Category-based Screening in Choice of Complementary Products

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ABSTRACT

Consumers often make complex choices involving complementary categories such as cell phones and service plans. In the fast-growing high-tech and entertainment industries, products from complementary categories are often incompatible with one another (e.g., some models of Motorola phones will not work with Verizon wireless plans). This research shows that when choosing a pair of such complementary products, an individual is likely to use a two-stage decision strategy: screening by one category first to narrow down the number of pairs for further evaluation in the second stage. In the presence of incompatibility, screening by one category vs. by the other, may lead to very different choice outcomes. The authors develop a behavioral theory-driven choice model that accounts for both preference heterogeneity and structural heterogeneity of decision strategies to examine the extent to which consumers engage in category-based screening. Analysis of data from a 2 × 2 conjoint choice experiment reveals that individuals tend to screen a category with higher intra-category differentiation and congruent with their decision goals. The authors further suggest possible marketing actions that a firm may take to promote the use of a specific decision strategy that leads consumers to choosing its product.

Keywords: category-based screening, complementary products, decision heuristics, structural heterogeneity, Bayesian

How do consumers choose among complementary products, such as a cell phone and a service plan, when some of the offerings may be incompatible? In many industries, such as the fast-growing technology and entertainment industries, products from complementary categories are often not compatible with one another. For example, different cell phone models (e.g., iPhone vs. Motorola RAZR V3t) are compatible with different wireless service plans (e.g., Cingular vs. T-Mobile); different portable music devices (e.g., iPod vs. Sony MP3) are compatible with different on-line music subscription services (e.g., iTunes vs. Rhapsody); and different high-definition DVD titles (e.g., Columbia's *Big Fish* vs. Universal's *Apollo 13*) are compatible with different DVD players (e.g., Sony's Blu-ray player vs. Toshiba's HD DVD player).

Consumers may find simultaneous evaluation of products from complementary categories to be cognitively demanding. To simplify such complex decisions, many online retailers, such as Amazon.com, provide filtering tools which consumers can use to first screen products from one category (e.g., cell phones) to narrow down the list of compatible pairs of complementary products for further evaluation. To what extent do consumers screen by category vis-à-vis simultaneously evaluate products from multiple categories? If consumers engage in category-based screening, can some individual and category-related factors influence consumers to choose a certain category to screen first? Despite extensive knowledge in the academic field about how consumers use attribute-based screening as decision heuristics (Bettman 1979; Gilbride and Allenby 2004; Huber and Klein 1991), the use of category-based screening is not well understood. For firms offering products in complementary categories, understanding driving forces of consumers' screening strategies is crucial because different strategies can lead to different choice outcomes. Our research therefore is not only of theoretical interest, but also suggests how firms can devise effective marketing strategies in response to consumers' propensity to engage in category-based screening.

In this research, we conceptualize that when choosing complementary products, a consumer may engage in a two-stage decision strategy. In the first stage, category-based screening is used to form a choice set. A pair of complementary products enters her choice set only if the utility of the product from the screening category (e.g., the cell phone) exceeds a certain threshold. In the second stage, she chooses a pair of complementary products that has the highest utility (e.g., phone-plan combined utility) from this choice set. Then we examine how category and individual-related factors, namely *intra-category differentiation* (i.e., the degree of differentiation among competing products within a category) and *decision goal* (i.e., the primary benefit the individual seeks), influence which category is used to screen in the first stage.

To empirically test our research propositions, we construct a behavioral theory-driven choice model that accounts for heterogeneity among individuals in both preferences and decision strategies (i.e., structural heterogeneity). Combined with Bayesian data augmentation, this approach is capable of identifying each individual's underlying decision strategy, such as two-stage vs. single-stage; and conditional on two-stage, screening by one category vs. by the other in the first stage. We collect data using a 2 (intra-category differentiation conditions) × 2 (decision goals) between-subject conjoint choice experiment. Our results provide empirical evidence that a single-stage decision strategy alone cannot adequately describe the observed choices in our data. More importantly, individuals tend to screen by the category that has higher intra-category differentiation and is congruent with their decision goals.

We further illustrate several managerial implications of our results. In particular, we demonstrate that a firm with a superior product might benefit from product strategies that increase differentiation within its own category; whereas a firm with an inferior product might benefit from strategies that increase differentiation within its complementary category. From the communication standpoint, we also find that a firm with a superior product tends to benefit from promoting its own product while a firm with an inferior product tends to benefit from promoting a complementary product that is compatible with its product. These results are particularly interesting because they suggest that firms offering superior vs. inferior products in complementary categories should take different courses of actions to compete more effectively.

Our research is related to, yet deviates, in several important ways, from two research streams in marketing: multi-category choice and consumer decision strategies. Prior research on multi-category choice (c.f. Russell et al. 1999 and Seetharaman et al. 2005 for excellent reviews) examines how individuals make choices across multiple categories in the contexts of consumer packaged good, where products from different categories (e.g., toothpaste and toothbrush) are perfectly compatible with one another. Our research broadens this literature to many other contexts where incompatibility exists between categories, and thus choice of one product may preclude choice of another product from a different category.

Furthermore, the extensive literature on consumer decision strategies or heuristics (e.g., Bettman 1979; Bettman, Johnson, and Payne 1990) and two-stage choice (e.g. Gilbride and Allenby 2004; Roberts and Lattin 1991) primarily focuses on individuals' use of different types of *attribute-based* decision strategies (e.g., conjunctive, elimination-by-aspect) to simplify choice of products from a *single category*. The unique aspect of our research is that we investigate the possible use, and more importantly, the *factors* that influence such use, of *category-based* decision strategies in choice of products from *complementary categories*.

The remainder of the paper is organized as follows. We first review relevant literature and propose our conceptual framework. We then present our modeling framework. Next, we describe our experimental design, estimation method, empirical findings, and strategic implications of our results. Finally, we discuss limitations of our study and suggest avenues for future research.

LITERATURE AND CONCEPTUAL FRAMEWORK

Previous research on multi-category choice has examined choices among products that are perfectly compatible with one another. These include product bundles (Chung and Rao 2003), assortments (Bradlow and Rao 2000), and products from complementary or unrelated categories (Ainslie and Rossi 1998; Manchanda, Ansari, and Gupta 1999; Russell et al. 1999; Seetharaman et al. 2005). These contexts are in direct contrast with many others commonly encountered in the marketplace, where choice of one product may preclude choice of a desirable complementary product. To capture the impact of different decision strategies on choices in such contexts (see Figure 1 for a stylized example), we use the notion of phased decision making.

Phased decision making has been studied as a simplifying strategy when consumers make complex choice decisions (Bettman 1979; Bettman, Johnson, and Payne 1990). A number of modeling approaches have conceptualized it as a two-stage, consideration-then-choice process. When phased decisions are observed or elicited, consideration sets have been modeled as the result of optimal information search (Hauser and Wernerfelt 1990; Roberts and Lattin 1991). That is, an additional alternative is included in a choice set only when the expected marginal benefit of including the alternative exceeds the marginal cognitive cost of considering it.

When composition of each choice set is unobserved, such as in scanner panel data, one approach is to include only those brands recently purchased or currently promoted in a choice set (Bronnenberg and Vanhonacker 1996; Siddarth, Bucklin, and Morrison 1995). Another approach enumerates all combinations of a subset of products as possible choice sets (Andrews and Srinivasan 1995). More recent modeling approaches have switched attention to developing two-stage choice models where choice sets are induced by attribute-based screening heuristics (Gilbride and Allenby 2004; 2006; Moe 2006). Most related to our approach, Gilbride and Allenby (2004) model the formation of choice sets as driven by individuals' use of conjunctive or disjunctive rule to screen out alternatives whose attribute values are below specified cutoffs. While this prior research focuses on *attribute-based* screening in choice of a *single-category product*, we propose that in choice of *complementary products*, individuals may analogously use *category-based* screening. We also further develop in-depth understanding of the underlying behavioral process by examining the factors that may influence the selection of the screening category. Such investigation is generally lacking in prior studies.

Category-based screening is further supported by research on choice bracketing. This research suggests that when making multiple choices, such as from multiple categories, individuals tend to make each choice in isolation (i.e., use narrow bracketing), as opposed to evaluate alternatives simultaneously (i.e., use broad bracketing; Kahneman and Lovallo 1993; Read, Loewenstein, and Rabin 1999; Simonson 1990). The use of such heuristics is attributed to individuals' limitation in cognitive capacity and reliance on pre-existing categorical heuristics, particularly when faced with complex decisions (Johnson and Meyer 1984; Johnson, Meyer, and Ghose 1989). This research also shows that use of narrow vs. broad bracketing can lead to different choice outcomes. One explanation is that broad bracketing, unlike narrow bracketing, allows consumers to make trade-offs across multiple choices (Camerer et al. 1997; Heath and Soll 1996). Interestingly, incompatibility between categories has not been suggested as another plausible explanation to why broad vs. narrow bracketing can lead to different choices.

