

Framing effects in mixed price bundling

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Abstract In mixed price bundling, the consumer has the choice of buying the individual products separately, as part of a bundle with a discounted price, or not purchasing them at all. Framing effects refer to how the price of the bundle is presented to the consumer. Past studies have focused on perceptual measures and aggregate level results, and have only looked at a subset of different types of price framing in any one study. In this paper we use discrete choice data to investigate whether price framing affects choice in mixed price bundles. We find that the joint, integrated frame results in the highest proportion of respondents choosing the bundle and the fewest choosing “none.” When the prices of items in a bundle are itemized, some consumers are more likely to compare prices separately to their reference prices to evaluate the attractiveness of the deal, but this actually reduces the probability of purchasing the bundle. However, the majority of consumers do not use reference prices and instead follow a simple economic choice model.

Keywords Bundling · Pricing · Framing effects · Hierarchical Bayes

1 Introduction

Bundling is the business practice of offering two or more products for sale as package. In *pure* bundling the component products are only sold as a package. In *mixed* bundling the consumer has the choice of buying two or more products separately, or together in a bundle. When a price discount is part of the bundle offer,

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the practice is characterized as “price bundling” (cf. [Stremersch and Tellis 2002](#)). Discounted prices are typically framed in one of three ways.

- Joint, integrated: “Pay \$X when you buy both product A and product B”
- Joint, segregated: “Pay \$Y for A and \$Z for B when you buy both”
- Leader, segregated: “Pay \$W for B when you buy A at the regular price”

In the last example, product B is referred to as the “price leader”, and managers must choose which product should be the “leader” if leader pricing is selected.

Past academic research on framing price bundles has measured *perceptions* of different bundles (as opposed to choice), has not compared joint vs. leader framing effects, and has focused on aggregate level effects (cf. [Harlem et al. 1995](#); [Kaicker et al. 1995](#); [Yadav 1994, 1995](#)). In contrast, this study investigates choice behavior, assesses the impact of all types of mixed bundling strategies, and tests different information processing models at the individual level. These goals are accomplished by using a discrete choice experimental design and hierarchical Bayes statistical techniques to measure the effect of reference prices or “transaction utility” on choices.

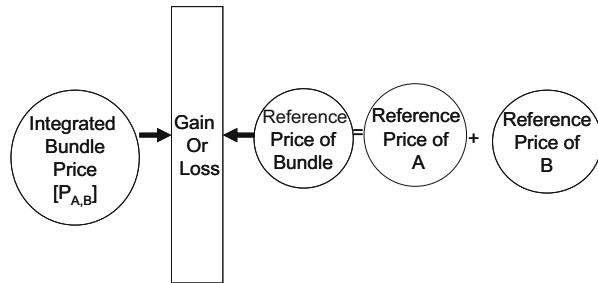
We find that the “integrated” frame results in the greatest proportion of consumers that choose the bundle and the smallest proportion choosing “none” in our discrete choice experiment. The statistical model suggests that when prices are integrated, consumers are less likely to rely on individual reference prices and calculations of “transaction utility.” In fact, we find that across experimental conditions, only a minority of respondents use reference prices when evaluating bundled offerings.

2 Economic and behavioral theory

As initially spelled out by [Stigler \(1968\)](#) and [Adams and Yellen \(1976\)](#), bundling is a device for capturing more consumer surplus by facilitating price discrimination across consumers who differ in their relative preference between two (or more) products. In mixed bundling, consumers face P_A , P_B , and the bundle price $P_{A,B}$. If reservation prices (RP_A and RP_B) are additive¹, then the bundle is purchased if $RP_A + RP_B \geq P_{A,B}$. The goal in mixed bundling is to choose $P_{A,B}$ such that total sales and profit are increased.

