RUNNING HEAD: The Phantom Decoy Effect in Perceptual Decision-making

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Abstract

A phantom decoy is an alternative that is superior to another “target” option, but is unavailable at the time of choice. In value-based decisions involving phantom decoys (e.g., consumer choices), individuals often show increased preference for the similar, inferior target option over a non-dominated competitor alternative. Unlike value-based decisions that are driven by subjective goals, perceptual decisions typically have an outside criterion that defines the goal of the task (e.g., target is present or absent). Despite their obvious differences, past research has documented a number of commonalities between both types of decisions. In a set of three experiments, we examine the influence of phantom options on simple perceptual decisions and point out a critical difference between perceptual and value-based decisions. Our results show that in perceptual choice, participants prefer competitor options to target options, the opposite of the pattern typically found in consumer choice. We use the results of the experiments to examine the predictions of four different models of context effects including loss aversion and dynamic, preference accumulation models. We find that accumulation models provide the best explanation for our results as well as being able to generalize to other context effects.

Keywords: phantom decoy, context effects, multi-alternative choice, perceptual decision-making

Word count: 8,944

THE PHANTOM DECOY EFFECT IN PERCEPTUAL DECISION-MAKING

When presented with multiple alternatives, preference has been shown to depend both upon the values of the attributes of the alternatives themselves and upon the comparisons made between them. These comparisons make up the context of a particular choice set, and a large volume of previous research has shown that changes in the context of a choice set can influence preference. For example, consider a situation were you are deciding among three dishes at a conference dinner. Your options are lobster, tilapia, or vegetable lasagna. You immediately decide that the lobster sounds the best. However, when the waiter comes to take your order, he announces that the lobster is sold out for the night. You then decide to go with the tilapia over the vegetable lasagna. Now consider a slightly different version of the same problem. In this scenario, your dinner options are tilapia, vegetable lasagna, and spaghetti with meatballs. You immediately prefer the spaghetti with meatballs, but find out later that it is unavailable. In this situation, you choose the vegetable lasagna over the tilapia. This simple example illustrates that preferences between two options (tilapia and vegetable lasagna) are dependent on a third unavailable option. This phenomenon is known as the phantom decoy effect (Pratkanis & Farquhar, 1992; Pettibone & Wedell, 2000; Pettibone & Wedell, 2007).

Beside the phantom decoy, other types of decoys have been studied including the asymmetrically dominated (AD) decoy (Huber, Payne, & Puto, 1982) and the compromise (COM) decoy (Simonson, 1989), both of which differ upon the type of contextual comparisons they provide as well as upon their availability to be chosen. In most cases, these decoys have been shown to increase preference for a “target” alternative that has similar attributes to the decoy (e.g., spaghetti with meatballs increases preference for vegetable lasagna). These effects have largely been shown to be robust (see Frederick, Lee, and Baskin (2014) for some exceptions) and have been useful in generating multiple models for explaining the contextual sensitivity of preference. In an experiment using typical consumer products as alternatives, Pettibone & Wedell (2000) demonstrated that participants preferred the alternative that was targeted by phantom decoy 57% of the time, compared to only 43% of the time when it was not targeted. Both COM and AD decoys have shown similar effect sizes in consumer choice, with the exception that participants tend to choose an available compromise decoy more often than other types of available decoys.

Decoy effects have typically been studied in value-based decision-making (i.e., choices made on the basis of a decision-maker's subjective goals), using stimuli such as consumer products (Wedell & Pettibone, 1996) and job candidates (Highhouse, 1996). In contrast to value-based decisions, perceptual decisions require individuals to determine an unknown state of the world (e.g., target present or absent) using noisy sensory information (Gold & Shadlen, 2007). Like value-based decisions, people make perceptual decisions everyday. These decisions are typically made quickly without much deliberation, for example, deciding if a traffic light is red or green. Even though there is a clear difference between perceptual and value-based decisions, the two types of decisions both require individuals to process uncertain information before a choice can be made. Some researchers (Busemeyer, Jessup, Johnson, & Townsend, 2006; Shadlen, Kiani, Hanks, & Churchland, 2008; Summerfield & Tsetsos, 2012; Symmonds & Dolan, 2012) have even suggested that both types of decisions involve the same underlying mechanisms.

Recently, researchers have shown that asymmetric dominance and compromise effects occur in perceptual choice tasks as well as value-based decisions (Choplin & Hummel, 2005; Trueblood, Brown, Heathcote, & Busemeyer, 2013), suggesting that the processes that lead to decoy effects may involve fundamental processes (at a low cognitive level) rather than higher-level heuristics. Phantom decoy effects, however, have not been demonstrated in perceptual choice. The phantom decoy, unlike other decoys (i.e., AD and COM decoys), is a superior but unavailable option that typically results in increased preference for a similar target alternative that it dominates (Pettibone & Wedell, 2007). This paper examines the influence of phantom decoys in perceptual decisions and points out a crucial difference between these decisions and value-based ones. We also use the results of our experiments to test the predictions of four different models of phantom decoy effects.

Overview of Decoy Effects

In order to understand the phantom decoy, we first explain decoy effects in general and the asymmetric dominance and compromise effects in specific. Decoy effects typically manipulate context by the addition of a third alternative into a two alternative choice set (Figure 1). The target (T) and the competitor (C) alternatives are typically described on two dimensions, such as cars described on miles per gallon of gas (Dimension 1) and ride quality (Dimension 2), and are constructed to be equally attractive due to trading off an increase on one attribute for a decrease upon the other. This equality in attractiveness is represented by the dotted line in the figure that indicates the equi-preference contour in the set.

The AD decoy is constructed so as to be dominated by the target but not the competitor. For example, in the domain of cars, the AD decoy would share the value of the target on ride quality (Dimension 2) but would be inferior on miles per gallon of gas (Dimension 1) making it a worse option than the target. The COM decoy extends the range of evaluation on both dimensions, making the target a compromise between the more extreme decoy and competitor. In the majority of prior research, introducing either the AD (Huber et al., 1982) or the COM

(Simonson, 1989) decoys into the choice set increases preference for the target and decreases preference for the competitor, violating rational choice theory and creating the potential for preference reversals by flipping the locations of the decoys to favor the competitor.