For category-based screening, we further propose that choice of the screening category will be influenced by two factors: intra-category differentiation and decision goal. *Intra-category differentiation*—the degree of differentiation among competing products within a category—can influence which category an individual screens through two possible mechanisms. First, an increase in the variety or diversity of a stimulus elicits more attention (Kahneman 1973) and promotes more elaborate network encoding in memory (Bradley et al. 1992). Second, differences, as opposed to communalities, across alternatives enable consumers to discriminate among these alternatives (Houston, Sherman, and Baker 1989; 1991). Therefore, consumers tend to believe that such differences are diagnostic for decision making (Lynch, Marmorstein, and Weigold 1988), and pay more attention to such differences. As a result, we postulate that *an individual is more likely to screen the category that has higher intra-category differentiation*.

The second factor, *decision goal*, is broadly defined as the primary benefit that an individual seeks (Huffman and Houston 1993). In our context, it means whether an individual seeks the best phone, or the best plan, or the best phone-plan pair. Prior research has demonstrated that goals affect what information consumers attend to and how they use this information to form evaluation (Huffman and Houston 1993; Mandel and Johnson 2002). When consumers have multiple goals, they tend to focus on the most important goals before sequentially attending to other goals (Markman and Brendl 2000). Therefore, we posit that *an individual is more likely to screen the category that is most congruent with her decision goal*.

MODELING

We present our model in the context of an individual's choice among compatible pairs of cell phones (p) and service plans (s). For ease of exposition, we suppress the subscripts for each individual i and choice task t in all subsequent equations. Each phone-plan pair j , $\{p_j,s_j\}$, is a decision unit. The deterministic component of individual i's indirect utility of the pair, $V_{\{p_j,s_j\}}$, comprises of the deterministic component related to the phone, V_{p_j} , and that related to the plan, V_{s_j} :

(1) $$V_{\{p_j,s_j\}} = V_{p_j} + V_{s_j} .$$

V_{p_j} and V_{s_j} are further formulated as linear compensatory functions of the phone's features X_{p_j} and the plan's features X_{s_j} , respectively:

(2) $$V_{p_j} = X_{p_j}\beta_p \text{ and } V_{s_j} = X_{s_j}\beta_s ,$$

where β_p and β_s are individual-specific part-worths that reflect the individual's preference for each phone attribute and each plan feature, respectively.

Our model accommodates several possible decision strategies: single-stage, two-stage with screening-by-phones in the first stage, and two-stage with screening-by-plans in the first stage. Next, we will describe each decision strategy separately before combining them into a unified model with structural heterogeneity.

If an individual uses a *single-stage* decision strategy, then, consistent with the random utility theory, she selects the pair with the highest utility among all pairs available in the choice task. That is, her probability of choosing pair $\{p_j,s_j\}$ is:

(3) $$\Pr(y = \{p_j, s_j\}) = \Pr(V_{\{p_j,s_j\}} + \varepsilon_j \geq V_{\{p_k,s_k\}} + \varepsilon_k,\ \forall\{p_k, s_k\}) ,$$

Under the assumption that the error terms, ε_j and ε_k, follow an i.i.d. Type I Extreme Value distribution (McFadden 1973), this probability equals $\frac{\exp(V_{\{p_j,s_j\}})}{\sum_k \exp(V_{\{p_k,s_k\}})}$.

If the individual uses a *two-stage* strategy with *screening-by-phones* in the first stage, then all phone-plan pairs that enter her choice set, $\{p_k,s_k\} \in \Omega$, are identified by an indicator function I (similar to Gilbride and Allenby 2004):

(4) $$I\left(\frac{V_{p_k} - V_{\min_p}}{V_{\max_p} - V_{\min_p}} \geq \theta_p\right) = 1,$$

where $V_{\min_p}$ and $V_{\max_p}$ are the minimum and maximum, respectively, indirect utilities of the phones available in the choice task. That is, each phone-plan pair $\{p_k,s_k\}$ that enters the choice set Ω satisfies the condition of $\frac{V_{p_k} - V_{\min_p}}{V_{\max_p} - V_{\min_p}} \geq \theta_p$, where $0 \leq \theta_p \leq 1$. In other words, given the range of the indirect utilities of the worst to the best phone in the choice task, phone p_k needs to be among the top θ_p*100 percentile in order to enter the choice set (therefore we name θ_p simply as a percentile cutoff).

In contrast to a screening criterion based on an absolute cutoff that is invariant across choice tasks, $V_{p_k} \geq V_{cut-off}$ (Gilbride and Allenby 2004), the proposed percentile cutoff is adaptive to available phones in different choice tasks (Huber and Klein 1991). The use of a percentile cutoff (Cooke et al. 2004; Niedrich, Sharma, and Wedell 2001) is also supported by the previous literature that suggests that individuals often evaluate an option *relative* to the other available options (Leclerc, Hsee and Nunes 2005; Prelec, Wernerfelt, and Zettelmeyer 1997) and preferences are context-dependent (Huber, Payne, and Puto 1982; Huber and Puto 1983; Tversky and Simonson 1993).

In the second stage, only those phone-plan pairs from the choice set are evaluated and the pair with the highest utility is chosen. Thus, a phone-plan pair *{p_j,s_j}* is chosen with probability

$$\text{(5)}\quad \Pr(y=\{p_j,s_j\})=\Pr(V_{\{p_j,s_j\}}+\varepsilon_j \geq V_{\{p_k,s_k\}}+\varepsilon_k, \forall\{p_k,s_k\} \text{ such that } I\left(\frac{V_{p_k}-V_{\min_p}}{V_{\max_p}-V_{\min_p}} \geq \theta_p\right)=1).$$

Similarly, if the individual uses a *two-stage* strategy with *screening-by-plans* in the first stage, then a pair *{p_j,s_j}* is chosen with probability

$$\text{(6)}\quad \Pr(y=\{p_j,s_j\})=\{\Pr(V_{\{p_j,s_j\}}+\varepsilon_j \geq V_{\{p_k,s_k\}}+\varepsilon_k, \forall\{p_k,s_k\} \text{ such that } I\left(\frac{V_{s_k}-V_{\min_s}}{V_{\max_s}-V_{\min_s}} \geq \theta_s\right)=1).$$

Now we can introduce our unified model with structural heterogeneity (Yang and Allenby 2000). This model associates a multinomially distributed probability mass (ϕ_b, ϕ_p, ϕ_s) with each of the above possible decision strategies: single-stage (ϕ_b), two-stage with screening-by-phones in the first stage (ϕ_p), and two-stage with screening-by-plans in the first stage (ϕ_s). Thus, a pair *{p_j,s_j}* is chosen with probability:

$$\begin{aligned}
&\Pr(y=\{p_j,s_j\})=\phi_b \times \Pr(V_{\{p_j,s_j\}}+\varepsilon_j \geq V_{\{p_k,s_k\}}+\varepsilon_k, \forall\{p_k,s_k\}) \\
\text{(7)}\qquad &+\phi_p \times \Pr(V_{\{p_j,s_j\}}+\varepsilon_j \geq V_{\{p_k,s_k\}}+\varepsilon_k, \forall\{p_k,s_k\} \text{ such that } I\left(\frac{V_{p_k}-V_{\min_p}}{V_{\max_p}-V_{\min_p}} \geq \theta_p\right)=1) \\
&+\phi_s \times \Pr(V_{\{p_j,s_j\}}+\varepsilon_j \geq V_{\{p_k,s_k\}}+\varepsilon_k, \forall\{p_k,s_k\} \text{ such that } I\left(\frac{V_{s_k}-V_{\min_s}}{V_{\max_s}-V_{\min_s}} \geq \theta_s\right)=1),
\end{aligned}$$

where $\phi_b+\phi_p+\phi_s=1$.

This model is structurally identical to the consideration set model commonly seen in the literature (e.g. Andrews and Srinivasan 1995), where the choice probability of an option is often specified as $\Pr(y)=\sum_{\Omega}\Pr(\Omega)\times\Pr(y\mid\Omega)$, where Ω is a possible choice set. The main difference is that our model formulates a possible choice set Ω as resulting from the use of category-based screening heuristics, as opposed to purchase histories (Bronnenberg and Vanhonacker 1996), marketing mix activities (Siddarth, Bucklin, and Morrison 1995), or enumeration of all possible choice sets (Andrews and Srinivasan 1995). That is, unlike previous research, we rely on consumer behavior theories to conceptualize the construction of consideration sets. From the estimation standpoint, an enumeration-based consideration model, which nests our model, can become very cumbersome as the number of options increases. Our model does not suffer from this problem. With this specification, we are interested in structural heterogeneity probabilities associated with each possible decision strategy (ϕ_b, ϕ_p, ϕ_s), instead of Pr (Ω), the probability associated with each possible choice set.

