Persistence in Consumer Search

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ABSTRACT

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In this dissertation, I explore determinants, and some consequences, of persistence in consumer search. Many prominent thinkers have considered the problem of search in terms of optimal solutions (e.g., Stigler 1961) or their heuristic approximations (e.g., Simon 1955). In the following research, I explore persistence in search not merely as a function of economic calibration, but rather as an outcome determined by both cognitive and motivational processes. I provide evidence that normative models of search are insufficient to explain the behavior of those whom I study. Instead, I show cases in which search persistence is a function of prior behavior (Chapter 1) and prior beliefs (Chapter 2). I further propose a cognitive model of price search behavior (Chapter 3) that can predict many of the observed behaviors that would be considered mistakes in normative price search frameworks (e.g., variance neglect, reference point effects, local contrast effects).

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The tendency to explain behavior in terms of an actor's motivations and beliefs, as opposed to constraints and advantages provided by a situation, has been called the Fundamental Attribution Error (Ross 1971). The pervasive power of the situation has prompted people to assume the role of brutal prison guards (Zimbardo 2007), to administer electric shocks to a man with a heart condition (Milgram 1963), and to endorse one line — clearly shorter than the others — as being the longest in a group (Asch 1951). While most demonstrations of the Fundamental Attribution Error lead to people behaving in silly or even malicious ways, it is important to also acknowledge that a situation can facilitate good behavior. Any success I have had as a Ph.D. student is a testament to this fact. I have been surrounded by brilliant, caring people and given every opportunity for success. As such, anything insightful in this dissertation should be viewed in light of the Fundamental Attribution Error — this document would not exist without constant help and support from my advisors, teachers, peers, friends, and family.

Particular thanks go to my partner Katherine Reinholtz; my advisors Jonathan Levav and Oded Netzer; Dan Bartels; Don "Coach" Lehmann; Eva Ascarza; my parents Charles Reinholtz and Jeri Reinholtz; Jeff Parker; Malia Mason; Yael Zemack-Rugar; Leonard Lee; Michel Pham; Eric Johnson; John Boyer; Dell Rhodes; Katheryn Oleson; Todd Gureckis; Dana Carney; Dan Spacher; Claire Lin; Dan Ariely; John Lynch; Chung Ho; Laura Bartels; and Vee Onativia.

DEDICATION

For Avery.

INTRODUCTION

Consumers are searchers. We look for new and interesting products. We hunt for the best prices on products we want to buy. We explore new retailers, restaurants, and services. We consume information that will help us make better purchase decisions. All of these behaviors can be classified, to some extent, as consumer search. In this dissertation, I examine persistence in consumer search. More concretely, I look for factors that cause consumers to search more or less.

Previous research — particularly that done by economists — has looked extensively at how consumers should search (e.g., Stigler 1961) or, alternatively, for theoretical explanations of empirical phenomena related to search (e.g., Baye, Morgan, and Scholten 2004). More recently, researchers have begun to examine psychological factors that influence consumer search behavior (e.g., Brucks 1985). I attempt to extend the current understanding of consumer search by focusing specifically on the consumer's decision (often implicit) to continue or terminate search.

In chapter 1, I look at situations in which a consumer has to search for many things sequentially. I find that consumers adapt their search strategy based on the difficulty of the first decision, but tend to insufficiently update this strategy to account for the difficulty of subsequent decisions. This strategy "stickiness" leads to differences in aggregate search based on decision order: When decisions are ordered from easiest to most difficult consumers search more (in total) than when decisions are ordered from most difficult to easiest. I further examine the boundary conditions of this effect and find that simple interventions — making neighboring decisions more distinct or providing short breaks between decisions — can attenuate search strategy carryover and mitigate the differences in search persistence caused by task order.

In chapter 2, I look at persistence in consumer price search — situations in which a consumer is looking for an acceptable price for an item (or service) she wants to purchase. I compare the normative prescriptions from economic models of price search to actual consumer behavior and find several inconsistencies. Most importantly, I find that consumers tend to search *less* when price dispersion is greater whereas profit-maximizing models of consumer price search suggest they should instead search *more* when price dispersion is greater. I also find that the average cost of a product influences persistence in consumer search: Consumers persist longer at search for higher priced products whereas economic models suggest the average price should be an inconsequential factor. I propose that both of these effects are caused consumer inferences about price dispersion: For a given price (or average price) consumers form an expectation about the degree of price dispersion and insufficiently update this belief during their search.

In chapter 3, I describe a process model of consumer price search. The model is intended to be cognitively plausible. In other words, it supposes processes and representations that fall within the computational and mnemonic capacities of a typical human decision maker. At the core of the model is the notion that expected price dispersion is represented by a finite sample of possible prices (as opposed to a continuous probability distribution). Importantly, the proposed model can account for many observed behaviors in price search that are inconsistent with normative search theory (e.g. variance neglect, reference price effects, and local contrast effects).

In aggregate, the three chapters that follow offer new insights regarding the determinants of persistence in consumer search. In concert, they promote the view of a boundedly rational consumer who exploits her prior knowledge to make frugal approximations of normative behavior. Instead of basing persistence decisions on real-time cost-benefit calculations, a consumer is guided by her prior behavior in similar situations (Chapter 1) and her prior experience in the commercial marketplace (Chapter 2). These heuristics typically serve the consumer well, but — in certain situations — can lead to over- or under-persistence relative to her underlying preferences.

CHAPTER ONE:

Task Order Influences Persistence in Consumer Search

Consumers frequently engage in sequential decisions. For instance, grocery store shoppers fill their shopping baskets one item at a time, restaurant diners order their meal one course at a time, and computer buyers configure their laptops one component at a time. Each decision in the sequence might require choosing from a different number of options. Imagine that a homeowner who renovates her apartment engages in a sequence of decision steps: She might have to choose between 50 different tiles, 20 different wall paint colors, and five different wallpaper designs. In this chapter I explore how the order of the decisions — their sequential nature — influences the extent to which consumers persist at search for each individual decision.

Order is important in many contexts, from impression formation (Asch 1946) to judgments of hedonic experiences (Ariely and Zauberman 2000). However, previous research about order in consumer search has limited its focus to the effect of ordering options within a specific choice set (e.g., Dellaert and Häubl 2012; Dellaert and Stremersch 2005; Diehl 2005; Diehl, Kornish, and Lynch 2003; Häubl, Dellaert, and Donkers 2010). The relationship between decision order and consumer search has, to this point, remained unexplored (note: parts of this investigation overlap with Levav, Reinholtz, and Lin 2012).

Although there are many variables by which decisions can be ordered, the current investigation focuses on ordering decisions by their difficulty. In Studies 1.1 and 1.2, I operationalize decision difficulty as choice-set size. Besides being a variable of high managerial relevance, previous research has suggested that choice-set size can exert a substantial influence on consumers' psychology and consequently on their decisions. For example, large choice sets may demotivate purchases (Iyengar and Lepper 2000) or lead to decision simplification (Iyengar and Kamenica 2010). When people are given a large choice set, they may be less likely to make a purchase than when they are given a small choice set. Further, choice-set size may affect decision confidence and preference strength (Chernev 2003). Finally, varying a configuration sequence by choice-set size can change people's ultimate product choice, even in high-stakes decisions such as automobile purchases (Levav et al. 2010). In Study 1.3, I take a different approach and use an information search task in which difficulty is operationalized as the effort required to make a decision with certainty.

It is well known that consumers are adaptive decision makers whose decision strategies are contingent on features of the decision environment (Payne 1976; Payne, Bettman, and Johnson 1993; Simonson and Tversky 1992). In particular, people's cognitive limitations lead them to seek ways to simplify otherwise difficult decisions. For instance, cognitive constraints can drive people to simplify difficult decisions by adopting a satisficing strategy (identifying an acceptable item in a choice set), rather than a maximizing strategy (identifying the best option in a choice set; Simon 1955; 1956), as a way to limit their decision effort and thus conserve their cognitive resources (Payne, Bettman, and Johnson 1988).

Most of the prior experimental evidence regarding decision difficulty and adaptive decision-making has been limited to one-shot decisions. However, in many purchase situations (e.g., configuration decisions) consumers make a sequence of multiple decisions, rather than a single decision on its own. Suppose our homeowner from the example above begins the sequential process of renovation decisions by choosing from a small set of five wallpaper designs (a fairly easy decision). Previous research suggests that she would search a high proportion of the alternatives (Diehl 2005; Meyer 1997), presumably with a greater desire to maximize her choice outcome. What happens when she moves to a more difficult subsequent decision in which she must choose from a larger set of options (e.g., 20 wall paint colors)? Will she adapt to the more difficult environment by altering her search strategies, perhaps by adopting a satisficing heuristic?

Research on problem solving suggests that our homeowner might adapt her initial strategy based on the requirements of the first decision problem, but persist in using the same strategy in subsequent decisions regardless of its suitability. Classic demonstrations of *Einstellung* in problem solving indicate that once people learn a rule for successfully solving an initial series of problems, they frequently continue to apply this rule to later problems as well, even when easier rules are obvious. In Abraham Luchins's (1942) water-jug experiment, participants were asked to measure out a given amount of water using a combination of three jugs of various capacities. The practice trials consisted of problems that required a relatively complicated solution. In the target problem, even though there was a simpler solution that was easily detectable by control participants who had not engaged in practice trials, participants in the treatment group persisted in using the complicated solution.

Similarly, in the consumer domain, studies show that context-driven decision rules can persist even after the initial context is removed (Amir and Levav 2008; Häubl and Murray 2003). Broder and Schiffer's (2006) studies on sequential stock-market decisions show that once people adopt a decision strategy, they tend to persist with that strategy even when the decision environment changes and the strategy yields economically suboptimal outcomes. The tendency to retain response patterns, even when they cease to be beneficial, has been termed "behavioral stereotypy" (Schwartz 1982). In sum, prior research suggests that the initial search strategy used by a consumer may be "sticky," persisting in later decisions.

Boiling a Frog

> "If a frog jumps into a pot of boiling water, it jumps right out again, because it senses the danger. But the very same frog, if it jumps into a pot of lukewarm water that is slowly brought to a boil, will just sit there and it won't move. It will just sit there even as the temperature continues to go up and up." -Al Gore, *An Inconvenient Truth* (2006)

In this chapter, I argue that decision makers are much like the frog in the adage mentioned above. The frog forms an accurate initial impression of the water — either temperate or too hot — and adopts a reasonable strategy accordingly. If the water is boiling, the frog adopts a "get out" strategy. If the water is pleasantly warm, the frog adopts a "hang out" strategy. Both strategies are sensible — the boiling water should be avoided and the warm water should be enjoyed. The problem arises when the temperature of the lukewarm water is increased slowly: The frog's "hang out" strategy persists to the point where it is detrimental and the frog, unfortunately, becomes cooked. (It is worth noting that this adage is likely false, although a surprising number of living frogs have been boiled in the name of science; cf. Sedgwick 1888.)

Similarly, I argue, decision makers faced with a single choice are quite adaptive in choosing a reasonable strategy for behavior. If a decision is comparatively easy, such as choice between only a few products, a consumer will likely explore each option in some detail (i.e., a maximizing strategy). The problem again arises when the initial decision is succeeded by other decisions that are similar in some ways, but feature critical differences. The strategy adopted in the first decision might persist to these subsequent decisions, but might no longer be appropriate (or at least consistent with the decision maker's goals). For example, when the easy decision described above is followed by a more difficult decision — a choice between 30 products, for example — the previously cited research suggests that the initial strategy of diligent search might persist. Whereas a decision maker who encounters this more difficult problem without the sequential context would be more likely to adopt a less diligent strategy (i.e., a satisficing strategy), which she would find more appropriate for the task.

Critical to the frog-in-boiling-water metaphor is the notion of gradual change. When the water temperature is raised quickly, the frog is likely to notice the increase and escape the soon-to-be-boiling water. Similarly — I argue — a human decision maker confronted with a significant change in the decision environment is more likely to reevaluate her decision strategy. This possibility is supported by research on learning, person perception, and confirmatory processing, which demonstrates that people tend not to update their beliefs unless they encounter a salient failure of their initial hypothesis (Hastie and Kumar 1979; Hoch 1984; Hoch and Ha 1986; Srull, Lichtenstein, and Rothbart 1985). I examine this notion in the context of sequential decisions. I predict that more salient changes in task difficulty will increase the likelihood that consumers update their previously adopted decision strategies.

Overview of Empirical Evidence

In this chapter, I explore the notion of gradual change in the context of sequential decisions. In Study 1.1, I show that gradual changes can indeed lead to strategy persistence. When a decision maker starts with an easy decision, she is more likely to adopt a maximizing strategy in which she searches diligently through the available options. When the first easy decision is followed by similar, but more difficult decisions, she continues to apply this strategy of searching diligently. In contrast, when a decision maker starts with a more difficult decision, she is likely to adopt a satisficing strategy in which she searches less comprehensively. When the first difficult decision is followed by similar, but easier decisions, she continues to apply this satisficing strategy.

The remainder of the chapter is dedicated to examining boundary conditions for this frog-in-boiling-water effect. In a "bonus" task in Study 1.1, I show that the influence of a previously adopted strategy can indeed persist (to a degree) in a procedurally unrelated decision problem. In Study 1.2, I examine the gradient of change in the decision environment and show that bigger differences in the characteristics of the sequential decisions lead to less strategy persistence. Relating this to the frog metaphor: When the temperature of the water increases too quickly, the frog is more likely to notice the difference and adopt its decision strategy accordingly (i.e., it will jump out of the soon-to-be boiling water). Finally, in Study 1.3, I examine whether brief interruptions — a chance for participants to disengage from the decision sequence and perhaps think about the changing environment — attenuate strategy persistence. I find that interrupted participants are indeed more likely to switch strategies than those who move from decision-to-decision uninterrupted.

Study 1.1: Ordering Decisions by Choice Set Size Influences Search Persistence

In this study, I examine the basic frog-in-boiling-water effect. I manipulate a sequence of decisions between participants so they are ordered either easiest-to-hardest or hardest-to-easiest. When the easiest decision comes first, I predict that participants will adopt a diligent/maximizing decision strategy and search through the available products extensively. Conversely, when the hardest decision comes first, I predict that participants will adopt a less-diligent/satisficing decision strategy and search through the available products more limitedly. Importantly, because the sequential decisions are similar, I predict that the initial strategy a consumer adopts will persist to later decisions. I test for this by looking at aggregate differences in search behavior across the entire sequence of decisions. If participants in the easiest-to-hardest condition indeed adopt a more thorough decision strategy that persists to later decisions, these participants should search more in aggregate across all of the decisions (compared to participants in the hardest-to-easiest condition).

Further, I test for the possibility that the adopted decision strategy could carryover to a procedurally different search task. To do this, I include a "bonus" task after the initial sequence manipulation that is the same for all participants. While this task also involves search, it is a different manner of search than in the previous tasks. If decision strategies are sufficiently sticky, I expect to observe an effect of the sequence manipulation (and thus, presumably, of the persistent decision strategy) on search behavior in the bonus task as well.

Method

Eighty-nine participants, recruited from Amazon Mechanical Turk (AMT), completed this study. Participants were paid a fixed sum ($0.40) plus the possibility of earning up to $1.00 extra depending on their performance in a bonus task.

The study was described to participants as a "Cartoon Caption Study." Participants were told they would see three cartoons (each cartoon represented a separate task) and were instructed to select a caption for each cartoon from the available choice set of captions. Each caption was numbered sequentially and the choice-set size was prominently displayed on the button interface (a graphic depiction of the task is shown in Figure 1.1). Participants could advance through the choice set of possible captions, one at a time, using "Next" and "Previous" buttons. When participants decided on a caption for the cartoon, they would select the caption using a “Choose Caption” button. The program then proceeded to the next cartoon. The cartoons used as stimuli were borrowed from a major publication known to feature simple, single-pane cartoons. For each of the three cartoons, I randomly selected the choice set from a list of 500 reader-generated captions (retrieved from the publication’s website).

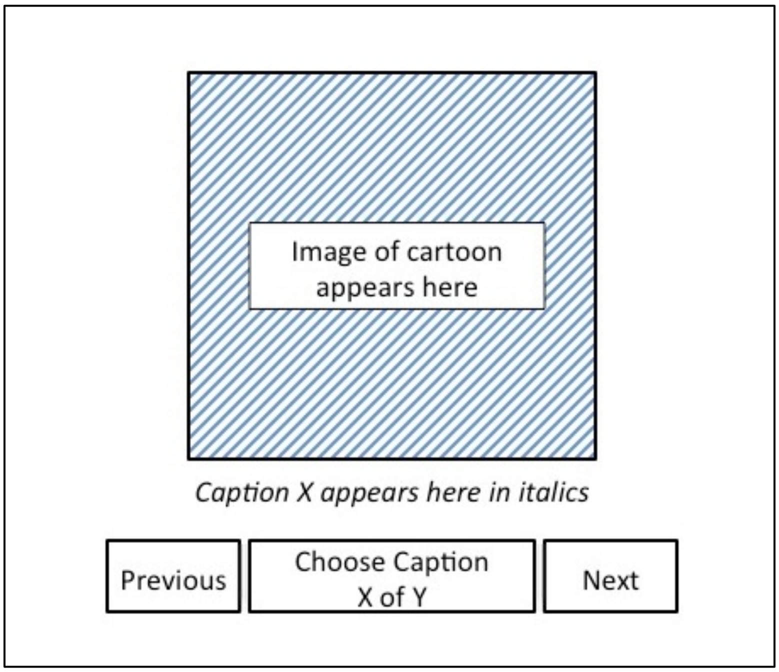


Figure 1.1. Search paradigm used in Study 1.1. Y represents the total number of available captions in the choice set (i.e., the choice-set size) and X represents the caption that is currently being displayed. Clicking “Next” would advance to caption X+1.