Phantom Decoy

In comparison, phantom decoys are constructed to dominate the target, but are presented to participants as unavailable. In the case of the car example, a range phantom decoy (P_R) would have the same value on miles per gallon of gas as the target (Dimension 1) but would be superior on ride quality (Dimension 2). In comparison to the competitor, this phantom would be superior overall but would have a lower value on miles per gallon of gas. The phantom decoy, then, simulates a situation where a highly attractive but unavailable alternative is present in the marketplace. In these cases, participants also prefer the target (Pratkinis & Farquar, 1992; Highhouse, 1996; Pettibone & Wedell, 2000, 2007) despite the fact that the decoy dominates it. Across a number of studies, the types of phantoms that have previously been tested vary depending upon two factors: location relative to the target and awareness of its unavailability. Past studies (Pettibone & Wedell, 2007; Scarpi & Pizzi, 2013), have used phantom decoys at different locations to examine how decoy placement influences the strength of the effect. In our experiments, we include five different decoy locations as shown in Figure 1.

For the phantom decoy to have an influence on preference, participants must compare it to the available alternatives in the set. Most prior research with consumer stimuli has attempted to hide the unavailability of the phantom in some way to make sure that participants consider it. The exact method of making participants aware of the unavailability of the phantom, however, may have an impact on the effect seen. In the majority of studies on phantom decoys, participants are presented the three alternatives in the set simultaneously without being aware that the decoy is unavailable. After a brief delay, 3 seconds in studies by Pettibone & Wedell (2000, 2007), but before a choice is made, participants are told that the phantom is unavailable and that they need to make their choice from the remaining items (we call this a known delay presentation). A second method, which we call unknown presentation, hides the unavailability of the phantom until after participants make a choice. If a participant chooses the phantom, only then are they told of its unavailability and are required to make a different choice. Scarpi and Pizzi (2013) found that this type of presentation resulted in preference for the competitor over the target for certain decoy locations. They argued that not knowing the phantom was unavailable in advance triggered a negative affective reaction due to the unexpected loss of choice freedom, decreasing the overall attractiveness of the target. Specifically, they showed that judgments of justice, decision satisfaction, and intent to repatronize after a decision all declined when compared to choice sets containing a known phantom. A third approach is to simply mark the phantom as unavailable from stimulus onset.

Models of the Phantom Decoy Effect

Finding a theoretical explanation of the phantom decoy effect, especially one that can simultaneously explain other types of decoys, has been difficult. Typically, models used to explain AD and COM effects have struggled to explain why participants choose the dominated target with the phantom decoy. In this section, we briefly review four different models of AD and COM effects and discuss their predictions regarding the phantom decoy.

Value-shift models

Value-shift models (Wedell & Pettibone, 1999) rely upon changes in the subjective valuation of attributes due to context, such as predicted by range-frequency theory (Parducci, 1974). In the case of the AD decoy, the extension of range on the target's worst attribute increases its subjective valuation, causing it to increase in overall value. The same extension of range does little to help the competitor, since it is already superior on that attribute. This model, however, does not predict COM. In this case, range is extended on both attributes, which should result in no increase in preference for the target since both extensions should cancel each other out (Pettibone & Wedell, 2000).

In the case of phantom decoys, other than the frequency phantom (P_F in Figure 1), the extension of range on the target's best attribute should actually make the target appear less attractive, and would favor the selection of the competitor. For example, in a two-item choice set, the target is the best on one attribute. Adding the range or the extended range phantom decoy (P_R and P_{ER} in Figure 1) extends the range on the best attribute of the target, pushing the target into the middle of the pack. In comparison, the competitor suffers relatively little loss of value because it already had the lowest value on that attribute. Indeed, this is what Pettibone and Wedell (2000) found when they looked at attribute value ratings individually for each alternative with the phantom decoy. Despite this shift, participants still preferred the target in choice, suggesting that while these processes still operate, they do not govern preference with the phantom decoy in consumer choice. However, in perceptual choice, these processes may still operate. If this is true, participants should choose the competitor as the largest shape in all awareness of unavailability conditions except for the known condition.

As for the frequency phantom, while there is no extension of range due to its presentation, the rankings of the three alternatives do change along the target's worst dimension. This makes the target move from being the second smallest on that dimension to the third. The presentation of the frequency phantom does not change the rank order along the target's best dimension as it shares that value with the target, leaving the competitor as the second smallest with or without the decoy. Assuming equal weighting of the dimensions, the change in rank order along the target's worst dimension should make it appear smaller overall while having little to no effect on the perception of size on the competitor. Thus, the competitor would also be favored in this condition.

Dynamic, preference accumulation models

Another direction for explaining the phantom decoy effect come from dynamic, preference accumulation based models, such as multialternative decision field theory (MDFT) (Roe, Busemeyer, & Townsend, 2001), the leaky competing accumulator (LCA) model (Usher & McClelland, 2004), and the multi-attribute linear ballistic accumulator (MLBA) model (Trueblood et al., 2014). In these models, preference for different options accumulates during the deliberation time. A decision is made when preference for one of the options reaches a threshold amount. These models have had great success at explaining dominated and non-dominated decoy effects, such at the AD and COM effects as well as the similarity effect (Tversky, 1972). Further, their general prediction that decoy effects should increase as participants spend more time considering their alternatives was found to be supported with both the asymmetrically dominated decoy and the compromise decoy (Pettibone, 2012). In the past, these models have not been specifically applied to the phantom decoy.

We examined predictions for the phantom decoy effect from one of the preference accumulation based models, MLBA. In this model, decisions are modeled as a race among different accumulators, which each correspond to a different alternative. The accumulators are linear and accumulate evidence deterministically during a trial (Brown & Heathcote, 2008). These simplifying assumptions lead to greater mathematical tractability than stochastic models such as MDFT and LCA. A choice is made when one of the accumulators reaches a decision threshold. The rate of evidence accumulation for a particular alternative is determined by comparing the alternative to each of the other items in the choice set. Specifically, comparisons are performed along each attribute where favorable comparisons (those where the alternative has a better attribute value) result in positive evaluations and unfavorable comparisons result in negative evaluations. All of the evaluations for a particular alternative are combined into a single value (the drift rate) that specifics how quickly the accumulator for that alternative will race. For more details, please see Appendix B.

MLBA predicts that individuals will prefer the competitor to the target for all phantom decoy locations as illustrated in Figure 1. In the model, there are more favorable comparisons between the competitor and phantom than the target and phantom because the competitor is superior to the phantom on one dimension. Essentially, the model is capturing the fact that the target and phantom are easy to compare (i.e., the options have similar attribute values) whereas the competitor and phantom are more difficult to compare (i.e., the options have dissimilar attribute values). This ultimately leads to a larger drift rate for the competitor as compared to the target. The shades in the figure show the *relative choice share of the target (RST)*, which is the number of times the target was selected divided by the number of times the target plus competitor was selected (Berkowitsch, Scheibehenne, & Rieskamp, 2014; Trueblood, 2015). RST values with light shades indicate values greater than .5 (i.e., preference for the target) and dark shades indicate values less than .5 (i.e., preference for the competitor) Simulation details are also provided in Appendix B. Similar to value shift models, MLBA predicts the competitor as the largest shape in all awareness of unavailability conditions except for the known condition.

