# De-obfuscating Context Effects in Decision-Making: A Simulation Study

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**Abstract**

The ‘attraction effect’ or ‘asymmetric dominance effect’ is a widely studied phenomenon in decision-making, challenging the principle of regularity in rational choice theory. It posits that the introduction of a third option, similar but inferior to one of the available options in a binary choice set, increases the choice share of the dominating option. While the standard attraction effect is pervasive, researchers have identified conditions where the effect is absent or reversed. One such condition is a strong prior trade-off, indicating a biased preference for one of the choices in the binary set, which mitigates the attraction effect. Despite logical explanations for this phenomenon, there is a lack of rigorous mathematical analysis.

Via model-agnostic simulations of Subjective Indifference Curves (SICs) we elucidate the cause of baseline asymmetry and highlight its consequences, including potential misses and false alarms in reporting context effects. The study critically examines measures used in the literature to assess these effects and offers guidelines to prevent errors in future studies, contributing to a deeper understanding of decision-making dynamics within multi-alternative, multi-attribute choice scenarios.

**Keywords:**
Subjective Indifference Curve, pair-triplet, triplet-triplet design, RST, baseline asymmetry.

## *INTRODUCTION*

According to one of the then unviolated theories of rational decision-making, 'regularity' (Luce 1977), if a choice set C1 has a few items, where C1 is a subset of choice set C2, the probability of choosing a common item from C2 should not be more than its corresponding probability of choice from set C1; in other words, the probability of choosing an item from a set cannot be increased by adding another item to the set. Formally, $\forall x \in C1 \subseteq C2, P(x|C1) \geq P(x|C2)$.

As an empirical illustration of violating this regularity principle, Huber, Payne, and Puto (1982) demonstrated the famous asymmetric dominance or attraction effect. Although, over the last 40 years, many pure, conceptual, and domain replications of the 'attraction effect' have been reported, studies have shown null or reversed effects in recent years. This has led some researchers to call the attraction effect 'fragile' or 'elusive,' (Spektor, Bhatia, and Gluth 2021) and question its 'practical validity'(Frederick, Lee, and Baskin 2014). As a response to some of these criticisms, Huber, Payne, and Puto (2014) listed various boundary conditions for the effect and suggested manipulation checks in future experiments.

Our focus in this article is one of the boundary conditions listed in (Huber, Payne, and Puto 2014); the prior trade-offs and the factors that lead to it. If the choice probabilities in the core set deviate significantly from an even 50%–50% split, an imbalance in target–competitor selection suggests a strong pre-existing trade-off that may be resistant to influence from the presence of a decoy. Huber, Payne, and Puto (2014) discussed a few logical reasons for the prior trade-offs, such as individual differences, prior rating of importance of the attributes, practice, etc. However, no rigorous mathematical analysis for the cause and effects of the prior trade-offs has been advanced.

Trueblood (2015), Simonson (2014) and Katsimpokis, Fontanesi, and Rieskamp (2022) have previously raised concerns about heterogeneity in values across subjects. Hutchinson, Kamakura, and Lynch (2000) and Liew, Howe, and Little (2016) have mentioned how strong attribute preferences or dimensional biases can affect the size of preference reversals measured. Huber, Payne, and Puto (2014) listed both prior trade-offs and cross-respondent value heterogeneity as two separate drivers inhibiting the attraction effect.

What if, at the population level, there is a bias towards one of the attribute dimensions? We propose that when the experimenters place the target, competitor, or decoys on the attribute space, they assume a global indifference curve that may differ from the true indifference curve of the population. If the experimenter does not have access to this true indifference curve, the target and competitor, as defined by the experimenter, may not lie on the proper indifference curve, and the relative placement of the decoys could differ for the sample subjects as well as in the two contexts for the same subjects in a ternary choice set design.