Participants were randomly assigned to either an increasing task difficulty condition or a decreasing task difficulty condition. In the increasing difficulty condition, participants first encountered a cartoon with a choice set of 50 possible captions, then a cartoon with a choice set of 150 possible captions, and finally a cartoon with a choice set of 250 possible captions (order of the actual cartoons was randomize). Participants in the decreasing difficulty condition encountered the reverse sequence (i.e., 250 captions, 150 captions, then 50 captions).

After completing the cartoon caption task, all participants were given an additional, bonus task. The bonus task was structured so that search persistence would be rewarded with a higher bonus payment. Participants were told that they would “draw” a random bonus payment (generated from a quasi-normal distribution bounded at $0.01 and $1.00). If participants were satisfied with their draw, they could accept it. However, participants could continue drawing new bonuses as long as they desired — the final bonus payment would be the largest overall bonus draw (this value was clearly displayed on the screen). I further emphasized that there was no risk in drawing an additional bonus. Each new draw could only increase their payment. The only penalty for drawing was time: Each draw took five seconds to materialize.

Because I hypothesize that a decision with a small choice set (i.e., an easy decision) will lead to a more exhaustive search strategy, I predict that participants who encounter the choice sets in an increasing order will sample a greater number of options than their counterparts who encounter the same-sized choice sets in a decreasing order. The bonus task provides a test of this hypothesized effect's boundary conditions: If an adopted decision strategy persists to closely related tasks, will it also persist (to some degree) to a mostly unrelated task?

Results

Strategy Adopted in First Task. I first examined whether participants adapted their search strategies based on the difficulty of the first task they encountered. Indeed, participants who first encountered a comparatively easy task searched a higher percent of the available options for the first task (M = 65%) than those who encountered a comparatively difficult task (M = 16%; $t(87) = 7.60$, $p < .001$). Forty-seven percent of participants who started with an easy task searched the entire choice set compared to only 6% of those who started with a difficult task (logistic regression: $z = 3.93$, $p < .001$). Thus it appears participants indeed adopted a different search strategy based on the difficulty of the decision (operationalized by choice-set size): Participants who started with an easier task adopted a more diligent search strategy than those who started with a harder task. This research replicates previous findings (Diehl 2005; Meyer 1997).

Strategy Persistence in Subsequent Tasks. More interesting, I next examined whether the search strategy adopted in the first task would persist to the following tasks. To do this, I looked at aggregate search across all three tasks. Participants who started with the easiest task and proceeded to more difficult tasks sampled more total options (M = 154) compared to those who started with a difficult task and proceeded to easier tasks (M = 88; $t(87) = 2.70$, $p = .008$). Because the three decision tasks were the same for all participants, the difference in search should be attributed to decision order. Participants who started with an easy decision adopted a more diligent search strategy and this strategy persisted to the later decisions. A particularly interesting comparison is the second task (i.e., the cartoon with the 150-item choice set). Participants who had just completed an easier task and thus had adopted more of a maximizing search strategy sampled more options (M = 47) than those who had just completed a harder task and had adopted more of a satisficing strategy (M = 26; $t(87) = 2.35$, $p = .02$). These results suggest that decisions strategies are indeed sticky — participants continued to apply a search strategy used in the first task to later tasks in the sequence. Results by condition are illustrated in Figure 2.2.

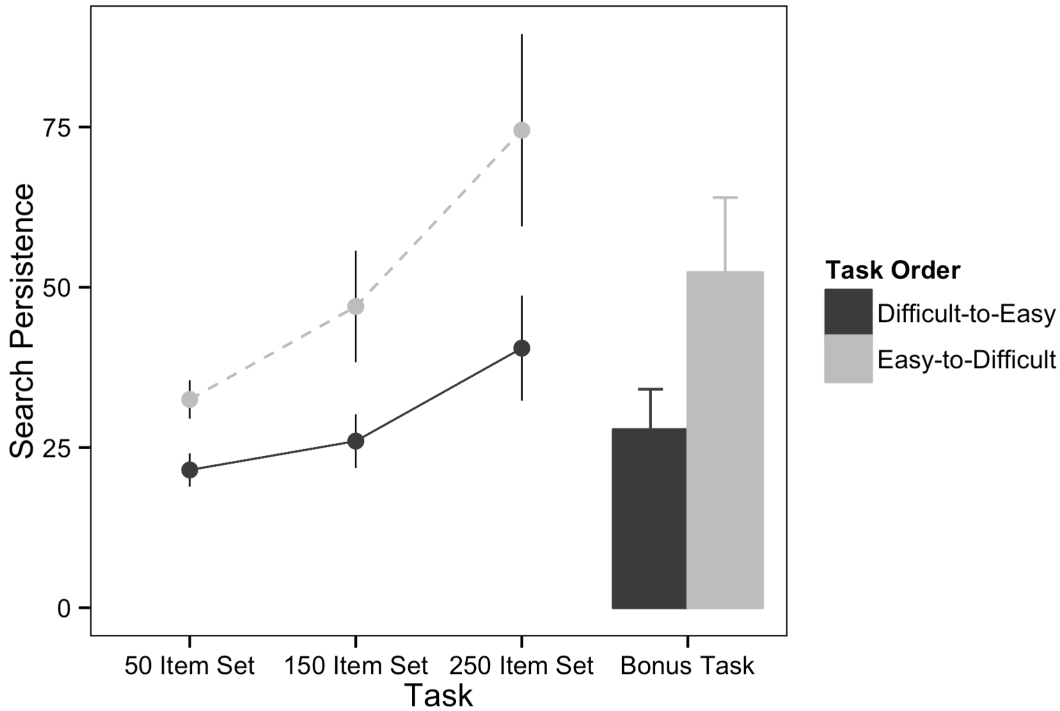


Figure 1.2. Search persistence by condition in Study 1.1. Error bars show standard errors.

Strategy Persistence to Bonus Task. As a first test of the frog-in-boiling-water boundary conditions, I examined whether the search strategy adopted in the cartoon task would carry over to the mostly unrelated bonus task. Search persistence at the bonus task should be reflected by participants' willingness to incur a higher cost (in time) for additional bonus draws (5 seconds per draw). Because draws carry no risk of lower bonus payments, a participant with a more diligent search strategy should continue drawing longer than one who has previous adopted a less diligent strategy, who should be more likely to settle for an earlier draw. Supporting the notion that decision strategies can persist even when the task context changes rather drastically, participants in the easiest-to-hardest condition requested more draws (M = 52.3) than their counterparts in the hardest-to-easiest condition (M = 27.8; $t(87) = 1.97$, $p = .05$). In other words, participants who adopted a more diligent search strategy based on the relative ease of the first cartoon task, not only searched more as the cartoon tasks became more difficult, but also searched more in the mostly unrelated, incentive-compatible bonus task which followed the cartoon tasks.

Discussion

The results of Study 1.1 provide evidence that decision strategies are indeed sticky in sequential choice contexts. Much like the frog that does not realize the water temperature is changing, a consumer who has adapted her decision strategy to the first task in a sequence fails to fully update this strategy as the task difficulty changes in subsequent tasks. This failure to update strategies manifests in changes in aggregate behavior across the entire sequence of tasks. Further, the effect of a previously adopted decision strategy persists even when the task context changes substantively. Perhaps then, the notion of gradual change is less important that the frog-in-boiling-water metaphor suggests. In the following study, I test more directly whether abrupt changes in the task attenuate the persistence of consumer decision strategies.

Study 1.2: Abrupt Change in Task Characteristic Promotes Strategy Reconsideration

In this study, I again give participants a series of decisions that require search. Instead of manipulating decision order — as I did in Study 1.1 — I manipulate the rate at which the difficulty of the decisions changes. All participants start with the same easy decision (which should prompt the adoption of a diligent search strategy) and finish with the same difficult decision. But, for the middle decisions, I manipulate whether the degree of difficulty changes gradually or, alternatively, whether it increases all at once. Returning to the frog-in-boiling-water metaphor, abrupt changes (increasing the water temperature quickly) should increase the likelihood that the previously adopted strategy is reconsidered. Thus, abrupt changes should attenuate the degree to which the original decision strategy persists.

Method

Seventy-three participants, recruited from the Columbia Business School Behavioral Lab subject pool, completed this experiment in exchange for $6.00. Participants were told that, as part of a marketing study, they were being asked to create a compact disk (CD) with four tracks (songs) using a computer-based customization interface. The interface is shown in Figure 1.3. In order to make participants' choices consequential, I informed them that after the study they would be able to download the CD that they configured. The options for each track were randomly selected from a pool of 2327 (presumably) unfamiliar songs.

Figure 1.3. Song selection interface used in Study 1.2.

Participants proceeded through a series of four song-selection screens, each corresponding to a track on the participant's CD. On each screen, they were presented with a list of songs (displayed by name) and asked to choose one for their CD. Participants could listen to a song by clicking on its name. The program was self-paced and participants could sample as many songs as they wished. They were also free to interrupt a song or listen to it again. Once participants chose a song for a given track, they continued to the next track and could not go back to change their decision.
The number of options for each track varied depending on the experimental condition.

The experimental design featured three conditions: one in which the difficulty of each choice increased gradually and two in which the difficulty increased abruptly. In the gradually increasing condition, participants first selected a song from a choice set of five, then proceeded to select their second song from a choice set of 10, then their third song from a choice set of 15, and then their fourth song from a choice set of 20. In the "matched" abrupt increase condition, participants once again first selected a song from a choice set of five and then proceeded to select their second song from a different choice set of 5. Following their second song selection, the abrupt jump occurred. Participants in the "matched" abrupt condition selected their third song from a choice set of 20 and their fourth song from a different choice set of 20. It is important to note that in both the gradually increasing condition and the "matched" abrupt condition, participants had the option to search 50 total songs (choice set sizes by condition: 5-10-15-20 vs. 5-5-20-20). Thus a fair comparison can be made across the two conditions regarding the total number of songs searched in aggregate across all four decisions.

Some participants were also assigned to a second abrupt increase condition in which the jump in difficulty occurred after the third song selection. These participants chose their first three songs from different choice sets of five and their last song from a choice set of 20. This condition was conducted to examine the role of cognitive depletion in this sequential decision paradigm (Baumeister et al. 1998; Levav et al. 2010). When selecting their fourth song, participants in this condition should be less "depleted" than those in the other two conditions as they have had only easy choices up to that point. Cognitive depletion would thus suggest that these participants should search more in the final choice set, as they should have the most remaining resources. Importantly, all participants search through a choice set of 20 for their final selection, so comparisons can be made across the three conditions in terms of search in final decision.

Results

Search in First Choice Set. Participants in every condition started with an easy choice: selecting one song from a choice set of five. Thus, all participants were equally likely to adopt a diligent search strategy for the fist decision. Indeed, there were no differences in the number of songs sampled in the first choice set between conditions ($F(2, 70) = .04$, $p = .96$). Participants across all conditions adopted a diligent strategy, sampling an average of 4.66 of the 5 songs. Further, 75% of participants sampled all five songs.

Total Search. I next compared total search between the gradually increasing difficulty condition and the "matched" abrupt increase in difficulty condition. Participants in both conditions had the ability to sample 50 total songs across all choices. If people are more likely to update their decision strategies in the face of a bigger change in the choice environment (i.e., the jump in decision difficulty), I should observe less total search in the abrupt increase condition compared to the gradually increasing condition. Indeed, this is what I find. Participants in the gradually increasing difficulty condition sampled an average of 37.5 songs (out of 50), while participants in the abrupt increase in difficulty condition sampled only 29.6 songs ($t(46) = 2.04$, $p = .047$). Thus it appears participants in the abrupt increase condition were more likely to abandon their diligent search strategy in favor of a more judicious search strategy following the more salient change in decision difficulty.

Search in Final Choice Set. As a final analysis, I examined the extent of search in the final decision, for which all participants selected a song from a choice set of 20. Participants in the gradually increasing condition sampled marginally more songs (M = 13.1) than participants the in the two abrupt increase conditions (M = 10.9; $t(71) = 1.27$, p = .21). This again suggests that the diligent strategy participants adopted in the first choice set was more likely to persist when changes in the decision environment were more gradual.

After the planned experimental analyses, I conducted additional exploratory analyses designed to determine which consumers were most likely to be affected by the abrupt (vs. gradual) change in the decision environment. In other words, I wanted to see if there were any differences between the consumers who maintained their diligence after the abrupt increase and those who switched to a less diligent strategy. To this end, I found a variable that predicted strategy persistence in the later decisions: the amount of time they spent on the first decision.

Because all participants started with a five song choice set, the time they spent on the first decision should be unaffected by the experimental manipulation. All participants searched thoroughly in this first choice set (in terms of number of songs), but some participants spent longer doing so than others. I ran a regression using the time participants spent on the first decision (logged for better normality), experimental condition (gradual vs. abrupt), and their interaction to predict the number of songs searched in the fourth decision. The regression yielded a significant interaction ($t(69)$ =

2.32, p = .02): Participants who spent the longest on the first decision were unaffected by the manipulation (at +1 *SD* on time spent: $t(69) = .22$, $p = .83$), while those who spent less time searching in the first decision were strongly affected by the abrupt increase in decision difficulty (at -1 *SD* on time spent: $t(69) = 3.12$, $p = .003$). This interaction is illustrated in Figure 1.4.

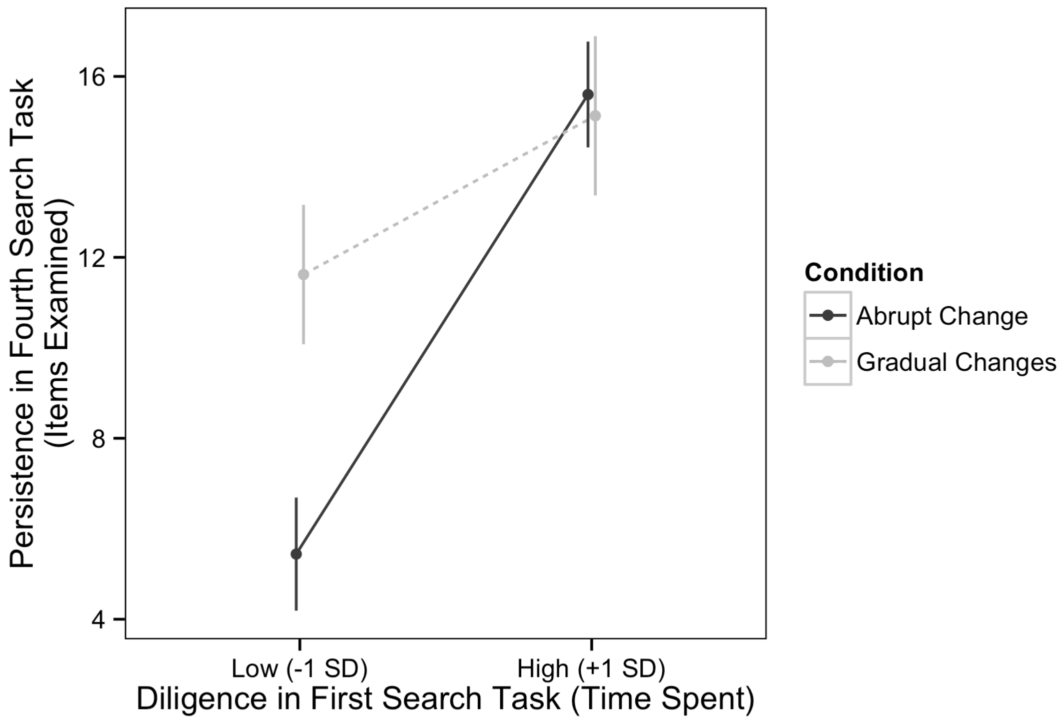


Figure 1.4. Participants who searched the longest in the first task (in terms of time) were unaffected by an abrupt change in the task environment. In contrast, participants who searched less in the first task (in terms of time) were more likely to switch to an even less diligent strategy after an abrupt change in task environment (compared to gradual changes). Error bars show standard errors.

One possible interpretation of this (*post hoc*) result is that certain participants are more predisposed to adopting a diligent strategy than others and, in this experiment, this predisposition is reflected by the amount of time they spent searching for their first song. For participants most predisposed to diligence (those who spent the most time on the first decision), abrupt changes in the task environment do not cause strategy change — perhaps because they do not wish to change their strategy. However, for participants less predisposed to adopting a diligent strategy (those who spent the least time on the first decision), abrupt changes in the task environment prompt strategy reconsideration and change.

Cognitive Depletion?. A possible interpretation of the decrease in total search in the "matched" abrupt increase condition is that participants were simply "depleted" after searching through a choice set of 20 options in their third decision and thus were unable to muster the energy to search extensively through the final choice set. To test for this possibility, I examined differences in search between the "matched" abrupt increase condition (choice set sizes: 5-5-20-20) and the abrupt increase condition in which the jump in difficulty occurred after the third choice set (choice set sizes: 5-5-5-20). Participants in the condition with the abrupt increase after the second choice set sampled marginally fewer songs (M = 9.3) than those in the condition with the abrupt increase after the third choice set (M = 12.4; $t(47)$ = 1.46, p = .15), suggesting that cognitive fatigue might influence persistence to a degree. However, participants who experienced the abrupt increase after the third choice set — and thus should be the least "depleted" — did not search more in the fourth choice set compared to those in the gradually increasing condition (M = 13.1; $t(47)$ = .38, p = .71), suggesting that cognitive fatigue alone cannot explain the results. If cognitive fatigue was the primary cause of differences between the conditions, those who were the least "depleted" should have persisted the longest at search, a result I do not find.

