

# TRANSACTION UTILITY THEORY AND THE FRAMING OF MULTIPART PRICING OF INFORMATION GOODS

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**Abstract:** In this paper we investigate how the framing of multipart pricing schemes impact consumer behavior in the purchase of bundles of information goods. Transaction utility theory suggests that customized bundles with *identical* composition and cost may yield different transactional utilities for the same consumer depending on how the pricing is framed. We show that a consumer's perception of the "merits of the deal" for an initial minimum bundle purchase can significantly impact probability of sale and bundle size. Specifically, we find that when consumers perceive higher initial transaction utility they are more likely to make purchase. However, for purchasing consumers lower perceived initial transaction utility correlates with larger bundle sizes. The results are derived empirically from a natural experiment of custom music CD sales. The results of this research suggest that sellers can effectively adjust the characteristics of multipart pricing schemes influence purchase decisions with regards to custom information good bundle creation.

**Keywords:** behavioral economics, consumer behavior, customized bundling, econometrics, information goods, multipart pricing, natural experiment, transaction utility

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## **1. Introduction**

Digitization of information goods makes them easily and cheaply distributed, transferred, reproduced, and transmuted (Shapiro and Varian 1999). These properties make information goods particularly well suited for new sales strategies that involve the disaggregation and combination of traditional information goods. Increasingly, information goods sellers are providing consumers the ability to purchase information good subunits, such as songs or television episodes, which have been traditionally purchased in preset bundles (Akst 2005).

Recent innovations in this context have involved selling consumer designed custom bundles of information goods. For example, several online services let consumers create customized music or video playlists for download and multiple publishers have provided services that allow consumers to create custom books by combining content from several sources.

In economic terms, there are important differences in custom and set bundles that impact sales strategies. For set bundles, sellers design a bundle of goods to aggregate heterogeneity in consumer valuation and willingness-to-pay across multiple products (Shapiro and Varian 1999). Productivity software packages (e.g., Microsoft Office) are a prime example of this approach, where software producers bundle multiple applications together to capitalize on varying demand and willingness-to-pay for separate applications. When the consumer is allowed to create a custom bundle she determines the content of the bundle (size, items, etc.), which translates into a loss of control for the seller. To overcome this loss of control, sellers often use a multipart pricing strategy for custom bundles that charges an initial tariff for the right to create a minimum bundle plus an incremental unit price for additional items. This approach can be seen in the pricing of mobile phone usage plans, custom CDs and playlists, and subscription services such as online video rentals.

Little research has explored the impact of multipart pricing strategies on consumer behavior in the context of information goods. Furthermore, most research on the pricing of information goods, including bundles of information goods, has been built on normative economic models. The normative model of an ideal and rational decision maker has proven to be useful in several economic settings; however, many prominent economists have argued that it does not provide an accurate description of how real people make decisions (e.g., Tversky and Kahneman 1986, Thaler 1985). Through innovative research, economic scholars have identified several decision anomalies in which the normative model does not accurately predict real-life decision making behavior (see Thaler 1994 for a series of interesting examples). An alternative framework, the behavioral model of economic decision making, can often provide better descriptive accuracy of real life situations, and insights from this approach have become widely accepted and applied in modern economic models of choice (e.g., Thaler and Sunstein 2008). A generalized result from the behavioral framework is that the framing and setting of a decision can have significant effects on choices.

In this paper, we apply theory from a behavioral model of economic decision making in the context of pricing and purchasing custom bundles of information goods. Specifically, we address the following research question. *How does the framing of a multipart pricing scheme influence consumer behavior in the construction and purchase of customized information good bundles?* By answering this research question, we hope to highlight the unique opportunities for new pricing strategies in this context. This study also draws attention to the importance of applying behavioral economic theories for the understanding of information goods distribution. Our research model is based on the theory of transactional utility, defined by Thaler (1985), and the effects of decision framing, outlined in Tversky and Kahneman (1986). We answer our

research question using a natural experiment in which consumers creating and purchasing customized music CDs were subjected to different multipart pricing schemes. Analysis of this real-world data provides strong empirical evidence that the framing of a multipart pricing scheme significantly impacts the size of bundles created by consumers as well as the probability of sale, even when the differing pricing schemes effectively result in the same final price to the consumer.

The remainder of this paper proceeds as follows. Section 2 provides an overview of related literature and conceptual foundations. Section 3 outlines our theoretical research model and hypotheses. Section 4 provides empirical evidence from real-world data on the sales of customized information good bundles to support our theoretical claims. Section 5 discusses theoretical and practical implications of this research. Section 6 provides concluding remarks.

## **2. Conceptual Foundations**

We first review the current knowledge on multipart pricing and how it applies in the context of information goods bundles. Next, we briefly outline the theoretical underpinnings of framing effects in behavioral decision making. Finally, we review transaction utility theory and how it relates to framing effects and multipart pricing.

### **2.1 Information Goods Bundles and Multipart Pricing**

Bundling is a marketing strategy of selling multiple products together as a single product; it provides several potential advantages to the seller, including reduced production costs, reduced transaction costs, complementarities among bundle components, and a means for averaging across heterogeneity in consumer valuations (Eppen et al. 1991, Bakos and Brynjolfsson 1999). Information goods are very well suited for use in bundling strategies. Bakos and Brynjolfsson (1999, 2000) showed that low marginal costs allow information goods producers to achieve

greater profits by taking advantage of the “predictive value of bundling”. Additionally, they found that offering a menu of different bundles is very useful when market segments of consumers differ systematically in their valuations. Geng et al. (2005) extended this research and provided guidelines for bundling information goods when consumers have decreasing marginal value for additional goods.

Customized bundling of information goods is a new strategy that takes advantage of the low transmission and reconfiguration costs associated with information goods distribution. In many industries, sellers now provide consumers with the ability to create custom bundles of information goods to match their unique preferences. Providing custom bundles of information goods typically requires the unbundling or disaggregation of traditional information good bundles into subunits, which can then be reconfigured into custom bundles by the consumer. For example, the publisher O’Reilly allows consumers to create custom books by assembling chapters from multiple books in its online library. Wilson et al. (1990) showed that unbundling becomes a favorable strategy if one or both of two conditions exist: profits of selling unbundled goods (in addition to bundles) exceed profits of selling bundles alone, taking into consideration cannibalization; or market growth can be achieved through the sale of unbundled goods.

Customized bundles are frequently sold under multipart pricing schemes as these pricing strategies are employed to deal with consumer heterogeneity. Consumers are often presented with a series of choice sets and depending on their consumption requirements will self-select into the various choice sets with graduated price levels (Narayanan et al. 2007). Multipart pricing schemes essentially have (but are not limited to) the following features: a minimum base fee, which the consumer has to pay for the consumption of a base level of goods, and a variable fee for consumption beyond the base level. Commonly, the per-unit tariff (price) charged for the

minimum base level is higher than that of the variable fee to prevent arbitrage opportunities as well as to encourage greater consumption (Essegaier et al. 2002). Similarly, a higher tariff for the minimum base level is at times required to offset any fixed costs incurred by the seller in providing the goods (Iyengar et al. 2008).