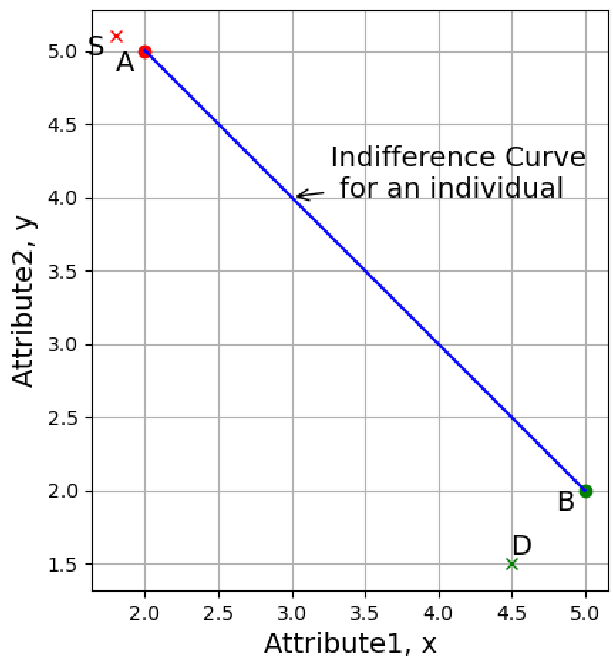
While this is more of a concern for experiments involving preference judgments, experiments involving perceptual tasks may also suffer from the same issues, resulting in baseline biases towards either of the attribute dimensions. Very few studies control for such bias (but see the calibration task in (Izakson, Zeevi, and Levy 2020) and the suggested lock-in amplification scheme in (Kaptein, Van Emden, and Iannuzzi 2016) for exceptions to this trend).

To quantify the size of distortions of the attraction effect potentially introduced by the difference between the experimenter-defined indifference curve (EDIC) and the true population indifference curve (TPIC), we simulated various TPICs varying their slopes. We also examined the consequences of these slopes deviating from the EDIC on measures of context effects. Before discussing the simulations themselves, however, we briefly discuss the primary effects we are interested in measuring and various instruments designed to measure them, as previously described in the literature.

### *Context effects*

The major context effects discussed in the literature are the similarity effect (Tversky 1972), attraction effect (Huber, Payne, and Puto 1982), and compromise effect (Simonson 1989). In this article, however, we focus primarily on the attraction effect and use the similarity effect as one of the empirical evidence modeled in the simulation.

**Figure 1:** Similarity Effect and Attraction Effect.




*Notes*: S is the similarity decoy targeting B, and D is the attraction decoy targeting B. The x and y axes represent attributes 1 and 2, respectively.

If an item S is added to a binary choice set {A, B} such that items A and S are placed close to each other on the attribute space as shown in 1 and that both are perceived to be similar, the choice share of B increases, $P(B|\{A, B, S\}) > P(B|\{A, B\})$. This similarity effect (Tversky 1972), in some form, had predicted violations of stochastic transitivity, a weaker form of rational choice rule, Independence from Irrelevant Alternatives (IIA[1]), though the model Tversky proposed adhered to the regularity principle. Subsequently, (Luce 1977)

[1]Strong IIA demands that the ratio of choice shares of two items should remain constant irrespective of the choice set in which they are presented.

declared regularity to be the only rational choice axiom that had remained unviolated.

As discussed earlier, the attraction effect was a demonstration of the violation of regularity. Suppose two items, A and B, are on the indifference curve in the attribute space as shown in 1, and a third item, D, inferior to B, is introduced in the set. If a clear dominance relationship is perceived between B and D such that D is dominated by B but not by A, the choice share of B increases from the binary set to the ternary set. $P(B|\{A, B, D\}) > P(B|\{A, B\})$.

***Various measures of context effects***

Traditionally, context effects had been demonstrated and quantified in a pair-triplet experimental design where the subjects give their baseline preference in a binary choice set ($\{A, B\}$) followed by their preference in a ternary choice set (the triplet). And the strength of the attraction effect, in this case, used to be expressed in terms of change in the probability of chices. If $\{A, B\}$ is the binary set and $\{A, B, D_a\}$ is the ternary set, $\Delta P_a = P(A|\{A, B, D_a\}) - P(A|\{A, B\})$, where $D_a$ is a decoy option targeting A and P(A) is the probability of choosing alternative A, expressed in terms of its choice frequency.