It should also be noted that the results from Study 1.1 are difficult to explain in terms cognitive depletion. Participants in the easy-to-hard condition searched more options during the primary tasks (which should be "depleting") then continued to search more options in the bonus task. The role of cognitive fatigue in sequential decisions has been explored in other papers (e.g., Levav et al. 2010) and future research should examine more explicitly the link between strategy persistence, motivation, and mental resources.

Study 1.3: Very Short Interruptions Promote Strategy Reconsideration

In this study, I examine another possible mechanism by which participants may recognize the need to update their decision strategy. In this study, I conduct a simple manipulation: Half the participants in the study proceed directly from task to task as in previous studies. For the other half, I implement a 7-second break between each task. My prediction is that by briefly interrupting participants after a task, they will be more likely to reconsider their previous decision strategy when engaging in the following task. In other words, I expect that previously adopted decision strategies will be less likely to persist after a very short break.

A second feature of this study is that I move away from the selection decision paradigms used in the previous two studies. Instead, I use a search task in which decision difficulty is manipulated by the amount of information a participant must acquire to make the decision with certainty. I use a paradigm adopted from Johannes Abeler and colleagues (2011) in which participants are asked to count the number of zeros in a grid. I award participant a bonus payment for correctly determining the number of zeros in the grid.

In this paradigm, the participant is faced with one of two options: (1) She can diligently search the grid and enumerate all of the zeros. Following this diligent strategy will typically yield the correct response and the corresponding bonus payment. (2) She can scan the grid quickly and estimate the number of zeros. Following this less diligent "guessing" strategy will yield the correct response less frequently and is thus less likely to beget a bonus payment. Yet, it is much faster and less effortful. Because participants have opportunity costs (they are AMT workers who have access to other profitable tasks), the appropriate strategy to adopt should be a function of both the difficulty of the task (i.e., how long diligent search will take) and the magnitude of the bonus payment (i.e., how profitable diligent search will be).

As the core manipulation in this experiment, I order the tasks by decision difficulty. Half of the participants encounter easy tasks first (only a few zeros to count) followed by more difficult tasks (many zeros to count). In this order, the cost of a diligent strategy increases with each choice set. The other half of the participants encounters the difficult tasks first followed by the easier tasks. In this order, the cost of a diligent strategy decreases with each choice set.

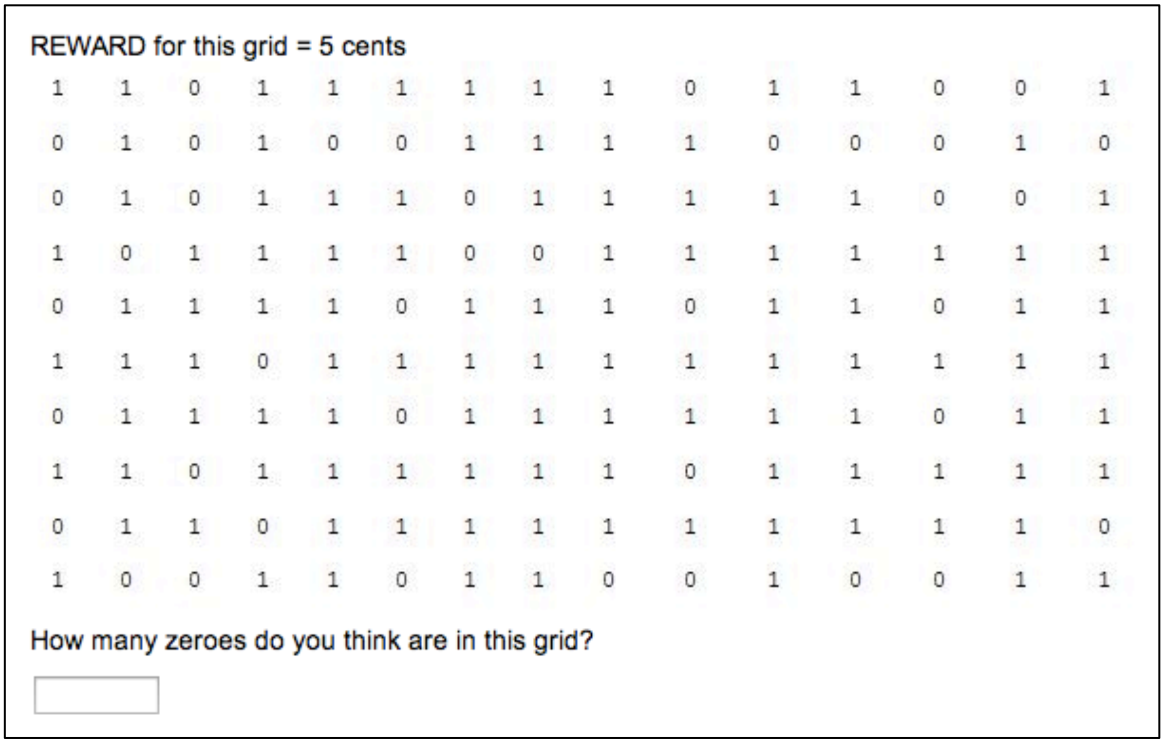
For participants who are paid a fixed sum for each correct answer, decision order will influence the attractiveness of the first task encountered. Participants in the easy-to-difficult condition will start with a task in which diligent search is an attractive option. However, participants in the difficult-to-easy condition will start with a task in which guessing is a more attractive option (as diligent search would take more time and effort than the associated bonus payment warrants). Thus the ordering manipulation should influence the strategy participants initially adopt (diligent search vs. guessing). If these strategies are "sticky," I should be able to observe a difference in performance across the entire sequence of tasks.

A final aspect of this study is that I manipulate the pay rate for correct answers. For half the participants, I pay a fixed amount per correct answer. Participants in this condition should find the easiest tasks a relatively good deal and thus should be motivated to employ a diligent search strategy. However, participants in this condition should find the hard tasks a bad deal and should thus be motivated to employ a guessing strategy. For the other half of participants, I pay a variable amount per correct answer based on the task's difficulty. I calibrated this amount so that all tasks (easy and hard) would be moderately attractive. Thus, there should be no change in motivation to employ a diligent (vs. guessing strategy) based on task difficulty.

In sum, I manipulate task order (easy-to-difficult vs. difficult-to-easy), the presence of interruptions (yes vs. no), and the pay rate (fixed vs. variable). I expect the frog-in-boiling-water effect to emerge when pay rate is fixed and there are no interruptions. I predict that interruptions — which will force participants to briefly disengage with the task sequence — will attenuate the frog-in-boiling-water effect. Finally, I predict no differences in the variable pay rate condition — as neither order nor increased contemplation should influence the relative attractiveness of one strategy versus the other at any point in the decision sequence.

Method

Three hundred and twenty-three participants (recruited through AMT) completed this experiment as part of a larger block of paid studies. Participants were randomly assigned to one condition in a 2 (difficulty: increasing vs. decreasing) x 2 (interruptions: yes vs. no) x 2 (pay rate: fixed vs. variable) between-subject design. Participants were told that they would be presented with seven search tasks and that each task would consist of finding and counting the number of zeros in a grid (Abeler et al. 2011). Participants were told that for each of the seven tasks, if they successfully counted — or, critically, guessed — the number of zeros, they would receive a bonus payment, the amount of which would be prominently displayed on the screen above the grid. An example stimulus is shown in Figure 1.5. The grids were designed such that they varied in difficulty. The easiest task featured only 17 zeros (out of 150) while the hardest featured 69 zeros.



REWARD for this grid = 5 cents

1	1	0	1	1	1	1	1	1	0	1	1	0	0	1
0	1	0	1	0	0	1	1	1	1	0	0	0	1	0
0	1	0	1	1	1	0	1	1	1	1	1	0	0	1
1	0	1	1	1	1	0	0	1	1	1	1	1	1	1
0	1	1	1	1	0	1	1	1	0	1	1	0	1	1
1	1	1	0	1	1	1	1	1	1	1	1	1	1	1
0	1	1	1	1	0	1	1	1	1	1	1	0	1	1
1	1	0	1	1	1	1	1	1	0	1	1	1	1	1
0	1	1	0	1	1	1	1	1	1	1	1	1	1	0
1	0	0	1	1	0	1	1	0	0	1	0	0	1	1

How many zeroes do you think are in this grid?

Figure 1.5. Sample stimulus for zero counting task (Study 1.3).

As mentioned previously, participants were explicitly told they could attempt to guess the correct number of zeros instead of expending search effort attempting to diligently enumerate them all. The difficulty of the tasks was calibrated so that diligent search for the correct answer would take approximately 30 seconds for the easiest puzzle and approximately 60 seconds in the hardest puzzle (actual median response times for successful answers were 28.5 seconds and 56.9 seconds, respectively). The participants in my experimental population expect, approximately, to earn 10 cents per minutes (respondents to this survey indicated a median desired pay rate of 12.5 cents/minutes). Thus in the fixed pay rate condition, searching diligently through the easiest grid was a relatively good deal (about 10 cents/minute), while searching through the most difficult grid was a relatively bad deal (about 5 cents/minute). A participant first encountering the easiest task in the fixed pay rate condition should be inclined to search the grid diligently, while a participant first encountering the most difficult task in the fixed pay rate condition should be inclined to perform a cursory search and field a guess, as the time cost for diligent search outweighs the expected benefit.

The frog-in-boiling-water hypothesis predicts (in the fixed pay rate condition) that participants in the easy-to-difficult condition will continue to apply a diligent strategy against their best interests as they encounter increasingly difficult, and time consuming, search tasks. Conversely, participants in the difficult-to-easy condition should experience the opposite issue: They will continue with a guessing strategy even as the benefits of switching to a diligent strategy begin to outweigh the costs. In sum, participants in the increasing difficulty condition are predicted to search too much (compared to their stated pay rates) as they continue to apply an exhaustive strategy long after it suits their interests, while participants in the decreasing difficulty condition are predicted to search too little as they continue to guess for tasks in which exhaustive search would be profitable. The interruptions are predicted to attenuate the differences between conditions — as interrupted participants are predicted to be more likely to adapt their strategies to the changing conditions.

The difficulty-adjusted pay rate condition was included as a control factor. The variable pay rate in this condition was calibrated so that each of the search tasks would be roughly equal in terms of their cost-benefit calculation (about 7.5 cents/minute). Thus participants in both the easy-to-difficult and the difficult-to-easy conditions should encounter a first puzzle with a reward inline with the cost associated with exhaustive search. Participants in these conditions have little incentive to change strategies, as the payment waxes (or wanes) in accordance with the effort required. In a sense, these participants are frogs in comfortably warm and unchanging water. No differences are predicted for these participants in terms of search strategy across the order or interruption manipulations.

Results

In analyzing the data, an assumption is made and should be explicit: I treat correct answers as evidence the participant is using a diligent enumeration strategy and incorrect answers as evidence the participant is guessing. Although this might not always be true (i.e., one could diligently count and happen to be wrong or could guess and happen to be correct), violations of this assumption should not interact with the experimental manipulations. Thus, the pattern of results I observe should not be invalidated by this assumption. Rather, the assumption should simply produce measurement noise within each condition.

To analyze the data, I look at the aggregate number of correct answers, which — I argue — is a noisy measure of the search strategy participants are using across all of the tasks. If a participant gets more correct answers, I take it as evidence she was using a diligent enumeration strategy on a greater number of the individual tasks. The number of correct answers by condition is shown in Figure 1.6.

I conducted a linear regression with the total number of correct answers as the dependent variable and the three manipulations — task order, presence of interruptions, and pay rate — and their interactions as the independent variances. The regression yielded a significant three-way interaction ($t(295) = 2.13$, $p = .034$). To explore this interaction, I followed the procedures outlined by Stephen Spiller and colleagues (2013).

First, I examined the simple interaction between task order and the interruption manipulation when correct answers paid the same amount (5 cents) regardless of task difficulty. As predicted, this simple interaction was significant ($t(295) = 2.70$, $p = .007$), so I further explored the simple simple effects.

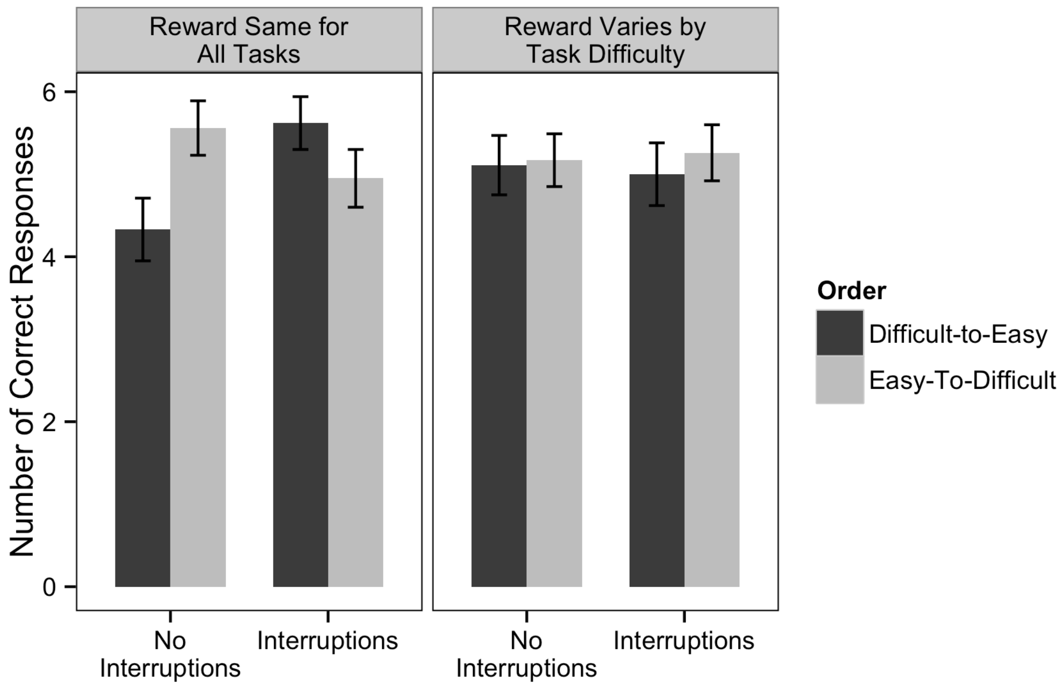


Figure 1.6. Aggregate performance by condition in Study 1.3. Correct answers suggest that participants are using a diligent search strategy, while incorrect answers suggest participants are using a guessing strategy. Error bars show standard errors.

Replicating the frog-in-boiling-water result from the previous two studies, participants (in the fixed pay condition) who were not interrupted and encountered the tasks in an easy-to-difficult order provided more correct answers ($M = 5.56$) than those that encountered the tasks in a difficult-to-easy order ($M = 4.33$; $t(295) = 2.43$, $p = .016$). These participants started with an easy task in which searching diligently was a relatively good deal. They presumably adopted a diligent strategy that then persisted as they encountered tasks where exhaustive enumeration was no longer cost-effective. In contrast, the participants who started with a hard task presumably adopted a guessing strategy, as the cost of diligent search would not have been worth the expected benefit.

This strategy also seems to have persisted — the participants in this condition appear to have been slow to abandon their guessing strategy as the alternative diligent strategy became increasingly profitable.

In the condition where participants were interrupted (and were paid a fixed amount per correct answer), the simple simple effect of task order was not significant ($t(295) = 1.37$, $p = .17$). In other words, the performance of participants in the easy-to-difficult condition was similar to that of participants in the difficult-to-easy condition. This is evidence that the interruptions attenuated the persistence of decision strategy from task to task. By simply forcing participants to take a brief break between tasks, they became better at adapting their strategy to the new task at hand.

Finally, I looked at the simple interaction between task order and the interruption manipulation when correct answers paid a variable amount based on their difficulty (2 cents for the easiest, 8 cents for the hardest). Neither this simple interaction ($t(295) = .29$, $p = .77$) nor the simple main effects of task order and the interruption manipulation (both $|t(295)|$s $< .22$, ps $> .82$) were significant. Thus, all participants in the variable pay rate condition performed approximately the same. This was expected, as the pay rate was calibrated to be a decent deal for each task. In other words, the cost-benefit calculation was about the same regardless of the task. Participants who started with an easy task or a hard task had approximately equivalent incentives to search diligently. And because the cost-benefit calculation was not changing as the tasks progressed, even a participant who reconsidered her strategy would likely choose to not change it.

Discussion

In this study, I replicated the frog-in-boiling-water effect found in the previous studies in a new decision task. Participants seem to have adopted a strategy based on the cost-benefit calculation of the first task that then persisted to subsequent tasks. Also, I identify a second boundary condition for strategy persistence: brief interruptions. Forcing participants to take a short break between tasks eliminated the effect of task order (increasing difficulty vs. decreasing difficulty). Relating this back to the frog metaphor, if you force the frog to briefly exit the water, it will be more likely to notice the increasing temperature when it reenters.

General Discussion

The present investigation contributes to a growing literature at the intersection of consumer search and choice (e.g., Häubl, Dellaert, and Donkers 2010; Kim, Albuquerque, and Bronnenberg 2010). In Study 1.1, I provide evidence for the basic frog-in-boiling-water effect: People search more in aggregate when decisions are ordered from easy to difficult. Additionally, following the sequence of either increasingly or decreasingly difficult search tasks, Study 1.1 featured a final "bonus" search task that was the same for all participants. Participants who encountered the easy-to-hard ordering of initial tasks persisted longer at this final task than those who encountered the hard-to-easy ordering, suggesting that adopted decision strategies can persist (to a degree) even when the superficial nature of the task changes quite drastically. Study 1.2 replicated the frog-in-boiling-water effect, but suggested a boundary condition: Decision strategies are less persistent when changes in the task characteristics are greater. In short, abrupt changes in environment can help people abandon a routinized strategy in favor of a more appropriate one. Further, Study 1.2 illuminates the type of people who might be most prone to the frog-in-boiling-water phenomenon: those who are least ardent adopters of the initial strategy. Finally, Study 1.3 introduces an intervention that reduces the frog-in-boiling-water effect: a short break between tasks. People who are forced to take a moment to stop (and presumably reflect), reengage with the next task in a manner more consistent with its difficulty.

