory of consumer and firm behavior, Ofek and Srinivasan (2002) derive the market valuation for an attribute improvement (MVAI) as the ratio of changes in market share with respect to the attribute improvement and price. Their derivation assumes the firm employs a common pricing strategy, charging the same price to all consumers.

Marketing academics have long been interested in the effects of personalizing the marketing mix (Rossi et al., 1996). Recently, online channels have stimulated industry interest in and enabled more widespread use of price personalization based on purchase history or other information. We consider the market value for product attribute improvements for the case of one-to-one price personalization. Our results demonstrate how to assess the profitability of attribute improvements in this interesting and important setting. Compared with the market valuation for an attribute improvement under common pricing, two important differences emerge. First, under common pricing, the profitability of an attribute improvement is driven by inducing more consumers, each of whom contributes the same margin, to buy. Thus, consumers with extreme choice probabilities are given less weight in the market valuation under common pricing as these consumers are less responsive to attribute improvements. Under personalized pricing, the profitability of an attribute improvement is driven by the extraction of consumer surplus from high value consumers. Thus, higher valuation consumers with higher choice probabilities are given greater weight in the market valuation under personalized pricing. Second, because the individual consumers play a more central role in the market valuation under personalized pricing, MVAI under one-to-one price personalization is not robust to extreme consumer-level valuations. Therefore, when engaged in personalized pricing, the identification and estimation of consumer-level valuations is of increased importance relative to the case of common pricing.

With additive linear utility, consumer-level valuations are identified as the ratio of attribute and price coefficients from the discrete choice model. This identification strategy has been shown to yield distributions for the valuations that lack finite moments in some cases and is particularly prone to yield extreme valuations. A simple alternative is to utilize a choice model directly identifies the valuations. Using a dataset on consumer stated preferences for camera mounts, we demonstrate the managerial relevance of our analysis. We estimate choice models that directly and indirectly identify consumer-level valuations for product attribute improvements. We then use these models to compute the MVAI implied by both models under personalized pricing strategies. Under personalized pricing, models that indirectly identify the consumer-level valuations result in MVAI estimates that suggest nearly

any attribute improvement for all products considered is profitable. In contrast, the model that directly identifies the consumer-level valuations provides a better fit to the data and results in a smaller set of profitable attribute improvements.

There are a number of avenues for future research. As noted, the problem of discrete product attributes remains a challenge. Our expressions for MVAI are based on a logit demand model. Future research may consider other empirical models of demand. Recent research investigates the price discrimination across multiple channels in the context of channel competition where manufacturers and retailers each have the ability to personalize price would be very challenging but may yield interesting insights. Lastly, our analysis considers single product firms. Firms may offer different product attributes via vertically differentiated product lines (Michalek, Ebbes, Adigüzel, Feinberg, & Papalambros, 2011). The impact of price personalization on product attribute decisions in a product line may be an interesting topic to consider. Sorting out the market value for a product attribute improvement in these cases should assist firms in making better product planning decisions.

Appendix A. MVAI with personalized price discounts

Consider our firms engaged in personalized pricing by offering a personalized discount, z_{im} , off of the regular price, p_m , common to all consumers. Such a discount could be in the form of a personalized coupon or a rebate. We will abstract away from targeting costs and redemption issues. Profits to firm m are $\pi_m = \sum_{i=1}^I \text{Pr}_{im}[p_m - z_{im} - c_m]$ while the MNL choice probabilities in this setting are

$$\begin{aligned} \text{Pr}_{im} &= \frac{\exp[x'_{im}\phi_i - \alpha_i(p_m - z_{im})]}{1 + \sum_{l=1}^M \exp[x'_{il}\phi_i - \alpha_i(p_l - z_{il})]} \\ &= \frac{\exp\left[\frac{x'_{im}\beta_i - (p_m - z_{im})}{\mu_i}\right]}{1 + \sum_{l=1}^M \exp\left[\frac{x'_{il}\beta_i - (p_l - z_{il})}{\mu_i}\right]}. \end{aligned} \quad (\text{A1})$$

We assume the regular prices are observable to all firms when choosing their personalized discounts. This is consistent with the notion that regular prices are a high level managerial decision slow to adjust in practice (Shaffer & Zhang, 2002). For each consumer, the manufacturer's first order condition for the discounting decision is

$$\frac{\partial \pi_{im}}{\partial z_{im}} = -\text{Pr}_{im} + \frac{\partial \text{Pr}_{im}}{\partial z_{im}} [p_m - z_{im} - c_m] = 0. \quad (\text{A2})$$

The total derivative of manufacturer profits with respect to the attribute change is

$$\frac{d\pi_m}{dx_m^k} = \sum_{i=1}^I \left[\frac{\partial \text{Pr}_{im}}{\partial x_m^k} [p_m - z_{im} - c_m] - \text{Pr}_{im} \frac{\partial c_m}{\partial x_m^k} \right]. \quad (\text{A3})$$

Plugging in the expression for $[p_m - z_{im} - c_m]$ from the first order condition and rearranging terms yields the following condition

$$\frac{d\pi_m}{dx_m^k} = I \left[\frac{1}{I} \sum_{i=1}^I \text{Pr}_{im} \left[\frac{\frac{\partial \text{Pr}_{im}}{\partial x_m^k}}{\frac{\partial \text{Pr}_{im}}{\partial z_{im}}} - S_m \left[\frac{\partial c_m}{\partial x_m^k} \right] \right] \right]. \quad (\text{A4})$$

Inspection of Eq. (A4) reveals for heterogeneous choice models parameterized in the space of θ , the MVAI will be given by $\frac{1}{I} \sum_{i=1}^I \text{Pr}_{im} \left[\frac{\phi_i^k}{\alpha_i} \right]$. For heterogeneous choice models parameterized in the space of λ , the MVAI will be given by $\frac{1}{I} \sum_{i=1}^I \text{Pr}_{im} [\beta_i^k]$.

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