To enhance the effect size and hence the statistical power of the studies, Wedell (1991) introduced a triplet-triplet design, where the focal options A and B were introduced with a decoy favoring one in one context and with another decoy favoring the other option in the next context, i.e. $\{A, B, D_a\}$ and $\{A, B, D_b\}$, where $D_a$ and $D_b$ are the decoys favoring A and B respectively in the two contexts. Wedell claimed there was a double opportunity to detect the effects in this triplet-triplet design. Subsequently, most of the context effect studies have used this triplet-triplet design. One measure of the effect in such a design, as used by Wedell (1991) and others (Liu and Trueblood 2023), is given below, by calculating the difference in choice shares between the two contexts as measured from the respective choice frequencies.

$$\Delta P_a = P(A|\{A, B, D_a\}) - P(A|\{A, B, D_b\}),$$

$$\Delta P_b = P(B|\{A, B, D_b\}) - P(B|\{A, B, D_a\}),$$

where $\Delta P_{\text{target}} > 0$ means an attraction effect and $\Delta P_{\text{target}} < 0$, a reversed attraction effect.

Another more popularly used metric of the effect is the Relative Share of Target (RST), as introduced by Berkowitsch, Scheibehenne, and Rieskamp (2014), which is,

$$RST = \frac{P(\text{target})}{P(\text{target or competitor})}, \text{i.e.,}$$

$$RST = \frac{n_{t,C1} + n_{t,C2}}{n_{t,C1} + n_{t,C2} + n_{c,C1} + n_{c,C2}},$$

where $n_{x,C\#}$ = choice frequency of x in the context C#, #:1,2, i.e., C1 and C2 represent the two contexts respectively and x: t (target), c (competitor).

To remove some of the biased results of RST, a revised version of RST, RST* was proposed by Katsimpokis, Fontanesi, and Rieskamp (2022) as follows (they call it RSTew),

$$\text{RST}^{*} = 0.5\left(\frac{n_{t,C1}}{n_{t,C1} + n_{c,C1}} + \frac{n_{t,C2}}{n_{t,C2} + n_{c,C2}}\right).$$

While Hutchinson, Kamakura, and Lynch (2000) and Huber, Payne, and Puto (2014) have commented that the triplet-triplet design was a test of menu dependence alone, Katsimpokis, Fontanesi, and Rieskamp (2022) showed that even a triplet-triplet design can be used to test the violation of regularity principle indirectly. They derived (also included in the Web Appendix) the following measures,

$$AST = 0.5\left(\frac{n_{t,C1}}{n_{t,C1} + n_{c,C1} + n_{d,C1}} + \frac{n_{t,C2}}{n_{t,C2} + n_{c,C2} + n_{d,C2}}\right),$$

$$ASC = 0.5\left(\frac{n_{c,C1}}{n_{t,C1} + n_{c,C1} + n_{d,C1}} + \frac{n_{c,C2}}{n_{t,C2} + n_{c,C2} + n_{d,C2}}\right),$$

where AST is the absolute Share of the Target, ASC is the absolute Share of the Competitor, and $n_{d,C1}$ and $n_{d,C2}$ are decoy-chosen frequencies in contexts 1 and 2, respectively. AST and ASC are specifically suggested as measures of attraction effect as they capture the violation of the regularity principle (AST $> 0.5$ shows an attraction effect, while ASC $> 0.5$ indicates a reversed attraction effect). However, in the triple-triplet design, RST and RST* are widely used in literature as measures of the strength of the context effects in general. We, next, discuss the hypothesized effects of SICs differing from EDIC on these various measures of context effects.

### *TPICs and their consequences*

We hypothesized that if TPIC differs from the EDIC, some of the measures of context effects in triplet-triplet design would show false alarms (FAs), i.e., they may indicate context effects even in the absence of one. Especially, $\Delta P$ and RSTs are prone to such biased outcomes. Owing to asymmetric placements of decoys with respect to the TPIC, different choice frequencies of the decoys in both the triplet contexts would lead to biased RST measures (Katsimpokis, Fontanesi, and Rieskamp 2022). For the same reason, $\Delta Pa$ and $\Delta Pb$ could also deviate significantly from zero, even in the absence of any real context effects. We test this by simulating a model of ideal (rational) agents varying in their baseline biases in the binary choice (the pair of core alternatives), while ensuring they adhere to strict IIA when faced with a ternary choice (the triplet).