Loss Aversion

Another proposed explanation for decoy effects, including the phantom decoy effect, is based on the relative-advantage model which works on the principle of loss-aversion (Tversky & Simonson, 1993). In multi-alternative, multi-attribute choice, loss aversion is characterized by the asymmetric weighting of positive and negative differences between the attributes of options. The relative-advantage model predicts that after setting the phantom as the reference point, participants are motivated to select the alternative (i.e. the target) that represents the least loss from it.

Perceptual choice tasks provide an opportunity to test the loss aversion hypothesis. In our task, participants are shown sets of three rectangles and are told to choose the largest one (see Figure 2 for an example). Loss aversion would imply that people weight a “loss” in height (width) between two rectangles more than an equivalent “gain” in width (height) between the same two rectangles. We argue that such an asymmetrical weighting does not make sense in our task. Thus, it is difficult to imagine a loss-aversion based process operating in a simple size judgment task, as participants have no potential loss other than the possibility of being wrong. Note that loss aversion is different from error aversion where people experience greater neural feedback from errors than correct responses. If phantom decoy effects were truly due to loss aversion, then one would expect to find no context effects in perceptual choice where loss aversion does not operate. More specifically, the relative-advantage model, which is based on loss-aversion, predicts no context effects if the loss aversion parameter is equal to one (i.e., no loss aversion).

Comparison-induced distortion theory

Another model that may account for AD, COM, and Phantom decoy effects, but has not been tested with all three, is Choplin and Hummel’s Comparison-Induced distortion Theory

(2002). They argue that the type of comparison that is made between alternatives depends upon the goal of the decision maker. If they are trying to find the best option, as is the case with the AD and COM decoys, participants will make comparisons that emphasize differences between the options, leading to distortions in perception that favor the target. In the case of the phantom, however, the decoy is the best option, which changes the goal of the task from finding differences with the decoy to finding similarity to the decoy. Searching for the option that is most similar to the decoy would lead to the choice of the target.

Experiment Overview

In our experiments we test the qualitative predictions of the four models described above. Both value-shift models and dynamic preference accumulation models predict that the phantom decoy will increase preference for the competitor over the target. The relative-advantage model (when the loss aversion parameter is greater than one) and comparison-induced distortion theory predict the opposite pattern – increased preference for the target over the competitor, In our task, we present participants with a series of choice sets containing three rectangles of varying sizes. Participants are asked to choose the shape that they feel is the largest (see Figure 2 for an example). The rectangles vary based on their height and width, with these dimensions serving the role of attributes in consumer choice. The target and competitor rectangles have the exact same area, but differ in their lengths along the two dimensions (i.e., they have different orientations). The phantom decoy (left rectangle in Figure 2) has a larger area than both the target and competitor rectangles and the same orientation as the target. Across all experiments, we tested the five phantom decoy locations as shown in Figure 1: range, extended range, frequency, near range-frequency, and far range-frequency. In Experiment 1, we tested them when informing participants of the unavailability of the phantom after a short delay (known with delay). In

Experiment 2, we only told participants of the unavailability of the decoy after they made their initial choice (unknown). Finally, in Experiment 3, we told participants of the unavailability of the decoy from stimulus onset (known without delay).

Experiment 1: Known with delay

In the first experiment, the phantom is known prior to choice; however, there is a delay between the initial presentation of the alternatives and announcement of the unavailable phantom. On each trial, participants view three rectangles and are instructed to choose the one with the largest area. Phantom options are clearly larger than the remaining two rectangles.

Method

84 undergraduate students from the University of California, Irvine participated for course credit. 31 participants completed the computer-based experiment in the laboratory. The remaining 53 participants completed the experiment online at a time of their choosing. Participants read the following cover story and instructions: “In this task you will imagine that you are a farmer who leases plots of land for growing crops. The plots of land will be shown to you as black rectangles. Your job is to choose the plot of land (i.e., rectangle) that you think as the largest area in order to maximize your growing space. At the beginning of each trial, you will be shown tree possible plots of land. Then, you will be asked to select the one you prefer.” Participants were also told that on some trials one of the rectangles might be labeled as unavailable. In this situation, they were instructed to choose between the two remaining rectangles. In previous experiments using similar rectangle stimuli, no differences were found between experiments using the farmland cover story and those without a cover story (Trueblood, 2015). Further, researchers have shown that incorporating gamelike features into standard experimental tasks, while leaving the basic task unchanged, does not alter behavior (Hawkins,

Rae, Nesbitt, Brown, 2013). Thus, we believe the cover story had little to no influence on our results.

The rectangle stimuli were similar to those used in Trueblood et al. (2013) and Trueblood (2015), which demonstrated context and reference-dependent effects in perception. The height and width of the rectangles acted as attribute dimensions analogous to miles per gallon and ride quality in our example about choosing cars. Previous experimental work has shown that height and width are perceived separately and then integrated to form area estimates (Anderson & Weiss, 1971). However, even if rectangles are perceived as unidimesional (e.g., in terms of aspect ratio), this does not change the implications of our results. Previous work has demonstrated multi-alternative context effects such as the AD effect with unidimensional stimuli (Choplin & Hummel, 2005).

At the beginning of each trial, three rectangles appeared horizontally on the screen with the instructions, “Here are the possible plots”. The rectangles were solid black and the background screen was white. The target and competitor rectangles had the same area, only differing in orientation. The phantom rectangle had a larger area than both the target and competitor and the same orientation as the target. For example, in Figure 2, the phantom rectangle is the leftmost one, the target is in the middle, and the competitor is the rightmost one. After, 2 seconds the instructions changed and informed participants to “Select the plot you prefer” and labels appeared below the rectangles. In previous experiments using similar rectangle stimuli (Trueblood et al., 2013; Trueblood, 2015; Trueblood, Brown, & Heathcote, in press), average response times ranged from about 1200 to 3000 ms. We set the delay to 2 seconds because this was roughly the median of response times in the previous studies. We wanted to make sure that participants had enough time to process all three rectangles before announcing the phantom as unavailable. The rectangles were numbered from left to right with phantom options labeled as “unavailable” in red font. The location of different rectangles (i.e., target, competitor, and phantom) was randomized across the trials.