To summarize, our modeling framework accounts for both preference heterogeneity and structural heterogeneity of decision strategies. Our goal is to estimate, from the observed choices, the probabilities associated with each possible decision strategy (ϕ_b, ϕ_p, ϕ_s) at the aggregate, as well as at the individual, level. Then we are able to compare, across experimental conditions, the aggregate, average probabilities of individuals screening-by-phones vs. screening-by-plans. Consistent with our research objective, this exercise will allow us to examine how *intra-category differentiation* and *decision goal* influence the selection of the screening category.

EMPIRICAL STUDY

Experimental Design and Data Collection

We conducted a choice-based conjoint experiment using complementary cell phones and service plans, both of which are very familiar to our student participants. Our pretest with 80 undergraduate students identified *manufacturer brand*, *price (with plan)*, *text messaging*, and *built-in camera* as the most important attributes for cell phones, and *service provider*, *monthly* *fee*, *contract length*, and *coverage area* for service plans. Using information from popular retail websites such as *www.cnet.com*, we further specified three levels for each attribute (Table 1).

Insert Table 1 Here

Our computer-based experiment had four phases. In Phase 1, each participant provided preference rankings (from 1 – most preferred to 3 – least preferred, corresponding to the three levels within each attribute) for one cell phone attribute (brand) and two service plan attributes (service provider; monthly fee). Rankings for all other attributes were presumed to have natural ordering and thus not solicited.

In Phase 2, each participant completed nine phone choice tasks (to choose one among three phones in each task) and nine plan choice tasks (to choose one among three plans in each task). The order of the phone tasks and plan tasks was randomly determined. The purpose of these single-category conjoint choice tasks was twofold: (i) to familiarize participants with the attribute levels in the upcoming complementary-category tasks; and (ii) to incorporate them into the part-worths estimation to improve efficiency.

In Phase 3, each participant completed ten complementary-category choice tasks. The first nine were used for model calibration and the last for holdout prediction. In each task, the participant was asked to imagine shopping for a new cell phone and a service plan, and then shown profiles of four phones, four plans, and their compatible relations (see Figure 2a for an example). Whether phones or plans were placed on the left side of the screen was randomly determined. The participant was then shown all compatible phone-plan pairs embedded in these four phones and four plans in a random order (e.g., Figure 3 shows the nine pairs embedded in Figure 2a) and asked to choose his/her favorite pair. We excluded the “no choice option” in order to engage participants in more thoughtful decision making and alleviate possible econometric identification issues in case a high proportion of choice tasks result in "no choice". This is also consistent with our interest in examining the influencing factors of decision strategies when a purchase decision needs to be made.

In the final Phase 4, each participant answered a few questions that would allow us to examine his/her familiarity with cell phones and service plans, our manipulation of *intra-category differentiation* and *decision goal*, and the decision strategies that he/she self-reported using when completing the complementary-category choice tasks.

Insert Figures 1 and 2 Here

To assess the effect of *intra-category differentiation* and *decision goal* on a participant's selection of the screening category, we randomly assigned participants to each of the 2 (higher phone differentiation vs. higher plan differentiation) × 2 (category goal vs. balanced goal) conditions. This design is parsimonious and enables us to examine the two questions of specific interests to us: (i) given that a participant has a balanced goal, does higher phone (plan) differentiation lead to a higher propensity to screen by phones (plans); and (ii) given that the phones (plans) are more differentiated, does a phone (plan) goal, as compared to a balanced goal, further increase a participant's tendency to screen by phones (plans)? Since it is rare to observe two product categories in the marketplace with the same degree of intra-category differentiation, it is more appealing to test the effect of decision goal above and beyond the effect of intra-category differentiation, than to simply test its main effect.

Next, we describe how we generated different intra-category differentiation and decision goal conditions. In conditions involving higher phone differentiation (see Figure 2a for an example), we used Java programming (whose details can be obtained from the authors) (i) to ensure that for each phone attribute, all three levels of the attribute were used for the four phones in a choice task; and (ii) to generate, for two randomly selected plan attribute, either a complete overlapping pattern (i.e., all four plans had the same level of an attribute) or a partial overlapping pattern (i.e.. three out of four plans had the same level of an attribute, whereas the fourth plan had a different level)[1]; and for the remaining two plan attributes, to randomly generate levels for each. Note that a complete or partial overlapping pattern was generated for only two out of the four plan attributes because we needed adequate variation across plans for model estimation, while ensuring adequate discrepancy between the two categories in terms of intra-category differentiation. Conditions involving higher plan differentiation were generated analogously.

To prime a specific decision goal, we simply provided instruction to participants. For instance, we used “for this purchase, you really want to get a cell phone that is right for you” to prime a phone goal, and “for this purchase you really want to get a phone and a plan that are both satisfactory for you” to prime a balanced goal.

Finally, after four phones and four plans had been generated for each choice task, compatible relations between them were generated real-time for each participant. Specifically, for each of the five randomly selected choice tasks, either two or three plans were randomly selected to be compatible with each phone. Whether two or three plans were randomly selected was also randomly determined. Similarly, for each of the remaining five tasks, either two or three phones were randomly selected to be compatible with each plan. In doing so, Java programming further ensures that the best phone (plan) was incompatible with the best or second-best plan (phone), as determined by the sum of the solicited and presumed rankings across attributes.

Since our research objective is to investigate what drives the use of any specific decision strategy, imposing this compatibility constraint prevents participants from trivially choosing their most desired combination of a phone and a plan, which does not allow us to econometrically identify the specific decision strategy used. We recognize that imposing this constraint may prompt individuals to carefully evaluate products from both categories simultaneously, thereby leading to a more conservative estimate of the use of category-base screening strategies. Nonetheless, as the same constraint was imposed across all experimental conditions, our subsequent hypothesis tests remain valid and serve our research objective.

We collected data from 216 undergraduate student participants (36% male; 64% female) at a large Midwest university. Each received $10 for his/her participation. Of all the participants, 82% had selected cell phones, service plans, or both by themselves in past purchases. Overall, participants considered service plans as more important (with an average score of 68 on a 0-to-100 constant sum scale) than cell phones. This is consistent with what we observe in the U.S. market that wireless service providers possess more market power than cell phone manufacturers in consumers' purchasing decisions (Budden 2004).

Estimation Method and Model Comparison

We use the Gibbs sampler (Gelfand and Smith 1990) to estimate individual-specific part-worths and parameters associated with each individual's decision strategies (see the Technical Appendix for further details). We generate 100,000 draws and keep every one-hundredth draw of the last 50,000 draws to compute posterior means and standard deviations of the parameters.

To estimate the screening cutoff, $0 \leq \theta_p \leq 1$, if a two-stage strategy with screening-by-phones is used, we used a grid search method (Chib 2001, page 3609) with three possible grid values: 1, .66, and .33. We then estimate the probability mass associated with each of these possible cutoff values ($\phi_{p1}, \phi_{p2}, \phi_{p3}$). A screening cutoff equal to 1 is equivalent to allowing only those phone-plan pairs that contain the best phone to enter a choice set. A screening cutoff equal to .66 or .33 allows phone-plan pairs that contain the best and possibly less preferred phone(s) to enter the choice set. A similar approach is used to estimate the screening cutoff, $0 \le \theta_s \le 1$, if a two-stage strategy with screening-by-plans is used. Then, the probability for a pair *{pj,sj}* to be chosen, as specified in Equation (7), can be now re-written as

$$
\begin{aligned}
&\Pr(y=\{p_j,s_j\}) = \phi_b \times \Pr(V_{\{p_j,s_j\}}+\varepsilon_j \ge V_{\{p_k,s_k\}}+\varepsilon_k, \forall\{p_k,s_k\}) \\
&+\sum_m \phi_{pm} \times \Pr(V_{\{p_j,s_j\}}+\varepsilon_j \ge V_{\{p_k,s_k\}}+\varepsilon_k, \forall\{p_k,s_k\} \text{ such that } I\left(\frac{V_{p_k}-V_{\min_p}}{V_{\max_p}-V_{\min_p}} \ge \theta_{pm}\right)=1) \\
&+\sum_m \phi_{sm} \times \Pr(V_{\{p_j,s_j\}}+\varepsilon_j \ge V_{\{p_k,s_k\}}+\varepsilon_k, \forall\{p_k,s_k\} \text{ such that } I\left(\frac{V_{s_k}-V_{\min_s}}{V_{\max_s}-V_{\min_s}} \ge \theta_{sm}\right)=1),
\end{aligned}
\tag{8}
$$

where $\phi_b + \sum_{m=1}^{3}\phi_{pm} + \sum_{m=1}^{3}\phi_{sm} = 1$, $\theta_{.1}=1, \theta_{.2}=.66, \text{and } \theta_{.3}=.33$. We define $\sum_{m=1}^{3}\phi_{pm}$ and $\sum_{m=1}^{3}\phi_{sm}$, as the probabilities of using a two-stage strategy with screening-by-phones and screening-by-plans, respectively.