We also hypothesized that when TPICs differ from EDIC, the strategy used by Wedell to increase the measured effect size can work against the intended goal. It may sometimes obfuscate the effects, uncaptured by even AST and ASC. The reason is that the two contexts' decoy placements on the attribute space are no longer symmetric to the true indifference curves. Hence, one context may show an attraction effect while the other might show a reversed attraction effect, which, when combined, can mute the overall effect. We call these 'misses' in detecting context effects. Again, we test this by including context-sensitive agents, by changing one of the parameters in the previously introduced model.

## ***SIMULATION METHODOLOGY***

We used a Python-based program to simulate agents with different TPICs. Items in the choice set were represented as points on the x-y plane. The x-y plane represents the attribute space, with the two primary attributes of interest representing the x and y-axis. Two items, A and B, from the binary choice set, are placed on the attribute space as two points, and we call the line joining them, i.e., AB, as the experimenter-defined indifference curve (EDIC). Note, here, that we assume a linear indifference curve for simplicity. True population indifference curves (TPICs) representing different possible population level indifference curves are lines with varying slopes. We assume that slope alone can characterize a linear indifference curve, meaning an infinite number of parallel indifference curves on this plane can represent one specific population. Leveraging this property, we simulated all TPICs as lines with different slopes, passing through point A, and proceeded with further mathematical analysis. Suppose two points U and W lie on the indifference curve. In that case, it means the corresponding population is indifferent to the two items represented by the points, i.e., when the subject from that population comes across the items in binary choice sets appearing enough times in between other trials, his choice frequencies for both will be roughly equal, i.e. $P(U|\{U, W\}) \approx P(W|\{U, W\}$.

A deviation from the TPIC is characterized by a signed perpendicular distance from it, such that points right to the TPIC will have a positive deviation and points to the left will have a negative deviation. As the direction along the positive x-axis represents the increasing strength of the attribute, items with positive deviation are considered 'better' than the corresponding foot of the perpendicular on the TPIC. This assumption is reasonable. The preference accumulation model by Bhatia (2013) also has a similar assumption.

The signed deviations from the TPIC serve as arguments to a softmax function [2] that outputs choice shares in terms of probabilities summing to one. Figure 2a shows line AB as the EDIC with the perpendicular line segments BB' representing the signed deviation of

[2] A justification of using a softmax function is discussed in the Web Appendix.

B from the B' points on respective TPICs. Figure 2b shows the simulated baseline choice shares in the binary choice set as a function of TPIC slopes.

We used a Temperature-Scaled SoftMax function to model choice shares. As mentioned earlier, a vector of signed perpendiculars corresponding to each element in the choice set serves as the argument for the softmax.

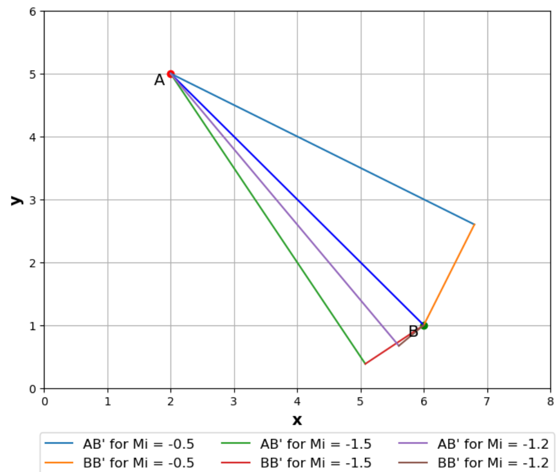
$$\text{softmax}(x_i) = \frac{e^{(\beta \cdot (x_i - \max(x)))}}{\sum_{j=1}^{N} e^{(\beta \cdot (x_j - \max(x)))}},$$

where, $x_i$ represents the $i$-th element of the input vector. $\max(x)$ calculates the maximum value within the input vector $x$. Subtracting the maximum value $\max(x)$ from the input values provides numerical stability. It ensures that the largest exponent in the numerator is zero, preventing overflow issues that might occur when dealing with large numbers in the exponential function. $\beta$ is a multiplicative coefficient that scales the input values before computing the softmax function, i.e., a higher $\beta$ amplifies the differences between the input values. $N$ denotes the size of the choice set: 2 for the pair and 3 for the triplets. The softmax function normalizes the scaled exponentiated values by dividing each exponentiated input by the sum of all exponentiated inputs. This normalization ensures that the output values lie in the range [0, 1] and sum up to 1, representing a valid probability distribution over the input values.