Multipart pricing makes economic sense for customized bundling because of the flexibility it provides both the consumer and seller. With respect to custom information good bundles, multipart pricing is a well-suited strategy since these bundles are designed by the consumer and therefore the resulting size and contents are variable. Multipart pricing relieves sellers from dealing with consumer heterogeneity and possible differences in costs<sup>1</sup> since consumers self-select into specific bundle contents, sizes, and prices. Furthermore, recent research has shown that multipart pricing and bundling complement each other well and can be used together in effective sales strategies for information goods (Bodily and Mohammed 2006).

With the exception of Lambrecht et al. (2007), the issue of consumer behavior under multipart pricing is largely unexplored (Lambrecht et al. 2007). In the examination of Internet access usage plans, Lambrecht and his colleagues found that consumers' usage uncertainty drives them to choose pricing schemes that have higher base tariffs but included more "free" usage allowances. They observed that demand uncertainty of how much one will use a good results in a significant bias towards flat-rate pricing schemes or schemes with higher usage allowance before the variable per unit fee sets in. One of the main difference between our study and Lambrecht's is instead of looking at how purchasing patterns drive consumer selection of the multipart pricing options available we look at how the framing a particular multipart scheme drives purchasing patterns.

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<sup>1</sup> Although information goods do not incur marginal costs to the producer, they may incur marginal costs to the retailer in the form of royalties (e.g., iTunes incurs royalty costs for selling each additional song online).

## 2.2 Framing Effects

The consumer choice process can be categorized into two distinct phases, an editing phase and an evaluation phase (Puto 1987). The editing phase is the initial phase where the consumer sets up and *frames* the decision task into simplified possible outcomes. In the subsequent evaluation phase, the consumer selects one of the framed outcomes with the highest perceived value. Framing has been shown to influence behavior in a predictable manner and one common form of framing, attribute framing (Levin et al. 1998), is commonly applied by sellers. Sellers can manipulate the framing of product attributes to impact consumer decision processes where different frames lead to different sales outcomes. For example, labeling meat, “80% fat free” is likely to make it appear more attractive than “20% fat”; even though the two statements are technically equivalent.

Framing effects are commonly considered in pricing strategies and are known to affect the manner of which consumers assess the perceived value of a purchase (Heath et al. 1995). In multipart pricing, sellers can manipulate framing effects in both the pricing of the tariff and the variable fees for additional items. It is obvious that when firms increase prices they can achieve higher profits per unit sold at the expense of lower sales volume. However, with multipart pricing schemes, firms have the discretion to vary the relative price proportion between the minimum base tariff and the variable fee without changing the total price for a bundle. Thus, unlike standard pricing, multipart pricing provides firms with the ability to make adjustments to the framing of the pricing scheme without impacting the total price. Hence, for multipart pricing schemes that result in identical final prices for a given bundle size, variance in relative price proportion between the minimum tariff and the incremental fees may have significant *framing effects* on consumer bundling and purchasing decisions.

Kahneman and Tversky (1979) suggest individuals experience non-linear utility functions and are more sensitive to losses than gains. This implies that the relative proportion in prices between the base tariff and incremental fees in a multipart pricing scheme can lead to differences in perceived gains and losses by consumers. To illustrate, a reasonable base tariff coupled with exorbitant incremental prices in multipart pricing may cause a consumer to experience gains for the initial bundle, but losses in the additional units added (e.g., mobile phone price plans). Alternatively, an exorbitant base tariff coupled with discounted incremental prices may lead to perceived losses for the minimum bundle and gains for subsequent unit additions (e.g., golf membership with high entrance fee but discounted green fees).

Difference in framing of a multipart pricing scheme can lead to differences in the utility experienced by a consumer from a purchase. The concept of transaction utility theory (Thaler 1985) provides the ideal theoretical lens to examine how framing effects impact perceived utility and consumption outcomes in a purchasing context.

### **2.3 Transaction Utility**

Thaler (1985) proposed that the utility experienced from purchasing a good can be decomposed into two components, *acquisition utility* and *transaction utility*, where acquisition utility “depends on the value of the good received compared to the outlay” and transaction utility “depends solely on the perceived merits of the ‘deal’ (p. 205)”. Acquisition utility is a function of the actual price paid for the product and the inherent valuation the consumer has for the product. The inherent valuation for a product is likely to be heterogeneous among consumers and internally determined by these individuals. On the other hand, transaction utility is a function of the price paid for the product and the consumer’s “equitable” reference price. The “equitable” reference price refers to what the consumer perceived to be a fair price for the product given the

sales context, which does not necessarily coincide with their inherent valuations. The reference price is likely to be affected by the environment and context in which the purchase is made and is therefore susceptible to framing effects present in the purchasing process (Urbany et al. 1988). For example, a consumer's reference price for a bottle of cold beer to be purchased for consumption on a beach may differ if she is purchasing it in a fancy hotel bar versus a run-down convenience store (Thaler 1985, p.206). Although the good and consumption experience will be the same, the consumer may expect to be charged different prices at the fancy hotel and convenience store because of the difference in purchasing context. Thaler's notion of transaction utility implies that the nature of the deal influences a consumer's purchasing decision and therefore it is the combination of both the acquisition utility and transaction utility that determines if a consumer will receive positive value from purchasing an item.

If one were to make the reasonable assumption that a consumer only purchases an item if the total value they experience from the purchase is non-negative, then Thaler's model suggests that a positive transaction utility could counterbalance negative acquisition utility and vice versa. For example, a consumer may desire steak for dinner and value the consumption of that steak at \$20. However, she decides to forgo the purchase because the restaurant she visits regularly has raised the price of steak from the usual \$15 to \$18. Even though the price is below her value equivalent for the steak, the "bad deal" relative to her reference price of \$15 offsets her acquisition utility<sup>2</sup>, resulting in negative total utility from the purchase. Conversely, the theory suggests that if transaction utility is significantly positive (i.e., the consumer perceives they are getting a very good deal) this might be enough outweigh negative acquisition utility and lead to a purchase. "Going out of business" and clearance sales often entice consumers with deep discounts to

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<sup>2</sup> For illustration purposes only, we assume simple additive value functions for both acquisition and transaction utility.

purchase goods they may never actually use or in which they find no real value. Of course transaction utility and acquisition utility can be simultaneously positive or simultaneously negative with obvious implications.

Although acquisition and transaction utilities play a role in consumer purchase decisions, in this paper we focus mainly the role of transaction utility in consumer behavior. The objective of this paper is to examine the framing effects of multipart pricing on bundling behavior. The contents of a custom bundle will be determined by the consumer and are highly dependent on their preferences and internal valuations. Hence, for any particular bundle purchased, by definition the acquisition utility is affected by the consumer's internal valuation, which is endogenously determined and less susceptible to contextual factors and framing effects. On the other hand, the "equitable" reference price is determined largely by the context of the sale, hence the transaction utility is highly dependent on the framing effects of a multipart pricing scheme. In the next section we develop a formal theoretical model of transaction utility in the context of multipart pricing of customizable information goods bundles.