Our choice of these specific cutoff values is driven by both theoretical and model identification considerations. From a theoretical standpoint, they are consistent with the range theory (Volkmann 1951), which posits that equal segments of the psychological scale are assigned to equal segments of the contextual range, and that evaluation of an option is based on the proportion of the contextual range that lies below the value of this option. From an estimation standpoint, with only four unique phones and four unique plans in each choice task, a larger number of possible cutoff values can be identified, but with lower precision (i.e., higher posterior variances in estimated probabilities associated these cutoff values), since different cutoff values may lead to identical choice sets. Such identification issue is more prominent for smaller cutoff values, since they tend to give rise to choice outcomes that are identical to those resulting from a single-stage decision strategy. We, however, advocate for more refined grid values in other empirical studies that involve a larger number of options.

We also compare our approach with three percentile cutoffs (Model 4 in Table 2) to one (Model 5 in Table 2) based on three quota cutoffs (Leclerc, Hsee and Nunes 2005; Feinberg and Huber 1996; Wernerfelt 1995). Specifically, a quota cutoff of 1, 2, and 3, respectively, mean that only phone-plan pairs that contain the individual's most preferred, top two most preferred, and top three most preferred phones (if screening-by-phones) or plans (if screening-by-plans) may enter the choice set. That is, the probability of choosing a phone-plan pair $\{p_j,s_j\}$ is:

$$
\begin{aligned}
(9)\qquad \Pr(y=\{p_j,s_j\}) = {} & \psi_b \times \Pr(V_{\{p_j,s_j\}}+\varepsilon_j \ge V_{\{p_k,s_k\}}+\varepsilon_k, \forall\{p_k,s_k\}) \\
& + \sum_m \psi_{pm} \times \Pr(V_{\{p_j,s_j\}}+\varepsilon_j \ge V_{\{p_k,s_k\}}+\varepsilon_k, \forall\{p_k,s_k\} \text{ such that } I\left(r_{p_k} \le m\right)=1) \\
& + \sum_m \psi_{sm} \times \Pr(V_{\{p_j,s_j\}}+\varepsilon_j \ge V_{\{p_k,s_k\}}+\varepsilon_k, \forall\{p_k,s_k\} \text{ such that } I\left(r_{s_k} \le m\right)=1),
\end{aligned}
$$

where $m = \text{quota} = 1,2,3$. And r_{p_k} (r_{s_k}) is the preference ranking for phone p_k (or plan s_k) based on the individual's part-worth estimates (from 1 – the best to 4 – the worst) among the four unique phones (plans) in a choice task. Similar to our model described in Equation (8), this model also has seven structural heterogeneity probabilities: one associated with a single-stage strategy (ψ_b); three associated with the three possible quota cutoffs, 1, 2, and 3, if screening-by-phones (ψ_{pm}; m=1,2,3); and three if screening-by-plans (ψ_{sm}; m=1,2,3). The choice of three percentile values (1, .66 and .33) thus provides a natural analog of, and a fair comparison with, the quota cut-off model.

While our decision to examine three specific percentile cutoffs in the proposed Model 4 is theory-driven, one might argue that from a modeling standpoint it is more flexible to allow continuous percentile cutoffs (Model 6 in Table 2). To do so, we re-specify Equation (8) as:

(10) $$\Pr(y=\{p_j,s_j\})=\phi_b\times\Pr(V_{\{p_j,s_j\}}+\varepsilon_j\geq V_{\{p_k,s_k\}}+\varepsilon_k,\forall\{p_k,s_k\})$$

$$+\phi_p\times\int_{\theta_p}\Pr(V_{\{p_j,s_j\}}+\varepsilon_j\geq V_{\{p_k,s_k\}}+\varepsilon_k,\forall\{p_k,s_k\}\text{ such that }I\left(\frac{V_{p_k}-V_{\min_p}}{V_{\max_p}-V_{\min_p}}\geq\theta_p\right)=1)p(\theta_p)d\theta_p$$

$$+\phi_s\times\int_{\theta_s}\Pr(V_{\{p_j,s_j\}}+\varepsilon_j\geq V_{\{p_k,s_k\}}+\varepsilon_k,\forall\{p_k,s_k\}\text{ such that }I\left(\frac{V_{s_k}-V_{\min_s}}{V_{\max_s}-V_{\min_s}}\geq\theta_s\right)=1)p(\theta_s)d\theta_s\ ,$$

where $\phi_b+\phi_p+\phi_s=1$. We also re-parameterize $\theta_p=\dfrac{\exp(\vartheta_p)}{1+\exp(\vartheta_p)}$ and $\theta_s=\dfrac{\exp(\vartheta_s)}{1+\exp(\vartheta_s)}$ so that $0<\theta_p,\theta_s<1$, and estimate ϑ_p and ϑ_s. Also since very small (or large) ϑ can give to rise to θ close to 0 (or 1), to improve stability of the estimate, we constrained the value of ϑ such that .01 $\leq\theta=\dfrac{\exp(\vartheta)}{1+\exp(\vartheta)}\leq .99$.

Insert Table 2 Here

We compare the in-sample fit of the proposed model (Model 4) with several other benchmark models using log marginal densities (LMD) (Newton and Raftery 1994) and in-sample choice probabilities. We also compare the predictive performance using out-of-sample choice probabilities (Table 2). Model 1 assumes that all individuals, albeit heterogeneous in preferences, use the same single-stage decision strategy, and evaluate all available phone-plan pairs in each choice task at once.

Model 2 extends Model 1 by further incorporating cross-category attribute level interactions into the utility function (Equation 1). Specially, we use five dummies[2] to capture the interactions between the phone and the plan within a pair and none turns out to be significant. This result shows that choice of a phone-plan pair other than the one with maximum combined utility in a task, if observed, is more likely to result from category-based screening, as opposed to negative interactions between attractive attribute levels across categories.

Model 3 is a Generalized Nested Logit (GNL) model (Swait 2001). While a Nested Logit model is suitable for a tree-type layout where each decision unit belongs to only one branch of the tree, a GNL model is appropriate for a network-type layout like ours[3]. For example, given there are four unique phones and four unique plans in each task, our GNL model has nine networks: P1, …, P4, S1, …, S4, and all pairs. Then each decision unit (e.g., a P1–S1 pair) belongs to multiple overlapping networks (e.g. P1 network, S1 network, and all pairs network). Similar to Models 1 and 2, Model 3 also assumes that each individual evaluates all available phone-plan pairs available in each task. However, it further allows each individual to have correlated preferences for different pairs. The estimated similarity (or inclusive value) parameters suggest that this GNL model can be reduced to a simpler Multinomial Logit model (Model 1). Note that the small discrepancy in the fit statistics between Model 1 and 3 may stem from the use of different random draws and the constraint imposed in order to estimate Model 3 (c.f. footnote 5).

The model comparison by far confirms that category-based screening can neither be explained away by cross-category interactions, nor captured by a more complicated error structure in a single-stage GNL model. While Models 1 ~ 3 incorporate preference heterogeneity, they assume that all individuals use a single-stage decision strategy to evaluate all available phone-plan pairs. Models 4 ~ 6 accommodate both preference heterogeneity and structural heterogeneity of decision strategies. Specifically, Model 4 (proposed model) uses three grids of percentile cutoffs in category-based screening (Equation 8), Model 5 three quota cutoffs (Equation 9), and Model 6 continuous percentile cut-offs (Equation 10). We also test two additional models with preference and structural heterogeneity: a model with enumeration of consideration sets (Model 7), and the proposed model with cross-category interactions in the utility Equation 1 (Model 8). More details about them are presented in the Web Appendix.

Our results (Table 2) reveal that Models 4 ~ 8 that account for structural heterogeneity in decision strategies provide much better in-sample fit, and slightly better predictive performance, than Models 1 ~ 3 that only allow for a single-stage decision strategy. This result is consistent with past studies that suggest that single-stage compensatory models often produce predictive accuracy comparable to those that accommodate various decision heuristics (Green and Srinivasan 1978; Johnson and Meyer 1984). Overall, these results collectively suggest that structural heterogeneity in decision strategies, above and beyond preference heterogeneity, explains a great proportion of variations in the observed choices. More specifically, they provide evidence that a single-stage choice model is insufficient in describing the choice process, and that two-stage decision strategies are more consistent with the observed choices in the presence of incompatibility between complementary categories.