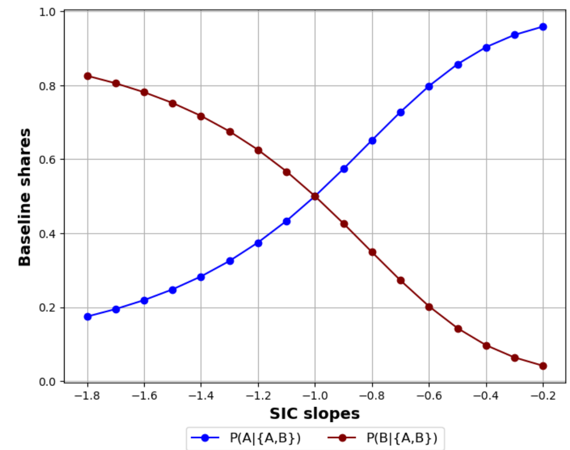
Figure 2a shows line AB as the EDIC with the perpendicular line segments BB' representing the signed deviation of B from the B' points on respective TPICs. Figure 2b shows the simulated baseline choice shares in the binary choice set as a function of TPIC slopes.

As we describe below, temperature scaling offers an effective parametric way of instantiating theoretical expectations for context effects. In our simulations, items A and B are presented either in pairs or in two triplets $\{A, B, D_a\}$ or $\{A, B, D_b\}$, where $D_a$ and $D_b$ are two decoy options targeting A and B, respectively. The two triplets serve as two choice contexts.

**Figure 2:** Subject Specific Indifference Curves (SICs)




**(a)** SICs, as represented by different slopes, $M_i$




**(b)** Baseline Shares vs SIC Slopes

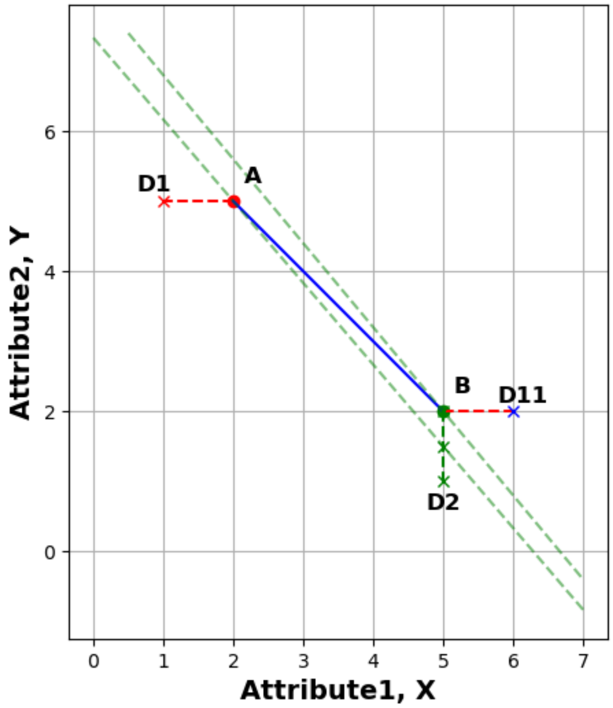
Our modeling goal was to artificially introduce a violation of IIA, mimicking one of the context effects as observed from the empirical data, such that in one of the two triplets, there is an attraction effect, while in the other, there is a reverse attraction effect. This would allow us to test the efficacy of the instruments used to capture context effects in a triplet-triplet design. We consider two conditions:

1. When there is a dominance perceived between the target and the attraction decoy, the choice share of the target increases in the triplet. (Attraction effect)

2. When a dominance relation is not perceived between the target and the decoy; rather, both are perceived to be similar, the choice share of the competitor would increase. (A similarity-effect driven reverse-attraction effect)

