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Measuring the Factors Influencing Purchasing Decisions: Evidence From Cursor Tracking and Cognitive Modeling

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Abstract. Whether to purchase a product is of fundamental importance to marketing, but purchasing behaviors vary widely across individuals and contexts. This paper proposes that a sizeable fraction of this variation is associated with differences in the time at which a product's desirability and its price are processed and utilized by consumers. To test this hypothesis, participants purchased different products while their mouse cursor movements associated with purchasing an option were recorded across three laboratory studies. These natural cursor movements and estimates from a cognitive model identified the time at which product desirability and price each began to influence decisions. On average, we found that product desirability impacted the decision-making process significantly earlier than price. Moreover, the difference in the time at which product and price influenced choice explained a sizeable fraction of the variation in the option that was purchased. Additional analysis and studies revealed that the time at which an attribute begins to influence decisions can be altered by simple marketing actions, such as a product's visual display and price discount framing, and that these actions have consequences for choice. Together, these results add to our understanding of how consumers make simple purchasing decisions.

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Many frequent consumer decisions concern whether to purchase a product at its listed price. Common examples include routine purchases (e.g., what entrée to order at a familiar restaurant), decisions with both limited and extensive information (e.g., which computer to purchase), and impulsive purchases (e.g., whether to get candy in the grocery store checkout lane). Given their prevalence within society, understanding the factors regarding how purchasing decisions are made is an important goal for marketers.

This paper proposes that the time at which a product's desirability and the price at which it is offered can differ and can explain a sizeable amount of the variation in purchasing decisions. In particular, we find that on average consumers are faster to process and utilize information about a product's desirability compared with its price but that there is variation in this relative processing time across individuals. This variation in processing time is associated with a sizeable amount of the differences observed in purchasing rates and is affected by simple marketing actions, such as altering the visual orientation of product features or framing the price as being offered at a discount. The data here suggest that this relative timing mechanism can have a sizeable impact on consumer choice.

To better illustrate the hypothesis, suppose that a consumer is deciding which of two entrées to order from a restaurant. The consumer has a choice between entrée X, offered at p_X, and entrée Y, offered at p_Y. Furthermore, suppose that the consumer prefers to have X compared with Y, but $p_X > p_Y$ such that there is a conflict between product and price desirability. The hypothesis here suggests that the likelihood of resolving this conflict in favor of the preferred entrée (i.e., choosing X over Y) depends on the time at which the consumer processes information about the desirability of an entrée relative to its price. Specifically, the faster the consumer processes product information, compared with price information, the more likely the consumer is to resolve the conflict in favor of the dominant product by selecting the higher priced option. Moreover, it is possible that this processing speed can be altered by simple marketing actions.

The proposals that attribute processing time can vary between product desirability and price, and that it affects consumer purchasing decisions is important for several reasons. First, managers frequently take actions that intend to manipulate consumer choice (e.g., price promotions, spatial display, choice set composition), but a coherent model-based understanding for how contextual effects impact choice has so far been elusive. The framework here could link related findings across choice contexts by placing several marketing actions within the same model. In other words, the effectiveness of a marketing action might be partly due to the time at which the action alters the integration of choice variables. Hence, a critical component here is to understand how processing timing differs across consumers, attributes, and the various contexts in which they are placed. Second, much of the existing literature assumes that preferences can be estimated via structural model parameters and are frequently thought to be fixed across contexts or adjusted slowly over time, perhaps as individuals learn from experiences. Given this, the proposal here offers a potential method to shift behavior through subtle changes that alter the ease of processing choice attributes compared with more traditional treatments that seek to alter consumer information (see, e.g., Bronnenberg et al. 2019).

In order to test the main hypotheses, we asked laboratory participants to make a series of incentivized purchasing decisions across three studies. Participants decided which of two snack foods (Study 1) or durable consumer products (Study 2), offered at different prices, they preferred to purchase.[1] We estimated the time at which the desirability of the product and price influenced these decisions using two metrics. First, drawing on a large literature from psychology, we tracked participants' mouse cursor locations as they made choices (Dotan et al. 2019) and examined how these cursor trajectories were affected by product desirability and price throughout the decision-making process, an empirical strategy we detail in the later sections. Second, we estimated a computational model of the choice integration process that is built on sequential sampling models and able to identify differences in the time at which an attribute begins to influence decisions (Ratcliff et al. 2016, Maier et al. 2020).

On average, product desirability influenced the decision process earlier than prices and individual variation in processing time explained a substantial amount of the variance in the product that was purchased. Moreover, a simple contextual manipulation that altered the spatial location of products and prices modulated the processing time of these variables and impacted purchasing choices. This suggests that the time at which features are processed can be manipulated by simple marketing actions with consequences for economic behavior.

Although these studies found evidence that the time at which the product and price are integrated can affect purchasing decisions, they only examined changes in the visual location of features as a possible manipulation. In a third study, we sought to test whether an additional marketing action altered attribute processing time and purchasing choices. In this study, participants made similar product purchasing decisions, but one of the prices at which a product was offered was framed as either discounted or not discounted, and this framing varied over trials. Importantly, there was no monetary difference in the final price between the framing conditions because the treatment noted only that the listed price was discounted. We found that the discount frame shifted the relative time at which price was processed to be earlier compared with the no-discount frame. Moreover, this difference in attribute starting time across the discount frames was associated with an increased propensity to choose the lower-priced option when it was discounted, consistent with the main hypothesis. Finally, the design allowed for a conceptual replication of the main findings from the previous two studies. Overall, these results suggest that some basic marketing actions alter consumer decisions through the proposed attribute timing mechanism.

Related Literature

Why should the time at which attributes are processed affect consumer choice? This proposal is partially motivated by work from cognitive psychology, including sequential sampling models, such as the drift diffusion model (DDM) (Ratcliff 1978, Ratcliff et al. 2003, Ratcliff and Smith 2004, Ratcliff et al. 2016) and decision field theory (Busemeyer and Townsend 1993, Diederich 1997, Roe et al. 2001, Busemeyer and Diederich 2002). Although these models differ in their precise specification, they all assume that choices are made using a relative value signal that is dynamically computed by integrating instantaneous noisy measures of the desirability of choice features associated with the choice set. Furthermore, a choice is made when the accumulated relative value signal becomes sufficiently strong in favor of a choice option. Evidence from the neuroscience literature suggests that these models are biologically plausible and that the brain may utilize similar decision processes (Britten et al. 1992, Gold and Shadlen 2007, Heekeren et al. 2008, Hare et al. 2011, Rangel and Clithero 2014).

Related to this work, a similar class of models has recently been employed at the intersection of economics and marketing. Some of this work has utilized the concept of sequential information sampling in order to integrate response times into economic models (Woodford 2014, Fudenberg et al. 2018, Frydman and Krajbich 2022). Additional work has found that the random utility model can be derived from these types of bounded accumulation models (Webb 2019) that the DDM explains belief formation in both economic and perceptual tasks (Frydman and Nave 2017) and that such models can be estimated from field data to aid with market segmentation (Chiong et al. 2019).

To further illustrate how these types of models make predictions about consumer choices, consider the consumer from earlier in the paper who is trying to decide which of two entrées to order: the one with the more desired food or the one at the more desired price (i.e., lower priced). Traditionally, most sequential sampling models have assumed that there is a single time point at which the relative value signal begins to account for all attributes in the choice set. As illustrated in Figure 1(a), before this time the relative value signal is driven entirely by noise, and after this time point it begins to account for the value of all attributes. The insight in this paper is that the relative value signal might account for some attributes of the decision before other attributes. In this sense, attributes that are processed earlier have a computational advantage in determining choice. For example, Figure 1(b) depicts a model where product desirability enters the relative value signal before price. Hence, there is a time period where decisions are driven only by the product and not by the price. On average, this moves evidence accumulation toward the option with the dominant product and increases the likelihood that option is chosen. Importantly, as depicted in the comparison between Figure 1(b) and Figure 1(c), the longer the duration in which only one attribute is integrated in the decision, the more likely a choice is shifted toward the option that dominates in that attribute.