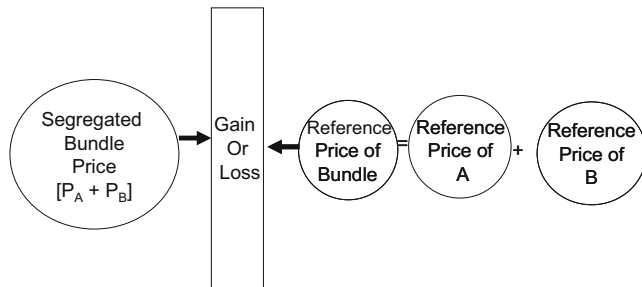
Behavioral research into price framing has been guided by Kahneman and Tversky’s (1979) prospect theory and Thaler’s (1985) model of mental accounting. These theories may help explain price framing effects by augmenting the economic model with a measure of “how good a deal” the consumer is getting. Figure 1 presents a stylized version of how these theories may apply under different pricing frames. Central to the behavioral approach is the calculation of “gains and losses” relative to a set of reference prices (not reservation prices as in the economic model) and the fact that “losses” are more detrimental than corresponding “gains.” When a single price for the bundle is presented, consumers must add together their reference

¹Additivity of reservation prices is a frequent assumption in economic analyses of price bundling. See [Jedidi et al. \(2003\)](#) for a discussion and empirical test of this assumption. Our empirical model follows the findings of [Jedidi et al.](#) and we do not assume additivity of reservation prices in our analysis.

Panel a.**Integrated Pricing – Combining Reference Prices**

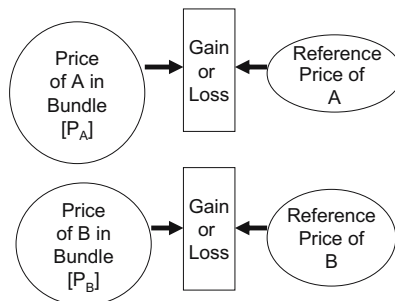
Single price for bundle $P_{A,B}$ presented to consumer.

Consumer adds together his/her reference prices to compare to price of bundle.

Panel b.**Segregated Pricing – Combining Prices and Combining Reference Prices**

Bundle price presented as two components, consumer adds two prices together $P_A + P_B$.

Consumer adds together his/her reference prices to compare to price of bundle.

Panel c.**Segregated Pricing – 2 Comparisons**

Bundle price presented as two components.

Consumer compares each price to each reference price.

Fig. 1 Evaluating bundled prices in different frames

prices for the two goods in order to compare their reference prices to the price of the bundle (Fig. 1a). In the case of segregated prices, it is not clear exactly how consumers process the prices of the products in the bundle or make comparisons to reference prices. Consumers may add together the prices of the products in the bundle, add together their reference prices, and make one comparison to calculate the “gain or loss” (Fig. 1b). Or, they may make two separate comparisons (Fig. 1c). A hierarchical statistical model is introduced to examine which of these theories best explain subjects’ choices.

Although the weight of past experimental studies does appear to favor integrated bundle pricing, the evidence is best described as mixed. [Yadav and Monroe \(1993\)](#) find that the additional savings represented in an integrated bundle price—after savings were presented separately for individual item sale prices—explained more variance in overall perceived transaction value than did the initial savings on the two items separately. Other research, however, suggests that the superiority of integrated bundle pricing is dependent upon the certainty and level of consumers’ starting price expectations. Unfortunately, though, there is no consensus on whether integrated pricing is better when bundle prices are below expectations ([Mazumdar and Jun 1993](#)), above expectations ([Harlam et al. 1995](#)), or only with certain mixtures of gains and losses ([Kaicker et al. 1995](#)). While these studies differed significantly in method, they have in common the use of consumer perception as the dependent variable and efforts to provide explicit attention to gains and losses in the pricing of both individual products, presenting reference prices and sometimes calculating gains and losses for subjects’ consideration.² Further, the studies are generally organized around the question of which frame consumers “prefer” (e.g., which makes them happier; [Mazumdar and Jun 1993](#)), some presenting different frames to the consumer simultaneously for comparison.

Leader pricing Other studies have provided additional insight into the question of which product of the pair should receive the discount when the leader form of segregated framing is used. This work varies on whether the best option is to give the discount to the component that is most preferred ([Yadav 1995](#)), or to the item in the pair that will be most likely to reduce the consumer’s sense of loss ([Janiszewski and Cunha 2004](#)). As with other prior research on framing effects, these studies both used dependent measures of customers’ perception of the comparative value reflected in the different bundle frames, presenting different frames simultaneously.

