Event-Splitting in Choice under Risk: The Role of Granularity and Prominence*†

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Event-splitting effects (ESEs) in choice under risk are well documented. We argue that their magnitude depends not only on granularity—i.e., how finely an event is partitioned—but also on prominence—i.e., where the resulting sub-events are placed. We develop the Position-Adjusted Reference Utility (PARU) model, which assigns weights to states based on both partitioning and placement, and test its comparative statics in a preregistered, fully incentivized online experiment using matrix displays. A first simple split increases choice of the option advantaged in the split state by about 19.5 percentage points, with diminishing marginal gains from further splits. Right relocation attenuates ESEs by roughly 9 percentage points and can offset the gains from additional splitting at higher split counts. Overall, our results show that the interaction between granularity and prominence is central: ESEs depend on how often events are partitioned and *where the resulting sub-events are placed.*

JEL classification: C91; D81; D91.

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1. Introduction

Risk is often communicated through segmented descriptions rather than as a single category. Insurance and warranty menus list multiple sub-risks that cannot be purchased separately; hospital brochures enumerate detailed side-effect categories; and digital comparison tables break down a single underlying hazard into several labeled components—e.g., different theft categories in bike insurance as depicted in Figure 1. Such representations have two natural degrees of freedom: how many pieces an event is split into (*granularity*) and where these pieces are placed in the interface (*prominence*). While granularity has been studied extensively through event-splitting effects (ESEs), positioning is typically treated as innocuous. Yet in practice, any additional sub-event must appear somewhere on the screen. As a result, partitioning a risk mechanically creates placement choices, and granularity and prominence can move together even when payoffs and probabilities are held fixed.

Which bicycle protection would you like?

Benefits	Theft 45,67 € Yearly	Repair 29,10 € Yearly	Theft & Repair 52,84 € Yearly
Simple theft	✓	✗	✓
Theft of bicycles and bicycle trailers even with batteries	✓	✗	✓
Burglary/theft	✓	✗	✓
Repair after accidents (also self-inflicted) incl. breakdown and fall damage	✗	✓	✓
Repair after vandalism	✗	✓	✓
Repair of electronic and moisture damage	✗	✓	✓

Figure 1: Bike insurance offer, inspired by HUK-COBURG (n.d.).

ESEs are well documented: presenting the same event as multiple sub-events can change choices even when outcomes and objective probabilities are unchanged (Starmer and Sugden, 1993; Humphrey, 1995). Although existing theoretical accounts of event-splitting often imply a subadditive granularity channel, there is little experimental evidence on whether additional splits strengthen this effect. ESEs also matter methodologically because partitioning the state space is a common ingredient in experiments on other display phenomena such as juxtaposition or correlation effects (Starmer and Sugden, 1993; Humphrey, 1995; Loewenfeld and Zheng, 2024; Ostermair, 2025).

If partitioning alters behavior on its own—and potentially through its interaction with placement—then observed "display effects" may partly reflect how the state space is partitioned and arranged. However, existing evidence provides limited guidance on whether different *split types*—pure partitioning versus partitioning with relocation—produce systematically different distortions, and on how granularity and prominence interact in shaping ESEs.

This paper develops and tests a unified framework in which ESEs arise from two display dimensions—*granularity* and *prominence*. Granularity operates through a *frequency channel*: outcomes can receive more weight when they are represented more often within a choice problem (Weber, 2007). Prominence operates through a *position channel*: components that are placed more prominently in the representation receive disproportionate weight (Ert and Fleischer, 2016; Wang et al., 2017; Zuschke, 2023). We formalize these mechanisms in the Position-Adjusted Reference Utility (PARU) model, which assigns weights at the level of states and allows these weights to depend on both partitioning and placement. A central implication is that ESEs need not be one-dimensional. Under simple splits, increasing granularity strengthens ESEs but with diminishing marginal impact. Under splits with relocation, granularity interacts with prominence: relocating split mass can attenuate ESEs and, when sufficiently strong, can offset the gains from additional splitting.

We test these predictions in a preregistered, fully incentivized online experiment (N=400, Prolific) using the standard matrix display as it provides a transparent and tightly controlled environment: it keeps outcomes and objective probabilities fully visible while allowing us to manipulate granularity (how finely a state is partitioned) and prominence (where the resulting pieces are placed) separately and jointly, e.g., by relocating split mass to the far right of the matrix. The design cleanly varies both the number of splits and the extent of right relocation across six constellations.