INSERT FIGURE 2 HERE

Participants completed five blocks of 78 trials for a total of 390 trials. Phantom decoys were located in one of five positions – range, range extreme, frequency, near range-frequency, and far range-frequency (see Figure 1). We call the three decoys located closest to the target “near decoys” (P_R, P_F, and P_{nRF} in Figure 1) and the remaining two decoys “far decoys” (P_{ER} and P_{fRF} in Figure 1). Near decoys were between 10-15% larger than the target and far decoys were between 20-25% larger than the target. Each block contained eight trials for each decoy location for a total of 40 trials. The trials for each decoy location were also divided so that each alternative served as the target for half of the trials (i.e., four trials per block). Counterbalancing the stimuli in this way avoids confounding the effects with biased guessing strategies. The remaining 38 trials in each block were filler trials, which took one of two different formats. There were phantom filler trials where one option was labeled unavailable and standard filler trials where all three options were available at choice. The standard filler trials contained one rectangle that clearly had a larger area than the rest, providing the participants with an objectively correct option. These trials helped participants stay engaged with the task. The standard filler trials also help prevent the adoption of a single strategy across all choice sets, as participants cannot always assume that the largest option is unavailable. All trials were randomized. Details about the stimuli are provided in Appendix A.

Results

We first examined the accuracy on the standard filler trials. Participants selected the dominant option 80% of the time, which was significantly greater than the guessing rate of 33% ($t(83) = 26.50$, $p < 0.001$). Because participants preferred the dominant option on the filler trials, we have good reason to believe that they also preferred the phantom on test trials. Next, we evaluated the influence of the phantom decoys using the RST value. If the RST is greater than .5, then the target is selected more often than the competitor. If the RST value is less than .5, then the competitor is preferred to the target. RST values equal to .5 imply the target and competitor are selected equally often showing an absence of any influence of the phantom decoy. The difference between RST values for lab and online versions of the experiment was not significant, $t(82) = -0.034$, $p = .973$, so the data were combined for all analyses. Following recent methods for analyzing context effects (Berkowitsch, Scheibehenne, & Rieskamp, 2014; Trueblood, 2015; Trueblood, Brown, & Heathcote, in press), we used a hierarchical Bayesian model to test whether the RST values were greater or less than 0.5. Our approach is illustrated as a graphical model in Figure 3 (Lee & Wagenmakers, 2014). For each decoy location, it was assumed that the number of times the target was chosen followed a binomial distribution with parameters θ and n where θ is the probability the target was selected and n is the total number of times the target plus the competitor was chosen ($T_{ij} + C_{ij}$ in Figure 3). In a hierarchical model, individuals have their own set of parameters sampled from distributions defined by hyperparameters, which capture group-level phenomena. When defining the person-specific parameters, a different θ parameter was assumed for each decoy location so that each individual had five θ parameters. These individual parameters were assumed to follow beta distributions with hyperparameters ϕ_j and κ_j ($j = 1…5$) defining the mean and concentration respectively. These parameters capture the group-level effect for each of the five types of decoy. We also assume that the five means ϕ_j

follow a beta distribution with parameters μ_ϕ and κ_ϕ, which capture the group-level effect across all five decoys combined.[1] Three MCMC chains were used to estimate the posterior distributions for the parameters (both person-specific and hierarchal) using JAGS.[2]

INSERT FIGURE 3 HERE

The 95% highest posterior density intervals (HDIs) for the hyperparameters ϕ_j and μ_ϕ represent the most credible posterior RST values from the Bayesian analysis for individual decoys and combined decoys, respectively (Kruschke, 2010). If this region lies above .5, then one can infer that the target was preferred to the competitor. Likewise, if this region lies below .5, then the competitor was preferred to the target. The hyperparameter μ_ϕ was less than .5 (95% HDI .453-.499) showing that there was a group-level preference for the competitor over the target when all five decoys were combined. Frequentist statistics provided the same conclusion ($F(1,83) = 25.10$, $p < .001$, $\eta^2 = 0.232$). Figure 4 (left comparison) shows the mean choice proportions for the target and competitor options averaged over the five different decoy locations. Examination of the hyperparameters ϕ_j showed that for four out of five decoys (all but the far range-frequency decoy), the competitor was preferred to the target. The HDI values for these parameters along with frequentist analyses are provided in the first column of Table 1.

INSERT FIGURE 4 HERE

INSERT TABLE 1 HERE

Conclusions

[1] The prior for μ_ϕ was a beta distribution with both shape parameters equal to 2. This prior is considered vague and provides low certainty about the value of μ_ϕ. It also slightly favors the null hypothesis that the RST across all decoys is equal to 0.5. The priors for κ_j and κ_ϕ were gamma distributions with shape and rate parameters equal to 0.001. This is also a vague prior and is commonly used on precision parameters because it is invariant to changes in measurement scale (Lee & Wagenmakers, 2014).

[2] Chain convergence was assessed by using the $\hat{R}$ statistic, which is similar to the F statistic. Specifically, if $\hat{R}$ is large, then the between-chain variance is larger than the within-chain variance. A $\hat{R}$ value close to 1 is ideal and values lower than 1.1 are considered satisfactory. All parameters had $\hat{R}$ less than 1.1.

The results of Experiment 1 show that the competitor option is selected more often than the target in perception with the majority of phantom decoy locations. This result is contrary to findings in value-based decision such as consumer choice where the target is often enhanced by the phantom decoy. Our results most closely match the predictions of value-shift models and dynamic preference accumulation models. However, neither model predicted the lack of an effect for the far range-frequency phantom. The relative-advantage model, which is based on loss aversion (Tversky & Simonson, 1993), and comparison-induced distortion theory cannot account for any of these findings.

Experiment 2: Unknown

In Experiment 1, the phantom decoy was announced as unavailable before participants made a decision. In the consumer choice literature, this procedure has typically elicited preference for the target option over the competitor. However, we find the opposite pattern in perception when participants are encouraged to actively process the decoy option through the inclusion of a delay period. Recently, Scarpi and Pizzi (2013) found competitor options are also preferred in consumer choice when the unavailability of the decoy option is unknown to individuals before choice. In this situation, phantom products are not signaled as unavailable until an individual tries to purchase them. Experiment 2 examines whether competitor options are also preferred in perception when phantom decoys are unknown.

Method

90 undergraduate students from the University of California, Irvine participated for course credit. 31 participants completed the computer-based experiment in the laboratory. The remaining 59 participants completed the experiment online at a time of their choosing. The stimuli and procedures were very similar to Experiment 1 except the delay period was removed

and the phantom decoy was only revealed as unavailable if selected. All three rectangles were numbered from left to right at the beginning of the trial. If participants selected the phantom decoy option, then the following message appeared below the rectangles in red front: “The plot you selected is unavailable. Please choose another one.” Participants were then forced to select between the remaining two rectangles.