As shown in Figure 3, in this simulation, the first condition is achieved when an SIC passing through A also passes through the line segment joining B and D2. This would make the points B and D2 fall on two opposite sides of the SIC, hence assigning opposite signs to the corresponding signed perpendiculars that will serve as the arguments to the softmax function. In other words, B is perceived as ‘better’ than its corresponding foot of the perpendicular

**Figure 3:** Attraction and reversed attraction in the two contexts




(and hence point A) on the SIC, while D2 is perceived as 'worse' than A. This makes a clear perceived dominance relationship between B and D2, satisfying the condition for the attraction effect (the first theory considered in this simulation). We model the effect on choice shares by simply setting $\beta = 4.5$ in the softmax function. This computation increases the choice share of B, reasonably mimicking an attraction effect targeting B.

Note, however, that for the same SIC, points A and D1 lie on the same side of the curve. This can be appreciated by noticing the parallel line passing through point B, but having the same slope, hence representing the same SIC. Because of this, both A and D1 are perceived to be worse as compared to B. We model this as a case of similarity where a clear dominance between A and D1 is not perceived; rather, both appear similar with respect to B. Hence, the similarity effect should operate, and we achieve it by again setting $\beta = 4.5$, which in turn, increases the choice share of B. This is technically a similarity-induced reversed attraction effect.

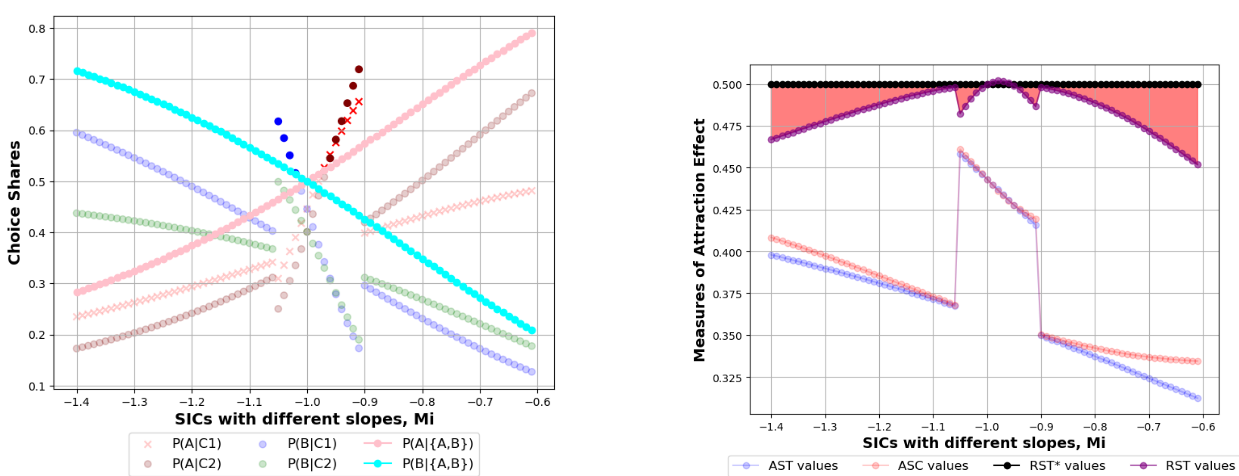
Taken together, for SIC slopes in a small range close to EDIC, for the same SICs, when

D1s produce reversed attraction effects, D2s produce attraction effects. Similarly, it can be shown that for an SIC through A, that passes between B and D11 (D11 is simply a proxy for D1 when the SIC is shown to have passed through A rather than through B), D2 produces a reversed attraction effect while D1 produces an attraction effect.

## *RESULTS*

Figure 4 shows results from our simulations for an individual agent. In particular, the filled dots in Figure 4a indicate instances of choice shares of A and B in triplets (C1: $\{A, B, D_a\}$, C2: $\{A, B, D_b\}$) whose values are clearly beyond their corresponding baseline values. These are cases of violations of regularity, a weaker form of IIA. Figure 4b shows how no existing measures of context effects, including the recently introduced AST and ASC, capture them. We call such instances 'misses' in the context of detecting context effects.

