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Fast, Then Slow: Choice Revisions Drive a Decline in the
Q:1 Q:2 Attraction Effect

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Abstract. We explore the nature and robustness of the attraction effect. The attraction effect can be seen as a persistent bias or as the result of heuristics that may not persist upon reflection. We provide robust experimental evidence that the attraction effect first rises and then falls over time when participants are incentivized to make a quick choice they can later revise. Participants in two experiments under continuous time pressure make choices among options with the aim to maximize an objective, measurable value. We find that participants disproportionately favor the asymmetrically dominant option in the first seconds and then revise their choices until the effect disappears or is significantly reduced. The effect survives only in the special and often studied case of indifference among options. We develop a tractable extension to the multiattribute linear ballistic accumulator model to allow for choice revisions. That model explains how choice revisions reduce context effects. We estimate its parameters at the individual level and document differences between fast and slow participants that also play a role in explaining the rise-and-fall pattern in the attraction effect. We extend the analysis to similarity and compromise effects. We find a very small similarity effect, which does not exhibit any dynamics, and a significant reverse compromise effect displaying a rise-and-fall pattern. Our findings, although limited to objective-value tasks, are consistent with context effects being short-term heuristics that can be superseded by more reflective cognitive strategies when decision makers have time and incentive to do so.

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Q:7 **Keywords:** asymmetric dominance • attraction effect • induced preferences • choice process • time constraint • rationality • heuristic • context effects

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1. Introduction

Choice among options can be influenced by their context in ways that make no sense from a rational point of view. This phenomenon is known as a *context effect* and was first evidenced by Tversky (1972). The best known and most widely documented of those context effects is the *attraction effect* ("AE"), also known as the *decoy* or *asymmetric dominance effect* (Huber et al. 1982). Under the AE, adding an option (*the decoy*) that is clearly dominated by another option in a choice set increases the likelihood that this option (*the target*) will be chosen at the
Q:9 Q:10 Q:11 expense of the other option (*the competitor*).

We aim to determine if the AE is a short-term phenomenon, which disappears when individuals are given time and incentives to revise their choices, or is a persistent feature of choice. We therefore elicit both fast, intuitive responses and reflective, slow revisions of the initial responses within the same choice tasks and for the same individuals. We do not focus on what a fast choice and a slow choice separately will look like nor on what kinds of choices fast and slow decision makers make. Rather, we focus on whether, when, and how decision makers under continuous time pressure move from fast to slow decision modes, revising their choices expressed in the early stages of the decision process.

Determining the nature of context effects is relevant to several ongoing debates in psychology, economics, and decision making. It relates to the recent literature in experimental economics focusing on the importance of error and cognitive uncertainty and their role in choice revisions (Enke and Graeber 2019, Benjamin et al. 2020, Nielsen and Rehbeck 2022). It also uses concepts from dual-process theories of choice in psychology (Kahneman 2011, Evans and Stanovich 2013). It further contributes to the debate in marketing and decision making on the persistence of context effects and on the link between choice and the speed of decision (Pettibone 2012, Cataldo and Cohen 2021).

We rely on a novel and intuitive objective-value induced preferences expenditure minimization task that allows us to measure the AE not only when options are indifferent—as is done by the bulk of the existing literature—but also when they differ in value. This choice task can be naturally extended to examine other context effects, such as the similarity and compromise effects. We further apply a continuous time-pressure choice-process Q:12 elicitation mechanism, originally ~~because of~~ Caplin et al. (2011), to elicit, for each subject and each choice task, what she thinks is the best choice at any given time. This allows us to obtain *both* a subject's fast, intuitive, heuristic choice and her slower, reflective, compensatory choice, ~~as well~~ when the subject switches choice. We finally develop an original extension of the multiattribute linear ballistic accumulator (MLBA) model (Trueblood et al. 2014) to jointly analyze choices, revisions, and response times. This model integrates choice revisions into the MLBA and allows us to fully exploit our data within a widely used structural model. Original modeling and choice task and an innovative elicitation mechanism combine into a comprehensive stack of tools that can be readily extended to other discrete choice environments, including preference-based or real-product tasks.

We show that the AE is mainly transitory, meaning that the effect follows, on average, a rise-and-fall pattern. The effect is strong in the first few seconds but then declines over a relatively short time span of 20 seconds. This result is robust to variations in stimuli, to different ways to measure the AE, to differences in design in two experiments, to differences in experimental samples (students and general consumers), and to differences in the objective values of options in a choice set. The AE survives as a persistent large effect *only* in the special case in which the target and competitor have the same value. This case, where subjects are indifferent, is the dominant focus of the existing literature (Huber et al. 2014, Lichters et al. 2015). Away from indifference and given enough time and incentives, the AE rises and then falls: to zero in one experiment and to about a third of the peak in another.

This result is ~~because of~~ two different factors: *choice revisions*, whereby subjects submit a first fast choice that favors the target and then revise their choices in favor of the competitor over time; and *subject heterogeneity*, whereby fast, intuitive subjects make quick choices in Q:13 favor of the target in the first seconds, whereas slower, reflective subjects start choosing later and are less subject to the AE, thus eroding the effect over time in the aggregate. Using our original extension of the MLBA with revisions, we provide aggregate and individual-level estimations of the intensity and dynamic ~~patterns~~ of the attraction effect. We show that similar patterns of rise and fall, heterogeneity, and revisions also hold for other context effects to the extent that those context effects arise in our experiments. In particular, we show very limited evidence for a similarity effect, which therefore does not rise or fall over time, and strong evidence of a rise-and-fall pattern for a reverse compromise effect, whereby a preference for extreme options appears early on but is reduced over time.

Section 2 surveys the main theoretical approaches to the AE either as the result of fast heuristic decision making or as a bias that ought to also impact slower, reflective choices. It covers the recent experimental literature investigating the nature of context effects by using time constraints or allowing for choice revisions. Section 3 presents our two experiments. It first introduces our continuous time-pressure choice-process elicitation mechanism and our objective-value task, and then, it provides the details and results of the experiments. The first experiment focuses on the AE with a sample of 111 mostly university students, whereas the second extends our methodology to the similarity and compromise effects with a sample of 198 subjects from the general population. Section 4 introduces our extension of the MLBA model to include choice revisions. We estimate a mixed-effects version of this model using Bayesian methods. This allows us to identify and interpret differences in decision styles across individuals. Section 5 discusses the importance, interpretation, and limitations of our results, focusing on their external validity and discussing their implications and potential extension to preference-based tasks.

All data and detailed scripts to reproduce our results are available at the GitHub repository of the paper (https://github.com/paolocrosetto/A-choice-process-explanation-of-the-attraction-effect-data). All materials for a full replication are available at the OSF page of Q:14 the project (https://osf.io/xr28d/).

2. Context and Related Literature

2.1. A Debate About the Nature of the Attraction Effect

The attraction effect has generated an enormous literature since it was first evidenced 40 years ago. This is because of its theoretical importance as a direct violation of the axiom of independence from irrelevant alternatives because of its counterintuitive nature and because of its applications in marketing. The AE has been widely replicated in marketing and consumer research (Huber and Puto 1983, Simonson 1989, Park and Kim 2005), cognitive psychology (Trueblood et al. 2013), neuroscience (Hu and Yu 2014), game theory (Wang et al. 2018), experimental economics (Herne 1999, Sonsino 2010, Kroll and Vogt 2012, Sürücü et al. 2019, Castillo 2020), and even in some studies on animal behavior (Shafir et al. 2002, Schuck-Paim et al. 2004).

We study the dynamic robustness of the attraction effect, focusing on whether it is a fast heuristic or a deeply rooted bias. Different theoretical approaches to the AE and other context effects support one or the other ~~option~~.

Several theories of choice predict an attraction effect as a stable feature of choice, independent of the time spent on a task or on the fast or slow nature of the choice. This is the case under reference-dependent utility coupled with loss aversion (Usher and McCelland 2004), under decision field theory (Roe et al. 2001), according to salience theory (Bordalo et al. 2013), using the elimination by aspect theory of Tversky (2003), assuming shifting decision weight across attributes (Ariely and Wallsten 1995), or assuming a form of trade-off aversion (Hedgcock and Rao 2009). However, those theories, although they explain why an AE may arise, do not do a good job in explaining when it does not arise, as shown in recent literature that focuses on factors that reduce or mute it.

For instance, the effect is reduced or muted when individuals have information about brands (Ratneshwar et al. 1987), when the product description is unambiguous and precise (Mishra et al. 1993), when the options are presented graphically rather than numerically (Frederick et al. 2014), when the products have negative rather than positive attributes (Malkoc et al. 2013), when individuals are not indifferent among options (Crosetto and Gaudeul 2016, Farmer et al. 2016), and with animals, when marginally changing the usual design (Cohen and Santos 2017). On the other hand, the effect is amplified when individuals are asked to justify their choices (Simonson 1989) and when the dominance relation is more focal (Król and Król 2019).

A different approach is therefore needed to rationalize the literature on the limits in the robustness of the attraction effect. We do so by thinking of the AE as the result of a heuristic. Heuristics are simple, intuitive choice rules that reduce the complexity of a problem by ignoring most information and yet, enabl~~ing~~ fast decisions that are generally sufficiently good (Gigerenzer et al. 2000). Heuristics are associated with the system 1, "satisficing" (Simon 1959), "intuitive," "fast" (Kahneman 2011), or "noncompensatory" (Tversky 1972, Dieckmann et al. 2009) thinking mode~~s~~ of dual-mode decision theories, which are compellingly defended and clarified in Evans and Stanovich (2013). Under this view, the AE, despite being a violation of rational choice, can be locally optimal, especially in cases in which there is little information, the signals are noisy, or the cognitive abilities of the decision maker do not allow for sufficient accuracy. The effect's persistence in time then depends on several factors, such as whether tools from system 2 are applied to a problem (Stanovich and West 2008). This depends on the nature of the problem and on whether decision makers recognize that system 1 may profitably be overridden.

2.2. Using Response Times to Settle the Debate

Several studies have focused on response times to determine whether the AE is best understood as a short-term heuristic or as a more stable feature of human choice. Existing studies mostly relied on (1) imposing time constraints for decision, (2) eliciting or manipulating the decision styles of the individuals, or (3) recording the time at which a decision is made while not imposing a time constraint.

Under method 1, Trueblood et al. (2014) look at decisions under time constraints and show a rise in the attraction effect as time pressure is lowered from one to two seconds and then, five seconds. Pettibone (2012) also find an increasing attraction and compromise effect with time (two, four, six, or eight seconds). As modeled in Trueblood et al. (2014) using the linear ballistic accumulator (LBA) model, high time pressure forces people into choices that allow for neither heuristic nor reflective decision making. With more time, context effects arise as people notice properties of the menus to guide their decision.

Under method 2, Mao and Oppewal (2012) find higher attraction effect among individuals who rely more on intuitive reasoning, as measured with the rational-experiential inventory. Masicampo and Baumeister (2008) and Pocheptsova et al. (2009) find a higher attraction effect with participants whose mental resources are depleted after a self-control task. Cognitive strain can also be manipulated with information overload, such as by increasing the number of attributes of alternatives. Payne et al. (1993, p. 36) then observe higher reliance on noncompensatory decision strategies.

Under method 3, Molloy et al. (2019) show that the attraction effect is present for individuals whose speed of decision is intermediate but not for others. Other effects do not appear to vary with time. Cataldo and Cohen (2021) show that subjects' relatively fast decisions display lower attraction and compromise effect, but higher similarity effect, than their relatively slow decisions.

A further approach, not yet applied to context effects, consists of imposing waiting times to subjects. This has been shown to be effective in triggering less impatient and more time-balanced choices in the laboratory and in the field (Imas et al. 2022) as well as in healthier food choices (Brownback et al. 2023).

This existing body of work suffers from several drawbacks. Extreme time pressure might induce intuitive replies[1] but gives no time to revise choices, thus barring the researchers from observing choice revisions and transitions to more deliberate thinking modes. Moreover, ~~no~~ method mentioned allows researchers to easily see how people combine decision styles when making decisions. There may be individuals who make preliminary, fast decisions and then revise those decisions if given more time; others who make fast decisions following their "gut instinct" and are unwilling to revise them; and yet others who do not trust their first impulse and take their time until they reach more deliberate decisions.