Results

As before, we first examined the accuracy on the standard filler trials. Participants selected the dominant option 66% of the time, which was significantly greater than chance ($t(89) = 15.90$, $p < 0.001$). Next, we examined the RST values using hierarchical Bayesian methods. Note that the difference between RST values for lab and online versions was not significant, $t(88) = -1.666$, $p = .099$, so the data were combined for all analyses. Also, the Bayesian model and fitting procedures were identical to those used for the previous experiment.

To examine the influence of the phantom decoy, we calculated the 95% HDIs for the hyperparameters ϕ_j and μ_ϕ. The hyperparameter μ_ϕ was less than .5 (95% HDI .451-.495) showing that there was a group-level preference for the competitor over the target when all five decoys were combined. Frequentist statistics provided the same conclusion ($F(1, 89) = 20.28$, $p < .001$, $\eta^2 = 0.186$). Figure 4 (middle comparison) shows the mean choice proportions for the target and competitor options averaged over the five different decoy locations. Examination of the hyperparameters ϕ_j showed that for all five decoys, the competitor was preferred to the target. The HDIs for these parameters along with frequentist analyses are provided in the second column of Table 1.

Conclusions

The results of Experiment 2 show that the competitor option is selected more often than the target when the phantom decoy is unknown. This finding is in agreement with the results of Experiment 1 and results in consumer choice (Scarpi & Pizzi, 2013). In general, competitor options are favored over target options in perception regardless of whether the phantom is known (with a delay) or unknown to individuals. Further, all decoy locations increased preference for the competitor. Similar to experiment 1, our results most closely match the predictions of both dynamic preference accumulation and value-shift models.

Experiment 3: Known without Delay

In Experiment 1, the phantom decoy was announced as unavailable after a 2 second delay. In the third experiment, we examined the necessity of this delay period by announcing the decoy as unavailable at the beginning of the trial. In this way, the decoy is irrelevant to the task. However, in many perceptual tasks, irrelevant information can have a substantial influence on behavior. For example, in the Eriksen Flanker Task (Eriksen & Eriksen, 1974), participants make decisions about targets, which are flanked by either congruent or incongruent noise stimuli. Results show that participants cannot prevent processing the irrelevant information. In our task, unintentional processing of the decoy option could influence behavior similarly to Experiment 1. Alternatively, the decoy might only be effective if it is actively compared to the other options during the trial. Recently, Noguchi and Stewart (2014) used eye tracking to show that visual attention plays an important role in decoy effects in consumer choice. If active comparisons between the decoy and other options are necessary for the effect, then we anticipate that the decoy will have little to no effect when announced as unavailable at the beginning of the trial.

Method

77 undergraduate students from the University of California, Irvine participated for course credit. 36 participants completed the computer-based experiment in the laboratory. The remaining 41 participants completed the experiment online at a time of their choosing. The stimuli and procedures were identical to Experiment 1 except the delay period was removed. The three rectangles were labeled at the start of the trial with the phantom decoy labeled as "unavailable" in red font.

Results

As before, we first examined the accuracy on the standard filler trials. Participants selected the dominant option 73% of the time, which was significantly greater than chance ($t(76) = 16.86$, $p < 0.001$). Next, we examined the RST values using hierarchical Bayesian methods. Note that the difference between RST values for lab and online versions was not significant, $t(75) = -0.160$, $p = .874$, so the data were combined for all analyses. Also, the Bayesian model and fitting procedures were identical to those used for the previous two experiments.

To examine the influence of the phantom decoy, we calculated the 95% HDIs for the hyperparameters ϕ_j and μ_ϕ. The hyperparameter μ_ϕ, which captures group level effects across different decoys, included the value .5 (95% HDI .480-.521) indicating that the target and competitor were selected roughly the same number of times. Frequentist statistics provided the same conclusion ($F(1, 76) = 0.005$, $p = .946$, $\eta^2 = 0.0$). Figure 4 (right comparison) shows the mean choice proportions for the target and competitor options averaged over the five different decoy locations. Examination of the hyperparameters ϕ_j showed that the target and competitor were equally preferred for all decoy locations. The HDIs for these parameters along with frequentist analyses are provided in the third column of Table 1.

Conclusions

The results of Experiment 3 show that the target and competitor are preferred equally when the decoy is announced as unavailable at the beginning of the trial. This suggests that actively directing attention towards the decoy option is necessary for producing the effect even in perceptual tasks. In Experiment 1, participants do not learn the decoy is unavailable until after a short delay. Because of the delay, participants actively consider the decoy at the beginning of the trial. The active comparison of the decoy with the remaining alternatives shifts preference toward the competitor and away from the target. The results of this experiment also follow predictions from value-shift and dynamic preference accumulation models.

General Discussion

Recently, several researchers have suggested that similar cognitive mechanisms might underlie perceptual and value-based decisions (Busemeyer, Jessup, Johnson, & Townsend, 2006; Shadlen, Kiani, Hanks, & Churchland, 2008; Summerfield & Tsetsos, 2012; Symmonds & Dolan, 2012). This hypothesis arises in part from similarities in modeling decision processes in these two domains using dynamic models such as the drift-diffusion model (Ratcliff, 1978), MDFT, LCA, and MLBA. Neuroscientists also use perceptual tasks to study the neurological basis of decision-making (Gold & Shadlen, 2007; Smith & Ratcliff, 2004). Because many researchers view perceptual decision-making as a window into general decision-making processes, it is crucial to thoroughly investigate the similarities and differences between perceptual and value-based domains. The current work illustrates one striking difference between perceptual and value-based decision-making. In value-based decision-making such as consumer products, phantom options often result in increased preference for similar, but slightly inferior alternatives. In contrast, our experiments show the opposite pattern of results in perception – phantom options increase preference for dissimilar, non-dominated alternatives. Note that Scarpi and Pizzi (2013) also showed that phantom options increase preference for competitor alternatives in consumer choice for both the range decoy (60.7% chose the competitor) and for the extended range decoy (72% chose the competitor) in the unknown presentation mode.

Previous experiments using perceptual (Choplin & Hummel, 2005; Trueblood et al., 2013; Trueblood, 2015) and psychophysical (Tsetsos, Chater, & Usher, 2012; Tsetsos, Usher, & McClelland, 2011) stimuli have revealed similarities in choice behavior between low-level and value-based decision tasks involving available decoys (e.g., AD and COM effects). These experiments suggest that decoy effects are not solely the result of value-based phenomena such as loss aversion (Tversky & Simonson, 1993). In perceptual tasks (e.g., decisions about the size of rectangles), there is no notion of gains and losses. Rather, these experiments support the hypothesis that decoy effects can also arise from fundamental processes.