Additionally, our comparison between Model 4 and Model 5 suggests that the proposed grid percentile cutoffs lead to slightly better in-sample fit and out-of-sample prediction. This is possibly because they allow the size of each individual's choice set to be dependent on the relative attractiveness of options, which vary from one task to another, whereas quota cutoffs do not provide such flexibility. The proposed Model 4 also provides better in-sample fit and out-of-sample prediction than Model 6 with continuous percentile cutoffs. This result is consistent with our earlier argument that very small cutoffs (e.g., cutoffs much lower than .33) admitted by Model 6 can give rise to choice outcomes identical to those that result from a single-stage strategy. Thus they are likely estimated with lower precision and, thereby, introduce larger variance in the part-worth estimates. Nonetheless, we will later show that both Model 4 and Model 6 lead to the same conclusions for our hypothesis testing.

Finally, Model 4, which accommodates only a subset of a much larger number of possible choice sets admitted by Model 7, not surprisingly, has worse in-sample fit than Model 7. Nonetheless, it provides slightly better predictive accuracy. This result seems to suggest over-fitting of Model 7. Furthermore, from an estimation standpoint, as the number of phone-plan pairs in each choice task increases, a model based on decision heuristics like ours, as opposed to a model based on enumeration like Model 7, becomes clearly more advantageous.

Part-Worth Estimates and Decision Strategies

We report the part-worth estimates from our proposed Model 4 in Table 3. All part-worth estimates appear reasonable. For example, for cell phones, participants prefer Motorola to LG and Nokia (prob($\beta_{\text{Motorola}} > 0$) > .95 but prob($\beta_{LG} > 0$) < .90, given Nokia is the baseline); \$10 to \$100 to \$200; maximum 150 characters text messaging to maximum 50 characters to no text messaging; and 1 mega pixels camera to 640 × 480 pixels to no camera.

Insert Table 3 Here

Table 4 displays the estimated aggregate probabilities of individuals using different decision strategies in each of the four experimental conditions. These probabilities were obtained by averaging over the individual level posterior distributions. The results show that even with the imposed compatibility constraint, which may lead to conservative estimates of the use of two-stage decision strategies, large probabilities of participants in our study seem to be using a two-stage decision strategy across all four experimental conditions. These probabilities vary from

.574 under the higher plan differentiation/balanced goal condition to .864 under the higher plan differentiation/plan goal condition. In the presence of incompatibility between complementary categories, use of category-based screening has important implications to the choice set formation and thus final choices.

Insert Table 4 Here

To assess the effect of *intra-category differentiation*, in the absence of the effect of decision goal, on the selection of the screening category, we compare the estimated average probabilities of participants screening by phones (and by plans alike) under the higher phone differentiation/balanced goal condition vs. higher plan differentiation/balanced goal condition. We report these probabilities for the proposed Model 4 with grid percentile cutoffs (also displayed in Table 4) and for Model 6 with continuous percentile cutoffs. The probability (prob($\phi_p > \phi_s$) > .95) of participants screening by phones (.279 for Model 4; .172 for Model 6) is significantly higher when the phone category is more differentiated than when the plan category is more differentiated (.144 for Model 4; .050 for Model 6). Similarly, the probability of participants screening by plans is higher (although not significant; with prob($\phi_s > \phi_p$) =.69 for Model 4; .88 for Model 6) when plans (.430 for Model 4; .453 for Model 6) are more differentiated than when phones are more differentiated (.389 for Model 4; .339 for Model 6). This insignificant difference occurs possibly because the majority of our participants considered plans as much more important than phones in their purchase decisions (recall that in our sample the average importance score is 68 for service plans and 32 for cell phones on a 0 to 100 constant sum scale). Therefore, if many participants already screen by plans, increased differentiation among plans will have a much smaller effect.

We further assess the incremental effects of *decision goal* on the selection of screening category when the category is already more differentiated. The probability (with prob($\phi_p > \phi_s$) >.95) of participants screening by phones under the higher phone differentiation/phone-goal condition (.418 for Model 4; .305 for Model 6) is significantly higher than that under the higher phone differentiation/balanced goal condition (.279 for Model 4; .172 for Model 6). Similarly, the probability (with prob($\phi_s > \phi_p$)>.95) of participants screening by plans under the higher plan differentiation/plan goal condition (.709 for Model 4; .766 for Model 6) is significantly higher than that under the higher plan differentiation/balanced goal condition (.430 for Model 4; .453 for Model 6).

Finally, to establish the face validity of our inference on individuals' use of various decision strategies, we compare the inferred decision strategy used by each individual with his or her self-reported decision strategy. The correlation is .532 between inferred and self-reported selection of phones as the screening category. And the correlation between inferred and self-reported selection of plans as the screening category is .398. Both are statistically significant.

Overall, our results show that participants tend to screen the category that has higher intra-category differentiation and is most congruent with their decision goals in the first stage. As we will show next, such knowledge can provide valuable guidance to managers regarding the selection of appropriate marketing strategies in an effort to increase their product's market share.

Illustration of Strategic Implications

Our findings suggest that given existing compatibility or strategic alliance with the complementary category, managers may be able to influence consumers' selection of the screening category, and thus lead them to choosing their products. For example, an increase in intra-category differentiation within a particular category (e.g., through new product introduction or product line pruning), or an increase in consumers' focus on this category (e.g., through effective branding or marketing communications), is likely to induce more consumers to screen this category, and hence benefit a superior product from this category (i.e., a product with higher market share). Conversely, an increase in intra-category differentiation within a complementary category, or an increase in consumers' attention to the complementary instead of own category, might induce more consumers to screen the complementary category, and as a result, increase the market share of an inferior product (i.e., a product with lower market share) compatible with a superior complementary product.

Insert Table 5 Here

To generate a more concrete example, we use the parameter estimates from the proposed model to simulate the preferences of, and decision strategies used by, 100,000 consumers. We then compute the aggregate market shares of P1 (to denote a superior phone with the highest market share within the phone category), P4 (an inferior phone with the lowest market share within the phone category), S1 (a superior service with the highest market share within the plan category), and S4 (an inferior service with the lowest market share within the plan category) from Figure 2, under each of the 2 (higher phone differentiation as displayed in Figure 2a vs. higher plan differentiation as displayed in Figure 2b[4]) × 2 (the majority or 90%, of consumers having a category goal and 10% having a balanced goal vs. 90% having a balanced goal and 10% having a category goal) conditions.

The results (Table 5) show that under the conditions of the majority having a balanced goal, the superior phone (P1) gains market share by 31.91% (from 26.29% to 34.68%) when its own category becomes more differentiated. Conversely, the inferior phone (P4) gains market share by 12.32% (from 9.09% to 10.21%) when the *complementary category* becomes more differentiated. Furthermore, under higher own-category differentiation conditions, the superior phone (P1) gains market share by 14.42% (from 34.68% to 39.68%) when more individuals have a category goal, whereas the inferior phone (P4) gains market share by 13.20% (from 8.03% to 9.09%) when more individuals have a balanced goal. We observe similar results for the superior plans and inferior plans.

In summary, our illustrated exercise suggests that a firm with a superior product might benefit from marketing strategies that increase differentiation within, and draw consumers' attention to, its own category; whereas a firm with an inferior product might benefit from strategies that increase differentiation within, and draw consumers' attention to, its complementary category. These findings are interesting because they allude to potential effective strategies which firms with inferior brands can devise to circumvent their shortcomings. We caution, though, that these managerial implications may be limited to our empirical context. Their generalizability warrants further research. Other interesting strategic implications of our findings, such as using strategic selection of compatible alliance to influence consumers' use of specific decision strategies, also invites more detailed investigation.

DISCUSSION

It is commonplace that products from complementary categories are incompatible with one another. This research shows that in such contexts, category-based screening explains observed choices better than a single-stage decision strategy. In the presence of incompatibility, screening by one category vs. by the other can lead to very different choice outcomes, and are thus consequential to firms' market shares and profitability. Building on behavior theories, we construct a choice model that accommodates a single-stage and a number of two-stage decision strategies. Combined with a 2 × 2 conjoint choice experiment, our model provides empirical evidence that consumers tend to screen the category that has higher *intra-category differentiation* and is congruent with their *decision goals*.