2.3. Eliciting Choice Revisions to Move Further

In this paper, we instead provide a method fine-tuned to focus on choice revisions. Choice revisions are an important and until recently, rather understudied component to understand choice and the formation of preferences. In our context, they allow us to rise above the debate about whether context effect are "fast" or "slow" by showing how they survive or not the transition from fast to slow. Revisions in choice have been investigated empirically in Benjamin et al. (2020) and Nielsen and Rehbeck (2022), who let people make choices across lotteries and then let them reconsider their choices after making it clear when those contradict expected utility axioms. They find that people revise their choices to be more consistent with those axioms, thus showing that first choices represent mistakes rather than actual preferences. Cherchye et al. (2020) examine variability in food choice across time on the basis that consistency in behavior indicates better fit with preferences, whereas variability might indicate choices that are more dependent on the context and less under self-control. They find that poorer, younger, and more impulsive individuals exhibit more variability in their choice. This correlates with research showing that poverty impedes cognitive function (Mani et al. 2013). On the theory side, Ferreira ~~(2018)~~ proposes that "confirmed choices" be used as an alternative to the notion of context-independent or reason-based choice. The choices that people do not wish to revise may be used as a practical proxy of welfare.

We propose that a first step in choice is subject to context effects and consists of eliminating less favored options from the choice set. This elimination operates according to some heuristics, such as dominance editing, and results in a bias for some options, such as the dominant option in the attraction effect. A second subsequent step in choice operates on the reduced subset of options that results from the first step. The context in this second step is different from that in the first step, so that resulting revised choices tend to reduce the context effect that results from first choices.

3. Two Experiments

We ran two experiments for this paper, the first focusing on the attraction effect and the other generalizing our findings to other context effects. The design of choice sets and details in the presentation of options differed across experiments.

3.1. General Methods

We focus in this section on things that are common to both experiments, in particular the task participants had, the way this task was presented, and the way we elicited choice using a continuous time-pressure choice-process mechanism. Details of the implementation, the subject pool, and the design of choice sets are given in Sections 3.2 and 3.3.

3.1.1. An Expenditure Minimization Task. Participants performed an intuitive *expenditure minimization task*. Their objective was to buy a fixed amount of gasoline from the different offers on display. They were given a fixed budget to do this and kept whatever they did not spend on gasoline as their payoff. The goal of participants was thus to choose the cheapest prices per liter, but this was not shown to them. Rather, options were presented as a quantity Q and a price P for each option, and the goal was to choose the option with the lowest price per liter P/Q. Participants had to perform this task several times, whereby menus of options included either two or three options, and quantity was shown either graphically, thus requiring participants to make an estimate of Q, or numerically. The price per liter was not shown, and the quantity and price of each option varied across screens.

This design replicates most features of traditional AE designs but within an induced-value setting, where an objectively better option can be computed. This allows us to overcome most of the limits of traditional designs used to study context effects at the price of moving away from homegrown preferences and into the realm of objective (but fuzzy) value comparisons. Although most of the context-effects literature relies on preference-based tasks, recent studies on the cognitive underpinnings of the effects have increasingly relied on objective-value tasks, such as Trueblood et al. (2013) using rectangles or Spektor et al. (2019) using pixel-art matrices.

Traditional AE designs propose a choice among items defined over two dimensions (location and size of apartments, quality and price of beers, and resolution and durability of TV sets), and participants must assess the utility trade-off of the two dimensions. Our task allows us to move the difficulty of combining multidimensional attributes from the (unobserved and not measurable) utility space to the cognitive difficulty of making price/size evaluations over (measurable) money. The presence of money allows us to evacuate preferences and objectively measure performance. The task is monodimensional; participants care about one dimension only (unit price P/Q), but the cognitive difficulty of comparing different quantities and prices makes it two-dimensional as long as the quantity/price evaluations involved are not trivial.

Our design allows us to seamlessly change incentives by varying the price of options and observing the behavior of participants at the indifference point—as in most of the existing literature—but also away from it—as done for instance by Crosetto and Gaudeul (2016) and Farmer et al. (2016). Furthermore, our design allows us to measure the attraction effect not only as an aggregate (between-subjects) effect but as an individual (within-subjects) effect, as we can compare decisions made for objectively similar menus that only differ in their context. This in turn allows us to go deeper in examining individual heterogeneity. Although the bulk of the literature has relied on between-subjects designs, more recent studies focusing on the mechanisms and modeling of context effects have moved to within-subjects designs and estimations, such as Trueblood et al. (2013, 2014), Berkowitsch et al. (2014), Noguchi and Stewart (2014), and Cataldo and Cohen (2019). Liew et al. (2016) convincingly argue, replicating two previous studies, that subjects heterogeneity is crucial when estimating context effects.

3.1.2. A Continuous Time-Pressure Choice-Process Elicitation Mechanism. We employ a continuous time-pressure choice-process elicitation mechanism originally ~~because of~~ Caplin et al. (2011). This allows us to elicit both fast, time-constrained responses and slow, deliberate revisions. The method applies a random stopping mechanism, which generates continuous time pressure as participants do not know at what point in time their choice will be taken into account. Crucially, this stopping point is randomly drawn ex post. Subjects face a choice screen for 20 seconds. They choose an option by clicking on it. They can change their mind at any time during the 20 seconds. At the end of the trial, one second is drawn at random, and the option chosen *at that second* is the one that is payoff relevant. If no option has been chosen at that second, then an option is chosen at random within the menu.

More formally, participants face a choice screen for T seconds. Their choice c_{it}, $t \in \{1, \ldots, T\}$, is automatically recorded as their most recently chosen option.[2] At the end of the allotted time, the data obtained from each subject are a vector containing all the choices, $\mathbb{C}_i = \{c_{it} | t = 1 \ldots T\}$. One time point t is then uniformly drawn, $t \sim U(1, T)$, and the choice recorded at that time c_{it} determines the subject's payoff. If no choice had been submitted by time t, then the participant is assigned a choice at random within the menu.

This elicitation mechanisms incentivizes the participants to submit a choice as soon as they think that they have improved on choosing at random. This is particularly relevant in the presence of decoys, as those are clearly dominated. A first fast choice for any option other than the decoy makes sure that the decoy will not be chosen by the random mechanism. Once a first choice is submitted, participants are incentivized to revise and improve, if possible, on their choice; the earlier a participant settles on what he thinks is the best option, the higher the probability that this option will be the one actually implemented. Nonetheless, the subject continuously faces an incentive to change his mind upon further reflection. With respect to a normal choice task, participants face continuous time pressure and are incentivized to reveal their view of what is the optimal choice over time. Moreover, with respect to standard time-pressure tasks, there is no exogenous time constraint by which a choice has to be made. Rather, subjects are free to be as fast or slow as they wish depending on their decision style or ability.

Our data allow us to look into the process of revision as people move from fast to slow choices. Indeed, we are able to lay bare and observe the choice *process*, including the revision stage that is hidden in other experimental designs where participants are asked for only one choice, which is final. This peculiar elicitation mechanism has been used elsewhere with the same aim—uncovering the choice process. The method has been used to study intuitive and reflective behavior in a guessing game (Agranov et al. 2015) or to investigate the role of dual processes in generosity (Kessler et al. 2017). Ours is the first paper to bring this method to bear in the context effect literature.

Other methods to track the choice process, such as eye tracking (Reutskaja et al. 2011, Noguchi and Stewart 2014) or mouse tracking (Lohse and Johnson 1996), allow researchers to see what decision makers look at but not what option they think best at each point of time. By incentivizing choice over time, we obtain information about what a participant would have chosen under different degrees of time pressure without having to exogenously impose a time limit. Although this does not give us the level of detail needed to inform elimination by aspect models of choice as done by Noguchi and Stewart (2014) using eye tracking, it allows us to directly observe intuitive *and* reflective replies to the same problem from the same subject and hence, to shed light on the decision *processes* underlying context effects.

3.2. Experiment 1

3.2.1. Methods

3.2.1.1. Treatments. Participants were exposed to the expenditure minimization task described in Section 3.1. We employ a mixed between- and within-subjects treatment structure.

Between subjects, we vary the stimuli used to visualize the expenditure minimization task. In the *graphical* treatment (Figure 1(a)), the quantity of gasoline of each option was displayed graphically by means of a partially filled jerrycan. The filled part indicated the quantity, and a dashed line indicated the target quantity (three liters) to be bought. In the *numeric* treatment (Figure 1(b)), the quantity was displayed as a simple number. This variation is inspired by the controversy over the robustness of the AE when the options are presented in a graphical or verbal rather than numerical form (Frederick et al. 2014, Huber et al. 2014, Yang and Lynn 2014).

Within subjects, we vary across repetitions of the base task the relative price of target and competitor. The competitor is allowed to have a price of 85%, 95%, 100%, 105%, and 115% of the target price in a symmetric design. This range includes the special case of indifference that is studied by the bulk of the literature, but it allows us to also study the attraction effect in situations in which it has monetary consequences.

3.2.1.2. Measure of the Attraction Effect. Subjects face 20 screens with a target, a competitor, and a decoy (Figure 2). The decoy has the same size as the target, making dominance in price easy to spot, whereas comparing the target and the competitor requires a mental computation of price per liter. We measure the attraction effect as the difference in the choice share of the target and the competitor at any point in time in the 20 allotted seconds. If the prices of the target and the competitor are equal, then we measure $\bar{A}_{ABC} - \bar{B}_{ABC}$, where $\bar{A}_{ABC}$ is the share of option A (the target) within choice set ABC (Figure 3(a)).[3] This is the simplest possible measure of the attraction effect, but it only works well in the special case of indifference among options, which is the case studied in most of the literature.

When the price of the target is not equal to that of the competitor, then the absolute choice shares move in the direction of the incentives. The difference in the choice shares of the target and of the competitor within a single menu does not then pin down the AE, as it is affected by both the AE and the difference in the value of the options. For instance, if the target is 10% less expensive than the competitor, its higher choice share reflects *both* an attraction effect *and* the relative convenience of the target. We therefore need to extend the simple measure introduced by comparing the choice share of the target when, say, its price is 85% of that of the competitor with

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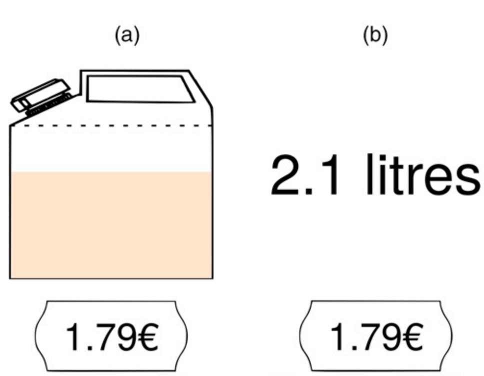
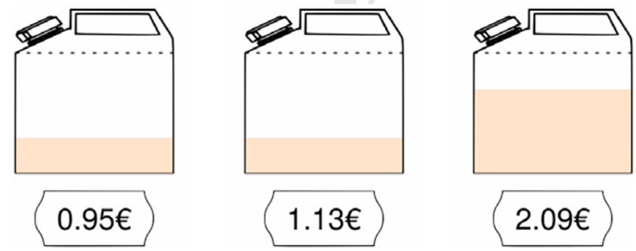
Figure 1. (Color online) Stimuli Used in Experiment 1



Notes. (a) Graphical treatment. (b) Numeric treatment.

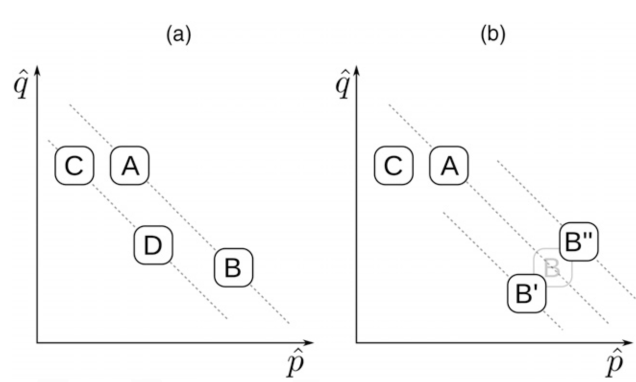
Figure 2. (Color online) A Choice Set in Experiment 1



the choice share of the competitor when *its own* price is 85% of that of the target. That is, we compute $\bar{A}_{AB'C} - \bar{B}''_{AB''C}$ (cf. Figure 3(b)). By comparing the choice share of option A across those two menus, we keep relative prices equal and thus, neutralize the relative price effect. This extension gives us a clean measure of the AE for any level of price difference.