In the present work, we illustrate a crucial difference between perceptual and value-based decisions. This naturally leads to the question of what causes this difference. One possibility is the influence of loss aversion in value-based decisions, which could reverse the direction of the effect found in perceptual choice. Recently, Yechiam and Hochman (2013) found that losses can enhance on-task attention, which might result in increased sensitivity to decoy effects in consumer choice. In consumer choice tasks, loss aversion could override lower-order processes resulting in preference for target alternatives when phantom decoys are present.

While loss aversion could modulate decoy effects in consumer choice, an important question is determining the basic cognitive processes that produce these effects when losses are not present. Based on the results of our experiments, range-frequency based value-shift processes (Pettibone & Wedell, 2000) and dynamic preference accumulation models provide possible explanations. However, value-shift models have limited explanatory power to capture a wide range of context effects. They can only account for asymmetrically dominated decoy effects, but not compromise effects and similarity effects as can dynamic preference accumulation models. Accumulation models such as MLBA (Trueblood et al., 2014) can account for all three standard context effects including the influence of time pressure on these effects. MLBA has also been shown to provide good quantitative fits to choice data from several different tasks. It is one of many dynamic models of multi-alternative, multi-attribute choice. Alternative dynamic models include MDFT, LCA, the associative accumulation model (Bhatia, 2013), and the 2N-ary choice tree (Wollschläger & Diederich, 2012). All of these models have been very successful in accounting for available decoy effects. Based the experimental results reported here, we believe dynamic models also hold a lot of promise for the phantom decoy effect.

Lastly, across the multiple successive trials that participants experienced, it is possible that participants may have developed an ad hoc heuristic that led to the preference for the competitor that may not happen in consumer studies where fewer trials are required (usually between 1 and 10). We believe this interpretation is unlikely for several reasons. First, the presence of two types of filler trials where either the largest alternative was available or an alternative equal in size to the others was unavailable should help to reduce the development of a heuristic based approach as it would not be needed or useful in approximately half of the trials. Second, presenting the trials in a random order within blocks should also help prevent this as Ps would be unable to predict which trials the heuristic would be useful in. Third, if a heuristic had been used, one would have expected a significant increase in preference for the competitor in the "known without delay" condition as well. If a useful heuristic was developed, there would be little reason not to use it in this condition simply because Ps did not need to wait to discover which rectangle was unavailable. Overall, while we cannot completely rule out an ad-hoc explanation for this data, we believe it is unlikely based upon our methods and pattern of results across experiments.

In sum, we have shown that perceptual decisions involving phantom options differ from those found in many value-based tasks. We have also argued that dynamic preference accumulation models have the potential to explain both perceptual phantom decoy effects as well as other context effects. Future work could examine these models in more detail and compare their predictions for phantom decoys.

Appendix A: Stimuli for Perceptual Experiments

Let X and Y denote the two rectangles in the choice set with equal area, but different orientations. Rectangle X was associated with a bivariate normal distribution with dimensions representing height and width in pixels. The distribution had mean (50, 80) and variance 2 on each dimension with no correlation. The height of option Y was determined from X by adding a random number from the interval [-2, 2] to the width of X. The width of option Y was selected so that X and Y had equal area.

Phantom range decoys were calculated by first randomly selecting an area, which was 10-15% larger than the target option. When X was the target, the decoy had the same height and the width was calculated using this value and the randomly selected area. When Y was the target, the decoy had the same width and the height was calculated using this value and the randomly selected area. Phantom extreme range decoys were calculated in similar manner. However, the area of the decoy was 20-25% larger than the target option.

Likewise, phantom frequency decoys were calculated by first randomly selecting an area, which was 10-15% larger than the target option. When X was the target, the decoy had the same width and the height was calculated using this value and the randomly selected area. When Y was the target, the decoy had the same height and the width was calculated using this value and the randomly selected area.

Phantom near range-frequency decoys were calculated by first randomly selecting an area, which was 10-15% larger than the target option. The height and width of the decoy were calculated so that the aspect ratio was the same as the target option. The same procedure was used for far range-frequency decoys. However, the area of the decoy was 20-25% larger than the target option.

Appendix B: Multiattribute Linear Ballistic Accumulator Model

The MLBA model (Trueblood et al., 2014) is an extension of the LBA (Brown & Heathcote, 2008), which explicitly specifies how drift rates arise from the evaluation of choice stimuli. On each trial, drift rates for each accumulator are drawn from normal distributions that have mean values, d_1, d_2, d_3,…, and a common standard deviation s. For an alternative i, MLBA defines the mean drift rate as $d_i = \sum_{i \neq j} V_{ij} + I_0$ where V_{ij} represents a comparison between options i and j, and I_0 is a baseline accumulation rate. The comparison V_{ij} is defined by a weighted difference in the subjective values of the options: $V_{ij} = w_{Pij}\left(u_{Pi} - u_{Pj}\right) + w_{Qij}\left(u_{Qi} - u_{Qj}\right)$ where P and Q denote the two attributes (such as height and width). The values w_{Pij} and w_{Qij} are similarity weights given by $w_{Pij} = \exp(-\lambda\, |\, u_{Pi} - u_{Pj}|)$ and likewise for w_{Qij}.

For the simulation illustrated in Figure 1, the target was defined by the attribute pair (4,6) and the competitor by the pair (6,4). The third option in the choice set was defined as a point in the attribute space with values ranging from 1 to 9 in increments of 0.1. The drift rate standard deviation was fixed to s = 1 and the baseline accumulation rate was fixed to $I_0 = 1$. Because similarity judgments are often asymmetrical (Tversky, 1977), MLBA allows for different values of λ depending on whether the difference in attribute values is positive (e.g., $u_{Pi} - u_{Pj} > 0$) or negative. For the simulation, positive differences used $\lambda_p = .2$ and negative differences used $\lambda_n = .4$. The decision threshold was fixed to χ = 2 and the start point parameter was fixed to A = 1. Note that the shading in Figure 1 is dependent on the specific parameter values. Other patterns of results are possible with different parameter sets.

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Table 1

Results for the three experiments. The 95% highest density intervals (HDIs) for the posterior relative choice share of the target (RST) from the hierarchical Bayesian analyses are provided. Intervals falling below 0.5 indicate preference for the competitor over the target. Frequentist statistics were also calculated for each comparison.