### **3. Research Model and Theory Development**

From prior literature we know that framing effects play an important role in consumer decision processes. The use of multipart pricing schemes in the sale of information goods bundles is becoming more commonplace and the framing of these schemes will likely affect bundling behavior. To develop empirical hypotheses about the nature of these effects, we build a model based the theory of transaction utility.

Thaler (1985) outlines a general theory of transaction utility as

$$w(k, p, p^*) = v(\bar{p}, -p) + v(-p: -p^*) \quad (1)$$

where  $w$  is the value of buying good  $k$  at price  $p$  with a reference price of  $p^*$ . The first term on the right hand side of equation (1) corresponds to the *acquisition utility* to the consumer of acquiring good  $k$  at price  $p$  when she has a value equivalent of  $\bar{p}$  for good  $k$ , where the value equivalent is the amount of money which would leave the consumer indifferent between receiving  $\bar{p}$  or  $k$  as a gift. The second term on the right had side of (1) corresponds to the *transaction utility* of purchasing good  $k$  at price  $p$  given a *reference price* of  $p^*$  for good  $k$ , where the reference price is the price the consumer expects to be charged or her perceived “equitable” or “just” price for good  $k$ .

We can use Thaler’s general model of transaction utility as the theoretical lens to guide the development of empirical hypotheses in the context of multipart pricing for customized bundles of information goods. Consider a multipart pricing scheme similar to many real-world scenarios in which the seller charges an initial price for a minimum sized bundle of information goods and then a unit price for each item added to the bundle thereafter. Define  $p_m$  as the actual price charged for the purchase of a customized initial bundle of information goods of size  $m$  under this multipart pricing scheme. In this context,  $p_m$  corresponds to the tariff charged to the consumer for the right to create and acquire the initial minimum bundle (Iyengar et al. 2008). Define  $p_1$  as the actual price charged for each item added to the customized bundle of information goods after  $m$ . For illustration consider the following example, an initial bundle consisting of two movie downloads is priced at \$19.99 and each additional download is priced at \$7.99. In this scenario  $p_m = \$19.99$ ,  $m = 2$ , and  $p_1 = \$7.99$ .

For some consumer purchasing under this multipart pricing scheme, define  $p^*_m$  as their reference price for a minimum initial bundle of size  $m$  and  $p^*_1$  as their reference price for an individual item added to a bundle past the initial minimum size. The reference price represents

an expected price; so,  $p^*_m$  is the price the consumer expects to be charged for the right to create the initial custom information goods bundle of size  $m$  given the sales context, and  $p^*_1$  is the price the consumer expects to be charged for each additional item added to the bundle given the sales context. We assume a single actual price  $p_i$  and a single reference price  $p^*_1$  for each additional item since most multipart pricing schemes for the sale of information goods typically employ a single unit price for additional items.

Let  $\bar{p}_i$  represent the value equivalent of the customer for item  $i$  in the customized bundle of information goods. Since the customized bundle will consist of multiple items, the value equivalent for the entire bundle will be the sum of the value equivalents for all individual items in the bundle. For a custom bundle of information goods sized  $n$ , where  $n \geq m$ , let the value equivalent for the bundle be  $\bar{p}_n = \sum_{i=1}^n \bar{p}_i$ . We assume that consumers add items to the bundle in order of decreasing value, i.e., items they value most (with the highest  $\bar{p}_i$ ) are added to the bundle first<sup>3</sup>. Also, let the total price paid for a custom bundle of size  $n$  be  $p_n$ , which is the sum of the tariff (initial bundle price) and the unit price for each item added past the initial bundle:  $p_n = p_m + (n - m)p_1$ . We can now represent the value of purchasing a customized bundle of  $n$  information goods,  $b_n$ , under a multipart pricing scheme with minimum size  $m$  using Thaler's model as

$$w(b_n, p_m, p_m^*, p_1^*, p_1, m) = v(\bar{p}_n, -p_n) + v(-p_m: -p_m^*) + (n - m)v(-p_1: -p_1^*). \quad (2)$$

The first term on the right hand side of (2) represents the acquisition utility the individual receives from purchasing the bundle of size  $n$ . The second term represents the *initial transaction utility* to the consumer or the value to the consumer of paying  $p_m$  for an initial bundle of  $m$  items when the expected or reference price for  $m$  items is  $p^*_m$ . The final term represents a sum of the

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<sup>3</sup> This is in line with Yadav (1994) which suggest that in evaluating bundle components, consumers are likely to consider items that they value the most first.

*incremental transaction utilities* associated with adding items to the bundle beyond  $m$  and up to  $n$  total items. The representation of total value shown in equation (2) is useful since it separately depicts the value the consumer experiences for acquiring the whole bundle, the value experienced by the consumer from the framing of the tariff for the initial bundle (or their perception of the initial deal), and the value the consumer experiences from the framing of each item added to the bundle past the initial  $m$  items.

It is reasonable to assume that a consumer deciding to purchase a customized bundle of information goods would like to maximize the total value,  $w$ , from the purchase. Although the total acquisition utility may be discovered by the consumer through the process of creating the bundle (Bettman et al. 1998), the initial transaction utility must be evaluated up front in order to start the purchasing process in a multipart pricing scenario. Since transaction utility is independent of the consumer's inherent valuations for items, perceived initial transaction utility is separate from any specific item choices for the initial bundle. From Thaler's definitions (1985), it is dependent only on the consumers' perceived evaluation of the merits of the deal. Furthermore, higher levels of initial transaction utility for the consumer should lead to higher overall value in the purchase. This insight follows from equation (2); for given values of acquisition and incremental transaction utility, a larger initial transaction utility will result in a larger total purchase value,  $w$ , since the two are positively correlated. This suggests that the better the perceived "deal" for the initial bundle of  $m$  items, the higher the potential total value from a purchase. It is well established that framing of prices affect consumer purchasing decisions. Therefore, it is straight forward to reason that the higher the potential total utility a consumer perceives, the more likely the consumer will make a purchase, which leads to our first empirical hypothesis:

**H1:** *In the context of multipart pricing of customizable information goods bundles, consumers perceiving higher initial transaction utility will be more likely to make a purchase.*

Our first hypothesis also follows from the work of Bettman et al. (1998) who found that consumers tend to construct their preferences and choices on the spot, under the influence of context and framing of the choice environment. It follows that the initial transaction utility perceived by the consumer is influenced by the framing of the initial tariff,  $p_m$ , charged in the multipart pricing scheme. A positively perceived initial transaction utility would likely provide a positive frame for perceived value derived from the total bundle purchase.