2.1 Introducing a choice context

This study investigates price framing effects in choice situations where there is an option of choosing either one of the items, choosing the bundle, or not choosing at all. In many (if not most) real choice contexts, consumers select not only among different brand options, but may also decide to defer choice ([Dhar and Simonson 2003](#); [Dhar 1997](#)). Consumers might opt for “no choice” because of difficulty in making trade-offs among options (cf. [Tversky and Shafir 1992](#)) or calculating the

²The exception is [Harlam et al. \(1995\)](#), who use self-explicated reservation prices as a proxy for reference prices and measure purchase intentions.

“gain or loss,” or because of preference or choice uncertainty (Lanzetta 1963; Urbany et al. 1989). A third explanation—emanating from the theory of rational search (Stigler 1961; Karni and Schwarz 1977; Rothschild 1974)—is that the evaluation of options is driven by both their assessments of the promoted goods, and outside considerations: A willingness to forego additional search or known outside goods is fundamental to the notion of a reservation price, or “willingness to pay.”

Although still an experimental setting, discrete choice offers an important extension to research on framing effects. Past perceptual research shows that price framing influences attitudes and implicates reference prices as the underlying mechanism. However, the effects observed there may be due partly to the fairly extensive information that was provided in those studies to allow subjects to estimate gains and losses. In contrast, when choice is the focus, the consumer may attend less to detailed gains and losses and more to judging the products against other options. A framework is offered here that provides a focus on choice, yet also provides insight into how consumers utilize reference prices.

2.2 Proposed framework

The first objective of this research is to determine if price framing effects can be measured in a discrete choice task, and if so, which price frame is superior. The second objective is to use the “gains and loss” framework illustrated in Fig. 1 to explain why choices may differ. Next, we formalize this framework.

Thaler (1985) proposes that consumers get two types of utility from a purchase: acquisition utility and transaction utility. Acquisition utility is similar to the economic notion of consumer surplus, the value of a good relative to its price. Transaction utility is the perceived value of the deal and is measured relative to some reference price. Let P_A^* be a consumer's reference price for good A and \overline{P}_A be the “value equivalent of” A, “the amount of money that would leave the individual indifferent between receiving” \overline{P}_A or A as a gift (Thaler 1985, p. 205). In standard economic theory, \overline{P}_A would be equal to the reservation price or RP_A using our notation from earlier. Thaler's now familiar representation goes as follows:

$$w(A, P_A, P_A^*) = v(\overline{P}_A, P_A) + \beta_{\text{gain}} v(P_A^*, P_A) I(P_A^* > P_A) + \beta_{\text{loss}} v(P_A^*, P_A) I(P_A > P_A^*) \quad (1)$$

where $w(A, P_A, P_A^*)$ is the value of buying good A, for price P_A , with reference price P_A^* . The first term on the right, $v(\overline{P}_A, P_A)$ represents the acquisition utility as a function of the price and the “value equivalent of” A. The remaining terms represent the transaction utility as a function of the price and the reference price, $v(P_A^*, P_A)$. $I(*)$ is the indicator function equaling 1 if the argument is satisfied, and 0 otherwise. (1) says that when the actual price is greater than the reference price, it is encoded as a loss, which has a different impact on transaction utility (β_{loss}) than if the price is less than the reference price (β_{gain}), which is encoded as a gain.

Our model seeks to explain choice behavior in a bundling context as a function of both price and framing effects. We assume that our subjects choose the option (product 1, product 2, both products together, or no choice) that produces the

greatest value, i.e. Eq. 1. We allow for different parameter values for individuals in Eq. 1 by using the subscript “ h ”. The model is represented as:

$$\begin{aligned} z_{h1t} &= \alpha_{h1} - P_{h1t} + \beta_{h,gain}(P_{h1}^* - P_{h1t})I(P_{h1}^* > P_{h1t}) + \beta_{h,loss}(P_{h1t} - P_{h1}^*)I(P_{h1t} > P_{h1}^*) + \varepsilon_{h1t} \\ z_{h2t} &= \alpha_{h2} - P_{h2t} + \beta_{h,gain}(P_{h2}^* - P_{h2t})I(P_{h2}^* > P_{h2t}) + \beta_{h,loss}(P_{h2t} - P_{h2}^*)I(P_{h2t} > P_{h2}^*) + \varepsilon_{h2t} \\ z_{h3t} &= \alpha_{h3} - P_{h3t} + \beta_{h,gain}(P_{h3}^* - P_{h3t})I(P_{h3}^* > P_{h3t}) + \beta_{h,loss}(P_{h3t} - P_{h3}^*)I(P_{h3t} > P_{h3}^*) + \varepsilon_{h3t} \end{aligned} \quad (2)$$

where the index $\{1, 2, 3\}$ represents the option of choosing product A individually, product B individually, or products A and B together as a bundle in a choice set. “ t ” reflects the number in a series of choice sets. We normalize the value function by setting $z_{none}=0$. The respondent then chooses the alternative with $\max\{z_{h1t}, z_{h2t}, z_{h3t}, 0\}$. We note that while our simple model allows for asymmetric treatment of gains and losses, we assume all effects are linear. This simple set-up provides a basis for comparing three models which each represent unique ways that consumers may evaluate the bundled offer:

Model 1. Simple reservation price model The value function represented by Eq. 1 contains the economic choice model of Jedidi et al. (2003) as a special case. If we set $\beta_{h,gain}=\beta_{h,loss}=0$ then we obtain their model where α_h ’s represent the reservation prices and the consumer chooses the option with the greatest consumer surplus. Following the theoretical model of Jedidi et al., we restrict the coefficient on price to equal -1 . Consistent with their empirical results, we allow for a separate intercept term for the bundle as opposed to restricting it to equal the sum of the intercepts for the individual products. We note that in the full model, the α_h ’s can no longer be interpreted as reservation prices.

Model 2. Combining reference prices When a mixed bundle is presented in a “joint, integrated” frame (Fig. 1a), the consumer must combine or add together the individual reference prices in order to determine the transaction utility, i.e. the gain or loss. Panel A suggests that the consumer compares the bundle price to a reference price which is the sum of the reference prices of the bundled goods A and B. However, panel B in Fig. 1 illustrates that combining reference prices can also occur when the sale prices for goods A and B have been presented separately. The consumer may add together the prices of each item in the bundle, compare that to the sum of the reference prices, and arrive at a gain/loss for the bundle. If this was the process most consumers followed, we would not see a difference in choices between integrated and segregated price frames.

Model 3. Two comparisons However, when prices in the bundle are segregated, the consumer may perform two separate price comparisons (panel C, two comparisons), and arrive at a gain/loss calculation for each item in the bundle. Although effortful, this matters because the value function in prospect theory treats gains and losses asymmetrically, and is the implicit model underlying many studies of consumer perception of bundling (Mazumdar and Jun 1993; Kaicker et al. 1995; Yadav and Monroe 1993). Table 1 provides numeric examples illustrating panels B and C in Fig. 1 in the context of the luggage products used in our empirical experiment.

In sum, our paper differs from others in the bundle framing literature in that (1) we use a discrete choice experiment; (2) subjects can purchase the bundle, either of the components alone, or neither of the components; (3) we contrast all the types of

Table 1 Example of calculating gain/loss in the value function when bundle prices are segregated

Price	Amount		
Tote reference price	\$70		
Garment bag reference price	\$80		
Presentation of prices in the bundle			
Tote	\$72		
Garment bag	\$73		
Combining			
Reference price (\$70 + \$80)	\$150		
Price bundle (\$72+\$73)	\$145	Gain	Loss
Gain and loss (\$150–\$145)		\$5	\$0
Two comparisons			
Reference price of tote	\$70		
Price of tote in bundle	\$72	Gain	Loss
Gain or Loss (\$70–\$72)		\$0	\$2
Reference price of garment bag	\$80		
Price of garment bag in bundle	\$73		
Gain or loss (\$80–\$73)		\$7	\$0
	Total	\$7	\$2

mixed price bundling strategies; (4) the proposed framework together with hierarchical Bayesian modeling provides a means for determining how many individual consumers use reference prices in their decision-making.