Bounded Adaptivity

The present findings raise several theoretical and practical implications. First, past research using one-shot decisions offers compelling evidence that consumers adapt their decision strategies according to the requirements of the choice task (Bettman, Luce, and Payne 1998; Payne, Bettman, and Johnson 1993). Here I argue that people are actually "sticky adapters" whose strategies are adapted to new contexts — such as the initial decision difficulty — but persist to a significant degree even in the face of changes in the decision environment. Second, the present findings indicate that the effect of decision difficulty on motivation may be contingent on consumers' previous experience. In particular, past research suggested that consumers faced with a difficulty decision (e.g., large number of options in a choice set) will be less motivated to make a purchase (Iyengar and Lepper 2000). Yet, participants in my experiments who were initially exposed to easy decision (e.g., those with small choice sets) and then were exposed to more difficult decisions (e.g., those with large choice sets) appeared to "keep up" and remained more motivated as indicated by their more extensive search relative to those who saw the reverse sequence.

On Mindsets and *Einstellung*

A possible explanation for the persistence of a decision strategy comes from work on consumer mindsets. Mindsets have been defined broadly in consumer research: They can refer to the cognitive or motor procedures (Wyer and Xu 2010), judgmental criteria (Xu and Wyer 2007), or goals (Keinan and Kivetz 2011) that are triggered by a task and subsequently generalized to different tasks or contexts. For instance, research suggests that considering a purchase in category *x* increases the probability of purchase in a subsequent, unrelated category *y* because the act of consideration places consumers in a "which-to-buy" mindset (Xu and Wyer 2007). Similarly, it has been suggested that an initial task that utilizes broader rather than narrower categories can lead people to create broader rather than finer grouping of items in a subsequent, unrelated task (Ülkümen, Chakravarti, and Morwitz 2010).

In this chapter, I show the effect of persistent decision strategies in sequential decisions that require search. Further, I attempt to address the question of when these adopted strategies (and possibly goals) persist. Study 1.1 suggests that the influence of a decision strategy (or mindset) can linger to a mostly unrelated task. However, Studies 1.2 and 1.3 show attenuating factors: Abrupt changes and brief interruptions can limit the carryover effects. When tasks seem more different (abrupt vs. gradual changes) or when forced to take a brief moment to disengage after a task (interruptions vs. no interruptions), people seem better able to adapt to the appropriate demands of the new task.

To the extent the present work can be characterized as studying consumer mindsets, it would suggest that: (1) Mindsets are more likely to persist when sequential tasks are more similar and (2) Mindsets are less likely to persist sequential tasks are further separated in time. Future research should more clearly delineate the boundary conditions of mindsets. A parallel can be drawn to research on non-conscious goals and automaticity (e.g., Bargh and Chartrand 1999). While these are both certainly influential factors in consumer behavior, effort should be made to explicate specifically when you should — and, critically, when you should not — observe their effects.

Conclusion

Sequential decisions are ubiquitous in the marketplace. Firms frequently impose order to these decisions through interfaces (e.g., customization engines) that reflect an engineer's perspective about how the decisions should be sequenced. Typically decisions are ordered such that the more central components are determined before the more peripheral ones. This research shows that more attention should be placed on understanding the psychological factors relevant to decision order. Firms may have the opportunity to influence the behavior of their customers in a desirable manner simply by restructuring a sequential choice environment around psychologically important variables.

CHAPTER TWO:

Variance Neglect in Consumer Search

Consumers often know exactly what they want, but are not sure how much they will have to pay to get it. In these situations, the consumer must search to find an acceptable price (if there is one) for the product or service they are seeking. Even when the product is homogenous (i.e., the same regardless of where it is purchased), the price of the product can vary substantially between retailers (e.g., Baye, Morgan, and Scholten 2004). By visiting more retailers ("visiting" is used here loosely, it can simply mean viewing the product on a retailer's website or, perhaps, requesting a price quote), the consumer can expect to find a better price. However, there are diminishing returns to search. The more retailers a consumer has visited, the less likely the next retailer she visits will have a better price than one she's already seen. There is also a cost to extending search. At the very least this cost is the consumer's time (which entails opportunity costs), but it can also be monetary if, for example, searching requires travel.

In the current investigation, I examine how the prices a consumer has previously seen during search influence her perception of the likely distribution of prices in the market and consequently her decision on whether or not to continue searching. Specifically, I look at the variance of previously observed prices and the information it can convey about the benefits of continued search. If prices are encountered randomly (i.e., if a consumer is not predisposed to visit specific retailers), previously seen prices can be used to infer the distribution of all possible prices in the marketplace. This inference is important: The variance of prices in the marketplace determines the economic value of continued search. If people can accurately infer price variance from previously seen prices, they are able to better optimize the effort they expend searching for a better price.

Following this logic, consumers searching for the best price should attend to the absolute (i.e., in dollars, not percent) differences in the prices they have previously seen. If previously seen prices are very similar to one another (low variance), it can be inferred that future (unseen) prices are also similar. When prices are more similar (i.e., closer in absolute magnitude), the benefit of continued search is lower. The extreme case is when the prices are identical. If there is no variation in price across retailers, there is no value in search. If a consumer can accurately infer a state of low price variance, she can save effort (and perhaps money) by terminating search.

In the alternative case, if previously observed prices are very dispersed (i.e., further apart in absolute magnitude, high variance), it can be inferred that future (unseen) prices are also very dispersed. In this case, the benefits of search are much greater. If a consumer can accurately infer a state of high price variance, she can exert increased search effort and expect to yield high savings with the best price she eventually finds.

This line of reasoning has been explicated in theoretical models of search (Rothschild 1974; Stigler 1961). This research argues and demonstrates that price dispersion — the variation in price across retailers — should be a primary driver of search persistence. Importantly, this economic research suggests that the absolute (i.e., dollar savings), rather than relative (i.e., percent savings), magnitude of price dispersion is what should matter. If two products have the same price dispersion across retailers but different average prices (e.g., one is expensive and one is cheap), the incentive for additional search is the same for both products. The intuition behind this will be explained more thoroughly in a subsequent section.

In contrast to the implications of economic models of search, I find the exact opposite pattern of behavior: Consumers tend to search less when price dispersion is high and tend to search more when price dispersion is low. Further, I find that the magnitude of prices (i.e., whether the product has a high price or a low price) has a strong impact on search persistence. This result is also inconsistent with normative search models, which suggest that the magnitude of price should be irrelevant to search persistence. I propose an explanation for both of these counter-normative effects: Consumers have ecologically rational *a priori* beliefs about the relationship between price magnitude and price dispersion. These beliefs serve as an adaptive function when the environment matches expectations, but can lead to negative consequences — accrual of unnecessary search costs or neglect of potentially good deals — when expectations are contradicted.

Normative Models of Persistence in Price Search

Economists have been studying the problem of price search for over 50 years. In its most basic form, price search involves a single consumer searching through a number of prices available for a single product. The consumer must purchase at one (and only one) price and her goal is to minimize total cost. Cost in consumer price search has two components. First, there is the actual price of the good for which price quotes are being sought. Cheaper is obviously better. Second, there is the cost of conducting search. The balancing act in consumer price search is to find a good enough price without incurring too much search cost. Without search costs, the optimal solution would be to search every possible price. With search costs, the optimal solution becomes more complicated. The crux of the issue is what is often called optimal stopping: The goal is to stop when the expected marginal benefit of continued search (finding an even lower price) becomes less than the marginal cost of continued search.

George Stigler (1961) was one of the first to apply economic rigor to the problem of price search (and the analogous problem of wage search; Stigler 1962). If the distribution of possible prices is known by the consumer in advance, Stigler showed that her expected search at the outset should be a fixed number of retailers determined by the dispersion of prices and the consumer's search costs. On average, the consumer should search N stores: The expected benefit of searching one more store after the $N\text{-}1^{th}$ would yield (on average) a big enough expected price discount to more than offset the search cost. However, going from the N^{th} store to the $N+1^{th}$ store would not yield a sufficient expected price discount to warrant the search cost incurred.

Stigler's approach is reasonable in many cases (e.g., if it takes a long time to receive a requested price quote) and yields "well-behaved" consumer demand functions, however it ignores the sequential aspects of each individual consumer's search progress. While a consumer could, at the outset, decide to search exactly N stores based on the expected costs and benefits, she would not always stop her search at the appropriate time. Sometimes she would under-persist and other times she would over-persist. I present a hypothetical example in the next paragraph to illustrate this fact.

Imagine a consumer knows that a given product is offered at exactly two prices — $10 and $30 — with the exact same probability (i.e., half the stores carry the product for $10 and half carry the product for $30). Further imagine the consumer must spend $4 to visit each store for the first time. If she searches one store, her search cost will be $4 and her expected price will be $20 (50% chance of $10 and 50% chance of $30) — a total expected cost of $24. If she searches 2 stores, her search cost will be $8 (2 × $4) and her expected price will be $15 dollars (75% chance of $10 and 25% chance of $30) — a total expected cost of $23. If she searches 3 stores, her search cost will be $12 (3 × $4) and her expected price will be $12.50 (87.5% chance of $10 and 12.5% chance of $30) — a total expected cost of $24.50. The best fixed-depth strategy, then, would be to search two stores — it has the lowest expected total cost ($23) compared to searching one store ($24) or searching three or more ($24.50+).

However, if the consumer goes to the first store and finds the price of the product to be $10 (which will happen half the time), it makes no sense to continue searching and visit the second store. In this case, following the fixed depth strategy would lead to over-persistence. Likewise, if the consumer visited two stores and happened to find the product selling for $30 at each (a 25% likely occurrence), it would be foolish not to continue searching — her expected gain of searching another store would be $10 (the expected price at the next store is $20 — a 50% chance of $10 and a 50% chance of $30) and the cost would only be $4 to visit the next store. In this case following the fixed depth strategy would lead to under-persistence.

Clearly, the sequential dynamics of search are important even when the distribution is known — the prices one happens to encounter at the beginning of search influence the cost-benefit calculation of continued search. Subsequent researchers (e.g., McCall 1970) showed that for known distributions, a price threshold rule yields optimal results. In other words, a consumer — knowing the expected distribution of prices — can set an acceptable price threshold before starting her search. A consumer should then persist at search until she encounters a price below the optimal threshold at which point she should cease search and accept the below-threshold price. This rule is easy to implement in the hypothetical example above: The searcher in this scenario should continue searching until she finds a price below $30. Until then, the expected benefit of search is always $10 (a 50% chance of saving $20) and the cost is fixed at $4. Fixed threshold stopping rules are appealing, not just because they are the optimal solution to a search problem with a known price distribution, but also because they would be easy for a consumer to implement. Herbert Simon (1955) proposed a threshold rule he called "satisficing" as a possible mechanism for boundedly-rational beings to make ecologically rational stopping decisions. A satisficing consumer would pick a reservation price and accept the first price she encountered below that reservation price.

Michael Rothschild (1974) added an additional piece of the theory by showing that a threshold rule was also the optimal solution for stopping price search when the distribution of prices is unknown to the consumer (who is assumed to have Dirichlet prior beliefs). Although the threshold is no longer fixed, Rothschild showed that an optimal stopping threshold could be calculated at any state/time with a given history of previously seen prices. In other words, at any point of time — even if the consumer does not know the exact nature of the price distribution — she should be able to calculate a threshold below which any price should be accepted.

For the current research, it is important to note that all of the previously described stopping rules share a common trait: Given a cost function for search, optimal persistence should be determined exclusively by the dispersion of prices. If prices vary widely across retailers, consumers should search more. If prices vary only modestly, consumers should search less. Critically, what matters is how much the prices vary on absolute, not relative, terms. The intuition behind this fact might be best illustrated in an example: Imagine a consumer is searching for a new tablet computer. Retailers offer different prices for the same tablet computer — some sell it for $500, others for $550, and still others for $600. Imagine the same consumer is also searching for a new car. Some dealers sell the car for $38,500, others for $38,550, and still others for $38,600. Assuming search costs are the same for the two products, a consumer should (according to both optimal-threshold and fixed-depth rules) plan to spend equal time searching for both product categories. Even though paying $500 versus $600 for a tablet feels like saving more money than paying $38,500 versus $38,600 for a new car (e.g., Tversky and Kahneman 1981), objectively the value of search is the same in both cases. The mean price of the distribution should not matter (e.g., $550 vs. $38,550) — only the variance in prices across retailers.

The Present Investigation

In this chapter, I examine the extent to which consumers do, or do not, follow economic prescriptions when conducting price search. I use a simplified experimental paradigm in which participants are asked to find a "good" price for a specific product (i.e., there is no variation in quality, only price). They can "visit" retailers by incurring a cost (operationalized as a 3-second delay) and can stop search at any time by selecting a previously seen price (without cost). I measure persistence in search as the number of retailers visited before making a purchase. Prices in the studies are drawn randomly from a Gaussian distribution. Critically, I examine how the mean of the price distribution (i.e., the price magnitude) and standard deviation of the price distribution (i.e., the price dispersion) influence participants' persistence in the price search task.

In each class of economic model described above — those with fixed depth rules (e.g., Stigler 1961), those with fixed threshold rules (e.g., McCall 1970), and those with moving threshold rules (e.g., Rothschild 1974) — consumers should search more when the variance of the price distribution is greater (i.e., more dispersed prices). Further, the models uniformly agree that the mean of the price distribution (i.e., the average magnitude of the price) should not affect persistence in search. By manipulating the mean and variance of the price distribution in my experimental price search task, I am able to assess the degree to which consumers adhere to these prescriptions.

More importantly, if consumers do not adhere to economic prescriptions, it is worthwhile to examine what does, in fact, influence persistence in consumer price search. To this end, I explore inferential and representational processes in consumer cognition. I look at whether, given a single price observation for a product, consumers are able to form a mental representation of the possible price dispersion in the market. Further, I look at whether these representations affect the downstream behavior of search. If consumers infer greater price dispersion based on higher price magnitude, these beliefs could lead consumers to search more for higher priced products. Average price (or even a single price) would, in this case, act as a cue that more extensive search should be (or should not be) profitable. This inferential heuristic would often be appropriate, as higher priced products tend to have greater price dispersion (Pratt, Wise, and Zeckhauser 1979). However, some expensive products have low price dispersion and some cheap products have high price dispersion. If consumers fail to recognize this during price search, they risk accruing unnecessary search costs or missing out on opportunities for big savings.

Overview of Empirical Evidence

In Study 2.1, I present preliminary evidence of "variance neglect." Consumers fail to increase their search persistence in response to increased price dispersion. In fact, they search marginally less when price dispersion is higher — the exact opposite behavior prescribed by normative search theories. Further, in Study 2.1, I find consumers search marginally more when the average price of the product is higher (holding price dispersion constant). Normative models suggest that price magnitude should be an inconsequential factor in search. I propose a model that can account for these two seemingly counter-normative results based on consumer beliefs about the relationship between price magnitude and price dispersion. If consumers believe higher priced products should have more price variance, it would be consistent with these beliefs to search more for higher priced products. In Study 2.2, I provide evidence that consumers indeed believe higher priced products should have higher price variance. In Study 2.3, I show that these beliefs correlate with persistence in search. Those who expect more dispersion at a given price persist longer at search than those who expect less dispersion. Finally, in Study 2.4, I provide evidence that these beliefs are ecologically rational: When the marketplace corresponds to consumer expectations about the relationship between price magnitude and price dispersion, consumers behave in a manner consistent with normative models. However, when the environment deviates from expectations, consumers respond in a maladaptive manner consistent with their prior beliefs: They search even more for higher priced products and search even less for the lower priced products. This suggests that consumers are slow to update their beliefs even when presented with contradictory information.

Study 2.1: The Influence of Price Dispersion and Price Magnitude on Search Persistence

In this study, I examine the extent to which consumers — when encountering an unknown distribution of prices — adhere to the normative models' prescriptions for price search. Namely, I test the extent to which price dispersion influences search persistence. Further, I test whether price magnitude (i.e., the average price of the product) influences search persistence. Economic models prescribe more search persistence when price dispersion is greater (i.e., more variance in prices) and no difference in search persistence based on the average price. Results from this study suggest that economic models do not accurately characterize people's price search behavior. Instead, they tend to search less when price dispersion is greater and more when average prices are higher.

Method

I recruited 300 participants from Amazon Mechanical Turk (AMT) with the following requirements: United States IP address, completed more than 50 HITs, and 95% approval rating or greater (the same requirements are used in subsequent studies). Seven participants did not engage in any search and are removed from the analysis. Participants were asked to imagine they were buying a new car. The exact same car was said to be available at "many" dealerships (the actual number of possible dealerships was 50). The participant's task was to search through as many dealerships as she wanted with the goal of finding a "good deal" on the car. Searching a new dealership entailed a time cost of three seconds, but previously seen dealerships could be revisited immediately.

Participants searched through dealerships using the interface displayed in Figure 2.1 (the experiment was programmed using JavaScript). Clicking the "Next" button advanced the participant to the subsequent dealer and, after a three second delay (if they had not visited the dealer before), showed the new dealer's price for the car. Clicking the "Previous" button allowed participants to revisit previously seen dealers and their prices. At any time, participants could terminate their search and select the currently displayed price by clicking the "Accept this deal" button.