Now we will consider the role of initial transaction utility in determining total bundle size. Prospect theory posits that consumer's view losses and gains differently. Kahneman and Tversky (1979) argue that people do not ignore sunk costs, and incorporating this with Thaler's concept of transaction utility, it is an intuitive notion that consumers may try to make up for an initial perceived loss experienced from purchasing a minimum bundle by acquiring incremental gains in utility by adding items to a bundle. This drive to recoup losses may result in larger bundle purchases. In other words, consumers may feel an urge to add more items to a custom bundle in order to "get their money's worth". From a theoretical perspective, this means that a value maximizing consumer who experiences low or negative initial transaction is likely to continue to add items to a bundle to offset initial perceived losses.

Let us assume our consumer will make a purchase of a customized bundle of information goods, i.e.,  $w \geq 0$ . Since the acquisition utility of the purchase is independent of the reference prices for initial and incremental bundle items, we can split total acquisition utility into initial and incremental acquisition utility and rewrite equation (2) as

$$w(b_n, p_m, p_m^*, p_1, m) = v(\bar{p}_m, -p_m) + v(-p_m: -p_m^*) + \sum_{i=m+1}^n [v(\bar{p}_i, p_1) + v(-p_1: -p_1^*)] \quad (3)$$

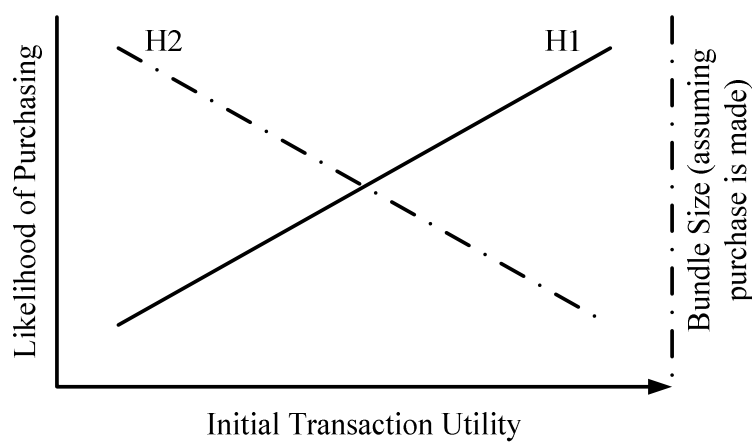
where the first term on the right hand side of (3) is the acquisition utility for the initial bundle of size  $m$ , the second term is the transaction utility for the initial bundle of size  $m$ , and the third term represents the sum of the incremental acquisition and transaction utilities for items  $m+1$  through  $n$ . Assuming a consumer is trying to maximize total utility  $w$ , it follows from (3) that lower value from the initial bundle of  $m$  items would result in a larger bundle size as long as the incremental utility,  $v(\bar{p}_i, p_1) + v(-p_1: -p_1^*)$ , remains positive. An interesting result of this thought experiment is that lower values of initial transaction utility should lead to larger total bundle sizes for a value maximizing consumer, assuming they will make a purchase. This is especially true if the “deal” the consumer perceives on the initial bundle is poor enough to inspire a behavior of recouping losses. This insight leads to our second empirical hypothesis:

**H2:** *When purchasing a customizable bundle of information goods under a multipart pricing scheme, consumers perceiving lower initial transaction utility will tend to create bundles of information goods that contain more items.*

The insights from the transaction utility theoretical framework suggest two seemingly countervailing effects of initial transaction utility on the consumption of customized bundles of information goods under a multipart pricing scheme. First, higher values of initial transaction utility should lead to higher perceived total value for the purchase, which should translate into a higher likelihood of purchase for a deciding consumer. However, for those actually making purchases, a lower level of initial transaction utility should lead to larger bundle sizes, since consumers may want to recoup initial losses and “get their money’s worth”. These theoretical results suggest that a seller must set initial bundle prices low enough as to entice buyers, but high

enough to induce recouping behavior and thus larger bundles. If initial prices are too low more consumers may purchase, but purchase small bundles; too high and consumers may not purchase at all. Figure 1 provides a graphical depiction and summary of our hypotheses. In the following section we empirically test the hypotheses using real-world data on the sales of customized music CDs.

**Figure 1. Summary of Hypotheses**



#### 4. Analysis and Results

We hypothesized differences in initial transaction utility experienced by the consumer during the bundle creation process impact the likelihood of sale and eventual bundle sizes purchased by consumers. In this section, we empirically test these hypotheses using data collected from a music retailer in a natural experiment setting.

##### 4.1. Research Context and Data

We obtained 20-months of browsing and sales data from a North American firm that provides a mechanism for selling customizable bundles of songs at physical retail points of sale. Data was collected from January 1<sup>st</sup>, 2005 through September 9<sup>th</sup>, 2006 on the browsing activity and sales of music from digital kiosks located at eleven retail locations, which were dispersed geographically across the United States. Each retail location contained two or more digital

kiosks. Each kiosk accessed a centralized digital music library that contained both full albums (over 70,000, whose tracks could be sold separately) and other individual music tracks (over 1 million). In all, 153,190 individual browsing sessions took place, of which 7046 (~5%) resulted in a purchase.

Using the digital kiosks, consumers purchased music by creating a custom playlist containing music tracks from artists and albums of their choice. Thirty second song samples were available to the consumers as they used the kiosk. The playlists were subsequently burned to physical CDs at the retail location and given to the consumer upon payment. The number of tracks in a customizable playlist was limited only by the space on the CD.<sup>4</sup> Two multipart pricing schemes were employed across the retail locations for the custom playlist sales. They were: (#1) \$3.99 for the first song and \$0.99 for each additional song and (#2) \$4.99 for the first two songs and \$0.99 for each additional song. Both pricing schemes have nearly identical prices for bundles of at least two songs (see Table 1a and 1b for illustration). The initial minimum bundle size and price differs across these two schemes, and thus the initial framing of each multipart pricing scheme is different. However, the price for adding songs to the bundle remains constant, and for bundles of at least two songs the total bundle price is practically identical.

We can assume that consumers have heterogeneous reference prices (hence transaction utility) for the same initial bundle and it is unrealistic to assume that one pricing scheme will always have higher initial perceived transaction utility than the other for all consumers. However, when a consumer is creating the minimum-sized initial bundle, it is reasonable to claim that on average, pricing scheme #1 (\$3.99 for 1 song) will have lower initial perceived transaction utility than pricing scheme #2 (\$4.99 for 2 songs, i.e., \$2.50 for 1 song).

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<sup>4</sup> And of course any budget constraint imposed on the individual consumer. Since this is a natural experiment, we do not have information on individual budget constraints but assume they are normally distributed.