	Exp 1: Known with Delay (n = 84)		Exp 2: Unknown (n = 90)		Exp 3: Known without Delay (n = 77)	
All decoys	0.453-0.499	$t(83) = -4.989$, $p < 0.001$	0.451-0.495	$t(89) = -4.484$, $p < 0.001$	0.480-0.521	$t(76) = 0.026$, $p = 0.979$
Range	0.450-0.483	$t(83) = -4.155$, $p < 0.001$	0.459-0.494	$t(89) = -2.262$, $p = 0.026$	0.487-0.520	$t(76) = 0.658$, $p = 0.513$
Range extreme	0.447-0.480	$t(83) = -4.538$, $p < 0.001$	0.438-0.475	$t(89) = -4.873$, $p < 0.001$	0.485-0.518	$t(76) = 0.155$, $p = 0.878$
Frequency	0.466-0.499	$t(83) = -1.981$, $p = 0.051$	0.462-0.496	$t(89) = -1.902$, $p = 0.060$	0.489-0.522	$t(76) = 0.983$, $p = 0.329$
Near Range-frequency	0.465-0.498	$t(83) = -2.101$, $p = 0.039$	0.462-0.495	$t(89) = -2.140$, $p = 0.035$	0.474-0.507	$t(76) = -1.467$, $p = 0.147$
Far Range-frequency	0.469-0.506	$t(83) = -0.871$, $p = 0.387$	0.457-0.489	$t(89) = -3.022$, $p = 0.003$	0.484-0.517	$t(76) = -0.011$, $p = 0.991$

Figure Captions

Figure 1. Placements of the standard asymmetrically dominated range decoy (**AD_R**), compromise decoy (**COM**), phantom range decoy (**P_R**), phantom extreme range decoy (**P_{ER}**), phantom frequency decoy (**P_F**), phantom near range-frequency decoy (**P_{nRF}**), and phantom far range-frequency decoy (**P_{fRF}**). The range phantom (**P_R**) serves to increase the range of evaluation along the best dimension of the target while sharing its value on the worst dimension. The extended range phantom (**P_{ER}**) is similar to the range phantom but extends the range of evaluation on the target's best dimension further. The frequency phantom (**P_F**) is placed between the target and the competitor on the worst attribute of the target while sharing its best attribute. The range-frequency phantom, shown here in near to the target (**P_{nRF}**) and far from the target (**P_{fRF}**) versions, combines both the range and frequency manipulations. All decoys target alternative **T = (4,6)** over alternative **C = (6,4)**. The dotted lines represent the equi-preference/size contours given equal weighting of the dimensions. The shade at each point reflects the RST when the decoy at that location is included in the choice set as calculated using the MLBA model (see Appendix B). Darker shades indicate increased preference for the competitor over the target.

Figure 2. An example of a trial from Experiment 1. Participants first viewed the information shown in the panel on the left for 2 seconds. Then, the screen was updated to show the information presented in the right panel. Participants could make their decision anytime after the update in information.

Figure 3. Hierarchical Bayesian model used to test whether the RST values were larger or smaller than 0.5 for the phantom decoy effect. Circular nodes indicate continuous values, square nodes indicate discrete values, shaded nodes correspond to known values, and unshaded nodes

represent unknown values. The bounding rectangles are called plates and are used to enclose independent replications of a graphical structure. There are two plates in the figure representing replications for the five different types of decoys (outer plate) and replications for different individuals (inner plate). The nodes labeled ϕ_j and κ_j ($j = 1 \ldots 5$) are the hyperparameters for each decoy type. Each individual has five θ parameters, which are drawn from beta distributions determined by the hyperparameters. The ϕ_j parameters also follow a beta distribution with parameters μ_ϕ and κ_ϕ, which captures the group-level effect across all five decoys combined.

Figure 4. Mean choice proportions for the target and competitor options averaged over five decoy locations for three different experiments, which manipulate the time when the phantom decoy is announced as unavailable. The mean and the standard error of the mean are shown above each bar.

Figure 1.

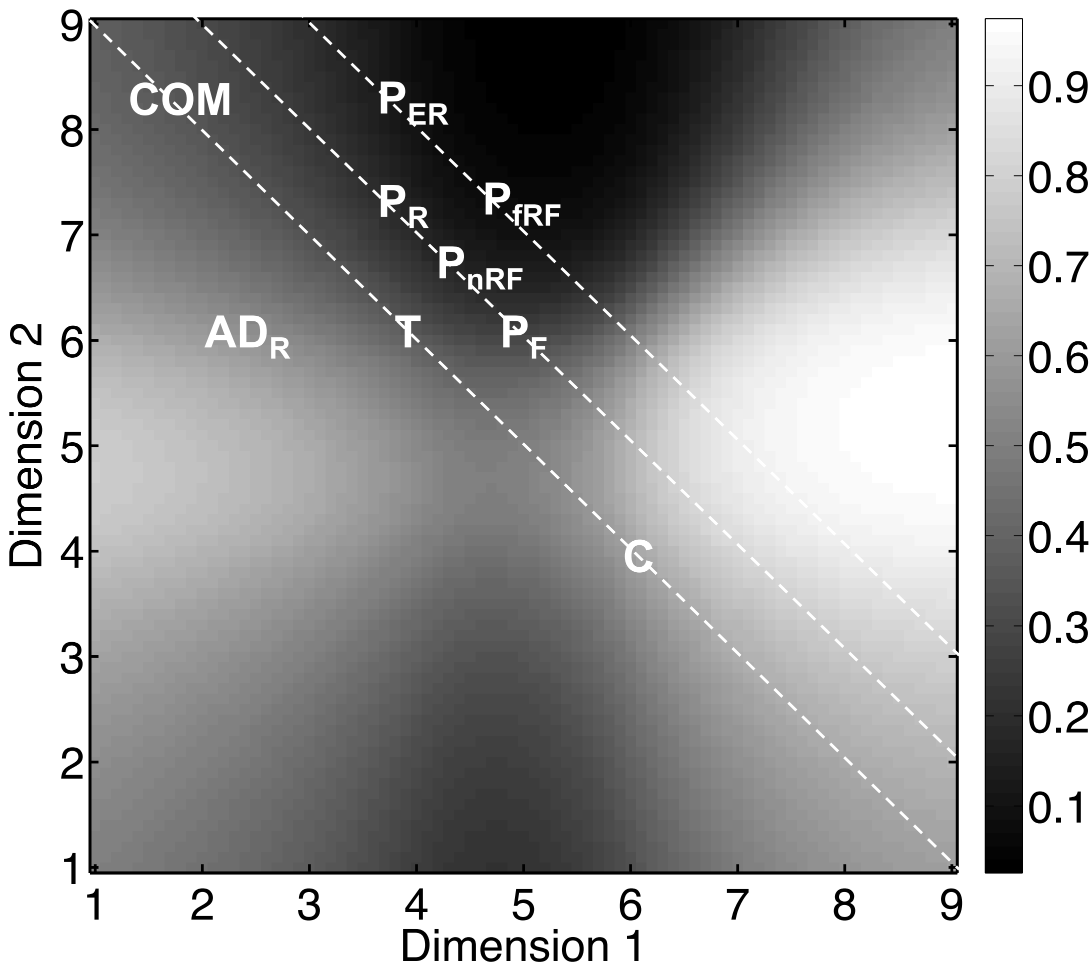

COM
P_ER
P_R
P_fRF
P_nRF
AD_R
T
P_F
C
Dimension 2
Dimension 1
1 2 3 4 5 6 7 8 9
0.1 0.2 0.3 0.4 0.5 0.6 0.7 0.8 0.9

Figure 2.