3 Method

3.1 Participants

A commercial market research company identified a nationally representative sample of consumers and administered an on-line survey on luggage choices. Only respondents who had purchased luggage in the past 10 years were permitted to complete the survey.

3.2 Procedure

A mixed bundling strategy requires that the products be separable in terms of use such that both products could be purchased and used independently of whether the other product was purchased or used. The items we selected were a tote bag and garment bag. The items had the same brand name (to control for inferences about quality).

A short questionnaire was developed and pre-tested with MBA and Executive MBA students ($n=80$).

3.3 Stimuli

Respondents were asked to imagine that they needed new luggage and had been actively looking for tote bags and garment bags. They were told that prices for

garment bags and tote bags ranged from \$59.99 to \$95.99, and were then shown an on-screen print advertisement for the TravelPro Crew 5 Garment Bag and the TravelPro Crew 5 Deluxe Tote that described the various features and benefits of the products. Respondents were asked to enter the lowest, average, and highest price they would expect to see for the garment bag, and then separately, for the tote. Respondents then saw a series of 6 choice sets where they could choose the garment bag, the tote bag, the bundle consisting of both the garment bag or the tote, or a final option labeled as “Neither: I would not purchase either one.” The survey closed with standard demographic questions.

Each respondent saw different randomly generated prices in each of his/her six choice tasks. A base price of \$79 was used for both the tote bag and the garment bag and prices of the individual items in each choice task were generated randomly as $\pm 20\%$ of the base price. Thus, the actual range of prices matched the price range given to respondents earlier in the survey. The total price of the bundle was randomly generated as 5–20% off the sum of the base prices. The price of the bundle was checked to make sure that it was at least 5% less than the sum of the listed price of each item. All prices were forced to end in \$XX.99.

3.4 Design

Respondents were randomly assigned to one of four price framing conditions: joint, integrated; joint, segregated; tote as price leader; or, garment bag as price leader. The presentation format for items in the bundle choice option varied according to the experimental condition. For the “joint, integrated” condition, only a single price was displayed, the randomly generated bundle price from above. In the “joint, segregated” condition, separate prices were listed for the tote and garment bag in the bundle, both of which were less than the list price of the individual items. The randomly generated price of the bundle was partitioned to each item such that the implied percentage discount from the individual list prices was the same for the tote and garment bag. For the price leader condition, the “non-leader” item in the bundle had a price equal to its individual list price in that choice set. The price for the “leader” was then the difference between the randomly generated bundle price, and the price for the non-leader item. Each subject saw the same bundling frame for each of their six choice sets.

4 Data and analysis

In this section we provide relevant summary data, test the hypothesis that framing matters, and estimate a simple statistical model that permits testing of alternative information processing models. A total of 336 respondents completed the on-line survey. Of those, 118 respondents selected “none” in each of the six choice tasks; these respondents were removed from the analysis as they were deemed to not “be in the market” for the listed products and/or the price range was not relevant for them. Table 2 displays the initial and final sample size in each of the experimental conditions.

Table 2 Initial and final sample sizes

	Joint, integrated pricing	Joint, segregated pricing	Tote as price leader	Garment bag as price leader
Initial	90	73	86	87
Final	61	47	51	59

Since the prices presented to respondents were randomly determined for each of the six choice sets, a one-way analysis of variance was conducted to test for systematic differences in prices across the four versions of the survey. The null hypothesis of no difference between the groups could not be rejected for the listed price of the garment bag ($p=0.221$), the tote ($p=0.304$), or the price of the bundle ($p=0.137$). Since there is no systematic difference in prices, an analysis of choice outcomes by framing condition was conducted. As is typical in discrete choice analysis, both choices and individuals are assumed to be independent. Table 3 presents a simple cross-tab of the results.

The “joint, integrated” price frame resulted in the highest percentage of choices for the bundle. A χ^2 test of independence between the framing effect and the choices is rejected ($p=0.011$) as is an asymptotic z test of the null hypothesis that the percent choosing the bundle in the “joint, integrated” condition is equal to that in the “joint, segregated” condition ($p=0.027$), “tote as price leader” ($p=0.003$), or “garment bag as price leader” ($p<0.001$). There is also evidence that the “joint, integrated” condition results in a smaller proportion of “none” choices than the “joint, segregated” condition ($p=0.078$), “tote as price leader” ($p=0.043$), or “garment bag as price leader” ($p=0.004$). We conclude that framing does matter, even in choice sets where respondents can choose the component products, the bundle, or none.