**Figure 4:** Misses in Detecting Context Effects

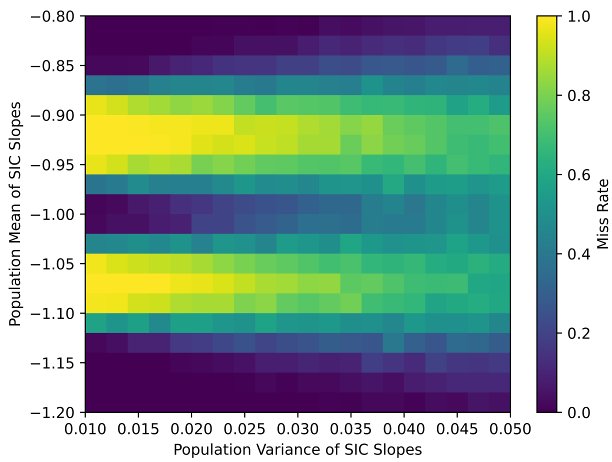



**(a)** Choice Shares **(b)** Measures of Context Effect

*Notes*: $C$: $C1(\{A, B, D_a\})$, $C2(\{A, B, D_b\})$. 4b shows only reversed attraction effects as indicated by RST.

What would this pattern of results at the level of an individual's SIC look like when reported as an average across multiple agents, each with an idiosyncratic SIC? To assess this, we sampled 30 simulated individuals from a population with SIC slopes sampled from a normal distribution with certain mean and variance value and calculated the average miss rate for the sample population. Conducting this simulation across different values of the population mean and variance produces a matrix of miss rate values, using RST as a measure of the effect. We plot this miss rate matrix as a heatmap in Figure 5, which shows very high miss rates for nearly all values of SIC that diverge from the EDIC. Thus, only experiments where the SIC lines up well with the EDIC are likely to yield results without misses.

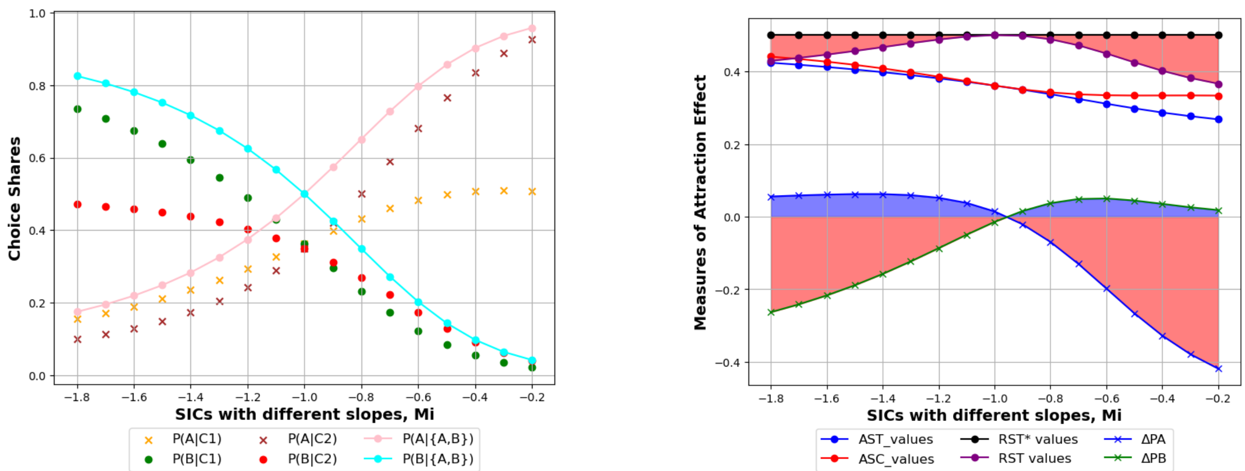
**Figure 5:** 2D Heatmap of Miss Rates




Note, also, that in the absence of any context effect, Luce's choice rule, independence from irrelevant alternative (IIA) should be adhered to, i.e., the ratio of choice shares of two items should remain constant irrespective of the context (choice set) in which they are presented; $\frac{P(X|C)}{P(Y|C)} = \text{Constant}$, irrespective of $C$; where $X$ and $Y$ are two items and $C$ is any context. This condition is easily achieved by setting $\beta = 1$ in the softmax function. Figure 6b clearly shows that some of the measures of context effects (RST and $\Delta P$) show negative effects for nearly all values of SIC slopes. We call these false alarms (FAs) in the detection of context effects. Notably, RST* does not appear to demonstrate false alarms, unlike other measures.