The results provide strong support for the joint role of granularity and prominence. A first split increases selection of the target (safer) option by about 19.5 percentage points, while moving from one to two splits adds about 6–7 percentage points; additional splitting beyond that yields little further gain. Prominence systematically moderates these effects: shifting split mass to the far right attenuates the ESE by roughly 9 percentage points relative to a simple split. Most importantly, when we vary both dimensions jointly, the net effect can flip: increasing splitting while adding further right relocation can reduce target selection, and a single simple split can have roughly the same behavioral impact as multiple splits combined with substantial right shifts.

Our contribution is fourfold. First, we provide experimental evidence on whether additional splits further strengthen ESEs. Second, we develop a unified framework that separates granularity from prominence and delivers sharp comparative statics across split types. Third, we offer experimental evidence on how these dimensions interact, documenting a trade-off that overturns the monotonicity intuition that "more splitting" necessarily produces stronger ESEs once relocation is allowed. Finally, our results speak to measurement in matrix-like displays and related formats: layout choices that affect prominence can meaningfully shape behavior and may interact with partitioning in ways that complicate the interpretation of display manipulations.

The remainder of the paper is organized as follows. Section 2 develops the theoretical framework and derives predictions. Section 3 states testable hypotheses and outlines the empirical strategy. Section 4 describes the experimental design and procedures. Section 5 reports the results. Section 6 discusses implications and limitations. Section 7 concludes.

Related Literature We contribute to three strands of literature. First, we add to the experimental literature on event-splitting effects (ESEs) in risky choice. ESEs were first identified by Starmer and Sugden (1993), who showed that earlier evidence for regret-theoretic juxtaposition effects was confounded by event-splitting; Humphrey (1995) subsequently reinforced this interpretation. More recent work documents analogous concerns in tests of salience theory (Loewenfeld and Zheng, 2024; Ostermair, 2025) and shows that ESEs can account for classical anomalies such as the common ratio effect (Schmidt and Seidl, 2014). A related set of studies investigates when ESEs emerge and persist, pointing to roles for zero-payoff aversion (Humphrey, 2001), learning about probabilities and attenuation with repeated judgments (Humphrey, 1999, 2006; Birnbaum and Schmidt, 2015), and heuristic choice processes that overweight frequently displayed events relative to cumulative probabilities (Weber, 2007). Against this background, our contribution is to provide a more fine-grained experimental analysis of event-splitting by examining whether additional splits further strengthen ESEs, separating granularity from prominence, and testing how different split types—and in particular relocation of split mass—systematically moderate ESEs.

Second, we contribute to the theoretical literature that seeks to account for ESEs. Most existing approaches explain ESEs through subadditive weighting or closely related mechanisms. In particular, basic subjective expected utility theory (SEUT) and weighted utility theory (WUT) dispense with prospect theory's editing stage and implement post-combination procedures (Starmer and Sugden, 1993; Humphrey, 1995). The prospective reference utility (PRU) model links weights to objective probabilities as well as to the number of states representing an event (Viscusi, 1989; Luce, 1998; Mukherjee, 2010). The transfer of attention exchange (TAX) model, in turn, captures event-splitting effects through systematic transfers of probability mass from higher to lower outcomes (Birnbaum, 1999, 2004, 2006, 2007), a mechanism supported by Weber (2007) and Schmidt and Seidl (2014). Our PARU model complements these accounts by adding a prominence component at the level of states. While existing models can account for a granularity channel to some extent through subadditive weighting or related mechanisms, they do not allow weights to depend on the position of states within the display. They therefore cannot distinguish between split types that differ only in the placement of split mass, nor can they address cases in which subadditivity need not hold once partitioning is combined with relocation. PARU fills this gap by allowing weights to depend jointly on objective probability, granularity, and prominence, thereby separating partitioning from placement and yielding sharp comparative statics across split types.

Beyond the literature on ESEs, our paper contributes to research on how spatial positioning shapes decision-making. A growing body of evidence documents that items placed early, higher up, or in otherwise prominent positions receive disproportionate weight, e.g., in insurance menus (Wang et al., 2017), in the ordering of attributes in product descriptions (Zuschke, 2023), and in ranked online environments such as hotel search results (Ert and Fleischer, 2016). Process evidence points in the same direction: visual search often follows systematic scan paths (Ryan et al., 2018), and early (and sometimes late) fixations can be predictive of final choices (Hu et al., 2024; Hirmas et al., 2024). Our contribution is to bring these insights into a transparent risky-choice setting where placement can be varied in a controlled way. In matrix displays, splitting necessarily creates additional elements that must be positioned, making prominence a natural moderator of event-splitting effects. Our design isolates these placement effects, both on their own and in interaction with splitting.