We believe that our research makes both theoretical and substantive contributions. It broadens the examination of decision heuristics from the attribute to the category level. It also provides insight into the driving forces behind the selection of specific category-based screening heuristics. Importantly, our study exemplifies the value of fusing behavior theories, experimental design, and econometric modeling in marketing research. The use of our behavioral theory-driven model not only leads to more parsimonious and meaningful conceptualization of choice (i.e., consideration) sets, but also allows for what-if analysis exercise which provides managerially relevant insights. Specifically, our simple illustrated example shows that firms with superior vs. inferior brands may benefit from different courses of strategic actions to induce consumers to engage in specific decision strategies. Coupled with the use of Bayesian inference, we also effectively account for consumer heterogeneity in both preferences and decision strategies in our two-stage choice model.

Despite our contributions, we recognize limitations of our study. Consistent with our earlier discussions, we acknowledge that imposing the incompatibility constraint in our empirical study may introduce endogeneity (Liu, Otter, and Allenby 2007) and lead to an underestimate of the use of category-based screening. While this constraint does not affect our hypothesis testing and actually provides stronger evidence in favor of our proposed model, the reported probabilities of the use of category-based screening should be viewed as conservative lowerbound estimates. Our results should also be interpreted as being conditional on consumers actually making a purchase decision, since we purposefully excluded the "no choice" option from our study design.

Our research also has some other limitations that may inspire future research. For instance, our model assumes compensatory evaluation of attributes within each product. With a much larger number of attributes than what we examine in this research, consumers might also screen products by attributes. Thus, future research needs to examine possible use of attribute-based and category-based screening simultaneously. Also, the proposed model can be generalized, via modification of the screening conditions in forming a choice set and its associated probability mass in Equation (8), to study other multi-category or multi-stage choices that may involve more than two complementary products, and thus screening by possibly more than one category.

Future research should also further examine how additional factors, such as search costs (e.g., induced by store locations), other types of goals (e.g., promotion vs. prevention goal), and choice dynamics (e.g., consumer learning), influence the selection of the screening categories or attributes; or more broadly, the order of such selection. As aforementioned, research in this area is generally lacking, albeit important to both theoretical development and managerial practice. Finally, our study takes the structure of incompatibility, or conversely compatible alliance, as given. In reality, compatibility or alliance structure is often a result of firms' strategic considerations. By forming powerful strategic alliance with partners in complementary industries (e.g. movie studios), firms (e.g. theater owners) can further differentiate themselves from competitors and benefit from the competitive advantages established by their complementary partners. While our research provides better understanding of macro-level firm strategies from a unique angle of examining micro-level consumer behavior, understanding firms' strategic selections of compatible alliances and how such selections affect consumer choice warrants fruitful future research.

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[1]More specifically, in two out of the ten complementary-category tasks, we generated complete overlapping for both of the two randomly selected plan attributes. In another four tasks we generated partial overlapping for both. And in the remaining four tasks, we generated complete overlapping for one, and partial overlapping for the other. The order of these tasks was also randomly determined.

[2]To circumvent over-parameterization, we choose to include only five interactions that are meaningful, and capture situations where consumers may avoid getting the most attractive attribute levels from both categories simultaneously. These five interactions are: $10 phone and $29 plan; max. 150 characters text messaging and no contract; max. 150 characters text messaging and national coverage; 1 mega-pixel camera and no contract; and 1-mega pixel camera and national coverage.

[3] One limitation of any Nested Logit or GNL model is that the structure of the network, i.e., the tree branches or networks, needs to be pre-specified before the parameters can be estimated. We therefore specify 9 such networks. Furthermore, since the identities of P1 ~ P4 and S1 ~ S4 vary across tasks, we thus define P1 ~ P4 as, respectively, the best, second best, third best, and worst phones, determined by the sum of solicited and presumed preference rankings across attributes.

[4] When moving from a higher phone differentiation (Figure 2a) to a higher plan differentiation (Figure 2b) condition, we (i) ensure that the market shares of P1and P4 within the phone category (and similarly the market shares of S1 and S4 within the plan category) remain almost unchanged by selecting an appropriate set of P2, P3, S2, and S3; and (ii) retain the same compatible relations. In doing so, the resulting changes in the market shares of P1, P4, S1, and S4 among all phone-plan pairs available in the market, will not be attributable to the change of market shares of P1, P4, S1, and S4 within their own respective categories.

TABLE 1
ATTRIBUTE-LEVELS FOR CELL PHONES AND SERVICE PLANS

Attribute	*Level*		
Cell Phone:			
Brand	Motorola	Nokia	LG
Price (w/ plan)	$10	$100	$200
Text messaging	N/A	Max. 50 Characters	Max. 150 Characters
Built-in camera	N/A	640 × 480 pixels	1 mega pixels
Service Plan:			
Service provider	Cingular	Sprint	Verizon
Monthly fee (w/ free anytime min)	$29.99 (200 min)	$59.99 (500 min)	$79.99 (800 min)
Contract length	No contract	1 year	2 years
Coverage area	Local	Regional	National

TABLE 2
MODEL COMPARISON

	Log Marginal Density	*In-sample Choice Prob*[1]	*Out-of-sample Choice Prob*[1]
Model 1: Single-stage Compensatory	-1958	.507	.434
Model 2: Single-stage Compensatory with Cross-category Interactions	-1927	.515	.434
Model 3: Generalized Nested Logit (GNL)	-2004	.494	.421
Model 4: Structural Heterogeneity with Grid Percentile Cutoffs (Proposed Model)	-1553	.596	.458
Model 5: Structural Heterogeneity with Quota Cutoffs	-1599	.582	.454
Model 6: Structural Heterogeneity with Continuous Percentile Cutoffs	-1634	.575	.453
Model 7: Structural Heterogeneity with Enumeration of Consideration Sets	-1460	.608	.449
Model 8: Proposed Model with Cross-category Interactions in the Utility Equation	-1588	.589	.455

[1] Mean Absolute Deviation (MAD) = 1 – Choice Prob.

TABLE 3
PART-WORTH ESTIMATES

Part-Worth	*Posterior Mean*	*Posterior Std.*
Cell Phone:		
LG[1]	.072	.094
Motorola	**.251**[2]	.085
$200 w/ plan	**-1.968**	.141
$10 w/ plan	**1.299**	.138
No text messaging	**-2.158**	.185
Max. 150 characters	**0.438**	.087
No camera	**-1.281**	.129
1 mega pixels camera	**.162**	.088
Service Plan:		
Verizon	**.371**	.084
Cingular	.055	.087
$79 (800 min.)	**-1.753**	.149
$29 (200 min.)	**-.303**	.179
2-year contract	**-.574**	.090
No contract	.063	.074
Local coverage	**-2.097**	.169
National coverage	**1.691**	.147

[1] The baseline levels for these attribute-levels are, respectively, Nokia, $100, max. 50 characters text messaging, 640 × 480 pixels camera; Sprint, $59 (500 min), 1-year contract, and regional coverage.

[2] These bolded numbers indicate that the probabilities of the parameters to be larger or smaller than zero are greater than .95.

TABLE 4
ESTIMATED PROBABILITIES OF PARTICIPANTS USING EACH DECISION STRATEGY

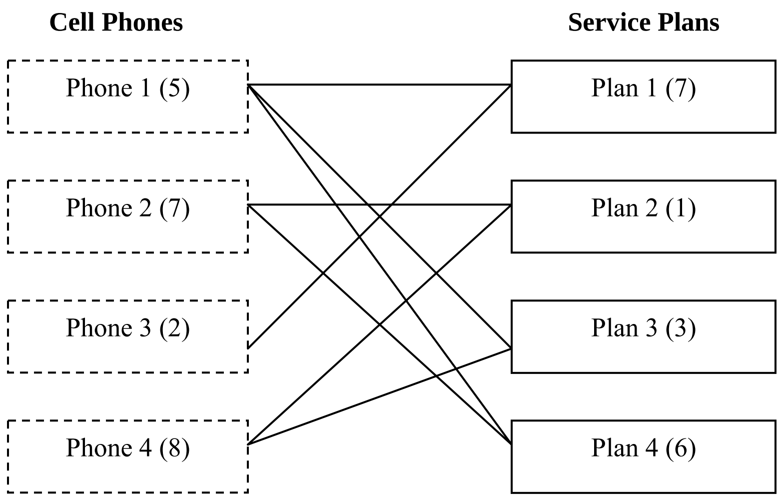
		Higher Phone Differentiation Posterior Mean	Posterior Std	*Higher Plan Differentiation* Posterior Mean	Posterior Std
Category Goal	**Single-stage**	**.378**	**.073**	**.136**	**.060**
	Screen by phone with cutoff = 1	.080	.032	.021	.005
	Screen by phone with cutoff = .66	.258	.066	.057	.024
	Screen by phone with cutoff = .33	.080	.049	.077	.037
	Two-stage with screening-by-phones (sum of the above three probabilities)	**.418 (a)**	**.062**	**.155 (e)**	**.035**
	Screen by plan with cutoff = 1	.086	.017	.337	.063
	Screen by plan with cutoff = .66	.042	.021	.266	.089
	Screen by plan with cutoff = .33	.076	.038	.106	.059
	Two-stage with screening-by-plans (sum of the above three probabilities)	**.204 (b)**	**.038**	**.709 (f)**	**.048**
Balanced Goal	**Single-stage**	**.332**	**.077**	**.426**	**.085**
	Screen by phone with cutoff = 1	.037	.016	.031	.009
	Screen by phone with cutoff = .66	.156	.058	.027	.010
	Screen by phone with cutoff = .33	.086	.048	.086	.049
	Two-stage with screening-by-phones (sum of the above three probabilities)	**.279 (c)**	**.286**	**.144 (g)**	**.049**
	Screen by plan with cutoff = 1	.095	.030	.171	.044
	Screen by plan with cutoff = .66	.187	.067	.133	.060
	Screen by plan with cutoff = .33	.108	.064	.126	.072
	Two-stage with screening-by-plans (sum of the above three probabilities)	**.389 (d)**	**.057**	**.430 (h)**	**.072**