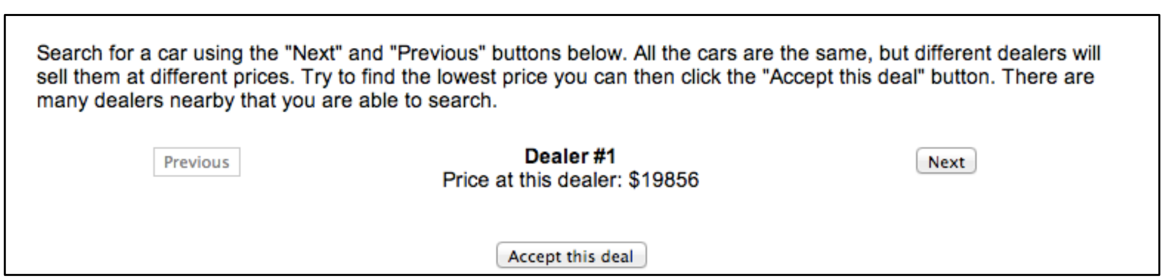


Figure 2.1. Experiment interface used in Study 2.1.

Critically, I manipulated the parameters of the price distribution between participants. Participants were randomly assigned to search prices drawn from one of five normal distributions (details presented below). To manipulate price dispersion, the standard deviation of the price distributions varied from $500 (low dispersion) to $2,500 (high dispersion). To manipulation price magnitude, the mean of the price distributions varied from $10,000 (low magnitude) to $30,000 (high magnitude). For a participant in the low dispersion (*SD* = $500), moderate price (*M* = $20,000) condition, the prices she would encounter for the car would be tightly clustered around $20,000 (e.g., Dealer #1: $19,532, Dealer #2: $20,075, Dealer #3: $19,827, etc.). Conversely, for a participant in the high dispersion (*SD* = $2,500), moderate price (*M* = $20,000) condition, the prices she would encounter would still be centered on $20,000, but would be further apart (e.g., Dealer #1: $17,435, Dealer #2: $25,532, Dealer #3: $20,669, etc.). Crucially, normative theory prescribes more searching when dispersion is higher: Participants in the high-dispersion condition have more to gain by persisting in search (in dollar savings) than participants in the low-dispersion condition.

Results

In this study (and subsequent studies), I find that search depth — the key dependent measure of interest — is not distributed normally (Shapiro-Wilk test: $W = .78$, $p < 10^{-16}$). Even after log-transforming search depth, the distribution still fails to meet the standard criteria of normality (Shapiro-Wilk test: $W = .98$, $p = .0002$). I therefore avoid using hypothesis tests that require a normality assumption (e.g., *t*-tests) and instead use non-parametric hypothesis tests (augmented by bootstrap simulations) when analyzing the results.

As a first analysis, I examined whether price dispersion (operationalized as the standard deviation of the price distribution) influenced search persistence holding the mean of the price distribution constant at $20,000. I tested three levels of price dispersion: low (*SD* = $500), moderate (*SD* = $1,500), and high (*SD* = $2,500). Although the economic incentive to continue search is greatest when dispersion is high, the participants did not conform to this normative prescription. In fact, participants searched moderately more when price dispersion was lowest (median number of dealerships visited = 10.5 vs. 8 and 9, Spearman's $\rho = -.05$, bootstrapped 95% CI [-.19, .10]) — the opposite behavior as would be expected from fully rational agents. Restricting the same analysis to participants who viewed seven or more prices (66% of participants) — and thus those who could more accurate estimate of price dispersion — reveals a significant negative relationship between price dispersion and search magnitude (Spearman's $\rho = -.18$, bootstrapped 95% CI [-.34, -.002]). Search depth by dispersion condition is shown in Figure 2.2. (Note: The same analyses were conducted using the standard deviation of the actual prices observed by the participant and yield similar results: Spearman's $\rho = -.04$ for all participants, Spearman's $\rho = -.12$ for only those who searched seven prices or more.)

While economic theory would prescribe increasing search depth (in aggregate) with respect to price dispersion, the data do not support this hypothesis. I bootstrapped 10,000 samples of the experimental conditions and found the economically prescribed trend (i.e., median search depth monotonically increasing in price dispersion) in only 5.2% of the samples. In contrast, I observed the opposite pattern (i.e., median search depth monotonically decreasing in price dispersion) in 43% of the samples. Further in the same bootstrap analysis, the median search depth for the low dispersion condition was greater than the average of the two higher dispersion conditions in 87% of the samples.

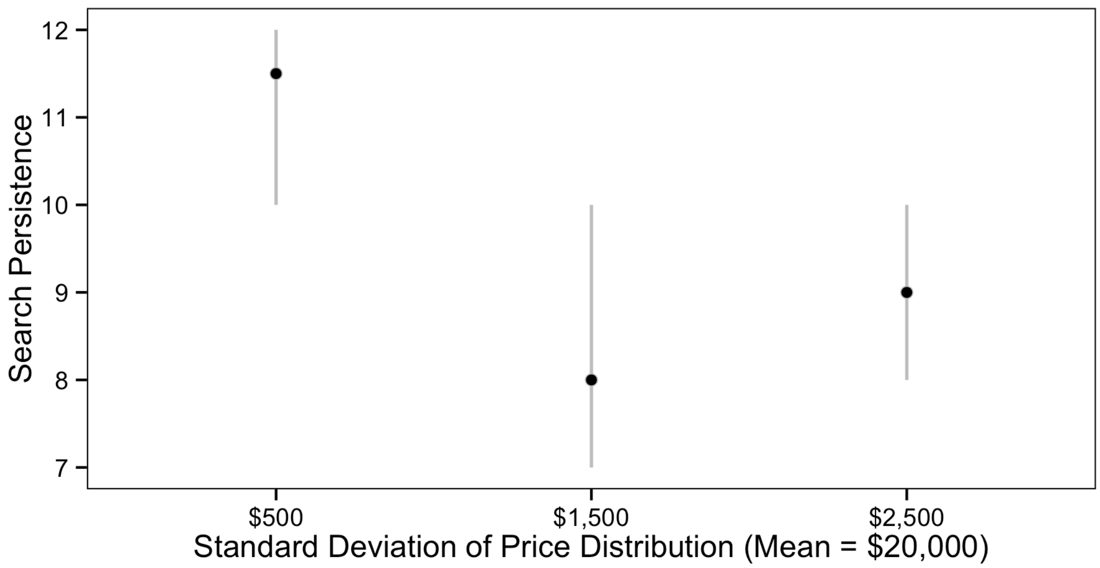


Figure 2.2. Search persistence holding price magnitude constant and varying price dispersion. Dots indicate median search depth by experimental condition and gray bars approximate the standard error (bootstrapped 68% confidence interval).

I conducted a second bootstrap analysis to determine the likelihood of the observed degree of difference in search depth under the null hypothesis (no differences between conditions). Only 3.7% percent of these samples yielded median search in the lowest dispersion condition greater (by two or more — the degree difference observed in the study) than the two higher dispersion conditions. These results suggest that participants, at the very least, are neglecting to account for price dispersion when determining whether to persist at search. Further, to the extent participants do account for price dispersion, they appear to do so in a manner contrary to what is suggested by optimal search models.

As a second analysis, I examined whether price magnitude (operationalized as the mean of the price distribution) influenced search persistence holding price dispersion constant (SD = $1,500). I tested three levels of price magnitude: low (M =

$10,000), moderate ($M$ = $20,000), and high ($M$ = $30,000). (Note: the moderate price magnitude condition is the same as in the previous analysis.) Economic models of search prescribe that price magnitude should be irrelevant to search persistence, as price dispersion is the critical factor. However, the data from this study suggest that participants tend to search more when price magnitude is highest (median number of dealerships visited = 10.5 vs. 8 and 9, Spearman's ρ = .09, bootstrapped 95% CI [-.05, .23]). Figure 2.3 shows this result graphically. I conducted another bootstrap analysis to determine the likelihood of observing greater median search persistence in the highest price magnitude condition (by two or more — the degree difference observed in the study) under the null hypothesis (no difference between experimental conditions). Once again, this analysis suggested this pattern did not arrive by chance. Only 2.2% of the simulations featured a result as strong as observed in the actual data.

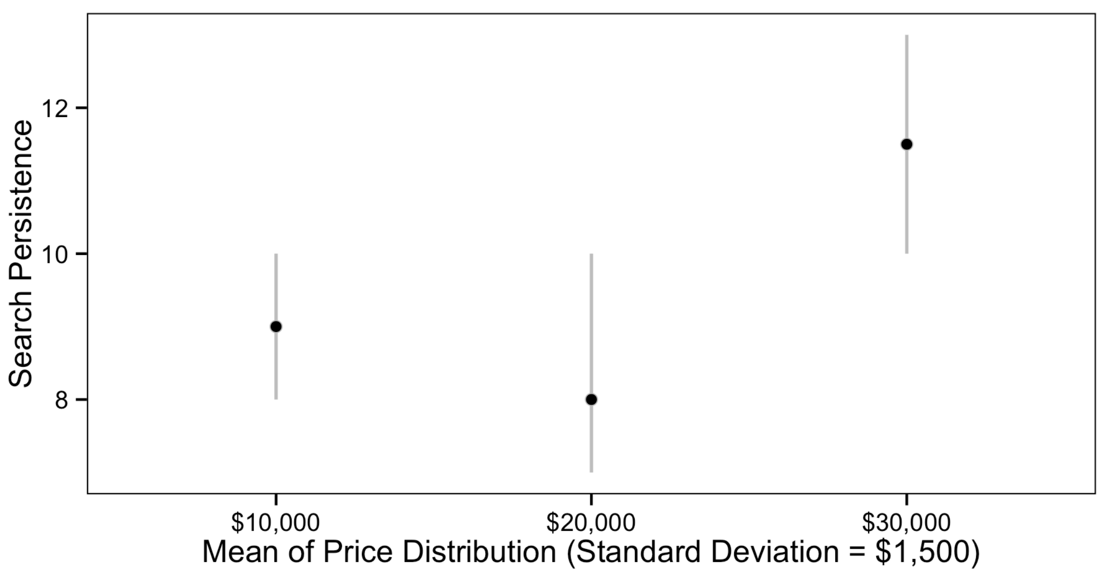


Figure 2.3. Search persistence holding price dispersion constant and varying price magnitude. Dots indicate median search depth by experimental condition and gray bars approximate the standard error (bootstrapped 68% confidence interval).

Discussion

In Study 2.1, I manipulated price dispersion and price magnitude and observed persistence in a simple price search task. Economic models of price search show that consumers should search more when price dispersion is high. However, I do not observe this behavior. Instead, it seems that the extent to which consumers incorporate price dispersion cues into search persistence, they do so in a manner opposite of what is suggested by economic models. In this study, consumers search the most when dispersion is lowest. A second result from Study 2.1 is that price magnitude, an inconsequential factor in economic models of search persistence, seems to produce differences is depth of search. Participants in Study 2.1 searched the most when price magnitude was high.

It appears that consumers are not appropriately sensitive to the primary diagnostic cue (i.e., price dispersion) during sequential search. Further, they appear sensitive to a cue that should, theoretically, be non-diagnostic (i.e., price magnitude). This raises the question: Why do consumers make these "mistakes?" In the remainder of this chapter, I propose that these deviations from normative search theory arise because consumers make inferences about price dispersion based on observed price magnitude. Specifically, I argue that consumers have *a priori* beliefs about the relationship between price magnitude and price dispersion. Given even a single price, I argue consumers will infer a level of price dispersion around that price (accounting for other situational information). Further, I argue that consumers believe there should be more price dispersion for more expensive items. Given these beliefs, variance neglect in search is not a misinterpretation of environmental cues, but rather a failure to update prior beliefs sufficiently in the presence of new information (i.e., the prices already encountered). In the next section, I present evidence that beliefs about the relationship between price magnitude and price dispersion are grounded in empirical reality. Further, because expensive items tend to have higher price dispersion, the behaviors I observe in Study 2.1 could be seen as ecologically rational (Pham 2007; Todd, Gigerenzer, and the ABC Research Group 2012).

The Empirical Relationship between Price Magnitude and Price Dispersion

Prices for the exact same product routinely vary between retailers (e.g., Isard 1977; Varian 1980). The reason for price dispersion has been a topic of much interest. Originally, search (or information) costs were implicated as the primary cause of price dispersion (e.g., Stigler 1961, but see Diamond 1971 and Rothschild 1973 for critiques of Stigler's approach and Burdett and Judd 1983 for a possible reconciliation). The gist of this argument is that a consumer who does not visit every retailer (due to costly search) will probabilistically pay a higher price than the lowest in the market (i.e., she will fail to visit the retailer with the absolute lowest price). Thus a retailer offering a price greater than the lowest available can still expect some sales (although it will be fewer than if the price was the lower) and will achieve a higher margin on these sales.

A challenge faced by search cost models of price dispersion is that the Internet has drastically reduced search costs in some markets, yet price dispersion in these markets remains relatively high (Baye, Morgan, and Scholten 2006; Brynjolfsson and Smith 2000). An alternative class of models, often called “clearinghouse” models because they assume the consumer has access to a directory of prices offered by different retailers, can explain price dispersion in the absence of search costs through consumer sophistication (Varian 1980), consumer loyalty (Rosenthal 1980), or costly price transmission (i.e., costly advertising, Baye and Morgan 2001). Behaviorally informed models have also been proposed, which can explain the persistence of price dispersion by imposing rationality constraints on consumers (e.g., limited computational abilities; Baye and Morgan 2004; Johnson et al. 2004).

More relevant to the current research: Observed price dispersion tends to be higher for more expensive products. For example, a survey of randomly selected consumer products in Boston revealed a power law relationship between observed mean price and observed standard deviation of price: Doubling the mean price corresponded to an 86% increase in standard deviation (Pratt, Wise, and Zeckhauser 1979). A subsequent survey replicated this result, showing a positive relationship between observed mean price and observed price range for various models of televisions, videocassette recorders, and microwave ovens across different retailers in a different U.S. city (Grewal and Marmorstein 1994). In short, the reality of the marketplace is that more expensive products tend to have greater absolute differences in price across retailers.

It is not well understood why more expensive products should have greater price dispersion across retailers. It may be simply that means and variances tend to be correlated in statistical distributions regardless of their nature (Neyman 1926). An economic rationale can be obtained by assuming price dispersion should be a function of aggregate consumer search (Stigler 1961). In this case, more expensive products may have greater price dispersion because they are purchased less frequently and thus represent a smaller portion of the average consumer's expenditures. If cheaper products are purchased more frequently, the benefits of extensive search can yield both immediate savings and future savings (i.e., better prices for subsequent purchases). Alternatively, psychologists have argued that references prices and diminishing marginal utility could alter the perceived benefits of search at different prices. This line of argument is related to the present investigation and I return to this topic in the general discussion. However, regardless of the cause — if search costs are the same — it remains more profitable to search from a high dispersion price distribution than a low dispersion price distribution.

Because price magnitude and price dispersion are correlated in the marketplace, consumers may — quite reasonably — learn to use price magnitude as a cue of price dispersion. Over time, a consumer might learn that searching extensively while shopping for a cheaper product typically yields minimal absolute savings. Additionally, she might learn that searching extensively while shopping for an expensive product can — occasionally, at least — yield significant absolute savings. Given the reality of the marketplace, a consumer who determined search persistence — for example, the number of stores she would visit — exclusively by the magnitude of the first price encountered, would tend to behave in a manner consistent with normative search models. However, the empirical relationship between price magnitude and price dispersion is not perfect. A consumer who relies solely on price magnitude to determine search persistence will often over-search (for high priced products with low dispersion) and under-search (for low priced products with high dispersion), wasting time or missing out on opportunities for savings.

Study 2.2: Consumer Beliefs about the Relationship between Price Magnitude and Price Dispersion

Previous research has shown that higher priced items tend to feature larger price dispersion, yet it is not clear whether the typical consumer knows this relationship exists. Economists in the 1970s were, for example, surprised by the degree of the relationship (Pratt, Wise, and Zeckhauser (1979) called it “puzzlingly high”, p. 205). Further, researchers have speculated that dispersion should decrease if consumers are more knowledgeable about the expected price distribution (Pratt, Wise, and Zeckhauser 1979; Sorenson 2000). This suggests the existent empirical relationship would not exist (or at least would be substantially weaker) if consumers indeed know that higher priced products are priced more disparately.

In this study, I attempt to measure consumer beliefs about the relationship between price magnitude and price dispersion. I present participants with six durable goods and an associated selling price for each ranging from $43 to $77,995. I then ask participants to guess the absolute minimum and maximum prices other consumers have paid for the exact same product. I find that consumers indeed expect higher price dispersion for more expensive products. Further, consumers are remarkably well calibrated in terms of the amount of price dispersion to expect at different price magnitudes.

Method

Three hundred participants, recruited through AMT, completed this survey as part of a larger block of studies. Each participant evaluated six durable consumer products with a corresponding selling price in random order. For each product, the participant was asked to guess the minimum price a consumer had paid for the exact same product and the maximum price a consumer had paid for the exact same product. These two measures are then combined to form a price range. An example stimulus is presented in Figure 2.4.