*Notes*: $C$: $C1(\{A, B, D_a\})$, $C2(\{A, B, D_b\})$. The choice shares of A and B in the triplets have values less than their corresponding baseline values in plot 6a. In 6b, The standard

**Figure 6:** False Alarms in the Detection of Context Effects




**(a)** Choice Shares

**(b)** Measures of Context Effects

attraction effect is shown in a blue-filled color, and the reversed attraction effect is shown in a red-filled color.

## *DISCUSSION*

Our results paint a picture of systematic undervaluation of the standard attraction effect by existing measures of the effect because of the inevitable deviation of participants' subjective indifference curves to choice attributes vis-a-vis experimenter defined indifference curves. In particular, both misses and false alarms in reversed attraction effect studies, such as the ones we simulate, undervalue the standard attraction effect. It is conceivable that this is one of the key reasons for the empirical controversy surrounding the characterization of the attraction effect (Huber, Payne, and Puto 2014; Frederick, Lee, and Baskin 2014; Spektor, Kellen, and Hotaling 2018; Spektor, Kellen, and Klauer 2022).

From the heatmap of miss rates, we can see that on both sides of EDIC at slope = -1, SICs with slopes up to -1.1 or -0.9 would produce maximum misses, and when translated to the ratios of baseline choice shares, $\frac{P(A|\{A,B\})}{P(B|\{A,B\})}$, they would mean approximately 0.43:0.57 and 0.57:0.43 respectively, rather than 0.5:0.5, which is not unreasonable to be found in the empirical evidence. For example, in the 12 experiments, 1A-1S in (Frederick, Lee, and Baskin

2014), all the studies have biased baseline choice shares and they found mostly reversed effects. Similarly, Liew, Howe, and Little (2016) have shown dimensional biases, but have concluded that averaging across the population consisting of dimensional biases is the cause of reduced context effects. While that is a valid conclusion, we make a different case here; two contexts will have different effects for the same individuals owing to the asymmetry of decoy placements with respect to the SICs. To ensure that our results are independent of the claims by Liew, Howe, and Little (2016), for the heatmap of RSTs for the simulated data, we sample from uni-modal distributions, rather than bimodal ones.

Following Wedell (1991), most studies showing reversed or reduced attraction effects (Spektor, Kellen, and Hotaling 2018; Spektor, Kellen, and Klauer 2022) have employed triplet-triplet designs, and as they have not reported binary baseline choice shares, the confounds we have highlighted in this paper apply to their results. To reiterate, RST* turns out to be a better measure than RST, as it does not produce false alarms. This conclusion supports the claims by Katsimpokis, Fontanesi, and Rieskamp (2022).

One of the limitations of our work is, as mentioned earlier, we have just focused on one of the boundary conditions of the effect that Huber, Payne, and Puto (2014) have already discussed, i.e., 'strong prior trade-off' and showed how the triplet-triplet measure could be misleading in the presence of the biased baseline shares. So, our work here adds to theirs. Also, we acknowledge that we have used only range decoys for the simulation, as they are known to produce maximum context effects. However, the simulation can be easily extended to accommodate other decoy types without affecting the interpretations.

## *CONCLUSION*

In summary, we show, via our simulations, that although the triplet-triplet design has been extensively used in the literature as a convenient way to capture the context effects, if subject-specific indifference curves differ from the experimenter-assumed indifference curve, there can be false alarms and misses in the detection of context effects using the existing measures that involve triplet-triplet designs. These false alarms and misses could result simply because the two decoys placed on the attribute space are no longer symmetrical to the true indifference curve.

As solutions to the issues with the extant instruments, we propose including pair-triplet measurements, wherever possible, in the experimental designs and accessing the subject-specific indifference curves to design the stimuli space accordingly. With the growing influence of digitization and user profiling in online shopping, baseline choice shares have become more accessible for marketers to leverage. Hence, the issues discussed and the proposed solutions equally apply to marketers who wish to incorporate the context effects into product designs and marketing strategies.

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