Our hypothesis testing related to the effect of *intra-category differentiation* shows that under balanced goal, prob (%(c) > %(g)) = .96 and prob (%(d) < %(h)) = .69.
And our hypothesis testing related to the effect of *decision goal* shows that under phone differentiation, prob (%(a) > %(c)) = .95; and under plan differentiation, prob (%(f) > %(h)) = 1.00.

TABLE 5
AN EXAMPLE OF THE EFFECT OF INTRA-CATEGORY DIFFERENTIATION AND CONSUMPTION GOAL ON MARKET SHARE (%)

	Superior Phone (P1)		**Inferior Phone (P4)**	
	Higher Phone Differentiation	*Higher Plan Differentiation*	*Higher Phone Differentiation*	*Higher Plan Differentiation*
Category Goal	39.68	21.39	8.03	11.70
Balanced Goal	34.68	26.29	9.09	10.21
	Superior Plan (S1)		**Inferior Plan (S4)**	
	Higher Phone Differentiation	*Higher Plan Differentiation*	*Higher Phone Differentiation*	*Higher Plan Differentiation*
Category Goal	24.27	41.57	14.13	8.76
Balanced Goal	30.70	35.87	11.84	9.79

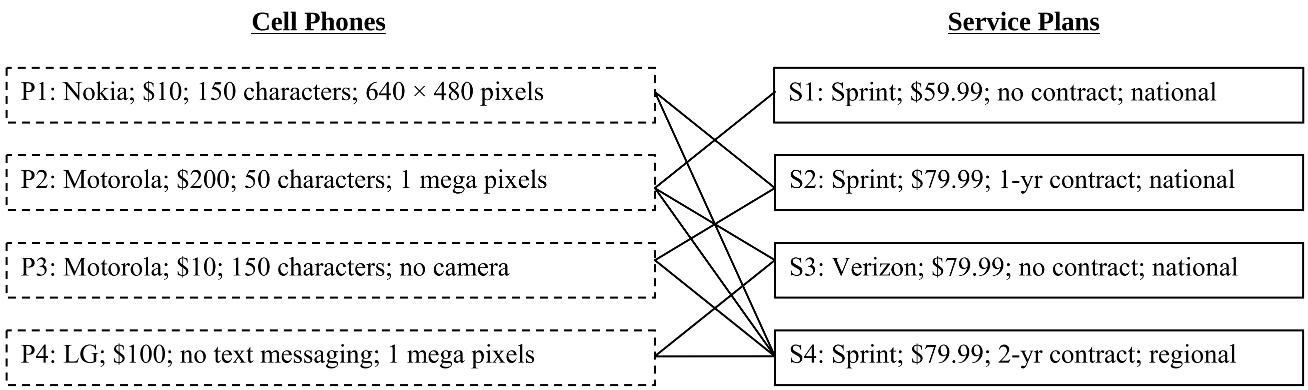
FIGURE 1:
AN EXAMPLE OF CHOICE OF COMPLEMENTARY PRODUCTS



The numbers in parentheses are utilities of each phone and each plan. And the link between a phone and a plan indicates a compatible relation. Based on this example, when choosing among phone-plan pairs, an individual is likely to select Phone 2 and Plan 4 (with the highest combined utility of 13 among all pairs) if she evaluates all pairs simultaneously. However, if she screens by phones first, she might select Phone 4 (with the highest utility among all phones) and then Plan 3. Similarly, if she screens by plans first, she might select Plan 1 and then Phone 1. Please keep in mind that this is only a styled example. Our proposed model actually allows for other situations where an individual admit more than simply the best phone (if she screens by phones) or the best plan (if she screens by plans) into her choice set.

FIGURE 2
TWO EXAMPLES OF CHOICE TASKS
(presented as 4 unique phones and 4 unique plans)

2a. Higher Phone Differentiation Condition



2b. Higher Plan Differentiation Condition

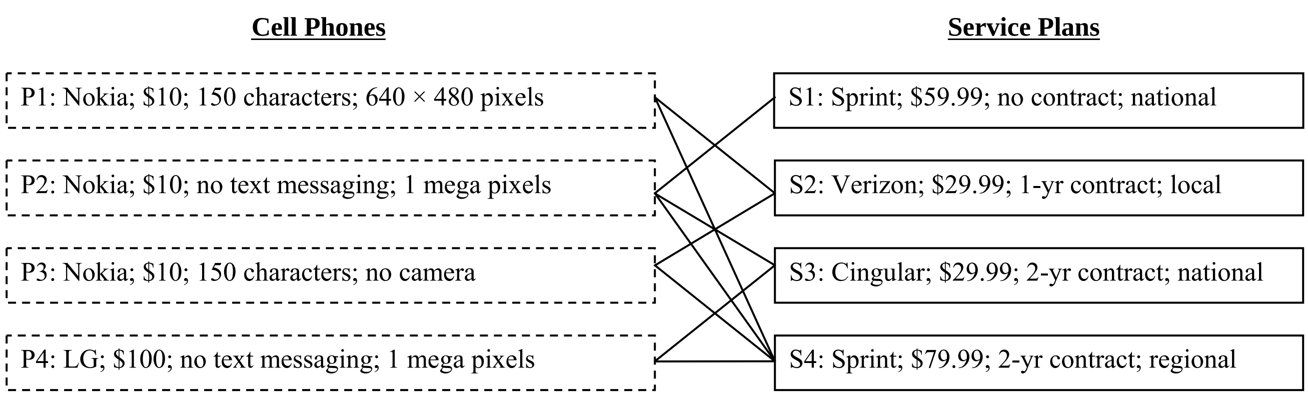


FIGURE 3
A CHOICE TASK EXAMPLE
(presented as phone-plan pairs)

P1: Nokia; $10; 150 characters; 640 × 480 pixels	S2: Sprint; $79.99; 1-yr contract; national
P1: Nokia; $10; 150 characters; 640 × 480 pixels	S4: Sprint; $79.99; 2-yr contract; regional
P2: Motorola; $200; 50 characters; 1 mega pixels	S1: Sprint; $59.99; no contract; national
P2: Motorola; $200; 50 characters; 1 mega pixels	S3: Verizon; $79.99; no contract; national
P2: Motorola; $200; 50 characters; 1 mega pixels	S4: Sprint; $79.99; 2-yr contract; regional
P3: Motorola; $10; 150 characters; no camera	S2: Sprint; $79.99; 1-yr contract; national
P3: Motorola; $10; 150 characters; no camera	S4: Sprint; $79.99; 2-yr contract; regional
P4: LG; $100; no text messaging; 1 mega pixels	S3: Verizon; $79.99; no contract; national
P4: LG; $100; no text messaging; 1 mega pixels	S4: Sprint; $79.99; 2-yr contract; regional