**Table 1a: Breakdown of Pricing Structure for Pricing Schemes #1 and #2**

	Pricing Scheme #1	Pricing Scheme #2
<i>Framing of the prices</i>	First song for \$3.99; \$0.99 for each additional song.	First two songs for \$4.99; \$0.99 for each additional song.
<i>Tariff for right to create bundle</i>	\$3.00	\$3.01
<i>Price per song in initial bundle</i>	\$0.99	\$0.99
<i>Initial bundle size</i>	1 song	2 songs
<i>Price per additional song</i>	\$0.99	\$0.99

**Table 1b: Pricing Schedule for Schemes #1 and #2**

Number of Songs in bundle	Pricing Scheme #1 (US\$)	Pricing Scheme #2 (US\$)
<b>1</b>	3.99	4.99*
<b>2</b>	4.98	4.99
<b>3</b>	5.97	5.98
<b>4</b>	6.96	6.97
<b>5</b>	7.95	7.96
⋮	⋮	⋮

\*It is possible to purchase a bundle of only one song under pricing scheme #2, but the minimum price of \$4.99 is still charged.

Each kiosk had access to same database of songs and store locations were either identical or very similar in terms of brand and sales environment. It is important to note that each store employed *only one* pricing scheme, and given that the pricing scheme is identical for all retail outlets within a geographic location, it is not likely that consumers were aware of an alternative pricing scheme other than the one presented to them.

Finally, consumers have heterogeneous value equivalents for a particular bundled product, as such; the acquisition utility is likely to also be heterogeneous across consumers. Furthermore, since consumers create their own custom playlists, their acquisition utility is highly dependent on their preferences and value perceptions for the specific items in their individualized bundle. No matter how consumers' preferences vary for the items they purchase, the framing of the multipart pricing scheme is consistent for all consumers visiting a specific retail location. We therefore make the reasonable assumption that acquisition utilities are normally distributed under both pricing schemes across all consumers.

In terms of our model of transaction utility, the total price for a bundle of any given size (of at least two) is the same for each scheme and since \$0.99 per additional song is consistent in both schemes the impact of the incremental transaction utility should be the same in each scheme. Additionally, acquisition utility is assumed to be normally distributed across both pricing schemes, since Thaler’s model separates these effects as transaction utilities. Therefore, the difference in the framing of the minimum bundle price is the only systematic manipulation across the two pricing scheme conditions. This provides an ideal natural experiment to evaluate how the framing of different initial transaction utilities, i.e., the consumer’s perceptions of the “merits of the deal” for the initial bundle, impact purchasing and bundling behavior.

## 4.2 Empirical Model

In this section, we describe the empirical model that is used to test our hypotheses. We begin by formalizing the hypothesized relationship as shown in Figure 1 into parameters for empirical testing. We let  $z_i$  be the binary variable that represents the outcome of a browsing session ( $z_i = 1$  for sold and  $z_i = 0$  for unsold). The probability of a bundle being sold hence can be represented by  $P(z_i = 1)$ . We further let  $z_i^*$  represent a latent variable that determines the outcome of the sale such that:

$$z_i^* = \alpha' \omega_i + u_i \quad (4)$$

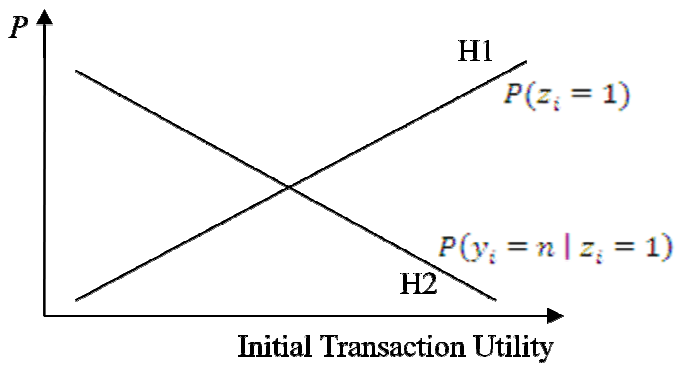
where  $z_i = 1$  iff  $z_i^* > 0$  and 0 otherwise

$$\therefore P(z_i = 1 \mid \omega_i) = P(z_i^* > 0 \mid \omega_i) \quad (5)$$

Here  $\omega_i$  is a vector that represents the factors impacting the probability of a sale.  $u_i$  represents the error term and  $\alpha'$  represents parameters for the relationship. Next, let  $y_i$  represents the final bundle size such that the probability of a bundle of size  $n$  given that it a purchase is made is represented by  $P(y_i = n \mid z_i = 1)$ . Given this set up, we parameterized our hypotheses as shown

in Figure 2. We expect that the probability of a purchase,  $P(z_i = 1)$ , will increase with initial bundle transaction utility and that the number of tracks in a bundle given a purchase is made,  $P(y_i = n | z_i = 1)$ , will decrease with initial bundle transaction utility. In terms of our natural experiment treatments, we expect pricing scheme #2 (\$4.99 for first two songs) to result in higher probability of sale and pricing scheme #1 (\$3.99 for the first song) to result larger bundle sizes given a purchase is made.

**Figure 2: Empirical Specification of Hypotheses Tested**



### 4.3 Analyzing Probability of Sale

We utilized the browsing and sales data described earlier to test the impact of initial transactional utility on the probability of sale. The probability of successful sale given that the consumer has browsed the music is represented by (5). As shown in (4), this probability  $P(z_i)$  is a function of vector  $\omega_i$ , which consists of the consumer's initial transaction utility and other control variables including, the browsing patterns prior to purchase (browsing duration, and number of samples browsed), geographical location, and time control. For the time control variable, we split the sample of sessions into two sub-samples based on the date of which they sample the music (0 for first half of the sample and 1 for later half). This variable controls for any potential novelty or learning effects given that our sample extends 20 months. Though it is impossible to track if the consumer is a repeat user, we hope that this dummy variable can be a

reasonable proxy to distinguish the difference. Also, to control for potential free-riding browsing behavior, we added the squared terms for browsing duration and number of songs sampled as additional control variables. These variables are to account for any potential quadratic relationship between browsing intensity and purchasing behavior due to hedonic browsing activity.

Our data provides us more details on the result of a browsing session than the simple sale/no sale binary outcome modeled in equation (4). The digital kiosk system classified the results of a browsing session into one of the following four outcomes: *listen only* – the consumer only samples; *songs selected, session abandoned* – the consumer starts a playlist but quits before completing it; *playlist burned but not purchased* – the consumer submits a completed playlist to be burned to a CD but did not complete the purchase; *successful purchase* – the consumer successfully purchases a custom CD. Of the four states, only the last state *successful purchase*, results in a sale. Given the ordinal nature of the outcome and opportunity to gain richer insight, we expanded the binary model in equation (4) and used an ordered logit regression model to estimate the relationship between initial transaction utility and browsing session outcome. The intuition presented in equation (4) is more general from a theoretical perspective; however, the ordered logit estimation<sup>5</sup> is more practical for our specific dataset.