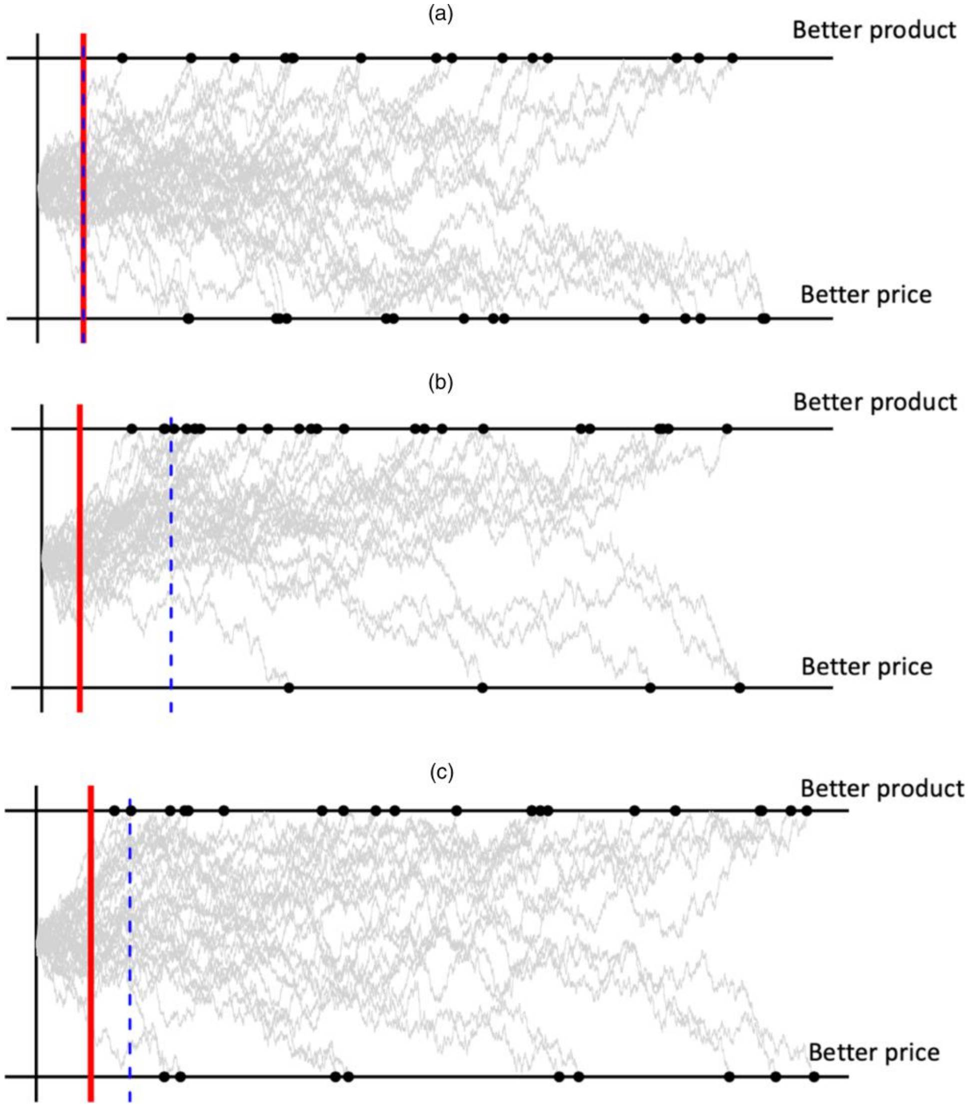
Consistent with this motivation, a growing literature has proposed that sequential sampling models can be designed and estimated in ways that allow the order or time at which distinct components of the choice process first affect evidence accumulation to be unpacked. In fact, recent work has proposed and fit multistage sequential sampling models that allow evidence accumulation to vary based on the time at which attributes are processing. For example, Maier et al. (2020) and Sullivan and Huettel (2021) explored a dietary choice paradigm and estimated a DDM where a food's health and taste can begin to impact the decision process at different times. Additionally, Diederich and Trueblood (2018) proposed a sequential sampling model over risky choice in a formalized dual process framework such that one system begins to influence the decision earlier than the other (Schneider and Shiffrin 1977, Kahneman and Frederick 2002, Lieberman 2003). This paper contributes to this growing literature by testing whether these insights can be applied to a new domain in consumer choices (e.g., purchasing decisions), relating estimates of an attribute's starting time to choice, and demonstrating that such starting times are flexible and manipulable through simple marketing actions. Other sequential sampling models that account for attention (e.g., the attentional DDM; see Krajbich et al. 2010) often assume that attention is randomly distributed throughout the choice set, which may be called into question if individuals consistently process some choice set features before others.

Additional motivation that the differential timing of attributes can alter choices is found in query theory (Johnson et al. 2007, Weber et al. 2007). This theory proposes that an option's value is constructed over time by posing and responding to queries about the option. For example, a consumer who is planning to purchase a new computer might first think about why they should purchase it and list appropriate reasons before thinking about why they should not purchase it. Critically, the order of such queries can affect valuations such that earlier queries more strongly influence value than later queries. Hence, this can lead to a similar effect found in the above sequential sampling motivation.

Given that the time at which attributes are processed can influence decisions, a natural question concerns the factors that affect an attribute's starting time. One possibility is that starting time is determined through both a stable, individual-specific component and a context-dependent component. This stable component could reflect an individual's preferences that have been formed over time. For example, budget-sensitive consumers may have learned to process price before product in order to minimize expenses and adhere to their budgets. However, it is also possible that budget-sensitive consumers are concerned about their budgets because they process this information earlier, which gives it a longer amount of time to affect choice, as in the models above. An additional component that determines attribute starting time might be sensitive to various contextual factors. One such factor could be any contextual change that alters the ease of processing attribute information. For example, changes in the visual display of an attribute might lead that attribute to be processed relatively faster or slower. Note that it is possible that these contextual changes may not reverse which attribute is processed earliest but may still alter the relative starting time difference between attributes, which, according to the models above, would impact choices. In this sense, starting time may be a combination of a volitional component, where individuals have some baseline starting time, and a nonvolitional component that allows contextual factors to alter relative starting time differences between attributes.

Previous work that has examined the relationship between attention and choice complements the idea that an attribute's starting time can be influenced by context-dependent variables. First, attributes that are ignored in the decision process should not influence choices. Hence, attention should be a prerequisite to an attribute influencing decisions. Moreover, previous work has demonstrated the existence of several relationships

Figure 1. (Color online) Drift Diffusion Model Simulations



Notes. Decision simulations between a more preferred product with a higher price (top barrier) and a less preferred product with a lower price (bottom barrier). In each simulation, depicted in light gray, a relative decision value signal evolves over time until it reaches a threshold and a choice is made, as indicated by a black circle. Time increases along the horizontal axis. Each panel differs in the time at which the product attribute (thick red line) and price attribute (dashed blue line) begin to influence decisions. (a) The product and price attribute begin to influence the decision process at the same time point. Hence, the likelihood of choosing each option is approximately equal. (b) The product attribute begins influence the decision process earlier than the price. As a result, choices are shifted to the option with the better product. (c) Although the product attribute still influences the decision process earlier than the price, the relative starting of the product compared with the price is smaller than the above panel. Thus, although decisions are still shifted toward the option with the better product, there is a higher probability of choosing the better-priced option compared with (b).

between attention and choice that are related to the above hypotheses. First, alternatives that are attended more frequently throughout the decision process are more likely to be chosen (Krajbich et al. 2010, Cavanagh et al. 2014, Pärnamets et al. 2015, Konovalov and Krajbich 2016, Stewart et al. 2016, Smith and Krajbich 2018). Second, exogenously varying attention to components of the choice set influences decisions through such manipulations as exposure time (Shimojo et al. 2003, Armel et al. 2008), visual salience (Shen and Urminsky 2013, Towal et al. 2013), the time at which a decision is prompted (Pärnamets et al. 2015, Fisher 2017, Tavares et al. 2017), and spatial-cuing (Mrkva et al. 2019).

These findings suggest a possible mechanism for how the manipulations in the studies reported here can influence an attribute's starting time and affect choice. Specifically, any contextual change that shifts attention to a particular attribute can lead to shifts in the relative time at which that attribute is processed and integrated in decisions. For example, attributes in more visually salient locations are more likely to be initially attended.

Hence, they may be processed before other attributes and begin to influence decisions at an earlier time point, as in Studies 1 and 2. Additionally, a discount frame might shift attention to the prices, which might increase how quickly this attribute is processed, as in Study 3. Although this framework suggests a link between attention and choice, it is important to note that the studies below do not directly measure visual attention. That is, they do not record eye fixations or other process data that can unpack the amount of attention displayed to an attribute. Rather, they build on this intuition for how attention influences choices and estimate attribute starting times through multiple methods.

Furthermore, the hypotheses here are additionally consistent with a broad literature that has found that rather than having precise preferences that are recalled from memory over all potential choice options, our preferences are instead constructed at the time of choice (Slovic 1995, Lichtenstein and Slovic 2006). This insight has been used to motivate classic work involving context effects that find that consumer valuations are influenced by irrelevant anchors (Tversky and Kahneman 1974, Johnson and Schkade 1989, Ariely et al. 2003) or irrelevant alternatives available in the choice set (Simonson 1989, Simonson and Tversky 1992). Similarly, the proposal that the relative starting time of attributes impacts purchasing rates is also consistent with previous work that has found that the order with which information is presented to individuals can influence choice. For example, previous work has found that information primacy (i.e., displayed first) (Anderson 1973, Wyer and Srull 1986, Page and Norris 1998), ordering of multi-option choice sets (Bruine de Bruin 2005, Mantonakis et al. 2009), and attribute ordering (Feldman and Lynch 1988, Russo et al. 1998, Johnson et al. 2007, Weber et al. 2007) can influence judgments and choices. This is consistent with work that has found price primacy effects (e.g., Karmarkar et al. 2015) in that how a product and its price are integrated together to form an underlying value depends on the presentation order of the product and price.

Although the above work suggests that the earlier information is processed the more likely it is to influence decisions compared with later information, certain theories have predicted the opposite relationship. One example comes from recency effects, which find that the last processed or attended piece of information can have a large impact on memory and choices (Wedel and Pieters 2000, Li and Epley 2009, Häubl et al. 2010), although other processes might also be at work in these findings (Tully and Meyvis 2016). In general, this work has asked individuals to remember information, whereas the tasks utilized in this paper do not rely as much on memory; instead, all choice set features are always visible to participants throughout the decision here. This may explain differences between the utilization of information given that information presented more recently tends to be better remembered (Hendrick and Costantini 1970). Other work has found that the last fixation can predict choices (Shimojo et al. 2003, Krajbich et al. 2010, Krajbich and Rangel 2011, Fisher 2017, Tavares et al. 2017), although it is unclear regarding the extent to which these terminal fixations causally influence choice. Moreover, this same work typically finds that there is also a correlation between initial fixations and choice, which is consistent with earlier attended features being predictive of choice.