For robustness, we also include an alternative measure of the AE using 20 further control screens. Subjects face the same screen two nonconsecutive times: once as in Figure 2 and once with a screen where no option plays the role of the decoy. This takes two different forms. In the *3vs2* measure, we drop the decoy and compute $\bar{A}_{ABC} - \bar{A}_{AB}$ (Figure 3(a)). This is akin to the measure that was mostly used, between subjects, in the early days of the attraction effect literature. In the *3vs3* measure, we keep three options but assign a different size to the decoy so that it is no more dominated by the target, and we compute $\bar{A}_{ABC} - \bar{A}_{ABD}$ (Figure 3(a)). Slightly different versions of this measure have been used more recently in the AE literature: for instance, by Trueblood et al. (2013) and Farmer et al. (2016). In both cases, we measure the AE as the difference in the choice share of the target in a screen with versus without a clearly dominated decoy. This additional measure can be readily applied to the cases of difference in relative price between

Figure 3. Design and Measures of the Attraction Effect



Notes. (a) Indifference. (b) Varying relative price. The vertical axis is $\hat{q}_i = \ln(q_i)$, and the horizontal axis is $\hat{p}_i = -\ln(p_i)$. Indifference lines $U = \ln(q_i) - \ln(p_i)$ thus correspond to all options such that $q/p = e^U$.

Q:15 the target and the competitor because it only ever compares shares of the target. Details are given in Online Appendix B.

3.2.1.3. Experimental Details and Procedures. We ran seven experimental sessions involving a total of 111 participants: 63 for the graphical treatment and 48 for the numeric treatment. The sessions took place in Grenoble, France in July 2017. Participants were recruited partly from students at a local engineering and economics school and partly from the general population from ads in local newspapers as well as from an existing database of potential participants in and around Grenoble, a midsized French city with a metro area of about half a million people. The resulting sample was 53% students, with the rest being workers or retired and unemployed people. Sample demographics are reported in detail in Table E.1 in Online Appendix E.

All sessions followed the same script. Upon entering, participants were randomly assigned a code and seated. Instructions were read aloud and displayed on the participants' computer screens. After instructions were read and all questions were answered, participants went through four practice screens. The screens used different stimuli but were otherwise identical to the ones used in the main task. Of the four screens, two showed choice sets of three choices with a decoy, one showed a choice set of three choices with no decoy, and another showed a choice set of two choices with no decoy. At the end of the four practice tasks, subjects saw a feedback screen, giving them information about the second randomly chosen to be binding, whether at that second they had or not submitted a choice, their choice at that moment (if no choice, the option randomly chosen by the computer), the total cost of the gasoline, and their profit. After all remaining questions, if any, had been answered, participants moved to the main task.

In the main task, participants saw a blank screen with a time counter for four seconds. The stimuli, with no possibility to choose, were shown for a further two seconds. Then, the screen became active, and the time bar at the bottom of the screen started filling up. Participants faced the screen for 20 seconds, during which they could click on any option at any time; then, the cycle started again. It took about 20 minutes to cycle through the 40 decision tasks, which were constructed as explain in Online Appendix M.1. The order of the 40 tasks was randomized across participants. The order of the options on the screen was also randomized but fixed for all participants.

At the end of the main task, participants were asked to fill in five different questionnaires. These were a sociodemographic questionnaire asking questions about gender, education, income, and profession; SOEP questions on general attitude to risk (Dohmen et al. 2011) and trust (Dohmen et al. 2008) and a question measuring loss aversion; a qualitative questionnaire to evaluate participants' understanding of the task and inquire into possible experimenter demand effects; the three-item Cognitive Reflection Test (CRT) questionnaire (Frederick 2005); and the Consumer Confusion Proneness questionnaire (Walsh et al. 2007).

The English translation of the original French instructions is in Online Appendix L. The web-based experimental software, written in php, as well as the original French instructions are available upon request.

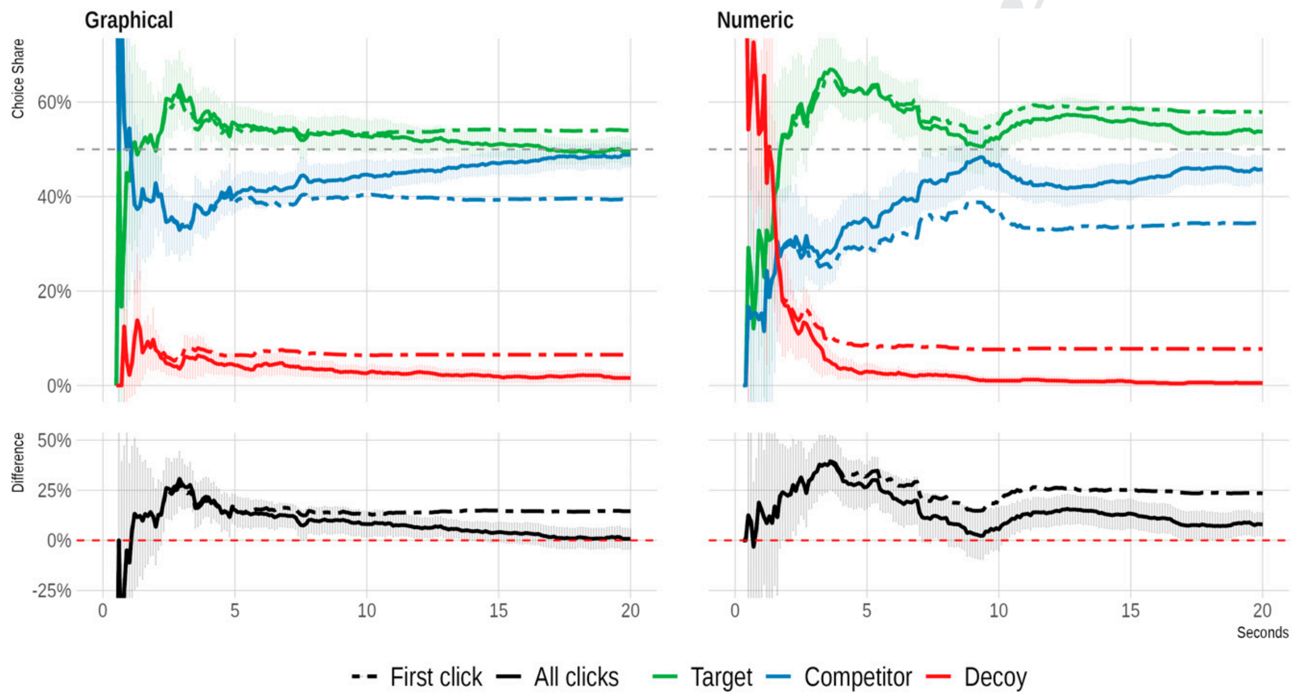
Participants received a €10 show-up fee. Moreover, 5 of the 40 screens were individually and independently drawn to be payoff relevant. Given this payoff rule, participants could earn up to a theoretical maximum of €15.49 in addition to the show-up fee. This would happen if they always made the profit-maximizing choice and the choice situations with the lowest prices were randomly drawn for payment. In practice, subject earned on average €10.00 in addition to the show-up fee (standard deviation of 1.57). Payoffs in the two treatments were virtually identical.

3.2.2. Results. In this section, we present descriptive statistics of participants' aggregate choice and revision patterns over time for the two treatments. Individual-level estimations of choice and time patterns are performed with a structural model in Section 4.

A majority of subjects adopted strategies involving revisions, and most of them transitioned from a first fast and intuitive reply to more reflective choices. This was more pronounced in the graphical treatment, where the first click is faster and the second slower than in the numeric treatment. Subjects clicked only once on a screen less than a third of the time (28.1% graphical, 30.6% numeric). The first clicks happen on average after about 5 seconds (5.28 numeric, 4.26 graphical), and the second clicks happen 4 seconds later, after about 9 seconds (8.77 numeric, 9.44 graphical).

Figure 4 shows the choice shares of target, competitor, and decoy in time. Error bars represent 95% confidence intervals and are calculated over the means of individual shares. The dashed lines represent the time pattern of choices when considering *the first click only* (error bars omitted for clarity). The solid lines take into account all clicks (i.e., include revisions). The lower panels show our measure of the attraction effect: the difference between the choice share of the target and the competitor. The attraction effect follows a rise-and-fall pattern. It first rises, reaches a maximum at about 25 percentage points advantage for the target, and then, gradually decreases and reaches nearly zero by the end of the allotted time. This is in part because ~~of~~ more accurate participants tak~~ing~~ their time to choose (the dashed lines stabilize at levels lower than the 25% peak) but mostly ~~because of~~ choice revisions (the difference between the dashed and solid lines). The effect is slightly more

Figure 4. (Color online) Choice Shares and Difference in Time for the First Click Only and for All Clicks by Treatment



pronounced in the numeric treatment, where it subsides earlier, than in the graphical treatment. Complete table data of the effect of first and second clicks on choice shares of options and response time are provided in Online Appendix C. This rise-and-fall pattern is robust to different ways of measuring the attraction effect by exploiting control screens with no or not obvious decoys (see Online Appendix B). The rise-and-fall pattern is also apparent from the very first trials; subjects do not need training on several trials to stop displaying the attraction effect over the 20 seconds of the task.[4]

We check the robustness of this pattern depending on the relative price of the target and competitor (Online Appendix A). We find that the effect is present in all cases, except in the case of indifference. This is because the fall in the relative share of the target is driven by revisions, which more closely approximate the objective difference in price between the target and the competitor. This driver does not operate when the target and the competitor are actually indifferent.

3.3. Experiment 2

In Experiment 2, we aimed for four distinct goals: replicate the results of Experiment 1 on a larger sample of diverse consumers, specifically excluding students; adopt a more robust measure for the attraction effect based on the work of Trueblood et al. (2014); optimize the stimuli and the choice screens to allow precise estimation of an MLBA model with revisions; and extend the analysis to the compromise and similarity effects. The cover story, the task, and the elicitation method were the same as the graphical treatment of Experiment 1.

3.3.1. Methods.

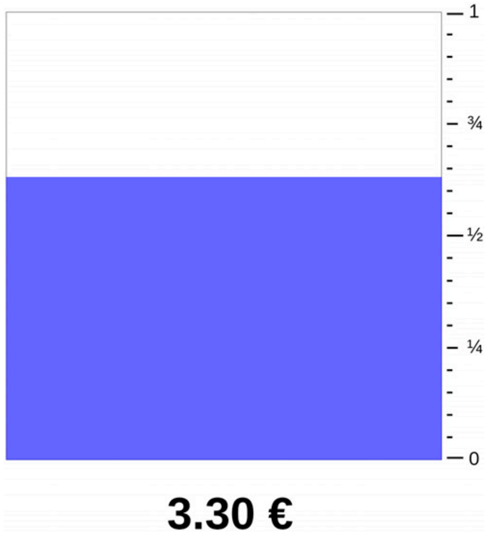
3.3.1.1. Stimuli and Measure. In Experiment 2, we used redesigned graphical stimuli to improve the ability to discern between offers. With respect to the stimuli of the graphical treatment of Experiment 1, we changed color to provide better contrast with the background, added a relative empty-full scale on the side to improve the comparability of offers, and used simple bars to show the size of the gas tank. Figure 5 shows an offer in Experiment 2.

The choice screens were chosen in order to implement the measure of context effects used by Trueblood et al. (2014). Figure 6(a) provides a graphical description of the stimuli for the case of the AE and indifference between the target and the competitor. Starting from two indifferent options A and B, we create the two choice sets ABC and ABD, with C being a decoy for A and D being a decoy for B. With reference to Figure 6(a), the measure of the attraction effect is given by

$$\text{effect} = \left(\frac{\bar{A}_{ABC} - \bar{B}_{ABC}}{2}\right) + \left(\frac{\bar{B}_{ABD} - \bar{A}_{ABD}}{2}\right)$$
$$\equiv \left(\frac{\bar{A}_{ABC} - \bar{A}_{ABD}}{2}\right) + \left(\frac{\bar{B}_{ABD} - \bar{B}_{ABC}}{2}\right),$$

where $\bar{A}_{ABC}$ is the choice share of option A in choice set

Figure 5. (Color online) Stimuli Used in Experiment 2



ABC. This measure distills the best features of ~~the main and control~~ measures of Experiment 1 into one unique measure.