To assess the goodness-of-fit of our model, we computed the deviance of the ordered logit model. Deviance is defined as the twice the negative values of the log-likelihood values (i.e.,  $-2LL$ ). The deviance values are then evaluated using a  $\chi^2$  –test. We observed that the likelihood ratio for the  $\chi^2$  –test is significant suggesting good model fit ( $\chi^2 = 27972.24$ ,  $p$ -value $<0.01$ ) (Hair et al. 2006). We next checked the extent to which the pricing scheme contributed to the observed

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<sup>5</sup> For conciseness, we do not provide details of the transformation of equation (5) into ordinal logit functional forms. Please refer to pp. 505 of Wooldridge (2002) for a generic representation. A technical appendix with the specific formulation is also available at request from the authors.

variance in the outcome of the sale above and beyond the effects of the control variables. To compute this test statistic, we first estimated the null model whereby we performed similar ordered-logit regressions, but omitting pricing scheme as the independent variable. We next computed the difference in deviance scores between the null and original full models that have the pricing scheme as an independent variable. The differences in deviance scores are subjected to the same likelihood ratio  $\chi^2$  –test. We observed that pricing scheme contributes significantly to the observed variance in sales outcome beyond the effects of the control variables ( $\chi^2 = 313.8$ ,  $p$ -value<0.01).

**Table 2: Impact of Pricing Scheme on Probability of Sale**

		Main Model
Dependent Var.	Independent Var.	Coefficient (Std. Dev.)
Odds of Sale (Ordered)	Pricing Scheme #1	-0.360*** (0.0214)
1. Listen only	Sample Count	0.0197*** (8.12E-04)
2. Songs selected abandoned	Sample Count (Squared)	-2.68E-05*** (1.40E-06)
3. Songs burned in disc but not purchased at counter	Session duration	9.36E-05*** (3.23E-05)
4. Successful purchase	Session duration (Squared)	-3.56E-11*** (1.24E-11)
	Time control	-0.104*** (0.0117)
	Constant & Location dummies <sup>^</sup>	Results suppressed for conciseness

Note: <sup>^</sup> Dummy variables for the different States the booth are located are suppressed for conciseness.  
\*\*\*  $p$ -value < 0.01

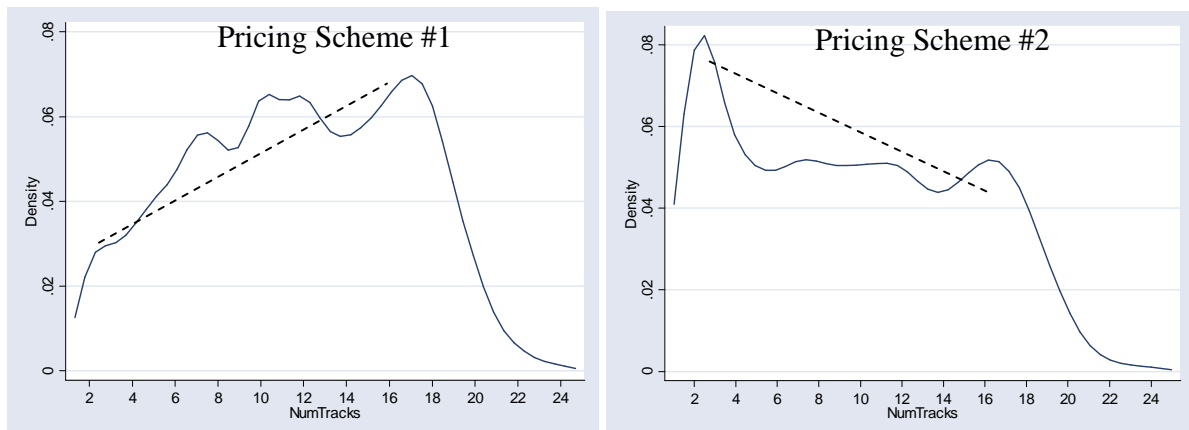
In support of H1, we observed that pricing scheme #2 results in higher probability of sale than pricing scheme #1. Holding other variables in the model constant, the log odds of pricing scheme #1 being in a higher outcome category is 0.360 less than that of pricing scheme #2 (see Table 2). This suggest that the odds of pricing scheme #1 being in a higher outcome is 0.698 times that of pricing scheme #2. Within the model, we observed that increased browsing activity

(e.g., browsing time and number of songs sampled) positively impacted the probability of sale. However, excessive browsing activity has a negative impact on the probability of sale, suggesting the presence of hedonic browsing and free-riding behavior in music sampling. Finally, the time control variable does not have a significant impact on sales probability.

#### 4.4 Analyzing Bundle Sizes

As shown in Table 1, other than the differences in the minimum bundle prices the two pricing schemes are nearly identical for bundles of at least two songs. However, we observed significant differences in the distribution of final bundle sizes. Figure 3 below shows the kernel distribution density of the bundle size under each pricing schemes.

**Figure 3: Distribution of Bundle Size for Pricing Scheme 1 and 2**



From these density distributions, it is apparent that there is a trend of increasing bundle sizes beyond the initial, minimum bundle for pricing scheme #1. There is a low concentration of consumers that purchase only two songs, and the number of consumers purchasing more than two songs generally increases up to a bundle size of 17. The mode bundle size is 17 for pricing scheme #1. Conversely for pricing scheme #2, we observed a decreasing trend of bundle sizes beyond the initial, minimum bundle size. There is an extremely high concentration of consumers

that purchased only two songs, and the concentration of individuals that purchase larger bundles declined in general. The mode bundle size is two for pricing scheme #2.

We also compared the means of the bundles in multiple ways. First, we compared the means for bundles one unit larger than minimum size to eliminate any minimum size anchoring biases (Tversky and Kahneman 1986). For example, between scheme #1 and #2, we chose to compare bundles with three or more units to eliminate the effect of individuals in scheme #2 anchoring on the initial bundle size of two. Intuitively, one would expect the larger minimum bundle requirement for scheme #2 would skew the average observed bundle size. We however observed that this was not true; instead pricing schemes with the smaller minimum bundle sizes and lower initial transaction utilities had the higher mean bundle size as hypothesized in H2.

**Table 3: Mean Differences in Bundle Sizes**

	Pricing Scheme #1	Pricing Scheme #2
	Mean (S.D.)	Mean (S.D.)
<b>For all bundles</b>	11.16 (0 .045)	9.22 (0 .093)
<b><i>t</i>-stat. (<i>p</i>-value)</b>	<i>19.21 (&lt;0.001)</i>	
<b>For bundles <math>\geq 2</math></b>	11.78 (0.042)	9.53 (0.092)
<b><i>t</i>-stat. (<i>p</i>-value)</b>	<i>23.38 (&lt;0.001)</i>	
<b>For bundles <math>\geq 3</math></b>	12.12 (0.041)	10.90 (0.090)
<b><i>t</i>-stat. (<i>p</i>-value)</b>	<i>12.64 (&lt;0.001)</i>	

To formally test the effect of the pricing scheme on the bundle size hypothesized in H2, we consider the potential two purchasing processes that could explain the determination of the final size of a bundle. In the first purchasing process a consumer first decide to make a purchase and then add items to a bundle until they reach an acceptable size (i.e., bundle size and content is determined given the consumer decided to purchase). In the second purchasing process a consumer may casually browse and create a bundle, but not decide to purchase until the bundle passes some threshold of value for the consumer (i.e., purchase is determined given bundle size

and contents). Since either of these processes could be a viable representation of a consumer's true decision process, we empirically modeled both using appropriate estimation techniques.