Table 3 Choice outcome by framing effect aggregated over individuals and choices

	Joint, integrated pricing	Joint, segregated pricing	Tote as price leader	Garment bag as price leader
Choice options presented	Garment bag \$XX Tote \$YY Garment bag and tote \$ZZZ Neither	Garment bag \$XX Tote \$YY Garment bag \$XX-x and tote \$YY-y Neither	Garment bag \$XX Tote \$YY Buy Garment bag for \$XX and get Tote for \$YY-y Neither	Garment bag \$XX Tote \$YY Buy Tote for \$YY and get Garment bag for \$XX-x Neither
Garment bag	7.7%	7.4%	10.8%	6.2%
Tote	15.3%	17.7%	16.3%	19.5%
Bundle	48.1%	39.4%	36.6%	35.0%
None	29.0%	35.5%	36.3%	39.9%
	100% $n=366$	100% $n=282$	100% $n=306$	100% $n=354$
No. of respondents	61	47	51	59

We observe no significant difference in the percentage choosing the bundle between the “tote as price leader” and the “garment bag as leader” conditions (asymptotic z test, $p=0.674$). After the fact, there are two bases in the literature on which we might have expected differences between these two conditions. Janiszewski and Cunha (2004) conclude that the discount should be assigned to the product for which the difference between the reference price and the offer price is on the steeper portion of the value function. Using the expected average market price as each respondent's reference price, we find a significant difference between the reference price for the garment bag (mean=\$80.54) and the tote (mean=\$70.05), (asymptotic z test, $p=0.002$). Despite the difference in reference prices and the equivalence in offer prices, we see no difference in the attractiveness of the bundle between the two price leader conditions.

In contrast, Yadav (1995) suggests that the most preferred item should be the lead product as consumers will put more “weight” on the preferred item when evaluating the bundle. We do not have an a priori measure of relative preference. However, Table 4 shows the proportion of respondents who chose each item (including the bundle) at least once across his/her six choice sets. Across the four experimental conditions, the tote was selected on its own more frequently than the garment bag (asymptotic z test, $p<0.001$). This suggests that the tote was the preferred item and we would have expected to see the “tote as price leader” generate more choices for the bundle than the “garment bag as price leader” condition.

4.1 Model results

Why did the integrated price frame result in the greatest proportion of respondents choosing the bundle and the smallest proportion choosing the “none” option? We can examine the roles played by reference prices and transaction utility in these choices by modeling the value of each choice alternative to be a function of reference and actual prices (as per Eq. 2). The aggregate model fit statistics tell us which of the three theoretical explanations best fit the data overall. The individual level parameters indicate how many subjects are using reference prices.

Each respondent's self-reported average expected market price for the garment bag and tote are used as proxies for the reference prices $\{P_{h1}^*, P_{h2}^*\}$ in Eq. 2. The reference price for the bundles $\{P_{h3}^*\}$ were calculated according to either the “combining prices” or “two comparison” information processing assumptions illustrated in Fig. 1 and Table 1. Separate models were estimated for each assumption. The price for the bundle P_{h3t} in the “joint, segregated” and price leader conditions was entered as the sum of the listed price of each item in the bundle.

Markov chain Monte Carlo (MCMC) methods were used to estimate the model in Eq. 2. We assume that the error terms ε are independently and identically distributed according to a standard normal distribution, $\varepsilon \sim N(0, 1)$ leading to a probit model³. (See Rossi et al. (2005) and references therein for more information on estimating

³The model of Jedidi et al. (2003) allows for correlated error terms, e.g. $\varepsilon \sim N(0, A)$ while ours restricts the covariance matrix to equal the identity matrix. With the price coefficient restricted to equal -1 , this should allow estimation of a full covariance matrix. However, using standard prior distributions, we were unable to obtain stable posterior distributions across all data sets and models with an unconstrained error covariance matrix. In order to facilitate comparisons, we adopted the more restrictive assumption.