The simple difference between the target and competitor is computed twice in order to clear the impact of a particular option on the measure and to average over size and price decoys. As can easily be seen by the two identical formulations of the measure, the measure is equivalent to taking the average of the main measure of Experiment 1 (target − competitor) across the two choice sets (~~leftmost definition~~) but also, to taking the average of the control measure of Experiment 1 (target in the presence versus absence of a decoy) but in a symmetric way, whereby the target takes the role of competitor and vice versa (~~rightmost definition~~).

The measure can be readily extended to a situation of different relative prices between the target and the competitor. In Figure 6(b), we can apply the measure to the choice sets AB′C and A′BD to get a clean measure of the attraction effect, whereby each option enjoys a better or worse price and plays the role of competitor and target. In this case, we compute

$$\text{effect} = \left(\frac{\bar{A}_{AB'C} - \bar{B}'_{AB'C}}{2}\right) + \left(\frac{\bar{B}_{A'BD} - \bar{A}'_{A'BD}}{2}\right)$$
$$\equiv \left(\frac{\bar{A}_{AB'C} - \bar{A}'_{A'BD}}{2}\right) + \left(\frac{\bar{B}_{A'BD} - \bar{B}'_{AB'C}}{2}\right).$$

The similarity and compromise effects are measured in exactly the same way; all that changes is the position of the decoys. In both cases, decoys belong to the same indifference line of the target and competitor. In the case of similarity, the decoy is very close to the competitor, and its presence is meant to make the dissimilar option—the target—stand out (Figure 6(c)). In the case of compromise, the decoys are located in such a way that the target becomes the "middle" option (i.e., is located exactly in the center of the line connecting the decoy and the competitor (Figure 6(d))). Both effects are also analyzed when varying relative prices, with the same mechanism shown for the attraction effect in Figure 6(b).

3.3.1.2. Experimental Details and Procedures. We ran nine experimental sessions involving a total of 198 participants. The sessions took place in Grenoble, France in September 2021. Participants were recruited from the same subject pool as Experiment 1 but excluding students. No person who participated in Experiment 1 was allowed to participate in Experiment 2. The sample was made nearly entirely of consumers, working (69%) or unemployed/retired (28%), with only 4% students—against 53% students for Experiment 1. Experiment 2 subjects were on average older with higher revenue, were slightly less educated, and scored lower on the CRT. Details of the demographics of the sample are reported in Table E.1 in Online Appendix E.

The procedures were kept as similar as possible to Experiment 1. With respect to Experiment 1, we improved the instructions, added control questions in between instructions and the training phase, and made two smaller training phases instead of a single larger one. All these changes were done to increase comprehension of the instructions and the elicitation mechanism. All other details were the same.

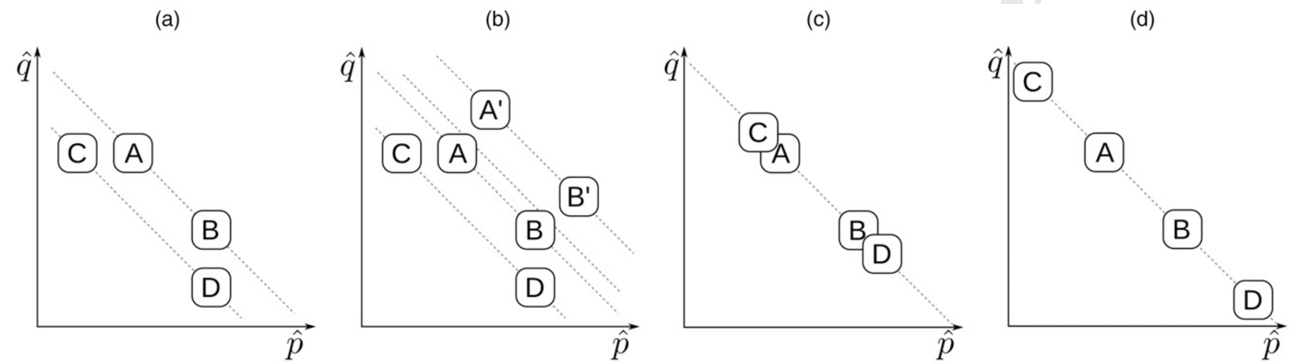
Subjects faced 42 screens in individually drawn random order. They were constructed as explain in Online Appendix M.2. It took about 20 minutes to cycle through all the decision screens. After the main task, subjects answered three questionnaires (down from six for Experiment 1). We kept the sociodemographic, risk attitude, and CRT questionnaires, as the comprehension, trust, and shopping questionnaires had no impact on our results for Experiment 1.

The English translation of the original French instructions is in Online Appendix L. The web-based experimental software (same as Experiment 1) as well as the original French instructions are available upon request. Participants received a €10 show-up fee. Eight randomly picked screens of the 42 were individually and independently drawn to be payoff relevant. Subjects earned on average €10.6 in addition to the show-up fee.

3.3.2. Results. As for Experiment 1, here we present descriptive statistics for the aggregate patterns of first choices and revisions; for individual-level estimations and structural modeling, see Section 4.

A majority of subjects revised their choice for all effects. Subjects clicked only once on a screen less than half the time for all effects (49.1% attraction, 42.5% similarity, 39.8% compromise). This ~~lower number of revisions,~~ especially for the AE, ~~is~~ possibly because ~~of~~

Figure 6. Design and Measures for Experiment 2



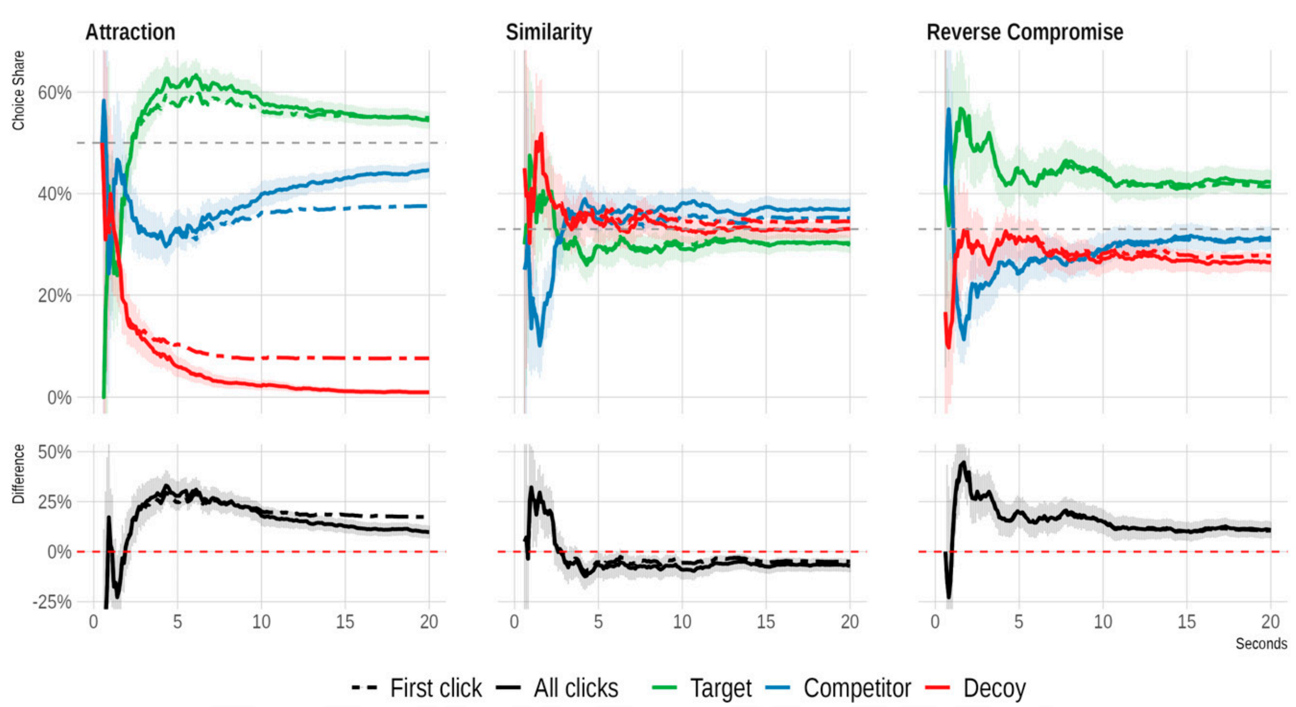
Notes. (a) Attraction: indifference. (b) Attraction: different values. (c) Similarity: indifference. (d) Compromise: indifference. The vertical axis is $\hat{q}_i = \ln(q_i)$, and the horizontal axis is $\hat{p}_i = -\ln(p_i)$. Indifference lines $U = \ln(q_i) - \ln(p_i)$ thus correspond to all options such that $q/p = e^U$.

the cleaner stimuli allow~~ing us~~ to more easily spot the decoy. The average time of first choices and successive revisions is ~~also~~ similar to that in Experiment 1, albeit slower across the board. First clicks happened on average after 5.75 seconds for the attraction effect (4.26 seconds in the comparable graphical treatment of Experiment 1), 6.29 for similarity, and 6.94 for compromise. Attraction is faster as subjects perceive the dominated decoy and choose in order to avoid being allocated the decoy in case of delayed first choice; it is not as fast as in Experiment 1, possibly because of the presence of ~~the~~ scale ~~giving incentives to subjects~~ to be precise. Second clicks take about 4 seconds more and happen on average at 9.37 seconds for attraction, 10.3 seconds for similarity, and 11.8 seconds for compromise.

Figure 7 shows the choice shares of target, competitor, and decoy in time for each effect (upper panels) and the measure of the effect in time (lower panels) for the first click (dashed lines) and all clicks (solid lines). Reference lines indicate the choice shares that should prevail absent any context effect. This is 50% for the attraction effect because the decoy is dominated and should never be chosen and 33% for the other effects because in this case, all options, including the decoy, sit on the same indifference line.

We closely replicate the attraction effect results of Experiment 1, with a clear rise-and-fall pattern, largely but not only driven by revisions. Differently from Experiment 1, the effect does not completely disappear but stays significantly different from zero until the very end. This

Figure 7. (Color online) Choice Shares and Difference in Time for the First Click Only and for All Clicks by Effect



might be ~~because of~~ the different demographic composition of the sample, which was made up of older, slightly less educated subjects and virtually no university students (see Table E.1 in Online Appendix E).

The same rise-and-fall pattern is observed for the similarity effect but at a much lower intensity and with a much shorter duration. The effect is limited to the first two and a half seconds, where only 10% (at one second) to 30% (at two seconds) of subjects have made a choice; it is hence a limited and ephemeral effect that is shown by the subpopulation of very fast first clickers. The effect settles to a very slight reverse similarity effect toward the end of the allotted time.

Unexpectedly, we fail to replicate the compromise effect. Our data rather highlight a *reverse compromise* effect, whereby the most extreme option—the decoy—is the most chosen one. Because in compromise screens, the decoy usually displays a very large quantity for a very small price or vice versa, this might have made it easier for subjects to compute the implicit unit price for that option because one dimension can be nearly disregarded. In the remainder of this section, we report the results for the reverse compromise effect that we found. This is done by considering as the target the option that was most extreme in either price or quantity and considering the middle option as the decoy (i.e., the option not frequently chosen), whose existence makes the extreme option stand out. Figure 7, right panel, is drawn by applying these different roles to the options. Using Figure 6(d) for reference, we consider, within choice set ABC, C to be the target, B to be the competitor, and A to be the decoy. This reverse compromise effect has been found elsewhere in the literature (for instance, in the by-alternative elicitation by Cataldo and Cohen 2019), and it *also* follows a rise-and-fall pattern, not disappearing by the end of the allotted time; as in the case of the surviving AE in Experiment 1, this might be driven by indifference among options. As in Experiment 1, the pattern is robust to different relative prices of the target versus the competitor (Online Appendix D).