First, we consider the process where the sales decision is given. This two stage process is aptly represented by the conditional probability function,  $P(y_i = n | z_i = 1)$  shown earlier in Figure 2. In the data collected, there exists numerous browsing sessions that did not result in a sale and only those that resulted in a sale will have a purchased bundle size. Hence, to obtain an unbiased estimate of the impact of initial minimum bundle price on the final bundle size, we have to consider the potential effects of sample selection (Heckman 1979)<sup>6</sup>. Another key characteristic of this context is that the dependent variable (i.e., bundle size) is a count variable that takes on only positive integer values. Conventional least-squares based sample selection estimation suggested by Heckman (1979) will not be appropriate due to the presence of count data as the dependent variable. Poisson or negative binomial regression models are known to provide more efficient estimators with count dependent variables (Wooldridge 2002).

A sample selection adjusted Poisson model first proposed by Greene (1994) and further improved by Terza (1998) provides the appropriate estimators for this context, where we have sample selection with count data. To employ this estimation, we first use a Poisson regression model to represent the factors that impact the final bundle size:

$$P(y_i = n) = \frac{e^{-\lambda_i} \lambda_i^{y_i}}{y_i!} \quad (6)$$

Where  $\lambda_i$  is the mean of the Poisson distribution and is a function of  $x_i$  such that  $\lambda_i = e^{\beta' x_i}$ . The vector,  $x_i$  represents variables that impact the final bundle size. They include the pricing scheme, time control, browsing duration, sample count and location controls as described earlier.  $\beta'$

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<sup>6</sup> The issue of sample selection was first raised by Heckman (1979), who illustrated that in analyzing the demographic factors that impact the wages of working women, it was necessary to consider the issue of self selection that arises when women choose not to enter the workforce (hence the absence of data) due to the very same demographic factors. Similar logic follows for factors that lead to different bundle sizes.

represents the parameters for the relationship. To estimate the Poisson function in light of sample selection, Greene (1994) suggested the need to account for the initial process that will result in a successful sale. This can be done by incorporating the estimates from the earlier process into the Poisson estimation as shown:

$$E(y_i|z_i = 1) = e^{\beta'x_i + \theta M_i} \quad (7)$$

$$\text{where } M_i = \frac{\phi(\alpha' \omega_i)}{\Phi(\alpha' \omega_i)}$$

$\phi$  represents the normal probability distribution function,  $\Phi$  represents the normal cumulative probability distribution function and  $\theta$  represents parameters for the equation. Here, the estimates of  $\alpha'$  and  $\omega_i$  are obtained from a binary probit estimation of the choice model presented in equation (4).<sup>7</sup> By taking natural logarithms on equation (7) we can estimate the relationship that will test H2 as shown earlier in Figure 2.

$$\ln E(y_i|z_i = 1) = \beta'x_i + \theta M_i \quad (8)$$

The estimation of the functional form (8) involves two stages. The first stage is a probit estimation which provides the estimates of the probability of a successful sale. The count portion (bundle size) is then estimated using a Poisson regression that is adjusted by the probability values from the probit model. Poisson regression was suitable as overdispersion was not observed in the data. The ratio between the Pearson  $\chi^2$  of the regression and the degrees of freedom was below 1 (Hilbe 2007) suggesting the absence of overdispersion.

In the sample selection corrected Poisson regression, we assumed that the final observed bundle size is a result of two empirical processes: the realization of a successful sale, followed by the determination of the bundle size. We next describe our estimation procedure for the

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<sup>7</sup> Here we use a binary choice model (probit) and not an ordered choice model to estimate  $\alpha'$  and  $\omega_i$ . The purpose of this 2-stage process is to account for the sample selection effects. As such, there exist only two outcomes i.e. either sold (with the dependent variable, bundle size present) or unsold (with the dependent variable, bundle size absent)

alternative potential purchasing process where the consumer first browses and creates a bundle and then makes a purchase decision if the bundle crosses a *hurdle* such that the bundle is of high enough value to the consumer. Presenting this alternative estimator serves important conceptual and empirical purposes. Conceptually, it is important to show that competing forms of abstraction of the estimation procedure should yield similar evidence for our hypothesis. Empirically, alternative estimators providing similar support for our hypotheses lends validity to the results presented.

To estimate this alternative estimator, we express the log-likelihood function of the process that determines the bundle size to be the following:

$$\mathcal{L} = \ln[P(z_i)] + \{\ln[1 - P(z_i)] + \ln P(y_i)\} \quad (9)$$

Mullahy (1986) showed that the log-likelihood function for this two-phase process can be estimated by incorporating a logit model to estimate the first phase, when the effective bundle size remains zero since no purchase has been made, followed by a zero-truncated negative binomial model to estimate the second phase, when the bundle size becomes a positive integer and the value hurdle has been crossed. The log-likelihood function (9) thus can be translated into a negative binomial hurdle model with a two-part log-likelihood function. Estimates for the empirical relationship are obtained by simultaneously estimating the maximum likelihood estimators for the two-part log-likelihood function<sup>8</sup>.

In Table 4, we present the estimation results. To assess model goodness-of-fit, we computed the deviance for both models. We observed that for both models, likelihood ratio  $\chi^2$  –tests for the deviance scores are significant, suggesting good model fit (Poisson:  $\chi^2 = 4217.69$ ,  $p$ -value<0.01; Hurdle/NB:  $\chi^2 = 772.13$ ,  $p$ -value<0.01). We also checked the extent to which the pricing scheme

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<sup>8</sup> For conciseness, we omit details of the log-likelihood function. A generic two-part log-likelihood function can be found in Hilbe (2007) pp.234. For specific representation, a technical appendix is also available at request from the authors.

contributed to the observed variance in the final bundle size over and above the effects of the control variables. We computed the change in deviance score in the same manner we did for the ordered logit model. For both the selection-corrected Poisson and hurdle models, we observed that pricing scheme contributed significantly to the observed variance in bundle size beyond the effects of the control variables (Poisson:  $\chi^2 = 300.84$ ,  $p\text{-value} < 0.01$ ; Hurdle/NB:  $\chi^2 = 74.6$ ,  $p\text{-value} < 0.01$ ).