Table 4 Percentage of respondents choosing item at least once across six choice sets

	Joint, integrated pricing (%)	Joint, segregated pricing (%)	Tote as price leader (%)	Garment bag as price leader (%)
Garment bag	26	23	33	17
Tote	39	40	37	46
Bundle	80	72	73	68

heterogeneous probit models via Bayesian methods.) We specify a hierarchical model with the distribution of heterogeneity as $\{\alpha_h, \beta_h\} \sim N(\theta, \Sigma)$ where θ is of dimension 5 for the full model and Σ is 5×5 . This model hierarchy allows estimation of all individual level parameters.⁴

4.1.1 Aggregate model fit

The posterior mean of the “hit probability” and the means square error (MSE) are provided in Table 5 together with the log marginal density (LMD). The “hit probability” is the predicted choice probability for the chosen alternative averaged across choice sets and individuals. The MSE is equal to $(1 - \text{hit prob})^2$ averaged across choice sets and individuals. A larger “hit probability” indicates a better fitting model; i.e., a superior ability to explain subjects’ choices. A smaller MSE indicates a better fitting model. The log marginal density (LMD) is a Bayesian measure of model adequacy proposed by [Newton and Raftery \(1994\)](#). The LMD contains an implicit penalty for the number of parameters in the model and favors the model with the highest value. Note however, that the LMD cannot be compared across different framing conditions because they contain different numbers of observations.

In Table 5, model 1, the reservation price model assumes that consumers do not use reference prices in evaluating individual products or the bundle. Formally, the gain and loss coefficients in Eq. 2 are held constant at zero, e.g. $\beta_{h,\text{gain}} = \beta_{h,\text{loss}} = 0$. Comparison of model 1 with the others isolates the effect of reference prices. Model 2 estimates the full Eq. 2 and assumes that subjects make comparisons of the total bundle price (whether it is given as integrated or they do the math when it is segregated; see panels A and B of Fig. 1) to the sum of individual item reference prices. The third set of columns in Table 5 capture model 3, which allows that subjects are utilizing the full reference price information as Thaler’s model suggests, evaluating gains and losses on each item by comparing sale prices to reference prices (Fig. 1c). Note that model 3 cannot be estimated for the joint, integrated bundle condition because respondents see only one price for the bundle and can’t compare individual reference prices.

⁴Prior distributions on θ and Σ were chosen to be proper, but as uninformative as possible while still resulting in stable posterior distributions for θ and Σ . The chains appeared to converge quickly but were allowed to run for 50,000 iterations to ensure that the initial conditions were dissipated. A sample of every 10th from the next 250,000 iterations was used to calculate posterior means and standard deviations for elements of the hyper-parameters θ and Σ . Model fit statistics were calculated using a sample of every 180th observation from the last 180,000 iterations. Full model results are available from the authors.

Table 5 Model fit statistics

Framing effect	Model 1 reservation price model			Model 2 (Fig. 1a and b) combining reference prices			Model 3 (Fig. 1c) 2 comparisons of reference prices		
	LMD	Hit prob	MSE	LMD	Hit prob	MSE	LMD	Hit prob	MSE
Joint, integrated	-304.3	0.8193	0.1420	-164.8	0.8138	0.1208			
Joint, segregated	-386.6	0.7596	0.2001	-166.3	0.7754	0.1491	-152.3	0.8037	0.1308
Tote leader	-388.7	0.7540	0.2023	-186.4	0.7972	0.1403	-177.8	0.8247	0.1245
Garment bag leader	-491.4	0.7522	0.2083	-230.8	0.7637	0.1610	-207.8	0.7910	0.1433

LMD Log marginal density, Newton and Raftery (1994); *Hit prob* posterior average choice probability of the chosen alternative; *MSE* posterior average of $(1 - \text{hit prob})^2$

LMD cannot be compared across versions due to different sample sizes. LMD and Hit prob favor the highest number. MSE favors the lowest number. Sample size of 1,000 used for all calculations. Every 180th from the last 180,00 iterations used.