2. A Framework for Event-Splitting and Prominence in Matrix Displays

We study choices between two risky options presented in the standard matrix display (Starmer and Sugden, 1989, 1993; Humphrey, 1995; Loewenfeld and Zheng, 2024; Ostermair, 2025, cf. Figure 2). Each column corresponds to a mutually exclusive state of the world. Column width equals the objective probability of that state, so the matrix can be interpreted as a partition of the unit interval $(0, 1]$: a state $s = (a, b]$ has probability $\Delta = b - a$, and its position is given by its location on the left-right axis (i.e., by a and b). This representation allows us to vary *granularity* (how many columns represent an event) and *prominence* (where these columns are placed) while keeping outcomes and probabilities fully transparent.

We will refer to an event as the set of states in which a given option yields a particular payoff. An event-splitting manipulation changes only the description of the event, i.e., by partitioning a state into sub-states that all carry the same payoff, while holding the underlying option constant.

State	0 s_1 0.4	0.4 s_2 1
A	20	0
B	0	15
Prob.	40%	60%

Figure 2: Example of the Matrix Display without Event-Splitting.

2.1. Splitting Operations: Simple Splits vs. Splits with Relocation

Consider a baseline state space $\mathcal{S} = \{s_1, ..., s_n\}$. Let s_j be the state that we "split" w-times, meaning we replace it by $w + 1$ sub-states $\{s_j^{(w)}, s_{n+1}^{(w)}, ..., s_{n+w}^{(w)}\}$ whose widths sum to Δ_j, and that all carry the same payoff as the original state s_j for each option. We distinguish two conceptually different operations (illustrated in Figure 3):

1. **Simple split (pure granularity)**: the sub-states jointly occupy exactly the original interval of s_j, and all other states keep their original left-right location. In other words, the event becomes more granular, but the overall layout of the matrix does not change.

2. **Split with relocation (granularity + prominence)**: at least one sub-state is moved to a different location within the matrix, which necessarily shifts the location of at least one non-split state. We label such manipulations by the direction in which the split mass is relocated:

   (i) a *right split* relocates at least one sub-state of s_j to a position strictly further to the right than in the baseline;

   (ii) a *left split* relocates at least one sub-state of s_j strictly to the left.

Figure 3 gives an example of splitting the first state into two sub-states without relocation (simple split; see Figure 3a) and with moving one sub-state to the right (right split; see Figure 3b).

2.2. The Position-Adjusted Reference Utility (PARU) Model

We propose a simple model that combines the two display dimensions introduced above, i.e., granularity and prominence, and maps them into probability weights. Our model builds on Prospective Reference Utility (Viscusi, 1989) by augmenting probability-based weighting with a position component: two states with identical objective probability may receive different weights depending on where they appear in the matrix. Standard subadditive models do not accommodate position-dependent weighting. Our formulation

State	0 s_1^1 0.1	0.1 s_3^1 0.4	0.4 s_2^1 1
A	20	20	0
B	0	0	15
Prob	10%	30%	60%

(a) One-Time Split without Shift (Simple Split).

State	0 s_1^1 0.1	0.1 s_2^1 0.7	0.7 s_3^1 1
A	20	0	20
B	0	15	0
Prob	10%	60%	30%

(b) One-Time Split with Shift to the Right (Right Split).

Figure 3: Matrices with Event-Splitting.

allows us to isolate the granularity and prominence channels and to study their interaction. We refer to this extended model as Position-Adjusted Reference Utility (PARU).

Let $v(\cdot)$ be a strictly increasing value function over monetary outcomes, i.e., $v : \mathcal{X} \subseteq \mathbb{R}_0^+ \mapsto \mathbb{R}_0^+$, with $v(0) = 0$. For an option A displayed on a state space $\mathcal{S} = \{s_1, ..., s_n\}$, PARU evaluates A as

$$V_{PARU}^{\mathcal{S}}(A) = \gamma \sum_{i=1}^{n} \frac{t(s_i)}{\sum_{k=1}^{n} t(s_k)} v(x_i^A) + (1-\gamma)\frac{1}{n}\sum_{i=1}^{n} v(x_i^A), \tag{PARU}$$

where $t : \mathcal{S} \mapsto \mathbb{R}_0^+$ is a position weighting function and $\gamma \in [0, 1]$.