From the regression results, we observed that all estimators provided strong support<sup>9</sup> for H2. After controlling for browsing duration, browsing behavior, time and location, we observed that the impact of pricing scheme on bundle size is positive and significant (coeff. = 0.246,  $p\text{-value} < 0.001$ ). The coefficients suggest that a change from pricing scheme #2 to #1 will result in an increase of 0.246 in the difference in the logs of expected bundle size. This means that after controlling for other exogenous factors, bundles purchased under pricing scheme #1 have on average 27.9% more items than those purchased under pricing scheme #2.

Notably, in the process of testing H2, we also found further empirical support for H1. In the first stage of estimation for both the selection-corrected Poisson model and the hurdle model, the binary choice estimation suggests that pricing scheme #1 is negatively correlated with the outcome of a sale (Probit coefficient = -0.383,  $p\text{-value} < 0.01$ ; Logit coefficient = -0.635,  $p\text{-value} < 0.01$ ). This supports our earlier finding from the ordered logit model that higher initial transaction costs lead to higher sales probability.

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<sup>9</sup> We will discuss the results provided by the selection corrected Poisson model; the reader can draw similar conclusions with other estimators presented

**Table 4: Impact of Pricing Scheme on Bundle Size**

Variables	Selection-Corrected Poisson regression	Hurdle Model: Logit- Negative Binomial
<hr/>		
Bundle Size D.V.	<b>Coeff.</b> <b>(S.D.)</b>	<b>Coeff.</b> <b>(S.D.)</b>
<b>Pricing Scheme 1</b>	0.246 *** (0.0143)	0.234 *** (0.027)
<b>Time Control</b>	-0.0514*** (0.00771)	-0.0589*** (0.0148)
<b>Session duration (in seconds)</b>	6.29E-06 *** (1.60E-06)	2.75E-05*** (7.12e-06)
<b>Sample Count</b>	1.05E-03 *** (3.80E-05)	1.13 E-03 *** (1.38E-04)
<b>Constant &amp; Location dummies<sup>^</sup></b>	Results suppressed for conciseness	
<hr/>		
Selection Function (Purchased) D.V.	<b>Coeff.</b> <b>(S.D.)</b>	<b>Coeff.</b> <b>(S.D.)</b>
<b>Pricing Scheme 1</b>	-0.383*** (0.0243)	-0.635 *** (0.0498)
<b>Time Control</b>	-0.0185 (0.0129)	0.0274 (0.0270)
<b>Session duration (in seconds)</b>	-4.09E-05 *** (6.93E-06)	-9.27e-06 (1.09E-05)
<b>Sample Count</b>	0.0112*** (1.94E-04)	0.0114*** (2.52E-04)
<b>Session duration (squared)</b>	1.55E-11 *** (2.96E-12)	-
<b>Sample Count (squared)</b>	-1.08E-05*** (2.49E-07)	-
<b>Constant &amp; Location dummies<sup>^</sup></b>	Results suppressed for conciseness	

**Note:** The selection function (bottom panel) measures the extent of which each independent variable affects the probability of sale by considering all browsing sessions (both sold and unsold). The coefficients in the top panel are the estimates of,  $\beta'$ , parameters of the independent variables that impact bundle size. These estimates consider the bundles created after taking into account the presence of sessions that did not result in a sale.

## 5. Discussion

Applying Thaler's Transaction Utility Theory and using data from a natural experiment, we found strong evidence that consumers react to the framing effects of a multipart pricing scheme. Departing from the usual application of normative models to explain consumer behavior in bundle purchases, we showed that consumers are susceptible to biases in their decision making process when faced with multipart pricing schemes. By increasing the unattractiveness of the initial bundle prices, consumers become less likely to purchase a bundle. All else equal, if consumers do purchase under low initial transaction utility conditions, they are likely to create

larger customizable bundles. Although the eventual prices and contents of two bundles may be the same, the process of which their prices are framed impacts their purchasing behavior, likely because of the the total transaction utility perceived by the consumers. This finding is in line with Thaler's argument that given the non-linear utility function, the addition of gains and losses that result in the *same* net gain (or loss) position might correspond to different net utility positions. For example, an individual winning a \$50 lottery twice in a week (addition of two gains), is likely to experience higher utility than another winning a single \$100 lottery.

### **5.1 Implications For Theory and Research**

There are several important theoretical and managerial implications of this research. In terms of extensions to theory and research, this paper highlights the need for additional examination of behavioral models of economic decision making and their application in the pricing of information goods. Most theoretical pricing models of information goods are normative in nature and behavioral aspects of the consumption of information goods are largely unexplored to date. The importance of normative economic theories on bundling is unquestionable. However, with the support of empirical evidence, we have demonstrated how consumer's bundling and purchasing behavior can be significantly impacted by differences in the framing of pricing schemes. This should encourage and inform future studies to consider decision anomalies and framing effects in the consumption of information goods.

Through this research, we highlight the significance of using a natural experiment to answer important research questions. Though opportunities for natural experiments are few and far between, the applications of such instances are suited in establishing robust conclusions through pseudo-controlled environments. Further, the natural setting in which the data is being collected

lends greater realism to the phenomenon, unlike lab controlled experiments which might not be feasible in real life conditions.

Finally, from a theoretical perspective, this study underscores the importance of transaction utility in understanding consumer purchasing behavior. In the context of multipart pricing for customizable bundling, this is an opportune instance to raise the awareness of the role of transaction utility in determining sales outcome. The flexible nature of multipart pricing can result in greater variations in transaction utilities than standard pricing, making examination of this phenomenon more meaningful. The application of transaction utility in studying multipart pricing also answers the call for more research on the behavioral impact of multipart pricing schemes (Lambrecht et al. 2007).

## **5.2 Implications for Practice**

From the sellers' point of view, the growth of customizable bundling of information goods calls for greater understanding of the usefulness of commonly employed multipart pricing mechanisms. This study provides insights about the impact of minimum initial prices on purchase probability and resulting bundle sizes. With this information, sellers are able to better calibrate the relative proportion between the minimum initial prices and the per unit incremental price to improve sales outcomes. We show that consumers are susceptible to framing effects, where high initial transaction utilities bring about lower purchasing propensity but triggers "recouping" behavior in bundle purchases. This suggest in designing the pricing scheme of a multipart pricing scheme, sellers should recognize the dualistic effects of initial transaction utilities and use it to their advantage.

## **6. Conclusion**

In this paper, we have established a useful theoretical model in the context of customized

information good bundling. We have provided both theoretically developed logical arguments and empirical evidence to support our propositions that the framing of multipart pricing schemes can significantly influence consumer purchasing behavior in this context. The results of our empirical investigation demonstrate a sensitivity of consumers to perceived transaction utility in the bundle creation process. The analysis of data from a natural experiment of custom CD purchases shows that framing of pricing schemes can significantly influence the probability of purchase and the size of customized bundles. When consumers experienced low initial transaction utility due to the minimum bundle pricing conditions, they had lower propensity to purchase, but if they decided to purchase they created larger bundles due to “recouping” effects. The reverse effect is also true.

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