Characterizing the order of processing stages in decision-making has received a large amount of attention in the psychology research, but these insights are rarely applied to questions at the heart of marketing. One frequently used tool, which is employed in this paper, involves recording finger or mouse cursor movements as individuals select choice options by pointing. Previous work has used this methodology to study the covert processing stages in decision-making (McKinstry et al. 2008, Scherbaum et al. 2010, Friedman et al. 2013, Sullivan et al. 2015, Buc Calderon et al. 2017, Dotan et al. 2018), and several recent review papers have proposed best practices for analyzing this type of data (Song and Nakayama 2009, Stillman et al. 2018, Dotan et al. 2019). A central claim in this literature is that such movements can unpack the decision-maker's cognitive process when movements are continuous and when movements have been initiated before all choice options are displayed (McKinstry et al. 2008, Chapman et al. 2010, Dotan and Dehaene 2013), both of which are followed in the studies reported in this paper. Moreover, this work has found that such movements are updated in real time and occur simultaneously to current cognitive processes (Dotan et al. 2019). Some previous work has temporarily occluded parts of the choice set, depending on the location of the mouse cursor, in order to understand how attention is deployed throughout the choice process (see, e.g., Willemsen and Johnson 2011 and Reeck et al. 2017); however, the focus here is on analyzing the path the cursor takes as a decision is made.

Several related works have used cursor tracking to learn about the decision process in tasks broadly related to consumer decision-making and are worth highlighting. Cheng and Gonzalez-Vallejo (2015) conducted an intertemporal choice task and found that cursor trajectories could be used to decompose the decision process into a conflict component, a decision uncertainty component, and a general locomotion factor. Stillman and Ferguson (2019) also studied an intertemporal choice setting and found that a measurement of conflict derived from cursor movements was associated with decision difficulty and predicted impatience. Stillman et al. (2020) studied decision-making under risk and found that cursor-tracking measurements of conflict predict risk preferences, and do so better than response times, and that conflict can be manipulated by a broad versus narrow bracketing frame. Rather than examining cursor-tracking metrics of conflict in purchasing decisions, the studies below focus on using starting time difference in attributes to predict choices.

Perhaps most related to this paper, Sullivan et al. (2015) and Lim et al. (2018) studied dietary decision-making and found that the health and taste attributes of foods can influence decision-making at different time points, and this can predict self-control in dietary choice. Although this work has argued that such movements throughout the decision can be used to decode the order with which individuals utilize distinct components (i.e., attributes) of the decision-making process, it has not addressed whether the relative timing of such processing stages are malleable through simple contextual changes, which is explored here. This contribution has dimensions of practical and theoretical importance for marketers. Practically, this can help lead to field manipulations that can impact purchasing decisions by shifting attribute timing. Theoretically, this contributes to a stronger understanding of why certain contextual factors lead to changes in decisions. Moreover, we relate these starting time differences to those derived from a cognitive model and show that they are capturing a similar underlying mechanism.

Finally, this paper complements previous work that has examined determinants of heterogeneity in price sensitivity. A portion of this prior work has investigated the relationship between advertising and price sensitivity, in some cases finding a positive relationship between price advertising and price sensitivity (Kaul and Wittink 1995) and in other cases finding mediators of the relationship between advertising and price sensitivity that increase or decrease the effect (Mitra and Lynch 1995). Other work has found that price sensitivity estimates from choice-based conjoint tasks can be altered by demographic or other screening questions that precede the conjoint task (Chakravarti et al. 2013). Price sensitivity is also influenced by the product category such that individuals are less likely to choose a more expensive product for categories they care less about (Bartels and Urminsky 2015), suggesting that price sensitivity estimates are category dependent. In the studies below, we explore related variants of price sensitivity, such as an individual's propensity to choose a more preferred product at a less preferred price. We find that a sizeable amount of the variation in this metric across people is explained by differences in the time at which product desirability and price begin to influence decisions. This suggests an additional mechanism that can lead to heterogeneity in price sensitivity.

Study 1: A Product Purchasing Task

Study 1 sought to address the following three questions.[2] First, is there a difference in the time at which a product's desirability and price begin to influence decisions? Second, is there a correlation between a product purchase decision and the time at which a product's desirability and price affect choices? Third, do simple changes in the visual orientation of products and prices influence when attributes affect decisions?

Method

Participants. Fifty-three students and community members participated in the study (mean age = 23.1; 69.8% female). All participants were asked to fast for three hours prior to the experiment, and compliance was verified through self-report upon arrival. We required that participants did not have any dietary restrictions (e.g, no vegetarians, no food allergies, etc.), had lived in the United States for at least five years, and did not have diabetes. Participants were paid a $5 show-up fee and received an additional $20 upon the completion of the experiment, which lasted approximately one hour. Based on participant responses in initial tasks and consistent with our preregistered analysis plan, we dropped two participants for reasons described below, leaving a final sample size of 51. The local Institutional Review Board approved the study.

Task. The study consisted of three distinct tasks that involved snack foods. The instructions for each task were described to participants immediately before each occurred and were displayed on a computer monitor. The participants read the instructions at their own pace and raised their hands if they needed the experimenter's help or further clarification.

In the first task, participants entered subjective ratings over 40 snack food products. Specifically, participants entered liking ratings for food products (e.g., "how much would you like to eat that food, and ONLY that food") on an integer scale from -2 (i.e., "dislike the food as much as possible") to 2 (i.e., "like the food as much as possible"). Participants were instructed that a rating of 0 meant that they were indifferent between eating and not eating the product (i.e., "you neither like nor dislike it"). These liking ratings provided a subjective measurement of each product's desirability and gave participants a chance to familiarize themselves with the products. A list of all foods and their average rating appear in Online Appendix Table 1.[3] Images were displayed and rated one at a time. In each trial, participants saw a 340×255 image of a food in the center of the screen and entered their rating by clicking the appropriate number on a rating scale below the image using their mouse cursor. The order of the products was randomized across participants.

In the second task, participants entered incentive-compatible bids over each snack food product. Bids were made in $0.25 intervals from $0 to $3 by using the mouse to click on a box that listed the appropriate bid.

These bids provided a subjective valuation of each product's desirability during the study. A list of all foods and their average bid appears in Online Appendix Table 1. As in the first task, images appeared one at a time, and participants entered their bid by clicking the appropriate amount on a bid scale displayed below the image using their mouse cursor. The order of the products was randomized across participants.

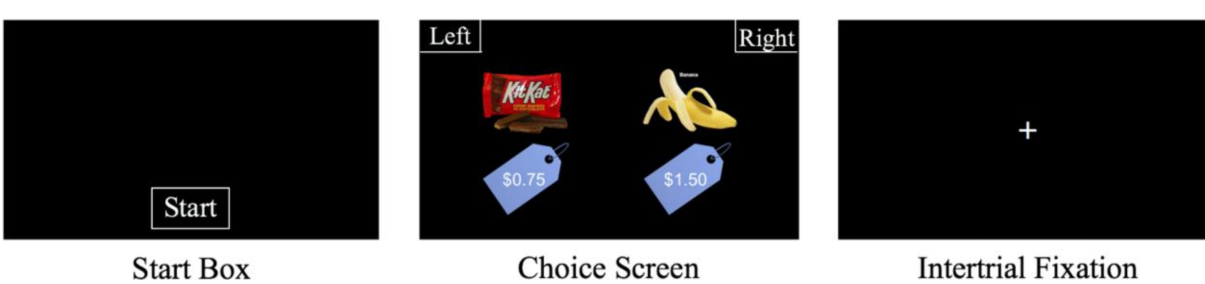
In the third task, which was the main task used to test our hypotheses, participants made 200 decisions between two food products offered for sale at various prices (Figure 2). Product-price choice sets were created as follows. In each trial, a food was paired with a price from the following set: {$0.01, $0.25, $0.50, $0.75, $1.00, $1.25, $1.50, $1.75, $2.00, $2.25, $2.50, $2.75, $3.00}. These prices represent a range over which the majority of the products would be sold in real consumer environments, such as convenience stores or grocery stores, and represent an almost identical scale to the bidding task, with the exception that the minimum price in this task is $0.01, rather than $0 in the bidding section. Prices were visually displayed as appearing on a price tag, as depicted in Figure 2. In each trial, prices were assigned randomly to each product, and a product offered across multiple trials was allowed to receive different prices throughout the study. Choices were made in 25 trial blocks, with short rests between each block, and each participant faced a unique choice set that spanned the possible combinations of their ratings.

Participants were asked to select the product-price pairing they preferred by moving the mouse cursor to the box labeled "Left" or "Right," which corresponded to the side of the screen they preferred. Figure 2 depicts a typical trial. The trial began with the display of a box containing the word "START" at the bottom center of a black screen. Once participants clicked inside of the start box, the trial began. The screen remained black until the participant began to move the mouse cursor, at which point the choice options were presented. This presentation delay was done to encourage smooth and natural mouse movements.[4] The location of each product-price pairing (left vs. right) was randomized, and the location of the products and prices (top vs. bottom) was randomized each trial. However, in order to simplify the choice comparison process, the product and price attributes were always located in the same spatial dimension for the two choice options (i.e., if the left product was on top, the right product was also on top). Choice trials were separated by an intertrial interval of one second when a black screen was shown. Although participants read detailed instructions about this task, they also completed five practice trials in order to gain experience with the task.

Participants' choices were incentive-compatible in that one trial from either the bidding section or the product-price section was implemented. Participants were informed that at the end of the experiment, one trial from either the bidding section or the product-price section would be selected at random and implemented. In order to encourage participants to take each question seriously, we emphasized that as a result of this rule they should treat each trial as if that were the single trial that would be implemented. Additionally, participants would have to remain in the laboratory after the experiment for 20 minutes, during which time they could complete homework or read a book they brought with them but were not allowed to use electronic devices such as computers or phones. If they purchased a food in the chosen trial, they would be allowed to eat that food while they waited; otherwise, they would not be able to eat.