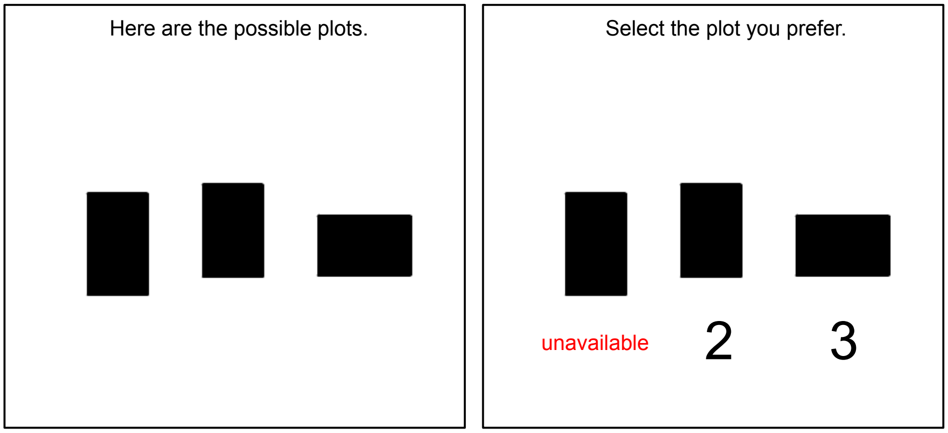
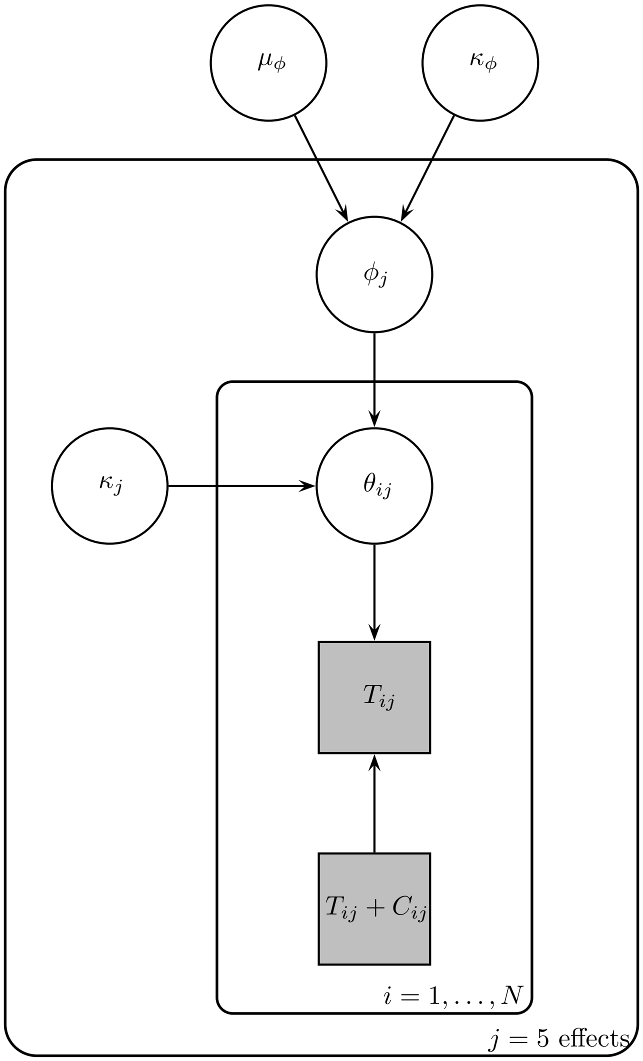

Here are the possible plots.
Select the plot you prefer.
unavailable
2
3

Figure 3.



$$\mu_\phi \sim \mathrm{Beta}(2, 2)$$

$$\kappa_\phi \sim \mathrm{Gamma}(0.001, 0.001)$$

$$\alpha_\phi = \mu_\phi \kappa_\phi$$

$$\beta_\phi = (1 - \mu_\phi)\kappa_\phi$$

$$\phi_j \sim \mathrm{Beta}(\alpha_\phi, \beta_\phi)$$

$$\kappa_j \sim \mathrm{Gamma}(0.001, 0.001)$$

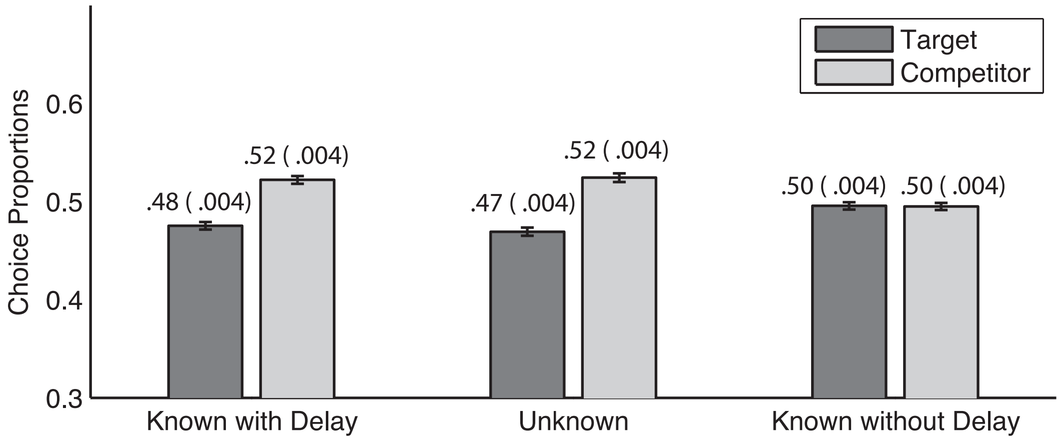
$$\alpha_j = \phi_j \kappa_j$$

$$\beta_j = (1 - \phi_j)\kappa_j$$

$$\theta_{ij} \sim \mathrm{Beta}(\alpha_j, \beta_j)$$

$$T_{ij} \sim \mathrm{Binomial}(\theta_{ij}, T_{ij} + C_{ij})$$

Figure 4.


Target
Competitor
Choice Proportions
0.6
0.5
0.4
0.3
.48 (.004)
.52 (.004)
.47 (.004)
.52 (.004)
.50 (.004)
.50 (.004)
Known with Delay
Unknown
Known without Delay