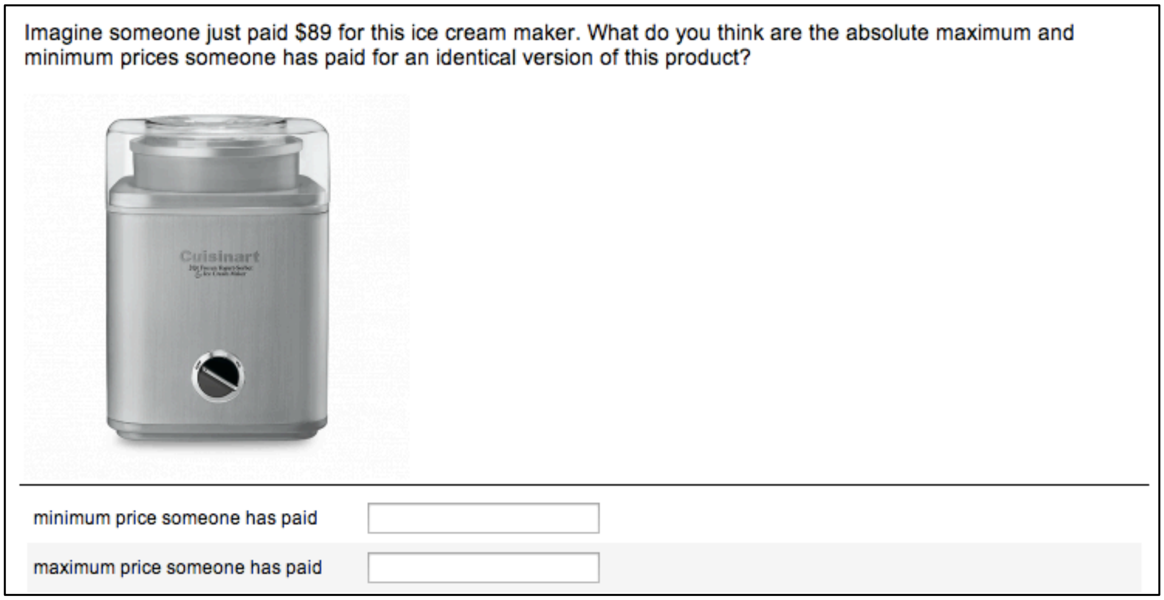


Figure 2.4. Sample stimulus from Study 2.2. Other products included a set of speakers ($409), a washing machine ($1,038), a recreational vehicle ($77,995), a jet ski ($8,499), and a watch ($43).

Results

As shown in Figure 2.5, participants in this study believed more expensive products would exhibit greater price dispersion. For each participant, I regressed the expressed price range (logged) on the price magnitude (the price given with the product, also logged). All 300 participants expressed a positive relationship between given price and expected price range (a positive beta coefficient in the regression). Further, participants seem well calibrated to the actual dispersion in the retail environment shown in previous reports (e.g., Pratt, Wise, and Zeckhauser 1979). The median participant beta (denoting the relationship between price magnitude and price dispersion) was .88 (bootstrapped 95% CI [.87, .89]). This is almost identical to .89, which was the empirical relationship previously found to exist in the marketplace for consumer goods (Pratt, Wise, and Zeckhauser 1979; Note: although this paper uses the standard deviation of prices as a measure of price dispersion and the current investigation uses price range, the beta terms are directly comparable given the assumption that price range is linearly related to the standard deviation of prices. In fact, if price range is approximated as four-and-a-half times the standard deviation of prices, the median intercept from the current investigation perfectly matches the previously found estimate of -1.52).

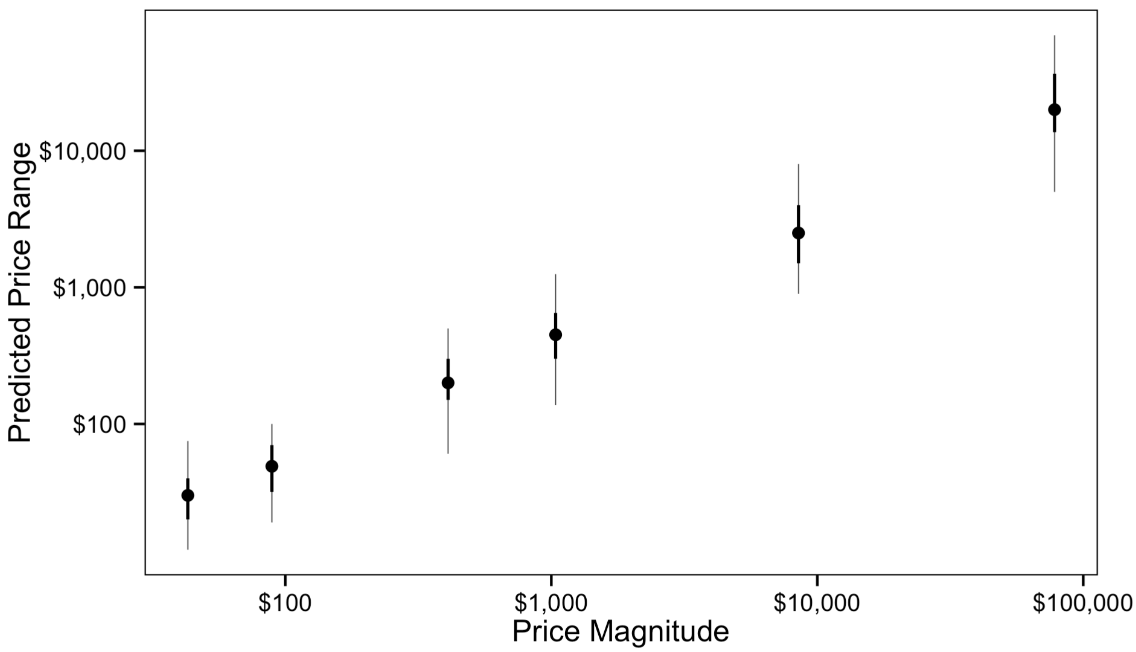


Figure 2.5. The range of prices consumers predicted to exist in the marketplace for six durable products at different price magnitudes (in log-log scale). Dots represent the median response, heavy black bars represent 50% of the data (the middle two quartiles) and light gray bars represent 90% of the data.

Discussion

Data from this study suggest participants indeed expect higher price dispersion for products with higher price magnitude. This belief correlates surprising well with the actual dispersion found in the marketplace at different levels of price magnitude. One possible criticism of this study is that participants may not have beliefs about the relationship between price magnitude and price dispersion, but may instead have beliefs about the price dispersion for the particular products under question. I address this criticism in the following study.

Because participants expect higher price dispersion around more expensive items, it would be consistent with these beliefs for participants to search more exhaustively for higher priced items: When dispersion is higher (in an absolute sense), the expected marginal benefit of continuing search is greater. Further, when price magnitude is held constant, it would again be consistent with these beliefs to search less when actual price dispersion is greater. When the actual price dispersion exceeds the expected price dispersion (i.e., a consumer's prior belief about price dispersion for a given price magnitude), the consumer will likely encounter a price that she perceives to be exceptionally good in fewer store visits. I illustrate the rationale behind this point in Figure 2.6.

The beliefs expressed in Study 2.2 could thereby map on to the results from Study 2.1: Participants searched more when the price magnitude was greater (and, presumably, they believed the price dispersion to be greater) and less (holding price magnitude constant) when price dispersion was greater. If beliefs about expected price dispersion (based on price magnitude) are influencing search persistence, a possible test is to look at individual differences in these beliefs: Participants who expect more price dispersion at a given price magnitude should persist longer when searching for a product priced at that magnitude. I examine this proposition in the following study.

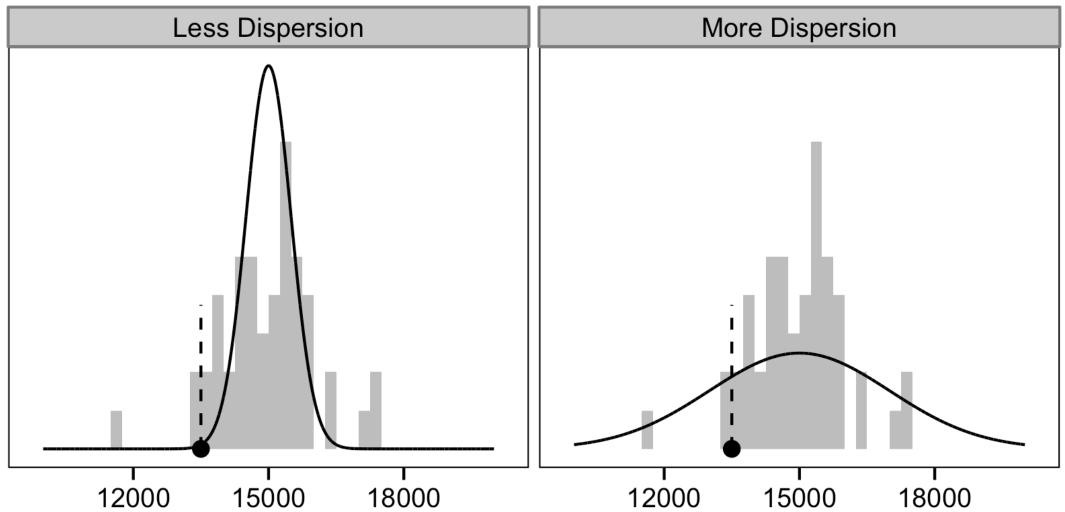


Figure 2.6. Illustration of how beliefs about price dispersion can influence search persistence. The gray histograms represent the "actual" distribution of prices available (M = $15,000, SD = $1,000). The black curves represent beliefs (less dispersion: M = $15,000, SD = $500, more dispersion: M = $15,000, SD = $2,000). When a person who believes there is less dispersion encounters the price of $13,500, she thinks it represents a good deal (.1% chance of encountering something better on the next visit) and is likely to terminate search. However, when a person who believes there is more dispersion encounters the price of $13,500, she thinks it represents an average deal (23% chance of encountering something better on the next visit) and is likely to persist further.

Study 2.3: Beliefs about Relationship between Price Magnitude and Price Dispersion Predict Differences in Search Persistence

If, as I propose, people's beliefs about the relationship between price magnitude and price dispersion influence search persistence, differences in search persistence should be observed based on the heterogeneity of these beliefs across people. If, for example, a consumer is searching for a good price for a product that has an average price of $15,000, her expectations for the price dispersion around $15,000 should influence her search persistence. If she believes that the dispersion in prices around $15,000 should equate to a standard deviation in prices of $2,000, but the actual standard deviation of prices is only $1,000, when she encounters a price that is actually a good deal (say, $13,500), she will be unlikely to perceive it to be a good deal, as her prior beliefs suggest that a better price could be found fairly easily. Conversely, if she believes that the dispersion should be $500, a price of $13,500 will seem like a much better deal than it actually is. This example is illustrated in the aforementioned Figure 2.6.

In the present study, I measure both beliefs about the relationship between price dispersion and price magnitude using a similar paradigm as in Study 2.2 and search persistence using a task similar to that in Study 2.1. I then examine the relationship between beliefs and search persistence and find the predicted correspondence: Participants who are projected to expect higher dispersion in the price search task persist longer than those who are projected to expect lower dispersion.

Method

One hundred sixty participants, recruited through AMT, participated in this study. The study consisted of three parts. In part one, participants completed a price search task in the same format as Study 2.1 (i.e., searching multiple dealerships for a new car). The mean and standard deviation of the price distribution were the same for all participants (*M* = $15,000, *SD* = $1,000). (An exploratory factor was included in the price search task: whether the price was a single value or a combination of a price plus a discount. This factor did not produce any significant differences in search behavior and controlling for it does not change the experimental results reported hereafter.)

In part two, participants completed a task similar to Study 2.2, in which they are given the price someone paid for a product and asked to guess the absolute minimum and maximum prices someone else has paid for the exact same product. An important change, however, is that participants were not told any information about the product: They are simply told, for example, “Someone just paid $312 for an item. What do you think the minimum price someone has paid for this item? What do you think the maximum price someone has paid for this item?” This removes the concern that the nature of the product (or product category) was driving the relationship observed in Study 2.2.

Finally, in part three, participants were asked a single exploratory item take from a standard maximizing tendency scale (Schwartz et al. 2002): “Do you agree with the following statement: I hold myself to a high standard?” This maximizing measure, perhaps surprisingly, did not correlate with search persistence (Spearman's ρ = -.04) and will not be discussed further.

Results

Beliefs about Price Dispersion. I first examined the expected price dispersion participants reported at different price magnitudes. Not surprisingly, I find a similar pattern of results as in Study 2.2. As shown in Figure 2.7, participants believed that more expensive products would have greater price dispersion. For each participant, I regressed reported range (logged) on the provided price magnitude (also logged). As in Study 2.2, every participant (except one who reported zero expected range for each product and is thus removed from this and future analyses) expressed a positive relationship between price magnitude and price range. The median participant beta (.74, bootstrapped 95% CI [.70, .79]) was slightly smaller in this study than Study 2.2 (median = .88), corresponding to a slightly lower level of expected dispersion at a given price magnitude. This may be due to the task characteristics (i.e., that a specific product was indicated in

Study 2.2 and not in the current study) or may be due to population differences (i.e., different participants on a different day).

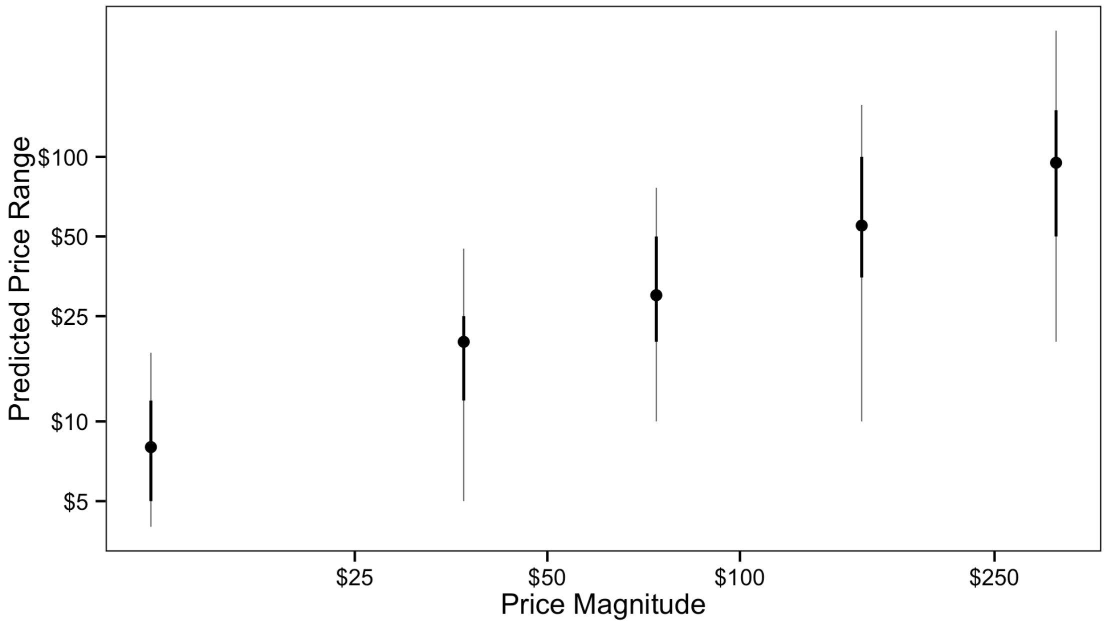


Figure 2.7. The range of prices consumers predicted to exist in the marketplace for five unknown products given a single retail price (in log-log scale). Dots represent the median response, heavy black bars represent 50% of the data (the middle two quartiles), and light gray bars represent 90% of the data.

Relationship between Beliefs and Search Persistence. Although all participants indicated a positive relationship between price dispersion and price magnitude, there was substantial heterogeneity in these beliefs (range of participant betas [.03, .134]). Using the coefficients from the participant-level regressions, I projected the expected price dispersion for each participant at a price magnitude of $15,000 — the actual price magnitude used in the price search task (part one of the study). The median participant expected the range of prices at this magnitude to be $1,534, while the 25th-percential participant expected a range of only $634 and the 75th-percential participant expected a range of $3,949.

I then examined how these expected differences in price dispersion corresponded to search persistence. As predicted, there was a significant positive relationship between expected price dispersion and depth of search in the price search task (Spearman's ρ = .21, bootstrapped 95% CI [.05, .36]; search persistence data from five participants are unavailable due to a programming error; all 154 remaining participants engaged in some search). Participants who expected more price dispersion at $15,000 (median split) searched more options (median = 14, bootstrapped 95% CI [12, 16]) than those who expected less price dispersion (median = 9, bootstrapped 95% CI [8, 12]; 97% of bootstrapped samples revealed a positive difference between the groups). The relationship between expected price dispersion and search depth is illustrated in Figure 2.8.

A possible concern with the study design is that participants completed both tasks in the same session and might make inferences about the second task based on aspects of the first task. Specifically, the variance in prices a participant observes in the first task (the price search task) might influence her estimates of price dispersion in the second task (the belief elicitation task). A participant who (by chance) observed less price variance in the first task might search less in that task (the normative response) and might also indicate expecting less variance at a given price in the belief elicitation task. This process would produce the observed effect in this study. However, the data suggest this is not the case: The correlation between the variance of observed prices in task one and the price dispersion beliefs expressed in task two (operationalized as the projected price dispersion at $15,000) was negative, not positive as the alternative account would require (Spearman's ρ = -.17).