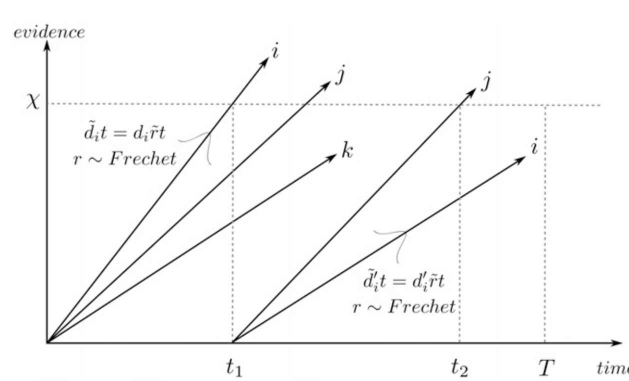
Overall, context effects in our experiment seem to generally follow a rise-and-fall pattern, but our stimuli do not always identify the effect we expected. As in Experiment 1, there is no role for learning across trials in our data; the rise-and-fall pattern is already established on the very first choice screens.

4. A Multiattribute Linear Ballistic Accumulator Model with Choice Revisions

We looked for a model that could account for both the speed and biases in choice but was simple enough to be extended to take account of choice revisions. We chose to model *decision times* by using the linear ballistic accumulation model (Brown and Heathcote 2008). This model is attractive because it has analytic solutions and thus, a likelihood function, allowing us to adapt standard estimation tools for its estimation. We elected to model *context effects* using the MLBA extension of the LBA model in Trueblood et al. (2014), as refined in Evans et al. (2019). This model can explain different types of context effects with a relatively low number of parameters that can be interpreted in intuitive ways. We simplified the LBA model into a *dynamic version of a Luce model of individual choice behavior* (Luce 2012), as explained in Colonius and Marley (2015). This allows us to go on to estimate our more complicated version of the LBA that allows for choice revisions. We estimate that model based on the methods outlined in Annis et al. (2017) for Bayesian estimation with Stan (Stan Development Team 2021).

Overall, the MLBA model compares well with alternatives, such as the multiattribute leaky competing accumulator model (Usher and McCelland 2004), the multialternative decision field theory ~~(MDFT)~~ (Roe et al. 2001), the association and accumulation model (Bhatia 2013), and the multialternative decision by sampling (Noguchi and Stewart 2018). Indeed, Evans et al. (2019) show that although all those model do a good job at predicting response times in context effect experiments, the MLBA outperforms them in predicting choice shares (Figures 4 and 5). Cataldo and Cohen (2021) find the same (Figures 6 and 7). They underline, however, that the MLBA is not very flexible in predicting variations in the share of different options as a function of decision times. It therefore does not allow us to reflect their finding that, within individuals, speed of decision influences the size of the context effects, whereas the MDFT appears to be better at reflecting this (Figure 8). Moreover, Molloy et al. (2019) underline the importance of including response times in inferences using the MLBA. Our extension of the MLBA takes account of the possibility to revise choices and thus, allows for a richer pattern of rise and fall in context effects over time.

Figure 8. First Choice and Revision Process



Notes. In this example, option i is chosen at time t_1. The set of options is reduced to i and second-best j for the revision. Choice is revised to option j at time t_2.

Our modeling fulfills several different aims. A first aim is to separate different factors in the decisions of individuals, namely the speed of their decisions, their precision, how biased they are by the context, and their willingness to revise choices. Following on this contribution, we are able to make a typology of decision makers, whereby some choose fast but in a biased way, whereas others choose slowly and are less biased. We extend this typology by also noticing that some of those who choose fast are also more flexible in their choice, meaning that they are willing to revise their choice after further consideration. Finally, we show that our model generalizes well to explain different patterns of choices and revisions over time under different contexts (dominance, similarity, and compromise). It can explain a variety of patterns in the dynamics of choice without requiring the introduction of additional ad hoc parameters.

In our model's "mechanical" explanation of the dynamics of choice, decision makers do not only make a choice among options but also, perform choice editing, whereby they eliminate options from the consideration set and then concentrate on the remaining options. This process of choice editing is also influenced by the context and results in changing the context of the decision. In our case, bias is reduced after choice editing because only two options then remain. Choice revisions therefore tend to reduce the contextual bias displayed in first choices. We show that our model generalizes well to contexts where choice editing is not as straightforward as under the attraction effect.

Overall, the main contribution of the model is to allow us to distinguish the process of choice editing from the influence of the context and to show how the two combine to give a satisfactory account of our observations. We underline the importance of the willingness to revise choices as a psychological factor that explains why and how context effects may decline when given enough time to reconsider past decisions.

In the following, we first present in Section 4.1 the model in three steps: first, the LBA back-end dealing with decision times; then, our extension of this back end to allow for revisions; and finally, the MLBA front end, which accounts for biases in favor or against options in a choice set depending on their context. We provide simulations to clearly link the model with the experimental findings. Then, we provide model estimates (Section 4.2), explore individual differences (Section 4.3), and produce postestimation predictions (Online Appendix K.1).

4.1. The Multiattribute Linear Ballistic Accumulator Model with Choice Revisions—A Model of Choice Revisions over Time

4.1.1. The MLBA Back End: Modeling Decision Times.

We use a simplified version of the original LBA model, where accumulation of evidence starts from a different point for each option and drifts are drawn from a normal distribution. Following Colonius and Marley (2015), we assume no starting point variability in the accumulator z_{it} and multiplicative draw of drifts from a Fréchet distribution. Indeed, maintaining the original version would require numerical integration to estimate the likelihood in the more complex model with revisions we present next. This is feasible, and we programmed it; however, it is computationally costly and thus, prohibitively slow with current software and computing capacity.

An option is chosen if it is the first to accumulate a level of evidence $\chi > 0$ in a race between options over time. Formally, denote $d = (d_i, d_j, d_k)$ a vector of the mean drift of options i, j, k. Those are constrained to be positive. The accumulator (or evidence) for option i at time t is $z_{it} = \tilde{d}_i(t - \tau)$. We let $\tilde{d}_i = d_i\tilde{r}$, with $\tilde{r}$ following a Fréchet distribution (also known as inverse Weibull); that is, $F(r) = e^{-r^{-\alpha}}$ for $r > 0$, 0 else, with $\alpha > 0$. τ is the consideration time: that is, the time needed before evidences accumulate.[5] Option i is chosen if it is the first Q:16
to accumulate $z_{it} = \chi$. We denote T the maximum time for making a choice. If the accumulator at T is less than χ, then no choice is observed. Figure 8 shows graphically the (linear) trajectory that each option follows, whereby evidence is on the ordinate and time is on the abscissa. The option with the highest slope is chosen at time $t = \frac{\chi}{d_i\tilde{r}}$. This is not always the option with the highest drift because of the random term $\tilde{r}$.

At time t', the accumulator for i will have reached level $z_{it} = d_i r t'$. This is higher than threshold χ at time t with probability $F_i(\chi, t) = p(z_{it} \geq \chi) = p(\frac{\chi}{d_i r} \leq t) = p(r \geq \frac{\chi}{d_i t}) = 1 - e^{-\left(\frac{d_i t}{\chi}\right)^{\alpha}}$. Decision times thus follow an extreme value distribution, such that $f_i(\chi, t) = \alpha \frac{d_i}{\chi}\left(\frac{d_i t}{\chi}\right)^{\alpha-1} e^{-\left(\frac{d_i t}{\chi}\right)^{\alpha}}$. That is, $f_i(\chi, t)$ follows a Weibull distribution with shape α and scale $\beta = \chi/d_i$. Option i will be chosen at time t with probability

$$
\begin{aligned}
f_i(t) &= p(t_i = t \cap t_j > t \cap t_k > t) \\
&= f_i(\chi, t)(1 - F_j(\chi, t))(1 - F_k(\chi, t)) \\
&= \alpha \frac{d_i}{\chi}\left(\frac{d_i t}{\chi}\right)^{\alpha-1} e^{-\sum\left(\frac{d_l t}{\chi}\right)^{\alpha}}.
\end{aligned}
$$

The cumulative distribution function of that event is $F_i(t) = \frac{d_i^{\alpha}}{\sum d_l^{\alpha}}\left(1 - e^{-\left(\frac{t}{\chi}\right)^{\alpha}\sum d_l^{\alpha}}\right)$. This means that for any decision time t, the probability that option i is the option chosen is $p_i = \frac{d_i^{\alpha}}{\sum d_l^{\alpha}}$, and the time at which an option is chosen is distributed according to c.d.f. $F(t) = 1 - e^{-\left(\frac{t}{\chi}\right)^{\alpha}\sum d_l^{\alpha}}$. This time distribution is independent of which specific option is under consideration.

Our model implies that the share of each option in terms of first choice does not vary with time. This characteristic will allow us to separate dynamics ~~because of~~

first choice (which are nonexistent in our model) and dynamics ~~because of~~ revisions in second choices. All dynamics we obtain theoretically can therefore only be ~~because of~~ revisions. We checked that our simplification was also justified empirically. This is the case as we do not observe changes in shares of first choices among options in our tasks at the individual level in our data. Note that this does not exclude some aggregate dynamics in first choices given individual differences in biases and speed of choices. We will underline those differences in the analysis of the results of our regressions.

4.1.2. Extending the MLBA to Take Account of Choice Revisions. We extend the MLBA to account for the possibility to revise choices. We call this the multiattribute linear ballistic accumulator model with choice revisions (MLBA-R): that is, an MLBA model with revisions. We assume that once the first option to reach threshold χ is chosen at time t_1, a new race is started between that option and the second-best option at that time: that is, the option with the second highest level of evidence in its favor at time t_1. If, for example, option i reaches χ at time t_1 and is the first to do so, then the second-best option is $j = \arg\max_{l \neq i} z_{lt_1}$. We illustrate this in Figure 8, where option k is eliminated from the consideration set when starting a second race between i and j.

The second-best option thus enters a second race with i, whereby drifts are computed and drawn again given the new context with only two options. In this second race, we allow for a possible tendency to either *stay* with the first option or switch to another option by multiplying the drift of the first option chosen by *stay* (see Section 4.1.3). If i wins again or no option reaches threshold χ before the time limit T, then the choice of i is maintained. If j wins at time t_2 and $t_2 < T$, the time limit, then the choice is revised to j. More details on the probability calculations to compute the log likelihood of our model are presented in Online Appendix F.

4.1.3. The MLBA Front End: Modeling Context Effects. The main innovation in Trueblood et al. (2014) is a model to generate the "drifts" d: that is, the average speed at which evidence accumulates for an option in the LBA model. This is what they call a "front-end" extension of the linear ballistic accumulator model. We adopt a further refinement, including an additional parameter γ as in Evans et al. (2019).

We explain here how we derive drifts d from a set of options i, j, k characterized by the vector $((x_{1i}, x_{2i}), (x_{1j}, x_{2j}), (x_{1k}, x_{2k}))$, whereby the objective value of an option i is $v_i = x_{1i} + x_{2i}$.[6]

A *first step* obtains (u_{1i}, u_{2i}) such that

$$u_{1i} = \frac{(x_{1i} + x_{2i})}{(1 + (x_{2i}/x_{1i})^m)^{1/m}} \text{ and } u_{2i} = \frac{(x_{1i} + x_{2i})}{(1 + (x_{1i}/x_{2i})^m)^{1/m}}.$$

Parameter m translates extremeness aversion. $m > 1$ results in aversion to extreme options: that is, to options where most of the value comes from one dimension only.[7] If $m = 1$, then $(u_{1i}, u_{2i}) = (x_{1i}, x_{2i})$. If $m < 1$, then we obtain a preference for extreme options.

A *second step* obtains weights (attention) given to the comparison of options i and j on dimension n. Those depend on the absolute value of the difference in the value of options, such that options that are close to each other on one dimension attract more attention. We have

$$w_{1ij} = exp(-\lambda |u_{1i} - u_{1j}|)$$
$$w_{2ij} = exp(-\beta\lambda |u_{2i} - u_{2j}|).$$

This value function translates how people go about pair comparisons on single dimensions, whereby values that are closer attract more attention, as shown in Noguchi and Stewart (2014).[8] Parameter β may differ from one to allow for a difference in how individuals go about comparisons across the two dimensions.