Bids were implemented using the rules of a Becker-DeGroot-Marschak auction (Becker et al. 1964), which is an incentive-compatible mechanism such that participants' best strategies were to bid what they believed was the true value of each food. This feature was explained and emphasized during the instructions. Specifically, the rules of the auction were that a participant entered a bid, b, for each food. At the end of the experiment, one of the 40 food products could have

Figure 2. (Color online) Study 1 Experimental Design



Notes. Participants completed a task where they made binary decisions over whether to purchase a product-price pairing on the left- or right-hand side of a computer screen. After clicking on the start box, the screen went black until the participant began to move the mouse cursor, at which point the choice set was revealed. Participants then moved their mouse cursor to the left or right box at the top to make their selection. They were asked to make continuous and natural mouse movements when entering their response. After making a choice, participants saw an intertrial fixation before moving to the next trial.

been chosen to be the item that was implemented. If so, the computer chose and revealed a random number, x, from the set {\$0, \$0.25, \$0.50, \$0.75, \$1, \$1.25, \$1.50, \$1.75, \$2, \$2.25, \$2.50, \$2.75, \$3}. If $b \geq x$, then the participant purchased the snack and paid \$$x$. Otherwise, if $b < x$, then the participant did not purchase the snack and received nothing. If a trial from the product-price task was instead implemented, participants purchased their chosen product at its listed price.

At the end of the study, the participant was allowed to eat his or her snack, if the participant purchased one, while he or she completed additional survey questions and waited the required 20 minutes.

Mouse Cursor Tracking. The mouse cursor's position was tracked using Psychophysics Toolbox (Brainard 1997) with a temporal resolution of approximately 100 Hz in the product-price pairing section. The tracking for each trial began when the participant clicked in the start box and ended when the participant clicked in the left or right box to indicate a choice. In the below analysis, we shifted and normalized coordinates so that the point at which the cursor clicked in the start box was $(x,y) = (0,0)$, the pixel clicked to select the left option was $(-1,1)$, and the pixel clicked to select the right option was $(1,1)$. Participants were told that they should respond naturally by moving the mouse cursor continuously from the start button toward the top side of the screen of the desired choice option and that they should respond as quickly and accurately as possible.

Data Preprocessing. We followed two preprocessing steps that were preregistered in order to reduce the noise associated with trials when participants may have had difficulty complying with the instructions to make a continuous and rapid mouse movement. First, trials with a response time greater than two standard deviations above their task mean were excluded from further analysis for each participant (4.2% of all trials). The mean response time was 1.7 s (SD = 0.4 s). Second, we removed trials in which the mouse trajectory crossed the y-axis more than three times (10.5% of trials). These preprocessing steps were preregistered, consistent with prior research, and the numbers are comparable to previous work that has examined mouse cursor movements (see, e.g., Sullivan et al. 2015).

A final preprocessing step that was preregistered involved removing any participants who bid \$0 for all food products, because we would not be able to conduct the analysis detailed below. Two participants bid \$0 for all food products, which left a final sample size of 51 participants.

Mouse Cursor Trajectory Analyses. In order to analyze cursor trajectories, we normalized time in the below analysis. Specifically, every trial was divided into 101 equal-sized time bins. The start position was denoted as time $t = 1$, and the time when a choice was entered was denoted as time $t = 101$. The mean x and y positions of the cursor during each time bin were then computed. Hence, the mouse cursor trajectory data in each trial consisted of 101 horizontal and vertical locations of the cursor. Note that such normalization allows the comparison of similar decision process stages across participants who may have different underlying processing latencies.

Second, we conducted a panel data regression analysis to examine how the cursor trajectory angle at every normalized time point was influenced by the values of the product (as given by the bid in the previous task) and price. In these regressions, the dependent variable was the trajectory angle at time t and was normalized such that $-45°$ indicated a direct movement toward choosing the left option, $0°$ indicated a movement directly upward, and $+45°$ indicated a direct movement toward choosing the right option. The independent variables were the interactions of indicator variables for the time period with the difference in the product's bid (i.e., $\text{bid}_{\text{right}} - \text{bid}_{\text{left}}$) and the interactions of indicator variables for the time period with the difference in prices (i.e., $\text{price}_{\text{right}} - \text{price}_{\text{left}}$). These regressions were conducted at the individual level.

Finally, we used these regression results to identify the earliest normalized time point at which the product and price had a significantly lasting influence on the mouse trajectories. We did this by computing the time point at which the product or price significantly influenced trajectories at the 5% level (two-sided hypothesis test) and continued to remain significant for the remainder of the normalized time units. Importantly, this test required that a variable maintain its significance from the identified time point through the end of the trial. We denote this starting time as the starting time at which an attribute (i.e., product or price) begins to significantly influence the decision process.

In other words, the starting point of attribute i was defined as the earliest time point t for which all the interactions between time and that attribute where $t' > t$ had an associated p value below 0.05. If there was no such t, then we assigned a starting time of 102, one normalized time unit after the final time point. This analysis allows us to compare the time at which products versus prices started to influence decisions and how this was correlated with the propensity to select the relatively less expensive option, directly testing the central hypothesis.

Results utilizing an additional preregistered cursor trajectory analysis are reported in Online Appendix A. Briefly, this method uses a series of linear regressions to estimate an attribute's starting time, as opposed to a panel data regression model. However, the two sets of results are quantitatively similar and correlated, and the main results hold across both metrics.

Computational Model Starting Time Estimates. As an additional technique to estimate starting time differences between price and product integration, we modified a standard DDM (Ratcliff 1978, Ratcliff et al. 2003, Ratcliff and Smith 2004, Ratcliff et al. 2016) to permit differences in the starting times for the product and price attributes. Previous work has estimated such models in alternative contexts (Maier et al. 2020, Sullivan and Huettel 2021).

The model assumes that decisions are made by integrating a relative decision value (RDV) signal over time until enough evidence is accumulated in favor of the left or right option. Additionally, the model makes predictions about response times because the time until a choice is made is equal to the time the barrier is crossed. The evolution of the RDV differs, depending on whether the product or price enters the decision process first and is given by

$$RDV_t = RDV_{t-1} + \mu + \epsilon_t,$$

where RDV_t indicates the value of the RDV signal at time t, ϵ_t is a draw from $N(0, 1)$ and reflects the stochastic nature of the process, and μ is equal to

$$\mu = \begin{cases} 0, & t < t^*_{\text{bid}} \text{ and } t < t^*_{\text{price}} \\ \omega_{\text{bid}}\text{bid}, & t \geq t^*_{\text{bid}} \text{ and } t < t^*_{\text{price}} \\ \omega_{\text{price}}\text{price}, & t < t^*_{\text{bid}} \text{ and } t \geq t^*_{\text{price}} \\ \omega_{\text{bid}}\text{bid} + \omega_{\text{price}}\text{price}, & t \geq t^*_{\text{bid}} \text{ and } t \geq t^*_{\text{price}}, \end{cases}$$

where ω_{bid} is the weighting factor that determines how much a product's bid contributes to the relative decision value, bid is the difference in product bid values between the left and right side, ω_{price} is the weighting factor that determines how much the listed price contributes to the relative decision value, price is the difference in product-price values between the left and right side, and t^*_{bid} and t^*_{price} are the starting time of the product and price, respectively.

Two additional parameters of the model, the bias and threshold, are also estimated and are standard when estimating DDMs. The bias describes the starting point for the evidence accumulation process and can be interpreted as a predisposition to choosing one of the options. The threshold is the size of the barrier separation and can be interpreted as the amount of evidence required to make a choice. The model was estimated for each participant, and additional details regarding the fitting procedure are provided in Online Appendix B.

To test the key hypotheses, we analyzed the estimated starting time for the product and price from the above model, t^*_{bid} and t^*_{price}. Note that these factors are able to be estimated separately from the weights due to differences in response times over trials.

It is worth noting two features about how the cursor-tracking metric detailed above compares to the starting time estimates from the modified DDM. First, the DDM in this section estimates starting time using only choices and response times but does not utilize cursor trajectories. Hence, the two methods provide starting time estimates that make use of nonoverlapping data. Second, the two metrics provide starting time estimates in different units. To clarify, the DDM estimates starting time in absolute time (in milliseconds), whereas the cursor-tracking metric estimates starting time in normalized time units. There are advantages to each method, which highlights the importance of testing whether results are robust between metrics.[5]

Results

Choices and Price Aversion. We first investigated the relationship between the option a participant chose and the properties of the choice set that were offered in each trial of the product purchasing task with cursor tracking. Consistent with participants utilizing both the product and price attributes to make their decisions, choices were impacted by the relative product values (i.e., $\text{product}_{\text{right}} - \text{product}_{\text{left}}$) and relative prices (i.e., $\text{price}_{\text{right}} - \text{price}_{\text{left}}$), as evidenced by a logistic mixed-effects regression of choosing the option on the right hand side of the screen regressed on the relative product and price differences ($\beta_{\text{product}} = 3.28$, $p < 0.001$, $\beta_{\text{price}} = -0.86$, $p < 0.001$). This suggests that participants utilized both of the product's attributes when making decisions, as expected.

Second, we examined whether there was variation across participants in the propensity to choose a less preferred product at a more preferred price (i.e., lower price) between participants. To do this, we computed a participant-specific measurement of "price aversion" as follows. First, we restricted the data set from the cursor-tracking section to only those trials in which participants faced a conflict between a more preferred product, as defined by a participant's bids from the second task, that was offered at less preferred price (i.e., a higher price) compared with the other option in the choice set. Note that we determined whether participants faced a product-price conflict by using their responses from the bidding task, meaning that we identified conflict trials at the participant level. Next, we calculated each participant's price aversion ratio (PAR) as the fraction of conflict trials in which each participant chose the option with the lower price, rather than the better product, in conflict trials. Hence, participants with a higher PAR were more likely to choose the choice option that had the lower price and the less desirable product.

Critically, we found substantial variation in price aversion across participants (mean = 29.4%, SD = 20.0%). This is important because we were interested in the extent to which this metric was associated with differences in the timing with which product and prices first started to influence the decision process.