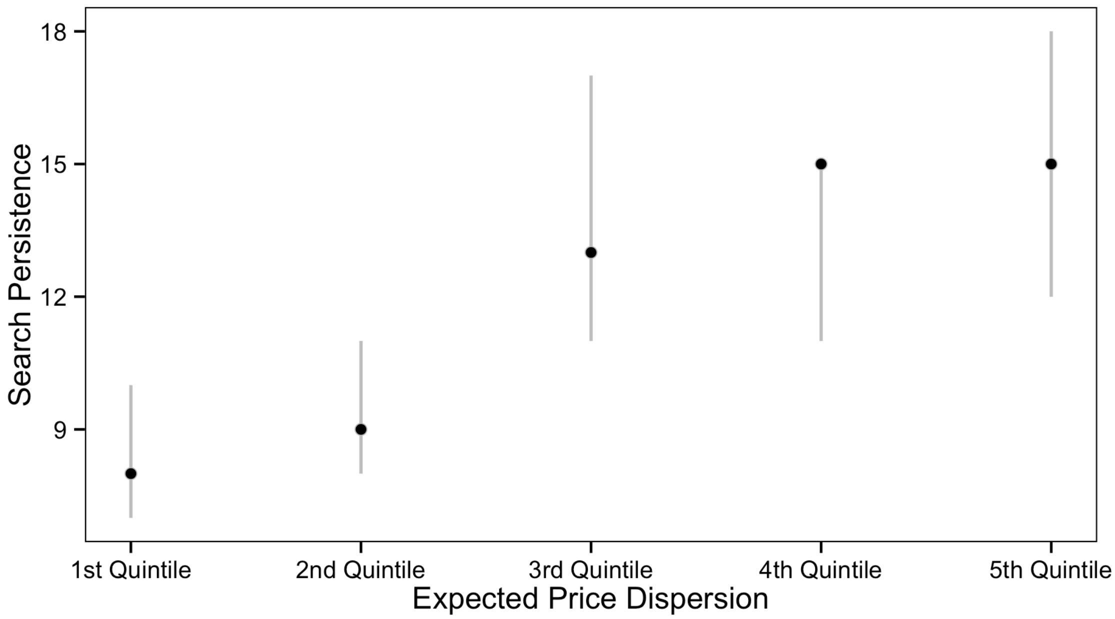


Figure 2.8. Median search depth by price-dispersion expectations. Participants were binned into five quintiles based on the price dispersion they were projected to expect at $15,000. Participants with the lowest expected dispersion are in the "1st Quintile" and participants with the highest expected dispersion are in the "5th Quintile." Dots represent the median search depth for each bin (*N* = 30 or 31) and the gray bars represent the bootstrapped 68% confidence interval for the median (which approximates the standard error). Note there is an increasing trend: Those participants who expected the more price dispersion searched more than those who expected less.

Discussion

In Study 2.3, I provide evidence that a consumer's expected price dispersion at a given price magnitude influences search persistence at that price magnitude. Participants in the study who believed there would be greater price dispersion for a product with the mean price of $15,000 searched more retailers (in this case car dealerships) than those who expected less price dispersion. In the following study, I examine how these beliefs about price dispersion (i.e., how it relates to price magnitude) influence search behavior in various environments. These beliefs should lead to behavior consistent with microeconomic models of search when the environment corresponds to beliefs (i.e., when more expensive products have greater price dispersion). However, when the environment violates consumers' prior beliefs (i.e., when less expensive products have greater price dispersion), it is not clear whether (or how quickly) consumers will update their expectations about price dispersion when faced with belief inconsistent information (i.e., the first prices they encounter).

Study 2.4: Simultaneous Price Search in Different Dispersion Environments

In this study, I utilize a new paradigm in which participants simultaneously search for good prices for two different products. Searching for multiple products at the same time is a common occurrence in daily life. For example, booking a business trip often involves simultaneously searching for a flight, rental car, and hotel. Likewise, trips to the grocery store usually consist of looking for good deals on multiple different products. Besides being externally valid, this paradigm allows me to observe the same participant searching through two different price distributions. This within-participant design yields several benefits.

First, I am able to vary both price magnitude and price dispersion within participant. This allows for more powerful statistical tests because I am able to control for each individual participant's tendency to persist at search. Further, this design gives the participant a better chance at determining the relative value of search for each product. After seeing several prices for each product, a perceptive participant could infer which of the two products is likely to have greater price dispersion (and thus should receive more search effort). In fact, after observing only three prices for each product, the observed standard deviations will indicate for which product search will be more profitable 80% of the time (based on the distribution parameters used in the study). Thus, the design provides participants with a realistic opportunity to quickly acquire information about the relative value of search and allocate their effort accordingly. In this sense, observing variance neglect in this paradigm is stronger evidence that consumers are failing to use the available diagnostic cues to determine their persistence in price search.

A second, related, benefit is that searching for one product in this design entails an opportunity cost that I (as the researcher) am able to observe. Specifically, the participant can be seen as allocating search effort between the two products. Effort allocated to searching for one of the products is effort not allocated to searching for the other product. I am thus able to quantify the misallocation of search effort for each consumer and — counterfactually — to estimate how much each participant could have saved by allocating her search effort more appropriately.

A final benefit is that, between participants, I am able to manipulate the “state of the world” for each consumer. Specifically, I am able to manipulate the relationship between price magnitude and price dispersion across the two products. For some participants, price magnitude will correlate positively with price dispersion (i.e., the more expensive product will have greater price dispersion). This “state of the world” should match participants' prior expectations. Thus, participants who based their search persistence on price magnitude should exhibit behavior consistent with the prescriptions of normative models of search (i.e., more search for the product with more price dispersion). However, for other participants, price magnitude will correlate negatively with price dispersion. Based on their expectations, participants should be predisposed to search more for the higher priced product (which in this case will have lower price dispersion). I am able to observe whether participants in this condition update their beliefs and adjust their search strategies accordingly.

As I have argued, inferring price dispersion from price magnitude is ecologically rational: Typically, higher priced products will have higher price variance. However, there are exceptions to this rule. For example, in the data collected by Pratt, Wise, and Zeckhauser (1979), a Raleigh Grand Prix is a relatively expensive product (*M* = $145) with relatively low price dispersion (*SD* = $6) and a canvas cover for a truck is a relatively cheap product (*M* = $40) with relatively high price dispersion (*SD* = $29). If participants can detect these less common cases during price search, they can save both time and money. This experiment is able to test whether consumers can identify these types of situations, by varying the "state of the world" to which they are exposed.

Method

Two hundred participants, recruited from AMT, completed this study as part of a larger block of studies (one participant could not be matched to a response and is thus excluded from the analyses; two additional participants did not engage in any search and are also excluded). Participants were given a similar description of the price search task as in previous studies with one critical exception: Participants were told they would be searching for two flights simultaneously. (Flights were used in this study instead of cars to better fit the experimental paradigm of simultaneous search.) The flights were described as different legs for the same trip. Further, participants were provided a monetary incentive to try to find a good deal: Five participants who found "good prices" would receive a $2 bonus payment after the task. (I awarded the bonus payment to the five best performers relative to their experimental condition.) The experimental interface is shown in Figure 2.9.

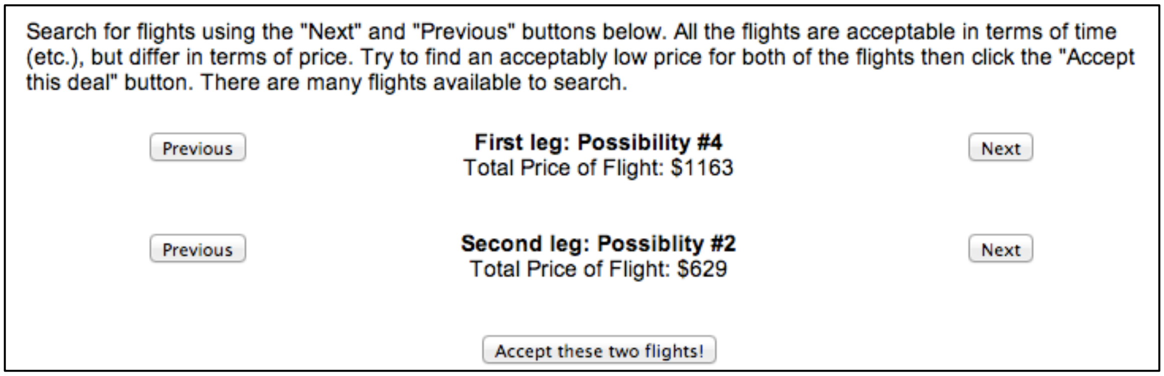


Figure 2.9. Experiment interface used in Study 2.4.

In the flight search task, participants searched simultaneously for a high priced flight (prices drawn from a normal distribution with a mean of $1,200) and a low priced flight (prices drawn from a normal distribution with a mean of $600). Order of the flights on the screen was counterbalanced. The dispersion of the flight prices (operationalized as the standard deviation of the price distributions) varied by experimental condition. Participants were randomly assigned to one condition in a 2 (dispersion for high priced flight: high (*SD* = $90) vs. low (*SD* = $45)) × 2 (dispersion for low priced flight: high (*SD* = $90) vs. low (*SD* = $45)) design.

The experimental design yielded two conditions ("states of the world") in which both flights had equal price dispersion: a "high dispersion" condition (*SD* = $90 for both) and a "low dispersion" condition (*SD* = $45 for both). The design also yielded two conditions ("states of the world") in which the flights had unequal price dispersion. In one of these conditions, the differences in price dispersion matched participant expectations: The more expensive flight had greater price dispersion (*SD* = $90) and the cheaper flight had less price dispersion (*SD* = $45). In the other condition, the differences in price dispersion violated participant expectations: The more expensive flight had less price dispersion (*SD* = $45) and the cheaper flight had greater price dispersion (*SD* = $90).

The expected marginal return from search is greater when price dispersion is higher. Thus, when comparing the two equal price dispersion conditions, participants should search more when the price dispersion is greater for both flights compared to when it is smaller. However, if — as I propose — participants enter the task with expectations of price dispersion (based on the price magnitudes) and insufficiently adjust from these beliefs, the opposite behavior should emerge: Participants should search more when price dispersion is smaller for both options.

When comparing the two unequal price dispersion conditions, the economic prescription is that participants should search more for the high dispersion flight (regardless of whether it is the more or less expensive flight). In fact, the optimal ratio of search should favor the higher dispersion option approximately 2-to-1 (in aggregate). When the more expensive flight has greater price dispersion, the environment should match the expectations of participants and thus I expect their behavior to approximate the normative prescription. Because this is the typical state of the environment, this would be evidence that a heuristic for estimating dispersion by price magnitude is ecologically rational. That is, given the typical state of a consumer's environment, determining search persistence by price magnitude will usually yield sensible results.

While normative search theory and the proposed dispersion expectation theory make the same prediction for the condition in which the environment matches expectations, the predictions from the two theories diverge for the condition in which the environment contradicts expectations. When the cheaper flight has greater price dispersion, normative models of search would prescribe focusing search effort on this option (again, at approximately a 2-to-1 ratio). However, if beliefs about the expected dispersion guide search persistence, participants would still be predisposed to search more for the higher priced option (which happens to be low in price dispersion). It is unclear whether participants will learn from feedback and adjust their beliefs leading to behavior more inline with normative predictions. Or, alternatively, if their initial beliefs will persist and they will search even more for the high priced flight (because it will take even longer to find a price that is good based on their prior beliefs) and even less for the low priced flight (because they will find a good price based on their prior beliefs quickly).

In sum, economic theory always prescribes more search when price dispersion is higher. However, if — as I propose — consumers form an inference about the expected price dispersion based on price magnitude, you should expect: (1) participants to search more for the higher priced flight compared to the lower priced flight (within-subject), (2) participants to search more in aggregate when both flights have low price dispersion compared to when both flights have high price dispersion (between-subjects), and (3) participants to approximate the normative economic predictions when the "state of the world" features a positive correlation between price magnitude and price dispersion. For the condition in which the "state of the world" violates participants' expectations (i.e., price magnitude and price dispersion are negatively correlated), it is not clear based on the proposed inference theory how participants will behave. The environment provides participants with the opportunity to learn that their *a priori* beliefs are incorrect (and thus adjust behavior accordingly) through search. I test whether or not they will do so.

Results

As a first level of analysis, I examined search persistence for the high priced and low priced flights irrespective of experimental condition. Replicating the result pattern from Study 2.1, participants searched significantly more options for the higher priced flight (median = 12, bootstrapped 95% CI [11, 14]) than the lower priced flight (median = 7, bootstrapped 95% CI [5, 9]; 99.99% of bootstrapped samples revealed a positive difference). Further, within the higher priced flight, participants searched more options when the price dispersion was smaller (median = 14, bootstrapped 95% CI [11, 15]) than when dispersion was greater (median = 11, bootstrapped 95% CI [10, 13]; 86% of bootstrapped samples revealed a positive difference). Similarly, within the lower priced flight, participants searched more options when the price dispersion was smaller (median = 9, bootstrapped 95% CI [6.5, 10]) than when dispersion was greater (median = 5, bootstrapped 95% CI [4, 8]; 96% of bootstrapped samples revealed a positive difference). These differences — which are the opposite of the behavior prescribed by normative search theory — also replicate the pattern of results from Study 2.1. The results by condition are shown graphically in Figure 2.10.

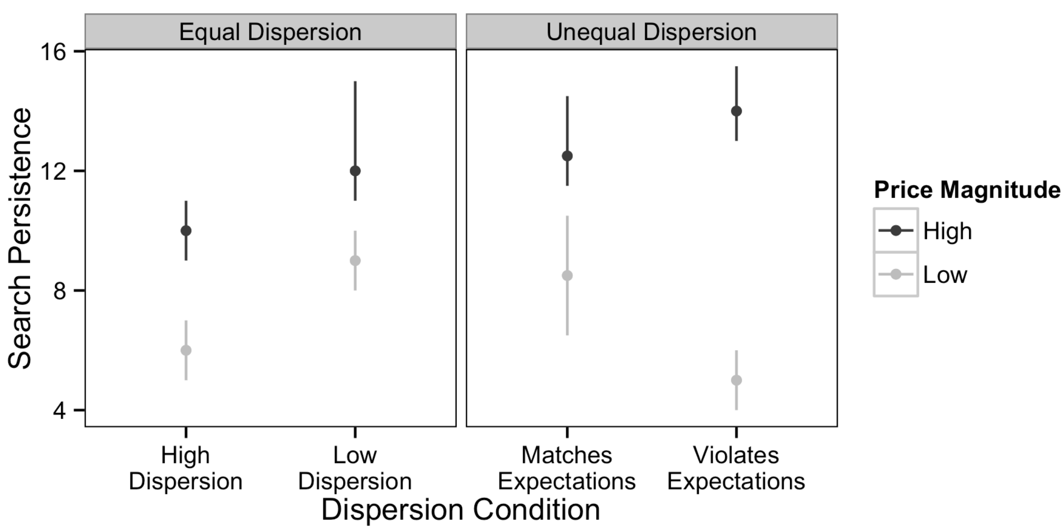


Figure 2.10. Search depth by condition in Study 2.4. Each participant searched simultaneously for a high priced flight (M = \$1,200) and a low priced flight (M = \$600). Thus each condition is represented by two dots representing the median search persistence for each of the two flights. Bars approximate the standard error (bootstrapped 68% confidence interval).

As a second level analysis, I examined search differences across both flights in the different dispersion environments. First, I looked at the two conditions in which both flights had equal price dispersion (left panel of Figure 2.10). When price dispersion was higher for both flights, participants — violating the prescription of normative search theory — searched less than when price dispersion was lower for both flights. In the high dispersion environment, the median search depth was 10 (bootstrapped 95% CI [8, 12]) for the more expensive flight and 6 (bootstrapped 95% CI [4, 9]) for the cheaper flight. In the low dispersion environment, the median search depth was 12 (bootstrapped 95% CI [10, 15.5]) for the more expensive flight and 9 (bootstrapped 95% CI [6, 10]) for the cheaper flight. 94% of bootstrapped samples revealed greater median search (summed) for the two flights in the low dispersion environment compared to the higher dispersion environment. This result is consistent with the proposed inferential process: When dispersion exceeded expectations, consumers searched less presumably because they were able to find an acceptable price (with respect to the price dispersion they inferred) in fewer searches.

I next looked at search differences across both flights in the two conditions with unequal price dispersion (right panel of Figure 2.10). In the condition where price dispersion matched expectations (i.e., the more expensive flight had greater price dispersion), participants — correctly, according to normative theory — indeed searched more for the flight with more price dispersion (median difference = 4, bootstrapped 95% CI [1.5, 8]). However, participants in the condition where price dispersion violated expectations (i.e., the more expensive flight had smaller price dispersion), participants — incorrectly, according to normative theory — searched less for the flight with more dispersion (median difference = -9, bootstrapped 95% CI [-12.5, -6]). Instead of shifting their search effort to the more profitable search option (which, in this case was the lower priced flight because it featured greater price dispersion), they instead focused their search effort on the less profitable option. Seventy-five percent of participants in this condition searched more for the low dispersion option compared to the high dispersion option.

When participants were placed in an environment that did not match their expectations (i.e., where price magnitude was negatively correlated with price dispersion), they failed to efficiently update their beliefs. Most participants had ample information — if they chose to attend to it — to learn that the lower priced product had more price dispersion (median observed SD = $94 for the lower priced product vs. $43 for the higher priced product). Instead of adapting their search strategy based on this information, they instead searched even more for the higher priced product (vs. the lower priced product) compared to participants in the condition in which the environment matched their prior expectations (median difference between search depth for high and low priced flights between conditions = 5, bootstrapped 95% CI [-0.5, 9.5]). This result is consistent with past research on "sticky" decision makers: Consumers frequently adopt a strategy for dealing with a specific decision which then persists to subsequent, often unrelated, decisions (Amir and Levav 2008; Broder and Schiffer 2006; Evangelidis and Levav 2013; Levav, Reinholtz, and Lin 2012; Luchins 1942).

I ran a counterfactual simulation to determine how much each participant could have saved by adopting a more appropriate search strategy. Holding their "search budget" constant (i.e., the total number of times they searched for both flights combined) and simply allocating equal search effort to both products would have saved the average participant $44 (the average price paid for both flights was $1650) in the condition where the environment violated prior expectations. In sum, variance neglect is persistent and costly even in environments where a direct comparison of variance can be made to a reference product.