A *third step* obtains the V matrix of binary comparisons, with elements

$$V_{ij} = w_{1ij}(u_{1i} - u_{1j}) + w_{2ij}(u_{2i} - u_{2j}).$$

In a *final step*, elements of this matrix are combined to obtain the vector of drifts for each option, $d = (d_i, d_j, d_k)$, whereby

$$d_i = I_0 + \gamma \sum_{j \neq i} V_{ij}.$$

This function suggests that options are compared in pairs rather than globally. Drifts are restricted to be greater than zero.

4.1.3.1. Calculation of Drifts in the Second Race. The same calculations can be made when comparing only two options with each other. In our model, this happens when revisions are being made, as this involves a comparison between only the first and second runners in the first race between options.

We introduce parameter *stay* to the model to translate a possible advantage or disadvantage to the first option chosen when the second race is run. This parameter makes psychological sense, as revising one's choice requires effort and also requires accepting that one's first choice was not optimal. This parameter also introduces memory of past choices in the choice process. A value *stay* > 1 means there is a tendency to stay with the first option chosen.[9] Denoting $d' = (d'_i, d'_j)$, whereby i is the option first chosen and j is the second best, we thus let[10]

$$d'_i = (I_0 + 2\gamma V_{ij}) \times stay \text{ and } d'_j = I_0 + 2\gamma V_{ji}.$$

We summarize our parameters in Table 1.

4.1.3.2. Interpretation of Parameters. I_0 translates randomness in choice, as this is the part of the drifts that

Table 1. Parameters and Allowable Ranges for the Multiattribute Linear Ballistic Accumulator Model with Revisions

Parameter	Description	Allowable range
I_0	Baseline input	$I_0 \geq 0$
γ	Choice accuracy	$\gamma \geq 0$
m	Exponent transforming objective to subjective values	$m > 0$
$\lambda, \beta\lambda$	Decay constant for attention weights, dimensions 1 and 2	$\lambda, \beta \geq 0$
stay	Tendency to stay with the first option chosen	$stay \in \mathbb{R}$
α	Shape of the time distribution	$\alpha > 0$
χ	Threshold amount of evidence required to trigger a choice	Fixed, $\chi = 1$
τ	Consideration time	Fixed, $\tau = \min(t)$

does not vary across options, whereas γ translates accuracy in choice: that is, how far the difference V_{ij} in weighted values between options influences choice. Higher I_0 and γ mean that choice will be made more quickly, and a higher I_0 relative to γ means that choices will be made more randomly. The mean speed of choice also varies with α, whereby an option with drift d facing an option with zero drift will be chosen at time $\chi\Gamma(1+1/\alpha)/d$ on average and whereby Γ is the gamma function, with special cases $\Gamma(n) = (n-1)!$ for $n \in \mathbb{N}$.

V_{ij} are computed with the parameters λ, m, and β, whereby parameters λ and m do most of the work in accounting for the attraction, similarity, and compromise effects. Higher λ results in larger differences in the attention given to options that are close together rather than farther away. In the case of the attraction effect, this draws relatively higher attention to the pair target-decoy because they are close together. Because the target is superior to the decoy, then this attention comes at the expense of the decoy and benefits the target versus the competitor. In the case of the similarity effect, then the pair that is close together also draws attention, but this attention is split between the two options because they are similar in value; this benefits the third far-away option. In the case of the compromise effect, then this parameter is not so important because all options are similarly far from each other. In this later case, however, parameter m comes into play; the more there is aversion to extreme options ($m>1$), the more the middle option will be favored. Conversely, if $m<1$, then extreme options will be preferred.

A special case that corresponds to rational fully informed choice, whereby an individual considers only the sum of the dimensions for each option, is $v_i = x_{1i} + x_{2i}$. This is so if $m=1$ and $\lambda=0$. Then, drifts for each of three options are simply $d_i = I_0 + \gamma \times ((v_i - v_j) + (v_i - v_k))$, whereby what matters is simply a comparison of the objective value of each option with respect to the alternatives.

Parameter β translates how differences on one dimension matter compared with differences on the other. For example, $\beta < 1$ if consumers pay more attention to differences in the second dimension, maybe because it is shown first in the lexicographical order when presenting options or because it is shown in a more intuitive way, such as with a figure.

4.1.4. Simulations. In order to illustrate the working of our model, we simulate decision times and choice shares for representative choice set comparisons, following the model of exposition in Trueblood et al. (2014). Table G.1 in Online Appendix G shows artificial stimuli for the simulations, whereby the objective value of an option is the sum of its two components. The target is the option that is chosen more often if the effect holds. Two choice sets are presented for each effect so as to keep two options the same and only vary the third decoy option. The magnitude of the context effect is the average choice share of the target across the two choice sets. This measure neutralizes the effect of differences between the target and the competitor other than the context in which they are presented.

We simulate choices using our model and parameters consistent with our subsequent estimates: $I_0 = 1$, $\gamma = 3$, $m = 2$, $\lambda = 0.5$, $\beta = 1$, $stay = 1$, $\alpha = 1$ $\chi = 1$, $\tau = 0.1$. We show resulting frequency of choices and revision patterns in Table 2 for the attraction effect, along with average choice speed.

With those parameters, the target in choice sets with attraction effect is chosen 54% of the time as a first choice. The decoy is chosen 3% of the time, mainly as a random choice within the first two seconds of choice ($\tau = 0.1$). This explains why choices of the target are made so fast. Revisions lead the share of the target back to 52%. This is because 32% of the original choices of the target are revised to the competitor and 28% of the choices of the competitor are revised to the target, which tends to equalize shares.[11] We also see that choices of the decoy are revised to the target rather than to the competitor, and otherwise, they are maintained. There is no choice made at all in about 6% of cases.

The same tables for the similarity and compromise effects are shown in Online Appendix H. We obtain a slight antisimilarity effect in first choices, whereby the similar competitor is chosen 36% of the time versus 34% for the target. There is no rebalancing after revisions. There is a compromise effect, whereby 55% of the first choices are for the compromise option. A rebalancing occurs after second choices, whereby the share of the target is revised down to 52%.

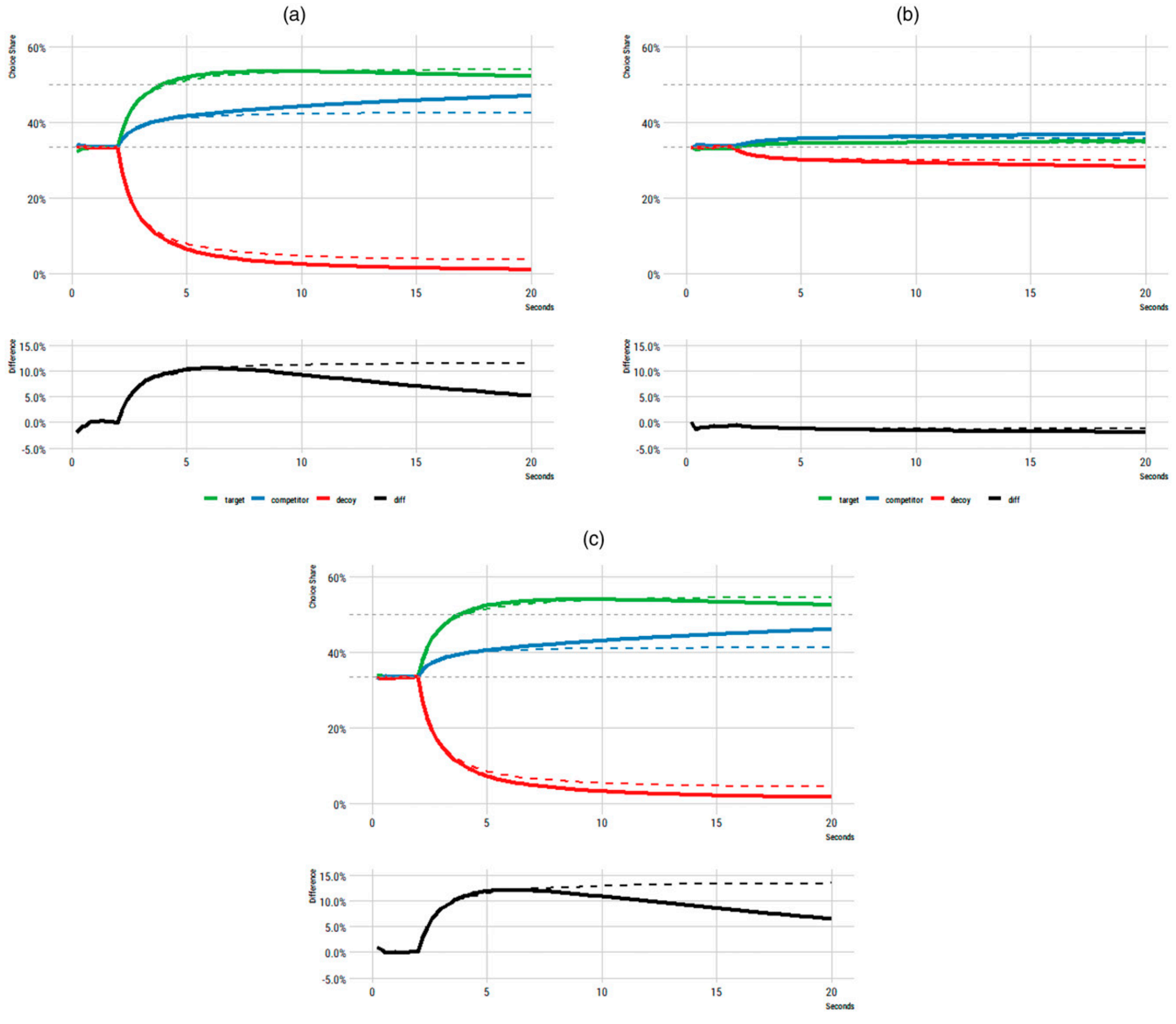
We see from those examples that if there are context effects in first choices, then they tend to be reduced after revisions are made.

Table 2. Simulated First Choices, Revisions, and Final Choice for the Attraction Effect

First choice			Revision			After revision	
Option	Share, %	Time	Option	Share, %	Time	Option	Share, %
Target	54	(6.92)	Competitor	32	(6.88)	Target	52
			Decoy	0	(–)		
			No revision	68	(–)		
Competitor	42	(6.81)	Target	28	(6.76)	Competitor	47
			Decoy	1	(8.18)		
			No revision	71			
Decoy	4	(1)	Target	87	(7.74)	Decoy	1
			Competitor	0	(–)		
			No revision	13			

Figure 9 shows the evolution of the share of each option for each effect as a proportion of choices made. We see there that the share of each option early on is 33%, as choices made before the minimum consideration time τ are made at random. The consideration time τ reflects the empirical distribution of decision

Figure 9. (Color online) Simulated Proportions of Choices Made over Time



Notes. (a) Attraction. (b) Similarity. (c) Compromise.

times, whereby a small proportion of choices are made very rapidly, with every option getting similar shares. Choice proportions then evolve as considered choices are made, climbing to their share of first choices as shown in Table 2.

Shares then adjust as revisions take account of other factors. For example, the shares of the target and of the competitor converge in attraction choice sets. Convergence is not fully to 50% because of the time limit, so not all have time to revise their choices. There is no convergence in similarity choice sets and convergence as under the attraction effect in compromise choice sets. Dotted lines on the graph show the share of options if only first choices were taken into account in order to visualize the difference ~~because of~~ revisions.