We find that models 2 and 3—which incorporate reference prices and transaction utility—fit the data substantially better than the simple reservation price model, model 1. For the “joint, integrated” frame, the LMD and MSE fit statistics both strongly favor the “combining” reference price model. Since the “hit probability” is essentially the same, we conclude that the “combining” reference price model fits better than the reservation price model by more accurately predicting “low probability” choices⁵. For the remaining price frames, all fit measures uniformly favor the “two comparison” reference price model. This is strong evidence that when prices of items in a bundle are itemized or segregated, some consumers compare reference prices to prices separately, as opposed to combining them. When gains and losses are treated asymmetrically, this can alter choice outcomes.

4.1.2 Individual level parameters

An examination of the individual level parameters however, suggests that not all respondents use reference prices in making choices. A strength of the hierarchical Bayesian model employed here is that we can look at the posterior distribution of individual level parameters. This reveals an interesting paradox. There are enough subjects attending to individual reference prices to produce a superior aggregate fit for model 3, the “two comparison” model, as reflected in Table 5, yet, the majority of respondents do not use reference prices. Recall that the simple reservation price model is nested in the other models when $\beta_{h,\text{gain}} = \beta_{h,\text{loss}} = 0$; based on the individual level parameters, we find that this model describes 53% of respondents.

Nonetheless, two items are worth noting. First, the “joint, integrated” frame has the highest percent of respondents with $\beta_{h,\text{gain}} = \beta_{h,\text{loss}} = 0$ (64%) suggesting that when prices are integrated, consumers are less likely to use reference prices and

⁵The LMD represents a logarithmic penalty function for being “wrong” and the MSE is a quadratic penalty function. These two measures tend to penalize “low probability predictions” more than the “hit probability,” which is a linear penalty function.

calculate transaction value. Second, since the “joint, integrated” frame has the highest proportion choosing the “bundle” in the choice experiment, framings that lead to using reference prices and calculating the transaction value apparently result in fewer choices for the bundled offering.

5 Conclusions

Our data suggest that, in a mixed price bundling context, a “joint, integrated” framing results in a significant increase in the probability that consumers choose the bundle. This increase in bundle choice probability comes from fewer consumers choosing the “none” option and thus represents a net expansion in the number of individual customers. The superiority of the “joint, integrated” frame extends previous findings because we document it in a discrete choice environment and use the same stimuli and population to test all the competing price frames: integrated, segregated, and leader price frames.

The individual level parameter estimates indicate that only a minority of respondents appear to be comparing reference prices as implied by prospect theory and mental accounting. This raises several questions. First, past research relied on aggregate level analysis when using “gains and losses” to explain different consumer evaluations of bundling. Could these past findings also have been driven by only a portion of respondents? Second, given that less than half of respondents apparently use reference prices, is this the true mechanism to explain differences in choice outcomes across framing effects? Or, is some other individual level construct necessary to understand the differences in observed bundle evaluations.⁶

There are several challenges to using discrete choice experiments to investigate price framing effects. First, participants may not be “fully engaged” in a repeated choice experiment when only the price varies from choice set to choice set. This would result in poor fitting models and an inability to discriminate between different behavioral theories. Second, the “reference price” may evolve over time as a respondent is exposed to different prices. To test this we fit a “dynamic reference” price model in which the reference price in each choice set was equal to the lowest price seen so far by the respondent; however, we were unable to measure an improvement in model fit. Third, there may be correlation between respondent's choices or between alternatives that is not fully captured by our heterogeneous probit model. These challenges may be addressed with richer data collection environments and/or statistical models.

Additional research using discrete choice experiments is warranted in our view because it more directly reflects the actual choice context confronting consumers in mixed bundling. In fact it can be argued that the primary goal of most mixed bundling offers is to cross-sell those consumers who already do or are likely to buy one component (cf. [Guiltinan 1987](#)). Thus, consumers who have a strong affinity for

⁶In addition, see the study by Grewal et al. (1998) that calls into question the independence of “acquisition value” and “transaction value.”

one component of a bundle may provide positive evaluations of the overall bundle (cf. Simonin and Ruth 1995; Gaeth et al. 1990; Yadav 1994) but this may not always translate into purchase of the bundle—especially when one option is to purchase only the strongly desired item.

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