Discussion

Study 2.4 replicates the basic results from Study 2.1: Participants tend to search more when price magnitude is higher and tend to search less when price dispersion is lower. Further, this study illustrates how these heuristics can be ecologically rational: When the environment features a positive correlation between price magnitude and price dispersion, the behavior of participants approximates the normative prescriptions. However, when the environment violates participant expectations (i.e., a negative correlation between price magnitude and price dispersion), participants adjust their search effort allocation in the opposite manner prescribed by economic theory. In other words, they search even more for the high priced option when the price dispersion is lower and search even less for the low priced option when price dispersion is higher. This result can be seen as participants insufficiently updating their beliefs and, instead of recognizing that their *a priori* conceptions of a good deal are suboptimal, accepting a price too quickly for the high dispersion (low priced) option and persisting too much at search for the low dispersion (high priced) option.

General Discussion

Summary and Implications

In this chapter, I argue that consumers have prior beliefs about what price dispersion to expect at a given price magnitude. In other words, when a consumer is looking for the best deal for a given product, she will form a representation about how the prices are likely to vary (in absolute magnitude) based on the average price (or first price) for that product. For more expensive products, consumers expect higher price variation. I argue that these beliefs, in turn, influence search persistence. When a consumer believes the price dispersion is greater than it actually is, she will likely persist too long at search. This is because the prices she encounters — even if they are good deals compared to the actual prices at other retailers — will not seem very good based on her prior expectations. Further, when a consumer believes that price dispersion is smaller than it actually is, she will exhibit the opposite behavior: She will likely accept an early encountered price that is only a marginal deal (by the standards of the actual prices available) because it will seem like an excellent deal based on her prior expectations.

Forming an expectation of price dispersion based on the average price is, for the most part, a reasonable heuristic. Price magnitude and price dispersion are strongly correlated in the marketplace. Further, judgments of averages are much easier to make (and more accurate) than those of variance (Beach and Scopp 1968), so a heuristically linking the two provides for cognitive efficiency. The problem with these expectations arises in two cases: (1) When a less expensive product has high price dispersion, consumers will often under-search and miss out on potentially large savings. (2) When a more expensive product has low price dispersion, consumers will often over-search and waste time and — sometimes — money.

Highlighting the second issue, many manufacturers of high priced products have adopted retail price management strategies, effectively limiting the dispersion in prices across retailers. One prominent practitioner of this strategy is Apple. Apple products tend to be expensive and feature limited price dispersion across retailers. One implication of this research is that consumers are likely over-searching for a good price on Apple products. Anecdotal evidence for this can be seen in Google Trends: Despite being purchased less often, the average frequency of search (in the United States) on

Google Shopping for the keyword “iPhone” is about seven times greater than the frequency of search for the keyword “Android.” Including “price” as an additional search term reveals an even stronger difference (a 22-to-1 ratio).

Psychophysics of Price

Previous research has suggested that relative — not absolute — savings motivate consumer search. For example, people expressed a higher willingness to incur the cost of a 20-minute commute to save $5 on a $15 calculator than to save $5 on a $125 calculator (Thaler 1985; Tversky and Kahneman 1981). Building from this research, Grewal and Marmorstein put forth a psychophysics-of-price hypothesis: “Consumers' willingness to spend time comparing prices to achieve a fixed amount of price savings is negatively related to the price of the item” (1994, p. 155). Indeed, consumers who had just purchased a durable item at a higher cost expressed a lower willingness to spend time to save an addition fixed amount (either $20 or $40).

The implications of the current investigation are largely consistent with these prior results. Indeed, participants in the previously described studies seemed less satisfied (measured by likelihood to continue search) with a fixed absolute discount from the mean price when the mean price was higher. However, there are several differences between my results and the results of the previous studies. First, in the current study I separate the effect of price magnitude and price variation. Second, I provide a belief-based explanation for why people may be willing to exert more search effort for higher priced items (Studies 2.2 and 2.3). Third, I am looking at a repeated observation search problem as opposed to one time choice, addressing and entirely different research question of stopping time based on price dispersion. Fourth, the current investigation presents a more optimistic view of consumer behavior: Participants in my studies were more willing to expend search energy for more expensive priced products holding price dispersion constant. So while a consumer might not want to drive 20 minutes to save $5 on a $125 calculator compared to a $15 calculator, my research suggests that the same consumer is more willing to search extensively for that same $125 calculator than she would be for the $15 model.

References Prices in Search

Previous research has also suggested that reference prices can lead to asymmetries in consumer search. Specifically, consumers have been shown to search more when they encounter prices above an established reference and less when they encounter prices below an established reference (McGee 2012). This finding is supported by prospect theory (Kahneman and Tversky 1979), which suggests that a loss of a fixed amount is more psychologically impactful than a gain of the same magnitude. The present investigation does not involve clear reference points, so it is unclear how reference effects could manifest in the observed results. If the first (or mean) price serves as a reference point, it is not clear why differences in search would be observed based on price magnitude. Alternatively, as mentioned in the previous section, the presented results are consistent with consumers having very low reference point and a concave value function. However, this account does not provide a direct explanation for the accuracy of consumers' price dispersion beliefs nor the correlation between these beliefs and search behavior.

Limitations and Future Directions

While the previous studies show a robust empirical trend in consumer search that contradicts predictions from normative search models, a few limitations should be mentioned. First — and most critically — the incentive for participants to find a good price is not always clear. For a consumer shopping for a real product, increasing search will (probabilistically) decrease the amount of money she will pay (and thus give up) upon purchase. Although I use an incentive compatible design in Study 2.4, it is unlikely to produce the same psychological impact as the prospect of saving/spending more significant sums of money. Future studies will attempt to address this issue by endowing participants with money at the start of the experiment and having them "spend" that money on the items for which they search. By allowing them to keep what they save, the experiments will more closely mimic actual consumer price search.

A related criticism involves the paradigm used and the extent to which it is externally valid. It is worth considering whether "search" in my experiments appropriately captures the relevant dynamics of real consumer search. I chose a paradigm that closely adhered to the assumptions typically made in the economics literature (e.g., known search cost, homogenous products), but future research should examine whether consumers behave differently when some of these parameters are relaxed (e.g., searching through different products from the same product category).

Future research should also address more directly the process of belief updating. In Studies 2.2 and 2.3, I provide evidence that consumers make price dispersion inferences based on price magnitude. Further I show that these inferences are predictive of search persistence. However, I do not show the process of how — if at all — consumers update their beliefs in response to observed prices. Beliefs must be updated to some extent, or else situations could arise in which participants would search indefinitely (i.e., a product with absolutely no variation in price across retailers). Study 2.4 suggests this updating process is likely to be slow, but more careful examination is warranted.

Finally, besides normative factors, there are many psychologically interesting variables that can be examined in the price search context. Future research could compare, for example, differences in price search behavior when the product is needed (e.g., a car repair) versus simply desired (e.g., a new record album). Other potentially interesting factors include temporal distance (e.g., searching for something to use now vs. later), gain-loss framing (e.g., searching through discounts vs. prices), reference points (e.g., previous prices paid), and product familiarity (e.g., is it a product for which the consumer has some *a priori* knowledge about possible prices).

Conclusion

Economic treatments of search theory and optimal stopping suggest that price dispersion should be the predominant determiner of consumer search. When price dispersion is higher, the marginal expected benefit of additional search is greater. However, I find that consumers do not follow this economic prescription. In fact, consumers tend to search less when price dispersion is greater and search more extensively for more expensive products, another deviation from normative search prescriptions. I propose that consumers' beliefs about the relationship between price magnitude and price dispersion can explain both of these results. Specifically, I argue that given a price magnitude, participants expect a certain level of price variation. This expected variation increases with price magnitude. Typically, these beliefs serve the consumer well, but when the environment violates consumer expectations they can lead to the accrual of unnecessary search costs or the failure to reap substantial savings.

The results in this chapter can inform managerial decisions regarding product pricing and promotion. An obvious implication is that retailers (and product managers) should expect customers to search more for higher priced products. A retailer in competition with a neighboring store might be well served by offering the best price on the more expensive products, but offering a slightly higher price (comparatively) on the cheaper products (as consumers will be less likely to search for these). A second potential implication involves pricing strategies. Brands that employ retail price management strategies (such as Apple) — and thus have less price dispersion for their products — might be best served making this clear to their customers. The present research suggests that a consumer who wants to buy an Apple computer might spend an extensive period searching for the best price (as she will expect more dispersion than actually exists). Some potential purchases may be lost during this period of search if the customer become frustrated or finds a competing product with a better price. By making it clear that the customer is unlikely to find a price below the suggested retail price, brands like Apple could try to persuade customers to limit their search effort. A final managerial implication involves advertising. A retailer might benefit from advertising their store in conjunction with their prices for high price, low dispersion products. As consumers will tend to search more for these products, this might be a way to get noticed by potential customers who are unfamiliar with the retailer. Although this might not translate into sales of the advertised product, it may have downstream benefits in terms of brand recognition and store consideration.

CHAPTER THREE:

A Cognitive Model of Persistence in Consumer Price Search

Consumers frequently engage in price search: The process of looking for a good price for a product or service they plan to purchase. For example, a consumer might know the exact type of computer she wants to buy, but does not know which retailer will sell it for the lowest price. She must then undergo a process of visiting retailers ("visiting" here can mean driving to the store, calling for a price quote, or simply accessing a website) to determine the possible prices available. The more retailers a consumer visits, the better price — on average — she will find. However, visiting retailers entails a cost (in time and/or money). The important tradeoff in price search is whether the expected marginal benefit of visiting another store (and possibly finding a better price) is greater than the expected cost of visiting that store. When the cost exceeds the expected benefit, a consumer should stop and select the best price she has previously seen.

Economic models have been developed for how consumers *should* conduct price search (e.g., Rothschild 1974; Stigler 1961). Yet consumers frequently violate the prescriptions of these models. Specifically, consumers have been observed to search more for higher priced products and products with less price dispersion (see Chapter 2). Consumers have also been shown to search more above a reference point than below (McGee 2012) and to be unduly influenced by recently seen options (Häubl, Delleart, and Donkers 2012).

In this chapter I develop the framework for a cognitively plausible model of consumer price search. At the core of the model is a process by which consumers are assumed to generate and update a reference distribution of possible prices. The reference distribution is assumed to be discrete and finite (i.e., composed of a sample of possible prices) and consumers are assumed to search until a previously seen price achieves a sufficient rank in the reference distribution (e.g., better than 90%). I describe the model and necessary parameters in a subsequent section.

The model proposed in this chapter is able to account for many of the "mistakes" consumers make with respect to normative models. The proposed distribution generation process provides an explanation for the observed influences of price magnitude and price dispersion. Holding price dispersion constant, the model predicts more search when price magnitude is higher. Holding price magnitude constant, the model predicts more search when price dispersion is lower. Further, the proposed distribution updating process provides an explanation for local contrast effects (i.e., the overweighting of recently encounter prices; Häubl, Delleart, and Donkers 2012) and the proposed generating process can account for reference point effects (McGee 2012).

Mental Representations of Statistical Distributions

Humans live in a stochastic world. Almost every choice — from choosing the best way to get home from work to choosing the best way to invest for retirement — involves a probabilistic component. Critically, the outcome space for most of these decisions is continuous: the length of a delay caused by rush hour traffic or the percent return for a given mutual fund. Yet the question of how humans represent knowledge of probability distributions (vs. binary probabilities) has received surprisingly little academic attention.

Past research has examined this question (indirectly, perhaps) using different methods to elicit a decision maker's subjective probability distribution (e.g., Garthwaite, Kadane, and O'Hagan 2005). Results suggest that a decision maker can fairly accurately retrieve (or construct) the central tendency (specifically the median or mode) of a represented probability distribution (Beach and Swenson 1966; Peterson and Miller

1964; Spencer 1961). However, attempts to accurately elicit the variance of a represented distribution have proved more difficult (e.g., Beach and Scopp 1968). A popular technique for attempting to elicit variance estimates involves asking participants for credible intervals (e.g., the upper and lower bound for 50% of the distribution). Participants in these studies tend to be overconfident, expressing intervals that are too small (Lichtenstein, Fischhoff, and Phillips 1982).

Research work, however, has shown that decision makers can express fairly accurate estimates of statistical variance when given the appropriate response format. Specifically, participants are quite adept at reconstructing a discrete distribution from memory when they are able to do so using a graphical interface (Goldstein and Rothchild 2014). Using a "balls and bins" type interface (Delavande and Rohwedder 2008), participants recreated distributions from which the mean and variance was calculated. These calculated estimates were much closer to those of the actual empirical distribution compared to estimates of mean and variance from the more common point and interval techniques.

In sum, previous research suggests that humans do not represent continuous probability distributions in terms of parameters such as mean and variance. Alternatively, it seems possible that humans represent continuous probability distributions as finite sets of discrete outcomes. This notion is consistent with recent models of decision making that posit humans make choices by retrieving only a limited number of items from memory (Giguère and Love 2013; Nosofsky and Palmeri 1997; Stewart, Chater, and Brown 2006).

In the model I describe in the next section, I assume that consumers indeed represent probability distributions as finite sets of possible outcomes. Specifically, I assume that consumers represent the distribution of possible prices for a product in the marketplace as a limited number of specific prices.

A Model of Consumer Price Search

In this section, I describe a computational process that can be used to model the behavior of consumers undertaking price search. Although I make assumptions in this model that are cognitively plausible (i.e., a human decision make could carry out the computations; see Gigerenzer, Hoffrage, and Goldstein 2008 for further discussion about cognitive plausibility), I do not mean to suggest that this model replicates the exact process by which consumers carry out price search. By specifying a model, I do — however — make explicit assumptions and testable predictions that can be examined in future research.

Reference Distribution

A key aspect of the proposed model is the reference distribution. When conducting price search, the consumer is assumed to possess a mental representation of the possible dispersion of prices that could exist in the marketplace. This distribution is assumed to be discrete and finite. In other words, it is composed of a set of *N* possible prices. For simplicity, I will call the specific prices in the reference distribution "particles" — a reference to particle filtering models of Bayesian updating (e.g., Pitt and Shephard 1999). The reference distribution of particles is updated upon seeing new prices and used to evaluate whether the current price (or a previously seen price) is good enough to merit stopping search.

Distribution Generation. If the consumer begins a price search task without any prior knowledge about the existent prices in the marketplace, I propose that the reference distribution of particles is created from *N* draws from a normal distribution with mean equal to the first price encountered and a standard deviation that is a function of the first price encountered. Specifically, I propose that the generating distribution will have:

$$M = PRICE_1$$

$$SD = e^{\alpha+\beta(ln(PRICE_1))}$$

This generating distribution is consistent with the power law relationship between price magnitude and price dispersion that has previously been documented in the marketplace (Pratt, Wise, and Zeckhauser 1979). More importantly, it is consistent with consumer expectations for price dispersion as elicited from a single price (see Chapter 2, Studies 2.2 and 2.3).

Two alternative cases merit brief discussion: (1) If a consumer has a reference price in mind (or one is provided), the reference price should be used to populate the initial price dispersion representation (instead of the first price encountered). (2) If consumers begin price search with specific expectations regarding the price dispersion for a given product/service, the initial distribution should be a function of these expectations. Methods to determine these specific expectations should be developed, but preliminary estimates can be acquired by surveying the actual price dispersion for the product/service in the marketplace and randomly sampling *N* of these prices to serve as the initial distribution of particles.

Distribution Updating. When the consumer encounters a new price, I assume the reference distribution is updated to account for this new information. The updating process consists of two steps:

First, the old distribution "decays." In other words, some of the previous N particles are removed/deleted from the represented price distribution. I propose modeling the processes as a fixed probability of decay for each particle (λ_{rep}). Thus, the probability that any given particle leaves the reference distribution is λ_{rep} and the probability that it remains in the distribution is 1- λ_{rep}.

After some of the particles decay, I propose they are replaced through a similar process that generated the initial distribution. Replacement particles are randomly drawn from a normal distribution with a mean of the most recently seen price (i.e., $M = PRICE_i$) and a standard deviation that is a function of the most recently seen price (i.e., $SD = e^{\alpha+\beta \ln(PRICEi)}$). Thus with each newly seen price, the central tendency of the distribution of particles shifts towards the most recently seen price.

Stopping Decision

In this model, the decision to terminate search and select a previously seen price is governed by a threshold rule. The threshold, τ, is not based on a specific price, but rather based rank in the reference distribution. If the lowest price a consumer has observed is better than τ particles in the reference distribution, the consumer will stop search and select that best price.

An additional parameter can be included in the model if previously seen prices must be stored in the consumer's memory. This parameter, λ_{mem}, represents the decay of previously seen prices in a consumer's memory and functions much like the decay parameter in the particle distribution. Each time the consumer sees a new price, the previously seen prices which remain in memory have a probability of λ_{mem} of being forgotten. The stopping rule then becomes whether the minimum *remembered* price is better than τ particles in the current reference distribution.

General Discussion

In this chapter, I motivate and define and computational model to approximate human behavior in price search. The proposed model can account for many of the observed deviations from normative search theory. First, because the variance of the generated reference distribution is a function of price magnitude, the model predicts less search when price magnitude is lower (holding price dispersion constant) and more search when price dispersion is lower (holding price magnitude constant). Second, because the reference distribution moves towards recently seen prices, local contrasts (i.e., the difference between subsequent prices) can influence stopping decisions. Finally, if a reference price is used to form the initial distribution, the model predicts more search when searching through prices above (vs. below) this reference point.

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