The main lesson from those graphs is that we obtain nonmonotonous patterns in the share of options if we include patterns of revisions in our model.[12] This is because first choices, which tend to occur early compared with second choices, favor one option because they consider all options and thus, the context. Revisions, on the other hand, involve comparisons between pairs of options (i.e., without the influence of a third option), so the effect of the context converges downward.[13]

4.2. Model Parameter Estimates

We estimate parameters in the model using Bayesian methods. We estimate a "basic" MLBA model that takes only first choices into account. We then estimate our extended MLBA-R model that includes choice revisions. We finally estimate a mixed-effects model (also known in the literature as a random-effects, multilevel, or hierarchical model). This allows parameters to vary by individual, so we obtain "regularized" mean estimates of the parameters and of their variability across individuals. The resulting estimates are more useful for broader inferences as they are independent of the particular individuals in our sample. We also obtain "regularized" estimates of the parameters for each individual. Those are more reliable than estimates we would obtain from independently estimating parameters for each individual. Indeed, those regularized estimates take account not only of the data for an individual but also, of information gained from estimates for other individuals. In mathematical terms, we let $p \sim \mathcal{N}(\mu_p, \tau_p)$ for parameter $p \in \{I, \gamma, m, \lambda, \beta, stay\}$ and thus, obtain estimates not only of μ_p, the mean of p, but also of τ_p, the standard deviation of p across individuals. Details on our estimation procedure are given in Online Appendix I.

Table 3 shows results of our estimation of parameters for the model with mixed effects. We split results in Experiment 1 by whether stimuli sizes were shown graphically or numerically (see Figure 1). We estimate all effects together in Experiment 2 rather than splitting estimates by effect based on the (verified) principle that our model of choice applies to all contexts, and parameters therefore should not depend on the context under consideration. Table J.1 in Online Appendix J shows results for the simpler models.

Parameter estimates in the mixed model are consistent with those of the other models, and differences across treatments are reduced. This makes sense because those are regularized estimates that abstract from individual variations to retrieve latent parameters. We also provide summary statistics for individual parameter estimates across individuals (Figure J.1 and Table J.2 in Online Appendix J).

The graphical treatments of Experiment 1 and Experiment 2 obtain very similar regularized parameter estimates and average individual parameter estimates. This

Table 3. Parameter Estimates: Model with Mixed Effects

	Experiment 1: Graphical		Experiment 1: Numeric		Experiment 2	
Parameters	Mean	90% CI	Mean	90% CI	Mean	90% CI
μ_I	2.30	[2.11; 2.50]	2.01	[1.69; 2.37]	1.84	[1.70; 1.99]
μ_γ	3.83	[3.52; 4.15]	3.83	[3.51; 4.16]	3.14	[2.82; 3.47]
μ_m	0.97	[0.94; 1.01]	1.00	[0.96; 1.04]	0.92	[0.89; 0.95]
μ_λ	0.15	[0.04; 0.36]	0.09	[0.03; 0.21]	0.08	[0.02; 0.20]
μ_β	0.72	[0.65; 0.80]	1.14	[1.07; 1.21]	0.71	[0.67; 0.76]
μ_{stay}	0.90	[0.79; 1.02]	0.85	[0.78; 0.92]	0.92	[0.82; 1.03]
τ_I	0.89	[0.75; 1.04]	1.29	[1.03; 1.59]	1.08	[0.97; 1.21]
τ_γ	1.39	[1.18; 1.64]	1.32	[1.09; 1.57]	1.68	[1.50; 1.87]
τ_m	0.16	[0.13; 0.18]	0.16	[0.14; 0.20]	0.20	[0.17; 0.22]
τ_λ	0.65	[0.54; 0.76]	0.30	[0.24; 0.37]	0.52	[0.46; 0.57]
τ_β	0.31	[0.25; 0.37]	0.26	[0.21; 0.31]	0.25	[0.22; 0.28]
τ_{stay}	0.64	[0.52; 0.77]	0.32	[0.26; 0.38]	0.82	[0.73; 0.92]
α	1.76	[1.72; 1.81]	1.80	[1.74; 1.86]	1.97	[1.95; 1.99]
LL	−700	[−742; −664]	−513	[−549; −483]	−6,637	[−6,756; −6,527]
N	63		48		198	
Tasks	20		20		36	

Note. 95% CI, 95% confidence interval.

is because the presentation of options was similar in both. The only differences across treatments relate to the numeric treatment of Experiment 1, where estimates of μ_β are higher than one, whereas they are lower than one in other treatments and where estimates of *stay* are lower than one, whereas they are not significantly different from one in other treatments. We also find that parameter m is less than one in Experiment 2 while not being significantly different from one in other treatments.

Parameter λ is significantly more than zero in all treatments, meaning that participants were more attentive to options that were close together. This explains how, in choice sets with similarity, options that were similar were more likely to be chosen than the dissimilar "target" option.[14]

Parameter β is significantly lower than one in the graphical treatments of Experiment 1 and Experiment 2, meaning that quantity differences were more important in the comparison process than price differences. This can be related to how quantities were more salient than prices in the graphical treatments, as they were shown graphically. Conversely, β was higher than one in the numeric treatment, indicating that price differences were given more attention than quantity differences in the valuation of options. This can be related to how quantities were presented in the same way (numerically) as prices in that treatment and price possibly being more focal.

Finally, participants were keen to switch from their first choice in the numeric treatment ($\mu_{stay} < 1$), possibly because the presentation of options was more complex, requiring the processing of many numbers. This may have made the first more intuitive choice more difficult, thus lowering confidence in it. The *stay* parameters were not significantly different from zero in other treatments.

As noted, estimates of m were lower in Experiment 2 than in Experiment 1. There was no aversion or preference for extreme options in Experiment 1 ($m \simeq 1$), whereas there was a preference for extreme options in Experiment 2 ($m < 1$). This is consistent with the *reverse* compromise effect we observe in Experiment 2.

Postestimation results are shown in Online Appendix K, where we consider choice shares and revision dynamics implied by our model and estimated parameters. The model translates empirical observations from a qualitative point of view (rise and fall of the attraction effect, revisions away from the target). However, we do not replicate the magnitude of the effects; for example, postestimates of the attraction effect are lower than observed in the data.

4.3. Individual Differences

We further assess differences across individuals by splitting individual parameter estimates obtained in the mixed-effects model into three component indicators based on the drift d_i of an option i in a choice set. From our model,

$$d_i = I_0 + \gamma f_i(m, \lambda, \beta),$$

whereby d_i measures how attractive an option i is when compared with j and k in a choice set. We note that $s_i = d_i^\alpha / \sum_j d_j^\alpha$ is the share of option i in terms of first choices in our model. Our first indicator is $speed = (I_0 + \gamma f')/\Gamma(1 + 1/\alpha)$, whereby we set $f' = 0.15$, the average difference in objective value between the target and decoy in our choice sets with attraction.[15] The second indicator is Q:17 $precision = d_T^\alpha / (d_T^\alpha + d_D^\alpha)$, the likelihood the target is chosen versus the decoy is they are the only two options in a choice set, there are no biases ($\lambda = 0, m = 1$), and the value difference between the two is 0.15.[16] This measures the relative contribution of chance in the choice of an option. Finally, the third indicator is $bias = sd(f_i, f_j, f_k)$ ~~as~~ the standard deviation of differences in values across options. This indicates how much the context[17] affects choice across options.[18] The advantage of using those indicators rather than parameter values is that there are fewer of them, and they allow us to abstract from complex interactions between λ, β, and m in determining bias for an option.

We show values of those indicators, averaged over individuals, in Table 4.[19]

We find that *speed* and *precision* are similar in Experiment 2 and in both treatments of Experiment 1. This is

Table 4. Speed, Precision, and Bias Based on Individual Parameter Estimates

	Experiment 1: Graphical		Experiment 1: Numeric		Experiment 2	
Parameters	Mean	90% CI	Mean	90% CI	Mean	90% CI
Speed	3.27	[1.41; 4.86]	3.13	[1.18; 5.42]	2.77	[1.17; 4.99]
Precision	0.73	[0.64; 0.88]	0.76	[0.64; 0.96]	0.75	[0.62; 0.91]
Bias (attraction)	0.21	[0.17; 0.27]	0.22	[0.18; 0.25]	0.20	[0.16; 0.25]
Bias (similarity)	0.06	[0.01; 0.20]	0.02	[0.00; 0.05]	0.05	[0.01; 0.13]
Bias (compromise)	0.14	[0.03; 0.41]	0.07	[0.02; 0.11]	0.13	[0.05; 0.27]
Stay	0.93	[0.41; 1.89]	0.82	[0.49; 1.12]	1.10	[0.40; 2.02]
N	63		48		198	

Note. 95% CI, 95% confidence interval.

even though there was a wider array of different types of tasks (effects) and the possibility to make more precise comparison of quantities in Experiment 2.

Bias was also similar across different experiments. It is higher in choice sets with attraction than in choice sets with similarity or compromise because options are equivalent in objective terms under those two effects, whereas the decoy is dominated in attraction tasks and so, is seldom chosen.

Parameter *stay* was not significantly different from one in all experiments. This means that unlike what we would have expected, there was no status quo effect, whereby participants are attached to their first choice. We will see in the analysis of correlation between those indicators that, indeed, those who on average made the fastest first choices were the least likely to maintain them; that is, they switched more willingly than slower participants.

We move on to analyzing correlations between individual speed, precision, and bias (Figure J.2 in Online Appendix J). We find a negative relation between speed and precision in all treatments. There is a positive relation between speed and bias in the attraction effect for Experiment 1 but not Experiment 2. There is, however, a positive relation between speed and bias for other effects in Experiment 2. There is no consistent relation between precision and bias. Finally, parameter *stay* is negatively correlated with speed and positively correlated with precision, significantly so in Experiment 2. There is, however, no consistent relation between stay and bias for any of the effects in Experiment 2.

In other words, *individuals who make faster choices are generally less precise and more biased*. Furthermore, those who make fast choices are less likely to maintain those choices, whereas those who make more precise choices are more likely to maintain them.[20]

5. Discussion

We study the choice process of individuals when faced with an objective-value choice task where context effects arise. Participants in our experiment are under constant time pressure and have the possibility to revise choices over time. We find that the attraction effect follows a rise-and-fall pattern over time. It is high in the first few seconds and then nearly disappears over a longer time span of 20 seconds. This rise-and-fall pattern is robust over two experiments with different samples, to using four different measures of the effect, and to differences in values between the target and the competitor. The AE sees no fall only in the special case of indifference among options; this is further limited to Experiment 1, whereas in Experiment 2, the rise-and-fall pattern replicates to all cases.

This rise-and-fall pattern stems from two main sources: choice revisions, whereby subjects submit a first choice favoring the target and then move away from it when revising their choice; and subject heterogeneity, whereby some subjects submit fast choices using the AE as a heuristic, whereas others take their time and submit AE-free slower, more reflective choices. We further refine the typology of decision makers by showing that many of the fast and biased individuals are willing to revise their biased first choices. They may be following an optimal strategy for choice under time constraint, whereby they use fast heuristics first and then switch to a more reflective mode if there is some time left.

We find that this rise-and-fall pattern is also present for other context effects to the admittedly limited extent that those effects materialize in our experiments. We develop an original extension to the MLBA model of Trueblood et al. (2014) to include the possibility to revise decisions. Regularized model parameter estimates at the individual level confirm differences in the processes of decisions across individuals. This confirms the practical interest of using the MLBA model to study context effects.

Crucially, our results hold in an objective-value, induced-preference task, where preferences do not differ across participants and there exists an objectively best option that can be identified through accurate measurement and computation. Within the limits imposed by our methodological choices, we can unambiguously say that the attraction effect is mostly the result of a short-term heuristic~~: that~~ is, for most subjects, superseded by more cognitively demanding processes after a few additional seconds~~;~~ ~~we~~ have some evidence that this rise-and-fall pattern holds for other context effects as well. On the other hand, the external validity of our findings depends on how well our experimental design translates into real-world choices that are driven by preferences, where an objectively best option that can be reached by computation and introspection might not exist and where there are opportunity costs to reconsidering a choice rather than moving on to other choices.