The term $\frac{t(s_i)}{\sum_{k=1}^{n} t(s_k)}$ in the first component of (PARU) can be interpreted as the weight that state s_i receives due to its position in the matrix. Hence, states are weighted both by their objective probability and by their prominence. The second component of (PARU) captures the granularity channel: a payoff receives more weight the more frequently it is represented across displayed states. The parameter γ governs the strength of the prominence component.

We impose two mild properties on $t(\cdot)$ that formalize left-to-right primacy while ensuring that pure partitioning does not mechanically change position weight:

(i) **Shift Monotonicity**: For $M = \{(a, b] \subseteq (0, 1] \mid b - a \equiv p \in (0, 1]\}$ it holds:

$$\forall (a_1, b_1], (a_2, b_2] \in M : a_1 < a_2 \Rightarrow t((a_1, b_1]) > t((a_2, b_2]). \tag{MON}$$

(ii) **Partition Additivity**: For $a < b < c$ it holds:

$$t((a, c]) = t((a, b]) + t((b, c]). \tag{ADD}$$

These two properties capture the idea that where an event is placed matters (MON), but merely slicing it into finer adjacent pieces does not create positional weight “out of thin air” (ADD).[1][2]

2.3. Event-Splitting Effects

We focus on choices between two risky options A and B. Let s_j denote the state in which option B is relatively most attractive (the “advantageous” state for the target option). Because splitting a state affects the evaluation of both options, we consider not only how a single option’s evaluation changes but how the comparison between the two options shifts. Accordingly, an ESE occurs if making the event more granular (splitting s_j into sub-states) increases the relative attractiveness of B compared to A. Thus, an ESE is said to occur if and only if

$$V^{\mathcal{S}^w}_{PARU}(B) - V^{\mathcal{S}^w}_{PARU}(A) > V^{\mathcal{S}}_{PARU}(B) - V^{\mathcal{S}}_{PARU}(A), \tag{ESE}$$

where $\mathcal{S}^w$ denotes the state space after splitting state s_j w-times.

Importantly, an ESE does *not* require pre-existing preferences between the two options to reverse. It *can*, however, if the induced relative increase in evaluation is sufficiently large. In our experimental design, we therefore operationalize the ESE in terms of preference switches: our test statistic assesses whether significantly more participants switch *towards* the target option than *away* from it.

Furthermore, define

$$\mathcal{M}(w) = \left[V^{\mathcal{S}^w}_{PARU}(B) - V^{\mathcal{S}^w}_{PARU}(A)\right] - \left[V^{\mathcal{S}}_{PARU}(B) - V^{\mathcal{S}}_{PARU}(A)\right] \tag{1}$$

as the *magnitude* of an ESE by splitting one state w-times. $\mathcal{M}(w)$ therefore captures the extent to which splitting increases an option’s attractiveness. To generate an ESE, it is necessary that $\mathcal{M}(w) > 0$.

2.4. Predictions of the PARU Model

A key advantage of PARU is that it delivers sharp comparative statics that map directly to our experimental design. Because our implementation starts from a baseline state space with $n = 2$ states, we present the implications for this simple case. Results for $n > 2$, as well as proofs of the propositions, are provided in Appendix A.

Proposition 1 characterizes the implications of simple splits in this setting.

[1] In particular, the (ADD) property ensures that, in our experimental design, simple splitting does not affect the positional weight assigned to a state, regardless of how this state is partitioned.

[2] A position weighting function that satisfies both properties is given by $t((a, b]) = (1 - a)^\alpha - (1 - b)^\alpha$, with $\alpha > 1$. A proof for this assertion is provided in Appendix A.

Proposition 1 (Simple Splits)**.** *Suppose* $\mathcal{S} = \{s_j, s_i\}$ *and* $[v(x_j^B) - v(x_j^A)] - [v(x_i^B) - v(x_i^A)] > 0$*. If the state* s_j *is subjected to a simple split, the following statements are fulfilled:*

(i) It holds $\mathcal{M}(w) > 0$*, i.e., the PARU model always predicts an ESE.*

(ii) $\mathcal{M}(w)$ *is strictly increasing in* w*, i.e., more splits have a stronger effect.*

(iii) For $w_2 > w_1 \geq 0$ *and fixed* $w_2 - w_1 = c$*,* $\mathcal{M}(w_2) - \mathcal{M}(w_1)$ *is strictly decreasing in* w_2*, i.e., the marginal effect of a further split is diminishing.*

With a simple split, PARU always predicts an ESE for the option that is relatively most attractive in the split state. Moreover, the ESE becomes stronger as the number of splits increases: partitioning the advantageous state into more sub-states amplifies the shift toward that option. At the same time, the model implies diminishing marginal effects, i.e, each additional split still amplifies the ESE, but by a progressively smaller amount.