TECHNICAL APPENDIX: ESTIMATION ALGORITHM

In this section, we will first illustrate how we estimate the proposed model that accounts for heterogeneity in both attribute preferences and use of decision strategies. Our approach to incorporate structural heterogeneity is similar to those in Yang and Allenby (2000), Gilbride and Allenby (2004), and Chib (2001, p.3609). As described in the data section, we conducted a choice-based conjoint study using both single-category and cross-category choice tasks. Let vectors y_{ip}^{1} and y_{is}^{1}, respectively, represent the choices participant *i* made in the nine single-category phone choice tasks, each involving three phones (*p*), and the nine single-category plan choice tasks, each involving three plans (*s*). Similarly, y_{i}^{2} denotes the choices participant *i* made in the first nine of ten cross-category choice tasks. Note that unlike in the single-category choice tasks in which the number of alternatives is fixed at three, the numbers of alternative phone-plan pairs in the cross-category choice tasks vary from task to task depending on the compatible relations between the four phones and four plans in the choice task. We use X_{p}^{1}, X_{s}^{1}, and X^{2}, respectively, to represent the attribute-levels of the phones in the single-category phone choice tasks, attribute-levels of the plans in single-category plan choice tasks, and attribute-levels of the compatible phone-plan pairs in the cross-category choice tasks. Heterogeneity in preferences and decision strategies is specified as below:

$$\beta_{ip} \sim MVN(\overline{\beta}_{p}, \Sigma_{\beta_{p}}) \qquad \beta_{is} \sim MVN(\overline{\beta}_{s}, \Sigma_{\beta_{s}})$$

$$\delta_{i} \sim Multinomial(\phi_{mb}, \phi_{m1p}, \phi_{m2p}, \phi_{m3p}, \phi_{m1s}, \phi_{m2s}, \phi_{m3s})\text{, where}$$

δ_{i} is an index taking values from 1 to 7, indicating which of the seven possible decision strategies participant i can use, m = 1, …, 4 experimental conditions of the conjoint study; b =

single-stage, *p*=screening by phones, *s*=screening by plans; 1 ~ 3 represents the three cutoffs of interest (1, .66, and .33).

The prior distributions of the hyper-parameters are assumed to be:

$$\overline{\beta}_p \sim MVN(\beta_0^p, \Lambda_{\beta_p}) \qquad \Sigma_{\beta_p} \sim IW(g_p, G_p)$$

$$\overline{\beta}_s \sim MVN(\beta_0^s, \Lambda_{\beta_s}) \qquad \Sigma_{\beta_s} \sim IW(g_s, G_s)$$

$$\phi_m \sim Dirichlet(\alpha_m)$$

A Gibb sampler is constructed as follows.

1. Generate $\beta_{ip} \mid y_{ip}^1, y_i^2, X_p^1, X^2, I(\delta_i, X^2, \beta_{ip}, \beta_{is}), \overline{\beta}_p, \Sigma_{\beta_p}$ using the Metropolis-Hasting. The index δ_i specifies the decision strategy participant *i* uses, and thus how the screening criterion should be specified. For example in our program, if δ_i=1, the screening criterion will be $I\left(\frac{V_{p_k} - V_{\min_p}}{V_{\max_p} - V_{\min_p}} \geq 1\right) = 1$, and only phone-plan pairs that satisfy this criterion will be included in the choice set Ω. β_{ip} are estimated based on $t_1 = 1,\ldots,9$ separate phone choice tasks and $t_2 = 1,\ldots,9$ cross-category choice tasks. We denote the probability of choosing the observed choice *j* in separate phone choice task t_1 as $pr_j^{1t_1}(\beta_{ip})$, and that in cross-category choice task t_2 as $pr_j^{2t_1}(\beta_{ip}, \delta_i)$. For cross-category choice tasks, the probability of choosing observed choice *j* is derived based only on option pairs in the choice set (determined by δ_i), and zero probability is assigned to option *j* if it does not belong to the choice set. This specification assures that new proposed estimates of β_{ip} that give rise to a choice set that does not contain the observed choice *j* in at least one of the joint choice tasks are accepted with probability of zero. That is, β_{ip}^{new} are accepted with probability

$$\min\left(\frac{\prod_{t_1} pr_j^{1t_1}(\beta_{ip}^{new}) \prod_{t_2} pr_j^{2t_2}(\beta_{ip}^{new}, \delta_i) MVN(\beta_{ip}^{new} - \overline{\beta}_p, D_{\beta_p})}{\prod_{t_1} pr_j^{1t_1}(\beta_{ip}^{old}) \prod_{t_2} pr_j^{2t_2}(\beta_{ip}^{old}, \delta_i) MVN(\beta_{ip}^{old} - \overline{\beta}_p, D_{\beta_p})}, 1\right).$$

2. Generate $\beta_{is} \mid y_{is}^1, y_i^2, X_s^1, X^2, I(\delta_i, X^2, \beta_{ip}, \beta_{is}), \overline{\beta}_s, \Sigma_{\beta_s}$ analogously to (1).

3. Generate $\delta_i \mid y_i^2, X^2, \beta_{ip}, \beta_{is}, \phi_m$ where δ_i is an index indicating participant *i*'s decision strategy. To determine δ_i, we need to cycle through our seven possible strategies of interest. Each candidate index $(\delta_i^l), l = 1,...7$ is then drawn with probability

$$\frac{\prod_{t_2} pr_j^{2t_2}(\beta_{ip}, \delta_i^l)\phi_{lm}}{\sum_k \prod_{t_2} pr_j^{2t_2}(\beta_{ip}, \delta_i^k)\phi_{km}}, k=1,...,7.$$

Similar to 1, this estimation procedure assures that a strategy that leads to zero probability of choosing observed choice *j* (i.e., choice j does not belong to the choice set) is drawn with zero probability.

4. Generate $\phi_m \mid \{\delta_{im}\}$, for $m = 1, \ldots, 4$ experimental conditions and M_m is the number of participants in condition *m*:

$$\phi_m \sim Dirichlet\left(\sum_{i=1}^{M_m} I(\delta_i = 1) + \alpha_1, \ldots, \sum_{i=1}^{M_m} I(\delta_i = 7) + \alpha_7\right).$$

Please refer to Allenby, Arora, and Ginter (1998) for how to generate Dirichlet draws using gamma distribution.

5 ~ 8. Generating $\overline{\beta}_p$ (5), $\overline{\beta}_s$ (6), Σ_{β_p} (7), and Σ_{β_s} (8) is standard. Therefore, we omit the presentation for brevity.

Note that although our goal is to estimate average probabilities of participants engaging in different decision strategies across experimental conditions (posterior means of ϕ_m), we can also average the number of times (all across MCMC draws) that each δ_i^l, l=1,…7 is drawn for participant *i*. These averages can be interpreted as the average probabilities of participant *i* using different decision strategies.

WEB APPENDIX: ADDITONAL INFORMATION ON MODELS 7 AND 8

Model 7 conceptualizes that individuals use enumeration, as opposed to category-based screening, to form choice sets. Nonetheless, a complete enumeration (Andrews and Srinivasan 1995) cannot be directly applied in our study. This is because unlike in the scanner panel data, where there are a relatively small, and often fixed, number of brands, both the *number* (ranging from 7 to 11) and the *identities* of the phone-plan pairs in our study vary across tasks. Thus, it is not only computationally expensive to enumerate all possible choice sets (ranging from $2^7–1$ to $2^{11}–1$), but more importantly, conceptually meaningless to associate a probability mass to each choice set that has different identities (or compositions) across tasks (Chiang, Chib, and Narasimhan 1999).

We circumvent the *number* problem by constructing the same number of 29 possible choice sets within each task: 14 from enumerating based on 4 unique phones (P1, …, P4, P1/P2, …, P3/P4, P1/P2/P3, …, P2/P3/P4); 14 from enumerating based on 4 unique plans, plus 1 with all available pairs in a task. We circumvent the *identity* problem by further labeling, before enumerating, the four unique phones in each task as, respectively, the best (P1), second best (P2), third best (P3), and worst phone (P4), as determined by estimated part-worths. Similar labeling applies for the four unique plans before they are enumerated. Then a choice set, say {P1}, has a consistent identity, across all tasks, as the choice set that contains only the best phone (and its compatible plans) in a task. Thus, this approach allows meaningful interpretation of the probabilities associated with each of these 29 possible choice sets.

Following a similar approach, we also estimated an alternative version of Model 7 that enumerates all possible choice sets that consist of compatible pairs of the top phones and plans (e.g., a choice set {P2, S3} consists of all compatible pairs of the top two phones and top three plans). The result shows that, similar to Model 7, this model provides better in-sample fit than the proposed model (log marginal density of -1527 and in-sample choice probability of .599) and worse out-of-sample fit (out-of-sample choice probability of .455). Since this model also mimics a strategy of screening by both categories, this result actually provides additional evidence that besides being most appropriate for our research objectives of testing the driving factors of the selection of the screening category, the proposed model of screening-by-one category is capable of describing the observed choices.

As for Model 8, following Model 2 of single-stage compensatory with cross-category interactions, we include the same five interactions in the utility Equation (1).The result shows that such inclusion leads to poorer fit both in-sample and out-of-sample. In fact, none of the estimates related to the interaction terms is significantly different from zero.