5.1. Rationalizing Results from the Literature

If we take our results at face value, we can consider the attraction effect as a simple, fast decision strategy, akin to a heuristic. Doing so allows us to rationalize several disconnected results from the literature. The large list of settings in which the AE fails can be grouped in two different strands: settings in which other heuristics allow the participants to do better and settings where the subject is incentivized to switch away from heuristic decision making and toward "slow," "reflective," and "maximizing" strategies. Switch to competing heuristics more appropriate to the problem at hand can, for instance, explain why the AE is muted in the presence of other focal cues (like brand) (Ratneshwar et al. 1987), when the product description is detailed and unambiguous (Mishra et al. 1993), or when the products are known and familiar to the consumer (Ratneshwar et al. 1987). Difficulty in recognizing and being relatively certain of dominance can explain the muting of the AE with pictorial representation of products (Frederick et al. 2014, Yang and Lynn 2014) and in real-world choices (Trendl et al. 2021). Switching to "System 2," slow decision modes can explain the disappearance of the effect when the target and the competitor differ in value (Crosetto and Gaudeul 2016, Farmer et al. 2016). The interpretation of AE as a heuristic that is used if and until it is superseded by other processes is also supported by the fact that the AE survives *only* in conditions of indifference (i.e., when there is no need to move on to finer strategies), but at the same time, it does appear, albeit temporarily, away from indifference when according to the very pioneers of the effect, *it should not* ("when there are strong prior preferences, the classic model of choice will apply" (Huber et al. 2014)).

Q: 18

The view of the AE as a simple dominance-based heuristic is backed by several other existing results in the literature. Mao and Oppewal (2012) showed the AE to be more pronounced among consumers with an intuitive thinking style as measured by an abridged version of the rational-experiential inventory questionnaire (Epstein et al. 1996). Pocheptsova et al. (2009) showed that the AE increases when participants' cognitive resources were depleted (Masicampo and Baumeister 2008) and when participants were tired. Hu and Yu (2014) showed in an fMRI study that the AE was associated with activation in areas of the brain linked with heuristics and that those participants who had lower AE had activation in areas linked to cognitive control. Howes et al. (2016) showed that context effects, as heuristics in general, can be optimal when signals are noisy or decision makers are inaccurate in their assessment of options.

5.2. Ability and Willingness to Switch Decision Modes

More generally, our findings show that participants can switch between decision modes when given incentives to do so. This point was made already in early literature on the topic (Payne et al. 1988, 1993) that argued that participants use phased decision strategies, whereby they employ different types of processing at different phases of the decision. Our experiment allows us to provide some clear, incentivized, and measurable empirical evidence behind the use of such phased decision processes. Our findings also resonate with a very recent literature on the possibility to correct behavioral biases by confronting participants with their inconsistencies and offering them different ways to revise their submitted choices or state their confidence in them (Enke and Graeber 2019, Benjamin et al. 2020, Nielsen and Rehbeck 2022).

Our main finding of a rise-and-fall pattern for the AE does not directly contradict previous research that shows that less time pressure increases context effects (Dhar et al. 2000, Pettibone 2012, Trueblood et al. 2014). Indeed, our task does not *force* participants into quick decisions but puts them in a situation where they trade off speed and accuracy, and hence, it gives them *incentives* to reveal whether their dynamic answering strategy relies on using a fast heuristic and then revising their choice, on just using the former, or on waiting until they can provide a refined, accurate answer. We indeed do replicate the fact that in the first few seconds, the effect shoots up; however, unlike in other experiments, which stop time after two, four, six, ~~and~~ eight seconds and do not allow for revisions, we give more time and keep on observing. This allows participants to make slow choices if they wish to and to revise their early fast choices. This results in the overall effect falling down to nearly zero in Experiment 1—except in the special case of indifference between target and competitor—and to about a third of the peak in Experiment 2.

5.3. Are the Findings Externally Valid?

The peculiar task chosen for our study limits nonetheless the claims we can make with respect to the external validity of our findings. Our results might even support an opposite claim (i.e., vouch for the robustness of the attraction effect) because it manages to survive, albeit to a small extent and in situations of indifference, in a very hostile setting where we should not observe it. From this perspective, our results show that given enough time and incentives and in a context where using a reflective decision mode can make a difference, subjects move away from their intuitive first responses and toward behavior that can be described as consistent with rational choice principles. However, our results are silent on whether these conditions hold in real-choice situations and what the attraction effect pattern would look like in a more realistic setting involving preferences and weighing of fuzzily evaluated options in utility space and where subjects face the opportunity cost of time and could hence move fast to other decisions (Imas et al. 2022). Most of the previous literature on the attraction effect never forced subjects to give a fast reply, implying that subjects autonomously chose to stop thinking and move on to the next task; to the extent that this is true in real-choice situations, those might not exhibit the rise-and-fall pattern documented in this paper.

5.4. Are the Findings Relevant to Other Contexts?

The extent to which our results will apply outside of our admittedly special setting is hence an open question, which can be addressed experimentally or empirically. We believe that in many settings, however, time, tools, and incentives for subjects to revise and refine their choices *do* exist. They might learn to make first intuitive choices and then revise them either by taking more parameters into account or by relying on advice from other consumers, on specialized information by experts, or on advice from friends and family. They may also simply do so because of the incentives involved when the amounts at stake increase. Documenting a rise-and-fall pattern and a decrease in time of context effects when given incentives in preference-based tasks and across a variety of conditions constitutes a much needed research program. This is nonetheless beyond the scope of our paper, whose aim is to document the pattern and provide evidence of its robustness.

It is also possible that our design creates artefactual incentives for participants to adopt a *fast then slow* heuristic. Indeed, our choice process elicitation mechanism gives an incentive for rational decision makers, who are aware of their cognitive limits, to provide a first intuitive reply and to then revise it. If a rational decision maker could make a fast, accurate first reply, she should do it. However, if she knows that she needs time to provide an accurate choice, then it is in her best interest to submit a provisional choice in favor of a good-enough option before possibly revising her choice. Thus, the rise-and-fall pattern could be a direct consequence of our design because it produces incentives to *both* overstate the early preference for the target *and* to mobilize tools to revise one's choices.

We believe this artefactual effect to be a minor concern. First, it is unrelated to the external validity of our findings because in real-choice situations, consumers could use the exact same reasoning—provide an intuitive reply based on dominance in case of limited time and cognitive resources ~~or~~ think through the choice if time and incentives allow for it. This is in line with old and robust evidence that the attraction effect is mainly ~~because of~~ dominance (Wedell 1991). Our design just allows us to observe both strategies ~~that~~ in the real world~~,~~ might apply to different choices on a single choice task, as if under a magnifying glass. Second, despite the incentive to be *fast then slow*, a sizable share of participants did *not* switch from the fast heuristic to the slow, accuracy-based choice; some preferred to wait and submit a later more accurate choice, and others chose to follow only the fast heuristic and stop revisions. Subjects could and did follow ~~their~~ preferred choice path within our incentive scheme.

5.5. Summary and Conclusion

Our findings about the rise-and-fall pattern of the attraction effect help to make sense and generalize the debate in marketing on the existence and robustness of the AE, and they provide a starting point from which to build experiments to assess the actual relevance of the effect in real-choice situations.

We show that subjects do revise choices in the direction prescribed by rational choice theory in an objective-value task where an optimal choice is available and objectively computable, albeit fuzzily. We show that in this setting, context effects provide a reliable fast heuristic, and our subjects exploit it in the first seconds, leading to a large effect—up to 25 additional percentage points in choice share. However, in all situations where accurate choice does matter, the effect dwindles to near zero for highly cognitively skilled participants (Experiment 1) or to a small size for more representative consumers (Experiment 2).

If our results were to carry over to preference-based tasks, it would mean that context effects are best understood as a short-term heuristic, which might stick in the long term only in cases where subjects do not have the incentives, or the tools, to move on to slower, more deliberate thinking modes. This, however, is an open question that lies beyond the scope of the current paper. In this work, we have provided, as a first step, initial evidence of a robust rise-and-fall pattern in a rather artificial setting. Whether the attraction effect and other context effects do indeed follow a rise-and-fall pattern and disappear when subjects face more realistic choices is therefore still an open question. However, we have developed a set of tools—a custom experimental design and an attuned modeling framework based on the MLBA—that make these further explorations possible.

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Endnotes

[1] It might merely induce subjects to fall back to the strategy developed in the usually not time-constrained instructions phase; see Crosetto and Güth (2021).

[2] Participants do not need to click every second on their most preferred option. They simply click when they want to make a choice and when they want to change their choice.

[3] The figure is merely a stylized representation of the problem that abstracts away from actual parameters, and it is given as a simple tool to compare our overall design with the existing literature.

[4] For the numeric treatment, Figure 4 shows a double-dip pattern, whereby the attraction effect drops to zero at around 10 seconds, then rises, and falls again. This pattern is not replicated at different levels of relative prices (see Figure A.1 in Online Appendix A) nor when applying alternative measures of the attraction effect (see Online Appendix B). We hence do not venture interpreting it.

[5] In the following, to simplify the writing, we take as a given that τ has already been subtracted from times t. We reintroduce τ later on in the simulations; this parameter allows us to take account of very rapid, random choices that occur in early stages of the choice timeline.

[6] In our experiment, the ratio quantity over price q/p is what must be maximized. This can be translated into $\ln q - \ln p$. We then characterize each option so $x_{1i} = \hat{p}_i = \ln(p_{max}) - \ln(p_i)$ and $x_{2i} = \hat{q}_i = \ln(q_i) - \ln(q_{min})$, whereby (p_{max}, q_{min}) correspond to the highest possible shown price among the tasks and q_{min} is the lowest possible quantity among the tasks. The value of option i is then $v_i = x_{1i} + x_{2i} = \hat{p}_i + \hat{q}_i = \ln(p_{max}) - \ln(p) + \ln(q) - \ln(q_{min})$. The option with the highest value v is also the one with the highest ratio q/p. We chose p_{max} and q_{min} to correspond to maximum and minimum values of those parameters in the experiment, but we acknowledge that those reference values may vary over time as participants learn from options shown to them.

[7] For example, an option with values (4, 6) on dimensions 1 and 2, respectively, is not as good as an option with values (5, 5), even if their objective value is the sum of both dimensions.

[8] Unlike in Trueblood et al. (2014), we do not let λ differ depending on whether $u_{ni} - u_{nj}$ is positive (λ^+) or negative (λ^-) because we did not find significant differences between those two parameters.

[9] We note that $stay < 1$ can lead to a reversal in context~~ual~~ effects over time, whereby the early favored option is disproportionately disfavored later on. This could happen if, for example, some participants overestimate the extent to which bias affected their first choice.

[10] Note how γ is multiplied by two here so as to be consistent with γ when there are three options. Alternatively, one could also have written $d_i = I_0 + \gamma \sum_{j \neq i} \frac{V_{ij}}{2}$ when there are three options and $d_i = I_0 + \gamma V_{ij}$ when there are two options, so that speed depends on the average difference in value with other options rather than their sum.

[11] Given the time limit T, not all deciders are fast enough to have the time to make a second choice, so the choice shares does not fully converge to 50% each.

[12] Remember that those changes in shares can only be ~~because of~~ revisions, as we simplified the model so that shares would stay the same over time if there were no revisions (see Section 4). Q:21

[13] Note that revisions themselves still depend on how extreme an option is versus another, for example. They therefore also reflect a bias, but that bias is not ~~because of~~ the original context effect.

[14] The standard similarity effect is such that introduction of a similar "decoy" option lowers the share of the other similar "competitor" option, so the share of each similar option is lower than that of the dissimilar "target" option (although the sum of their shares may still be higher). In our experiment, the similarity effect is so strong that this more than compensates for the splitting of attention across both similar options, and the dissimilar "target" options end up being chosen less often than either of the similar options.

[15] $\chi\Gamma(1 + 1/\alpha)/d$ is the average time at which an option with drift d is chosen in our model. The higher is speed, the lower is decision time.

[16] In this case, $d_T = I_0 + 0.15\gamma$ and $d_D = max(I_0 - 0.15\gamma, 0)$.

[17] Remember that $\sum_i f_i = 0$, so we do not need to consider average levels of f.

[18] Note that $bias = 0$ if all options have the same unit price and choice is made on that basis only (i.e., if $m = 1, \lambda = 0$).

[19] We use choice sets in Online Appendix G for comparability between Experiments 1 and 2. For each effect, we take average values when considering both a choice set with a decoy on quantity and its converse with a decoy on price (cf. design of choice sets in Experiment 2).

[20] Allowing parameters of the model to differ depending on whether we consider first choices and second choice can allow us to refine this finding, whereby some individuals may make imprecise and biased fast first choices and then precise unbiased slow second choices. Running regressions allowing for so many degrees of freedom is difficult, however, but it is indeed the case that first choices are made faster on average than revisions to second choices.

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