Proposition 2 characterizes how ESEs differ across split types.

Proposition 2 (Splits with Relocation)**.** *Suppose* $\mathcal{S} = \{s_j, s_i\}$ *and* $[v(x_j^B) - v(x_j^A)] - [v(x_i^B) - v(x_i^A)] > 0$*. Then the PARU model implies:*

(i) If state s_j *is subjected to a right split, then*

$$\mathcal{M}(w) > 0 \iff \gamma < \frac{1}{1 + \frac{4+2w}{w} \cdot \frac{t(s_i^w) - t(s_i)}{t((0,1])}}. \tag{2}$$

Hence, under a right split, PARU predicts an ESE only for sufficiently small values of γ*.*

(ii) $\mathcal{M}(w)$ *is larger under a left split of* s_j *than under a simple split.*

(iii) $\mathcal{M}(w)$ *is smaller under a right split of* s_j *than under a simple split.*

Proposition 2 shows that relocating sub-states affects ESEs through the prominence component. Under a right split, PARU predicts an ESE only if position plays a sufficiently limited role, i.e., only for small enough γ: shifting probability mass to the right reduces the positional weight placed on s_j and can therefore eliminate the ESE when the prominence component is strong. By contrast, under a left split, the model always predicts an ESE, and this effect is even stronger than under a simple split, because relocating sub-states to the left increases the positional weight on s_j in addition to increasing its frequency. Finally, the ranking across split types, i.e., left splits producing larger effects than simple splits, and right splits producing smaller effects, does not depend on how many times the state has already been split. This implies a natural trade-off: when splitting becomes sufficiently fine, the negative impact of rightward relocation can offset, and potentially dominate, the positive effect of an additional split.

To illustrate the predictions of the PARU model, reconsider the example in Figure 2. The model implies that splitting state s_1 can generate two distinct effects. First, a simple split increases the attractiveness of option A. Second, if s_1 is split and one sub-state is relocated to the far right of the matrix, the net effect becomes ambiguous: the frequency gain from splitting can be offset by the change in positional weights induced by relocation, so that either A or B may benefit. By contrast, splitting state s_2 unambiguously favors option B, and the effect is further amplified when a sub-state is shifted to the far left of the matrix.

This example highlights the central mechanisms captured by PARU. (i) Under simple splits, the left–right placement of states is unchanged. In that case, the magnitude of an ESE depends only on granularity, i.e., how finely the advantageous state is partitioned into sub-states. (ii) Once sub-states are relocated to the left or right, positional weights change accordingly, and ESEs become sensitive to where probability mass is placed within the matrix. (iii) Consequently, left splits tend to strengthen ESEs, whereas right splits tend to dampen them.

3. Testable Hypotheses and Empirical Strategy

3.1. Hypotheses

Building on Section 2, we derive hypotheses for the two-state case implemented in our experiment. We study choice problems with payoff crossing: in one state, option B yields a higher payoff than A, while in the other state, A yields a higher payoff than B. Let s_j denote the advantageous state for B. In the experiment, we always split s_j to favor the target (safer) option B.

Our first hypothesis deals with the general existence of ESEs. According to Proposition 1, splitting the advantageous state s_j without any relocation should always favor option B.

Hypothesis 1 (Existence of ESEs)**.** *Splitting the advantageous state s_j without any relocation increases the share of subjects choosing option B relative to the corresponding unsplit baseline.*

We next consider repeated simple splits, i.e., increasing granularity without changing the overall layout of the matrix. Proposition 1 predicts that repeated simple splits of s_j increase the attractiveness of option B, but with diminishing marginal effects: each additional split raises B's appeal by progressively less.

Hypothesis 2 (Granularity: More Simple Splits Strengthen ESEs)**.** *Under simple splits, the share of subjects choosing B increases with the number of times s_j is split.*

Hypothesis 3 (Granularity: Diminishing Marginal Impact)**.** *Under simple splits, the incremental increase in the share choosing B becomes smaller with each additional split.*

We then turn to prominence and study how the left–right placement of the advantageous state affects choices. By (MON), displaying s_j further to the left increases its prominence and should therefore raise the attractiveness of option B. Moreover, Proposition 2 implies that a right split, i.e., relocating at least one sub-state to the right, should attenuate the effect of splitting on B relative to placements further to the left.