We note two critical features regarding the above price aversion metric. First, PAR is not calculated based on responses to all trials because some trials have one option with both a more desirable product and price. Given this, PAR is a simple behavioral measure that details the choices individuals make as they resolve product-price conflicts. Second, a critical component of this study was to examine how changes in the starting time of the product and price were associated with how individuals make tradeoffs between products. Identifying differences in starting time, as detailed in the above methods, involves utilizing all trials and each trial's stimulus values, even those for which there is no product-price conflict. Hence, although PAR is calculated only using the trials with a product-price conflict, the starting time estimates utilize all trials. Finally, we also report results that examine the general propensity to select the lower-priced option within all trials as an additional metric of price aversion.

Product and Price in the Choice Process. To examine whether the product and price influenced decision-making at different time points in the decision process, we examined the starting time estimates for each attribute.

First, we examined how cursor angle trajectories at each normalized time point were influenced by the product and price values in the product-price choice task. Using the above referenced individual participant regressions of cursor angle trajectory on a normalized time trend and its interaction with relative product and price values, the average estimated starting time for the product had a normalized time of 59.6 (SD = 14.4), and the average estimated starting time for the price had a normalized time of 82.3 (SD = 17.7). Under this metric, the product began to influence decisions significantly earlier than the price ($t(50) = 6.39$, $p < 0.001$).

Second, we examined the DDM estimates of starting time for each participant. Across participants, the average starting time for the product was 1.13 s (SD = 0.24 s), and the average starting time for the price was 1.38 s (SD = 0.63 s). Under this metric, the product began to influence decisions significantly earlier than the price ($t(50) = 3.08$, $p = 0.003$).

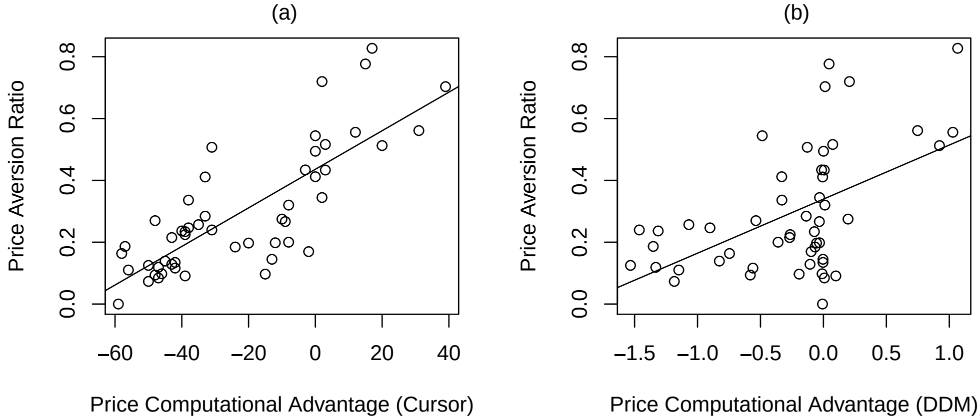
Third, we found a sizeable correlation between the two measures ($R^2 = 0.43$, $p < 0.001$; Online Appendix Figure 1), which suggests that these two starting time measures are capturing the same underlying cognitive process.[6] Overall, these results suggest that, on average, the product began to influence decisions earlier than the price, but there was variance in starting time across individuals.

Price Aversion and the Product and Price Starting Time. Although the above suggests that the time at which product and price information begin to influence decisions can differ between individuals, we next investigated whether such differences were associated with price aversion, as defined by participants' PAR.

We examined this by computing the computational advantage of the price, which we defined as the difference between the product's starting time and the price's starting time. Hence, for the cursor-tracking metric, a price computational advantage of x implies that the price began to impact cursor trajectories x normalized time units before the product. For the DDM estimates, a price computational advantage of x implies that the price began to impact the decision process x seconds before the product. We then examined whether there was an association between the price computational advantage and price aversion by conducting a linear regression of each participant's PAR on each participant's price computational advantage and using bootstrapped standard errors.

The results of this analysis are depicted in Figure 3. As the figure shows, there was a positive correlation

Figure 3. Price Aversion and Attribute Speed in Study 1



Notes. The price aversion ratio as a function of the price's computational advantage, defined as the starting time of the product: the starting time of the price for (a) the cursor metric in normalized time units and (b) DDM estimates in seconds. The linear regression line is displayed.

between the PAR and the computational advantage of the price for both the cursor-tracking metric ($R^2 = 0.63$, $p < 0.001$) and the DDM estimates ($R^2 = 0.27$, $p < 0.001$). This finding suggests that the earlier price begins to influence decisions, the more likely participants are to exhibit price aversion and hence, choose the option with the lower price rather than the more preferred product. Additionally, when both starting time estimates were simultaneously used to predict PAR, we found that only the cursor-tracking metric ($p < 0.001$), but not the DDM estimates ($p = 0.965$), were significantly associated with choices, which suggests that the DDM estimates do not provide distinct information compared with the cursor-tracking metric.

This analysis is robust to replacing PAR with the propensity to select the lower-priced option regardless of a conflict between product desirability and price. The results of this analysis are depicted in Online Appendix Figure 2. There was a positive correlation between the propensity to select the lower-priced option and the computational advantage of the price for both the cursor-tracking metric ($R^2 = 0.68$, $p < 0.001$) and the DDM estimates ($R^2 = 0.34$, $p < 0.001$).

Online Appendix C reports a robustness check to examine whether an attribute's decision weight could bias the estimate of starting time and lead to a spurious correlation between relative starting time and PAR. There was still evidence for the above relationship in the results that explicitly controlled for this potential problem.

Together, the results suggest that a sizeable amount of the variation in price aversion in this experiment can be explained by the relative time with which the product and price begin to influence the decision process.

Attribute Starting Time and Decision Weights. We next investigated the extent to which differences in the relative starting time of the product and price were associated with the weights each attribute received in determining choices. This was done separately for both the cursor-tracking metric and the DDM estimates.

To conduct this analysis, we first calculated participant-specific decision weights by conducting a logistic regression of whether the participant chose the right-hand option on the difference in bid and price values. Next, we calculated the weighted advantage of the product by computing the difference between the estimated product weight and the absolute value of the estimated price weight. Note that we used the absolute value of the estimated price weight because price weights were typically negative. We found a significant negative correlation between the weighted advantage of the product and the computational advantage of the price (cursor metric: $R^2 = 0.29$, $p < 0.001$; DDM metric: $R^2 = 0.18$, $p = 0.001$). This implies that those who had a higher relative weight for the product compared with the price also had the product begin to influence the decision earlier than the price.

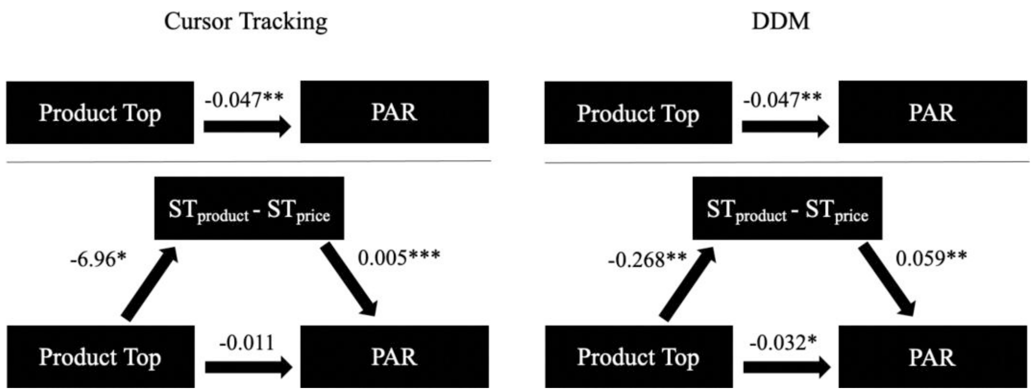
Moreover, we found that the weighted advantage of the product mediated the relationship between PAR and relative starting time (Online Appendix Figure 3). This suggests that one mechanism through which relative starting time influences PAR is through the weight assigned to each attribute.

Exogenous Fluctuations in Product and Price Timing. The above analyses treat the time at which the product and price impact choice as a participant-specific constant; however, it is possible that certain contexts can alter the time at which an attribute begins to influence decisions. We hypothesized that one such context could be the presentation format or the spatial location of products and prices. Specifically, when products were more visually prominent than prices, we hypothesized that products would begin to influence the decision process relatively earlier than prices compared with when products were less prominent than prices. In our task, we randomized the presentation of product and price images to the top versus bottom of the computer screen within participants. We reasoned that the location of the product and price could alter their visual prominence. This is based on previous work that has found that features at the top of a screen are often attended before those at the bottom (Sütterlin et al. 2008, Chandon et al. 2009, Chen and Pu 2010, Huang and Kuo 2011, Shi et al. 2013).

To test this, we first computed the computational advantage of the price when the product was on the top (and price was on the bottom) and separately when the product was on the bottom (and price was on the top) under the cursor-tracking metric. When the product was oriented at the top of the screen, the starting time of the product was 25.8 (SD = 26.9) normalized time units earlier than price; however, when the product was located at the bottom of the screen, the starting time of the product was only 18.9 (SD = 26.2) normalized time units earlier than the price. This difference in relative starting time was significant ($t(50) = 2.91$, $p = 0.005$) and consistent with the above hypothesis as the product began to impact decisions relatively earlier when it was visually prominent.

We found a similar result when using the estimates from the DDM. When the product was oriented at the top of the screen (i.e., more visually salient), the starting time of the product was 0.40s (SD = 0.61s) seconds earlier than price; however, when the product was located at the bottom of the screen, the starting time of the product was only 0.13 seconds (SD = 0.64 s) earlier than the price. This difference in relative starting time was significant ($t(50) = 3.17$, $p = 0.003$) and consistent with the direction of the hypothesis.

Figure 4. Mediation Analyses in Study 1



Notes. Analysis of the mediation effect that attribute starting time (cursor-tracking metric and DDM estimates) has on the relationship between spatial location and the price aversion ratio (PAR).
$^*p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

Second, we reasoned that if the time at which the attributes influenced decisions varied based on their spatial location, then differences in their timing would be reflected in the propensity to make a price-averse choice. To clarify, we hypothesized that because the product was processed earlier when it was at the top compared with the bottom of the screen, participants should be less price averse in trials when the product was at the top compared with the bottom of the screen. To test this, we separately computed each participant's PAR when (1) the product was at the top of the screen and (2) when the product was at the bottom and then compared these differences over participants. Among trials with a product-price conflict, we found that when the product was at the top of the screen participants chose the option with the lower price 27.0% (SD = 20.5) of the time; however, when the product was at the bottom of the screen participants chose the lower priced option 31.8% (SD = 20.8) of the time ($t(50) = 3.56$, $p < 0.001$), a 17.6% relative shift in price aversion. This is consistent with shifts in relative attribute processing times having downstream choice effects.

Finally, we further investigated the relationship between spatial location and PAR by examining whether relative starting time mediated the relationship between the two variables. As depicted in Figure 4, we found evidence for mediation in both the cursor-tracking and DDM metrics. Overall, these results provide evidence that shifts in attribute processing timing can result in meaningful differences in choices.

Study 2: Conceptual Replication in a Durable Product Category

Study 2 was designed to conceptually replicate the above findings and address two questions that remained. First, do the findings above generalize to a different product category? Second, did the order in which the participants completed the tasks (i.e., ratings, bids, choices) influence the results given that a large amount of cognitive processing over the products may have taken place in the rating and bidding tasks before purchasing decisions were made? To address these questions, we conducted a study similar to Study 1 that used durable consumer products and varied the order in which participants completed the three tasks. Overall, the previous results conceptually replicated in this new product category and did not appear to be influenced by task order.

Method

Participants. One-hundred five students and community members participated in the study (mean age = 21.3; 63.8% female). We required that participants had lived in the United States for at least five years. Participants were paid a $5 show-up fee and received an additional $20 upon the completion of the experiment, which lasted approximately one hour. As described below, participants also had the opportunity to earn an additional $40 payment at the end of the study. The local Institutional Review Board approved the study.

Task. The study consisted of three distinct tasks that were similar to Study 1 (i.e., ratings, bids, and choices), with the following caveats.

First, participants made decisions over durable consumer goods rather than snack foods.[7] Given the increased retail value of the durable consumer products compared with the snack foods used in the previous study, we altered the bids that participants were allowed to enter in the bid task to be between $0 and $30 in $3 increments. Additionally, the prices at which products were offered in the choice task were listed at integer amounts between $1 and $30. Moreover, rather than implementing one trial from the bid or choice task for each participant, participants were asked to select a number from one to 20. If the computer randomly chose the same number, then they would be paid a bonus payment of $30, and one trial would be randomly chosen to be implemented from either the bid task or the choice task. If the participant purchased a product in the randomly chosen trial, then the product would be mailed to them. This mechanism permitted incentivized responses from participants. Online Appendix Table 2 reports the average liking ratings and bids over foods.

Second, the order of the three tasks was randomized across participants. Specifically, participants were randomized to either complete the tasks in the order of (1) ratings, (2) bids, and (3) choices, exactly as in Study 1, or complete the tasks in the order of (1) choices, (2) ratings, and (3) bids. Because half the participants made choices before they entered ratings, we could not use ratings to create participant-specific choice sets. Rather, each participant viewed identical choice sets, with a randomized trial order across participants. One benefit of this is that comparisons of PAR between participants were based on identical stimuli.

All additional methods, including data preprocessing and analyses techniques, are identical to Study 1. Additional details appear in Online Appendix D.

Results

Choices and Price Aversion. We investigated the relationship between the option a participant chose and the properties of the choice set that were offered in each trial of the cursor-tracking task by conducting a logistic mixed-effects regression where choosing the option on the right-hand side of the screen was regressed on the relative product and price differences ($\beta_{product} = 0.19$, $p < 0.001$, $\beta_{price} = -0.11$, $p < 0.001$). This is consistent with participants utilizing both of the product's attributes when making decisions, as expected.

Second, we examined whether there was variation across participants in their PAR (e.g., the propensity to choose a less preferred product at a more preferred price). As before, we found substantial variation in PAR across participants (mean 39.4%, SD = 18.0%).

Product and Price in the Choice Process. Next, we examined whether the product and price influenced decision-making at different times in the choice process and whether any differences in timing were related to task order.

First, we examined whether cursor trajectories were influenced by the product and price feature values. The average starting time for the product was at a normalized time of 57.9 (SD = 16.1) and was 67.6 (SD = 20.8) for the price. Using this metric, the product began to influence decisions significantly earlier than the price ($t(104) = 3.80$, $p < 0.001$).

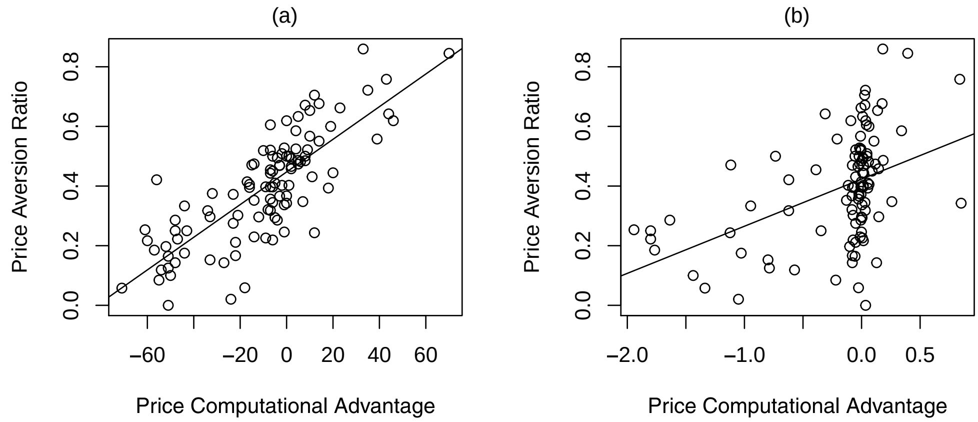
Second, we examined the results of the DDM estimates for each participant. Across participants, the average starting time for the product was 1.23 seconds (SD = 0.23 s) and the average starting time for the price was 1.41 seconds (SD = 0.53s). Using this metric, the product first influenced decisions significantly earlier than the price ($t(104) = 3.69$, $p < 0.001$).

As before, we found a correlation between estimates of starting time differences from the cursor metric and the DDM ($R^2 = 0.33$, $p < 0.001$), which suggests that these two different measures of starting time differences may be capturing a similar underlying cognitive process.

Finally, we investigated whether task order influenced the starting time. With respect to the cursor metric, we found that task order did not influence the starting time of the product (purchasing task first: mean = 59.3, SD = 16.0; purchasing task last: mean = 56.5, SD = 16.2; $t(102.8) = 0.88$, $p = 0.380$), the starting time of the price (purchasing task first: mean = 65.0, SD = 19.7; purchasing task last: mean = 70.1, SD = 21.6; $t(102.9) = 1.26$, $p = 0.209$), or the difference between product and price starting time (purchasing task first: mean = −5.7, SD = 24.1; purchasing task last: mean = −13.5, SD = 27.7; $t(102.3) = 1.55$, $p = 0.123$). Additionally, we found similar results when using the DDM estimates in that task order did not influence the starting time of the product (purchasing task first: mean = 1.21 s, SD = 0.25 s; purchasing task last: mean = 1.25 s, SD = 0.22 s; $t(99.8) = 0.76$, $p = 0.451$), the starting time of the price (purchasing task first: mean = 1.39 s, SD = 0.52 s; purchasing task last: mean = 1.44 s, SD = 0.55 s; $t(103.0) = 0.45$, $p = 0.654$), or the difference between product and price starting time (purchasing task first: mean = −0.18 s, SD = 0.49 s; purchasing task last: mean = −0.19s, SD = 0.53s; $t(103.0) = 0.12$, $p = 0.903$). Hence, to simplify the later analysis, we report results for the pooled sample rather than separately for each task order.

Price Aversion and the Product and Price Starting Time. Here, we test whether the above differences in attribute starting time were associated with PAR. Consistent with the results from Study 1, there was a positive correlation between the PAR and the computational advantage of the price (i.e., the difference between the product's starting time and the price's starting time) for both the cursor-tracking metric ($R^2 = 0.63$, $p < 0.001$) and the DDM estimates ($R^2 = 0.20$, $p < 0.001$), as depicted in Figure 5. This finding suggests that the earlier the price attribute starts to influence decisions, the more likely participants are to exhibit price aversion and hence, choose the option with the lower price rather than the more preferred product. As in Study 1, when both starting time estimates were simultaneously used to predict PAR, we found that

Figure 5. Price Aversion and Attribute Speed in Study 2



Notes. The price aversion ratio as a function of the price's computational advantage, defined as the starting time of the product: the starting time of the price for (a) the cursor metric in normalized time units and (b) DDM estimates in seconds. The linear regression line is displayed.

only the cursor-tracking metric ($p < 0.001$), but not the DDM estimates ($p = 0.863$), were significantly associated with choices.

Additionally, this analysis is robust to replacing PAR with the propensity to select the lower-priced option regardless of a conflict between product desirability and price, and the results are shown in Online Appendix Figure 4. There was a positive correlation between the propensity to select the lower-priced option and the computational advantage of the price for both the cursor-tracking metric ($R^2 = 0.46$, $p < 0.001$) and the DDM ($R^2 = 0.22$, $p < 0.001$).

Finally, we also explored whether the potential problem concerning the cursor metric that was detailed in Study 1 could be biasing the above results, even though it did not appear to have a sizeable impact in the previous study. The results are reported in Online Appendix C and again find that this potential issue did not bias the above results.

Overall, these results are consistent with the hypothesized relationship between attribute starting time and choice and conceptually replicate the results from Study 1.

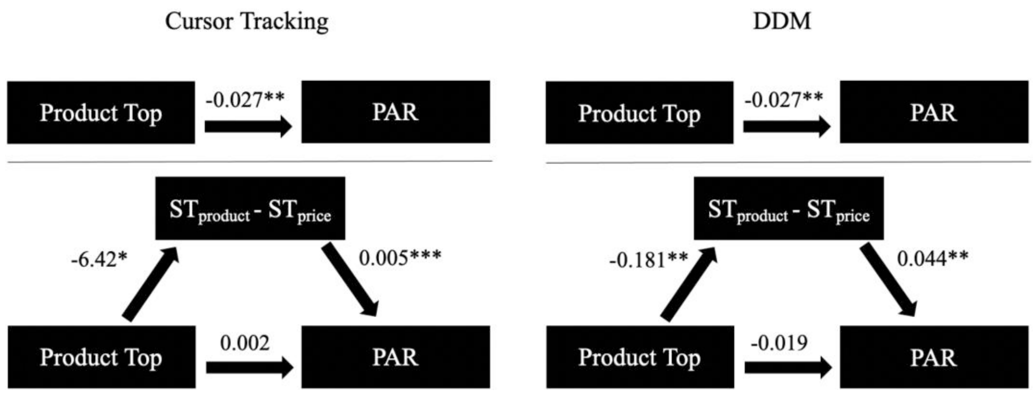
Attribute Starting Time and Decision Weights. We next investigated whether differences in the relative starting time of product and price were associated with the weights each attribute received in decisions, separately for both the cursor-tracking metric and the DDM estimates.

As before, we first calculated participant-specific decision weights by conducting a logistic regression of whether the participant chose the right-hand option on the difference in bid and price values. Next, we calculated the weighted advantage of the product by computing the difference between the estimated product weight and the absolute value of the estimated price weight. We found a significant negative correlation between the weighted advantage of the product and the computational advantage of the price (cursor metric: $R^2 = 0.47$, $p < 0.001$; DDM metric: $R^2 = 0.20$, $p < 0.001$). Moreover, we found that the weighted advantage of the product mediated the relationship between PAR and relative starting time (Online Appendix Figure 5). Overall, these results mimic the findings from the previous study.

Exogenous Fluctuations in Product and Price Timing. As in Study 1, we randomized the spatial location of the product and price for each trial. To test whether attribute starting time was systematically altered by the visual display, we computed the computational advantage of the price when the product was on the top (and price was on the bottom) and separately when the product was on the bottom (and price was on the top). Under the cursor-tracking metric, when the product was oriented at the top of the screen the starting time of the product was 14.0 (SD = 26.5) normalized time units earlier than price; however, when the product was located at the bottom of the screen the starting time of the product was only 7.6 (SD = 27.6) normalized time units earlier than the price. This difference in relative starting time was significant ($t(104) = 4.15$, $p < 0.001$) and went in the hypothesized direction.

We found a similar result using the estimates from the DDM. When the product was oriented at the top of the screen, the starting time of the product was 0.33 seconds (SD = 0.70 s) earlier than price; however, when the product was located at the bottom of the screen the starting time of the product was only 0.12 seconds (SD = 0.59 s) earlier than the price. This difference in relative starting time was significant ($t(104) = 3.14$, $p = 0.002$).

Figure 6. Mediation analyses in Study 2



Notes. Analysis of the mediation effect that attribute starting time (cursor-tracking metric and DDM estimates) has on the relationship between spatial location and the price aversion ratio (PAR).
$^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

Next, we tested whether these differences in attribute starting time translated to differences in choices. Specifically, we hypothesized that because price was processed earlier when it was at the top compared with the bottom of the screen, participants should be more price averse in trials when price was at the top compared with the bottom of the screen. To test this, we computed each participant's PAR when the price was at the top of the screen and when the price was at the bottom and then compared these differences across participants. We found that when the product was at the top of the screen the PAR was 38.0% (SD = 19.2); however, when the product was at the bottom of the screen the PAR was increased to 40.8% (SD = 18.4) ($t(104) = 2.64$, $p = 0.010$), a relative shift of 7.1% in price aversion.

Finally, we investigated the relationship between spatial location and PAR by examining whether relative starting time mediated the relationship between the two. As depicted in Figure 6, we found evidence for mediation in both the cursor-tracking and DDM metrics. Again, the results in this section conceptually replicate the findings from Study 1 in an additional choice domain.

Study 3: Discount Framing and Attribute Timing

The previous studies found that the relative time at which individuals utilize product desirability and prices was correlated with purchasing decisions and also found evidence that simple changes to their visual display can influence both this relative timing difference and choices. Study 3 sought to test whether an additional marketing action, framing a price as discounted, can induce differences in the time at which the product and price were processed and whether such differences in processing altered decisions.

Method

Participants. Forty-seven students and community members participated in the study (mean age = 22.3; 65.3% female). As in Study 1, participants were asked to fast for three hours prior to the experiment, and compliance was verified through self-report upon arrival; participants did not have any dietary restrictions (e.g., no vegetarians, no food allergies, etc.), had lived in the United States for at least five years, and did not have diabetes. Participants were paid a $5 show-up fee and received an additional $27 upon the completion of the experiment, which lasted approximately 70 minutes. The local Institutional Review Board approved the study.

Task. The study consisted of three tasks that involved snack foods, as in Study 1. The implementation of the first two tasks was identical to Study 1 and consisted of participants entering liking ratings and incentive-compatible bids over snack foods. Online Appendix Table 3 reports the average liking ratings and bids over foods.

In the third task, which was the main task used to test our hypotheses, participants made 250 decisions between two food products offered for sale at various prices (Figure 7); 125 product-price choice sets were constructed as in Study 1 such that in each trial a food was paired with a price from the same set as Study 1. In each trial, prices were assigned randomly to each product, and a product offered in multiple trials was allowed to receive different prices throughout the study. Critically, participants viewed each product-price pairing twice: once as a typical choice that would have been displayed in Study 1 (no-discount frame) and once when framed as having a discount of 50% applied to the lower-priced item (discount frame). Each of the 125 product-price sets were displayed twice: once in the discount frame and once in the no-discount

Figure 7. (Color online) Study 3 Experimental Design

Notes. Half the trials were conducted as in Study 1. In the other half the trials, the lowest-priced item was framed as having a price discount of 50%. Participants were informed that the final price of the items after any discount was displayed on the price tag. Each trial appeared once in the discount frame and once in the no-discount frame.

frame. Each of these choice sets contained the exact same products and associated prices. Participants were informed that in some trials a product could be offered at a discounted price, denoted with a different price tag, and the price on the tag would be the final price they would pay. This eliminated any computations they would need to make to compute the final price of the product, which fixed the difficulty of the choice between conditions. Hence, the stimuli were exactly the same between the two conditions, and the only difference was the visual cue that appeared in the discount frame. The order of discount and no-discount trials was randomized within participants.

The remainder of the task details were identical to Study 1 and are provided in Online Appendix E.

Mouse Cursor Tracking, Data Preprocessing, and Analyses. The implementation of cursor tracking and data preprocessing was identical to the previous studies. Additional study-specific details are reported in Online Appendix E. The analysis of starting time was also similar to the previous studies. Notably, we separately estimated starting time for the discount and nondiscount frame.

Results

First, we sought to test whether discount framing altered the time at which product desirability and price were utilized in the decision process. Using both the cursor-tracking metric and the DDM estimates, we estimated starting time for the product and price separately for the discount and no-discount trials. Under the cursor-tracking metric, a comparison of the computational advantage of the price (i.e., the difference between the product's starting time and the price's starting time) found that the starting time of the price was relatively earlier than the product when there was a discount (mean = −10.3, SD = 32.3) compared with when there was not a discount (mean = -23.7, SD = 28.3; $t(46) = 4.01$, $p < 0.001$). There was a similar result with the estimates from the DDM. A comparison of the computational advantage of the price found that the starting time of the price was relatively earlier than the product when there was a discount (mean = −0.16s, SD = 0.55s) compared with when there was not a discount (mean = −0.33s, SD = 0.66s; $t(46) = 2.74$, $p = 0.009$).

Overall, these results suggest that the discount frame encouraged prices to be used earlier in the decision process and encouraged product desirability to be used later in the decision process compared with the no-discount frame. This is consistent with discounts acting as a useful marketing tool to increase the purchase rate of discounted products; earlier integration of prices should lead to an increased likelihood of selecting the less expensive option.

We next tested how this difference in starting time was associated with choice. First, we examined whether the discount frame altered the PAR, which we computed separately for the discount and no-discount condition. When there was a discount, price aversion was 35.2% (SD = 23.7%) compared with 26.5% (SD = 21.2%) when there was no discount ($t(46) = 5.82$, $p < 0.001$). This indicates that the presence of the discount caused participants to increase the likelihood that they selected the option with the lower-priced product, when there was a tradeoff between product and price, by an absolute shift of 8.7%. This is consistent with what would be expected with an earlier starting point of price in the discount condition, because prices would have a longer duration of the decision to impact choice. Second, this result extended to examining all trials in that when there was a discount the lower-priced option was chosen 51.7% (SD = 19.0%) compared with 45.3% (SD = 17.4%) when there was no discount ($t(46) = 7.93$, $p < 0.001$) across all trials (i.e., not only those trials in which there was a conflict between product and price).

To further examine the relationship between the discount frame, differences in attribute starting time, and choices, we conducted a mediation analysis. Specifically, we investigated the relationship between the discount frame and PAR by examining whether relative starting time mediated the relationship between the two. As depicted in Online Appendix Figure 6, we found evidence for mediation in both the cursor-tracking and DDM metrics. This complements the spatial location mediation results from Studies 1 and 2 and further suggests that an underlying mechanism of a widely used marketing action is successful partially because it alters the time at which product desirability and price are integrated as purchase decisions are made.[8]

Finally, although not its central purpose, this study presents an opportunity to conceptually replicate the results from the previous studies. Namely, we examined whether there was a difference in attribute starting time between when the product and price first impacted the decision process and whether such differences were correlated with price aversion in the no-discount condition. We found that the results from Study 1 replicated in this experiment with similar effect sizes, and the details of all analyses are reported in Online Appendix F.

Discussion

This paper describes the results of three incentive-compatible studies designed to test whether differences in the processing time of a product's desirability and its price can explain a substantial amount of the variance observed in simple consumer purchasing decisions. Using a combination of cognitive modeling and drawing on research from the mouse cursor-tracking literature, we estimated the starting time of an attribute in two ways that were found to be correlated with one another. Consistent with the main hypothesis, we found that on average product desirability impacted the decision-making process significantly earlier than the price. Moreover, the difference in the time at which these attributes influenced decisions explained a sizeable fraction of the variation in which option was purchased. Interestingly, we found suggestive evidence that the time at which the product or price affects the decision is malleable and can be altered by simple contextual manipulations. The visual location of the product and price was associated with differences in attribute timing in the first two studies, and a discount frame altered the time at which attributes were processed in the third study. In all of these cases, differences in attribute timing were associated with differences in choices across contexts, which suggests that certain basic marketing actions might be successful, in part, because they alter the time at which attributes are processed.

One question about the above results concerns the direction of causality between attribute starting time and choice. For example, one possibility is that there are differences across individuals in the time at which product and price attributes are processed, and this timing difference causes differences in price aversion. A second possibility is that individuals might have varying levels of price aversion that alters the decision strategies they engage in and results in differences in when the product and price attributes are processed. Although the studies do not directly test two these possibilities, they do provide compelling evidence against solely the second possibility above. Specifically, it appears unlikely that the spatial location results in Studies 1 and 2 would arise if only the second link held. However, this does not suggest that one should conclude that the only causal link is from attribute starting time to choice. Rather, it is likely that a combination of these two models might most accurately describe the decision process.

The study here builds and contributes to several literatures. First, this work adds to a classic literature that has examined how consumers make simple purchasing decisions. The results suggest that purchasing decisions are dynamically resolved such that relevant attributes are integrated into a value signal at different time points. This finding broadly supports work in judgment and decision making that has found that the order in which information is presented influences choice (Russo et al. 1998, Bruine de Bruin 2005, Weber et al. 2007, Mantonakis et al. 2009) and also to work that has designed and tested dynamic models of choice where attributes can differentially bias decisions at different time points (Busemeyer and Townsend 1993, Ratcliff et al. 2016).

Second, the results are related to a growing literature that has used physiological and process-based data to better understand how individuals make decisions (Plassmann et al. 2015, Karmarkar and Yoon 2016, Schulte-Mecklenbeck et al. 2017). A sizeable fraction of the previous work in this domain has utilized neural data to both unpack the decision process (see, e.g., Plassmann et al. 2008 and Hare et al. 2011) and predict market level outcomes (Genevsky and Knutson 2015, Genevsky et al. 2017). Other work has used eye tracking or mouse cursor tracking to measure the attentional patterns consumers engage in (see, e.g., Willemsen and Johnson 2011 and Orquin and Mueller Loose 2013). In contrast to much of this work, the analysis here identifies when particular choice components first begin to impact the decision process in order to understand how decisional conflicts are resolved. The methodological tool used here could be more easily applied than many traditional processed-based or physiological tools because cursor tracking and cognitive models that make use of response times can be implemented across any environment where individuals use a mouse cursor or response time is passively collected.

The findings also suggest several interesting implications that managers could utilize and explore in future work. First, the results suggest a general framework for how managerial actions alter consumer choice and how such interventions could be designed. In particular, they suggest that any contextual variable (i.e., "nudges") that alters the time at which the product and price are integrated can alter purchasing rates. For example, price promotions could be an effective managerial tool not only because promotions offer increased monetary savings but also because of the possibility that they alter the time at which a price is utilized in consumer decisions. This latter reason originates from the idea that promotions can increase the prominence of the product's price and hence, encourage the time at which prices are integrated to be earlier in the decision process, which can result in consumers preferring a product with a lower price. A systematic investigation of how various managerial tools map into this framework is an important open question for future research. For example, does increasing quantity (i.e., offering more product within a box, such as "now includes 25% more" or offering a purchasing deal, such as "buy two get one free") operate in a similar computational method as the price discount frame tested in Study 3?

Second, given the ubiquity of digital marketing and the relative ease with which mouse cursor movements can be recorded, employing cursor tracking in field settings could lead to useful managerial insights. Many analytics companies already record cursor location as consumers view webpages but typically only use that data to create heat maps of where the mouse hovers on a page. It is possible that certain advertising contexts could lend themselves to examining the speed with which consumers skip, close, or click on different advertisements. Webpages run on JavaScript may have a reduced sampling rate compared with the studies here, but that sampling rate is likely still sufficiently frequent to make use of cursor trajectories. Additionally, the insights from the cognitive model can be utilized without cursor data as long as response time is recorded. Although the experiment here used a repeated trial paradigm to generate insights, it is possible that cursor-tracking data could be collected by a digital advertiser over multiple impressions in order to gain a better understanding of how individual consumers make decisions. Along these lines, market segmentation activities could uncover the "types" of consumers for which various choice attributes have different processing times.

Along these lines, we conducted an exercise using the data from Studies 1 and 2 in order to test the feasibility of such a segmentation approach. First, we divided the data into even and odd numbered trials. Using only the odd numbered trials, we estimated the relative starting time for the product and price. Next, we tested whether this starting time estimate could predict decisions (e.g., PAR) in the out-of-sample even numbered trials. We found a strong prediction for both Study 1 (cursor tracking: $R^2 = 0.60$, $p < 0.001$; DDM estimates: $R^2 = 0.18$, $p = 0.002$) and Study 2 (cursor tracking: $R^2 = 0.51$, $p < 0.001$; DDM estimates: $R^2 = 0.22$, $p < 0.001$). Given the burgeoning literature in digital marketing, we are optimistic that the tools utilized here can set a foundation to be more broadly applied for managerial decision making.

We conclude by emphasizing several limitations of the current experiments. First, the types of purchasing decisions explored here are likely to be relatively low-stakes compared with those that arise in certain other consumer environments. For example, purchasing more expensive products, such as housing or automobiles, could conceivably involve distinct mechanisms from those identified here. Although other types of purchasing decisions might be experimentally difficult to test, future work should attempt to design settings that test the generalizability of this mechanism in other environments. Second, although product desirability was treated as a single attribute, future work could decompose this attribute into multiple subcomponents. For example, understanding when a product's hedonic and utilitarian components or even when more neutral attributes begin to impact purchasing decisions could yield additional insights about the relationship between attribute processing time and consumer choice. Third, it is possible that the general trend where the product began to influence decisions earlier than the price is related to differences in the visual representation of each attribute (i.e., images vs. numbers), and future work should investigate this possibility. Nevertheless, even though the starting time for the product was, on average, earlier than the price, there was still a sizeable amount of variance in the relative starting time across individuals, and this variation was correlated with choices. Moreover, the design with product images and numerical prices is likely a fair approximation to the types of stimuli consumers encounter in online shopping environments.

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Endnotes

[1] One concern is whether the findings here are generalizable to real-world decisions, a comment that is often raised about laboratory experiments (see, e.g., Camerer 2015 and Camerer and Mobbs 2017). Notably, the laboratory tasks we present here can be framed as simple choice-based conjoint tasks that have been found to be predictive of choices in external validity scenarios (see, e.g., Ding et al. 2005, Ding 2007, Ding et al. 2009, Toubia et al. 2012, and Yang et al. 2015, 2018). Moreover, the tasks are incentive-compatible, so participants are making decisions that have real consequences.

[2] All studies were preregistered, but because of reviewer comments the analysis in the main text can differ from the preregistered analysis. For completeness, the original preregistered analysis that does not appear in the main text can be found in Online Appendix A.

[3] All food images used in the study are available in the online data repository.

[4] Alternatively, if the choice set was revealed immediately upon clicking the start button, then a participant could make his or her

decision before moving the mouse, disassociating any relationship between cursor movement and real-time decision processes.

[5] Normalizing time in the cursor-tracking analysis allows a simple way to compare across trials that have differences in response times from the same individual (Freeman and Ambady 2010, Kieslich et al. 2019). For example, if an individual takes two seconds on one trial and takes three seconds on another trial, then it can be difficult to compare absolute times across the individual's trials, because the first trial does not have data between two and three seconds. Second, normalized time permits a method to control for large differences in response times across participants, which could reflect differences in underlying cognitive-processing times. These differences could lead to problems when conducting analysis on absolute times, and as such times would reflect different stages of cognitive processing in different participants. On the other hand, it is also possible that normalizing all trials to an identical time interval "overweights" the observations from short trials, which makes it difficult to compare a time unit across trials and may hide real effects or lead to spurious effects (Gallivan and Chapman 2014).

[6] This analysis tests for a relationship between two variables that are both estimates. To account for this, we used bootstrapped standard errors from 100 samples when conducting such analyses throughout all studies.

[7] All product images used in Study 2 are available in the online data repository.

[8] Note that it is possible that the discount frame might independently alter decision weights (e.g., price might be relatively more important in the discount frame as participants prioritize getting a good deal) and relative starting time, and it is the decision weights that drive choice. To functionally rule out independent effects of the discount frame on decision weights and relative starting time, we conducted a mediation analysis and found that that relative starting time mediates the relationship between the discount frame and decision weights when using either starting time metric (Online Appendix Figure 7).

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