Hypothesis 4 (Prominence: Position of States)**.** *The share of subjects choosing B is higher when the advantageous state s_j is placed further to the left in the matrix.*

Hypothesis 5 (Granularity and Prominence: Relocation of Sub-States)**.** *Holding the number of splits fixed, the share choosing B is lower under a right split than under a simple split.*

3.2. Empirical Strategy

We test our hypotheses by comparing the share of subjects selecting the target option between two versions (split or unsplit) of the same choice problem. Given the within-subject design, we evaluate directional differences using one-sided exact McNemar tests for paired binary outcomes.

Let $Y_{ij} \in \{0, 1\}$ indicate whether subject i chose the target (safer) option in version j. For two versions j and k of the same problem, define

$$d_i = Y_{ij} - Y_{ik} \in \{-1, 0, 1\}, \tag{3}$$

which indicates whether subject i switched, and in which direction. Let $n_+ = |\{i : d_i = 1\}|$ and $n_- = |\{i : d_i = -1\}|$, and set $N_d = n_+ + n_-$. We test

$$H_0 : \mathbb{P}(d_i = 1 | d_i \neq 0) = \frac{1}{2} \tag{4}$$

against the one-sided alternative

$$H_1 : \mathbb{P}(d_i = 1 | d_i \neq 0) > \frac{1}{2} \tag{5}$$

using the exact binomial distribution. With $X \sim Bin(N_d, \frac{1}{2})$, the p-value is given by $\mathbb{P}(X \geq n_+)$. Ties ($d_i = 0$) are ignored. For comparisons without a directional prediction (e.g., certain split-versus-split contrasts), we report two-sided exact McNemar p-values.

To complement the non-parametric tests, we estimate the following linear probability model (LPM):

$$\texttt{ESE}_{ij} = \alpha + \beta_1 \texttt{number1}_{ij} + \beta_2 \texttt{number2}_{ij} + \beta_3 \texttt{shifted}_{ij} + \gamma^\top X_i + \epsilon_{ij}. \tag{6}$$

The dependent variable ESE is a binary indicator equal to one if a preference switch occurred in the predicted direction, and zero otherwise. In the baseline specification, ties (no switch) are excluded, with a full-sample robustness coding ties as zero (Table 12, Appendix C.3). Standard errors are clustered at the subject level.

The independent variables number1 and number2 are dummy indicators capturing whether the original state was split an additional 1 or 2 times, respectively. The variable shifted $\in [0, 1]$ measures whether a sub-state was shifted to the right and, if so, by how much relative to the size of the original state. For example, if a state of size 0.6 is divided into two sub-states of 0.3 and one is shifted to the right, shifted $= \frac{0.3}{0.6} = 0.5$. If two sub-states are shifted to the right, shifted is given by the sum of their relative sizes. The remaining regressors are control variables, described in Table 11 in Appendix C.3.

To assess whether the prominence effect varies with granularity, we estimate additional specifications including interaction terms between shifted and the split indicators number1 and number2.

As a robustness check, we also estimate linear probability models with the dependent variable selected (choice of the safer option). This approach uses the full sample as no computation of differences is needed and yields patterns consistent with the ESE-based analyses; see Appendix C.3, Table 15.

Furthermore, we estimate logit and probit models and report average marginal effects; results are also similar (Appendix Tables 16-17).

4. Experimental Design and Procedures

4.1. Experimental Design

In our experiment, we use a within-subjects design to test the hypotheses derived in Section 3. Each participant makes 24 binary choices presented sequentially. All choice problems are displayed in the matrix display, where each column corresponds to a state and column width is proportional to the state's objective probability. As illustrated in Figure 4, each option assigns payoffs—ranging from £0 to £25—to each integer number between 1 and 100. At the end of the experiment, the computer randomly chooses one of the 24 decisions for payment, and the participant's choice in that decision becomes payoff-relevant. A second random draw then selects an integer between 1 and 100, and the participant is paid the amount assigned to that integer by the chosen option. All integers from 1 to 100 are equally likely to be drawn.

We constructed six constellations to study different split types. Each constellation consists of four versions of the same choice problem: an unsplit baseline and three modified versions. Constellations 1 and 2 isolate granularity by varying the number of splits. They

	1 – 60	61 – 100
○	**£0**	**£20**
○	**£15**	**£0**
	60%	40%

Figure 4: Example Decision Problem.

differ only in whether the advantageous state is the first state (Constellation 1) or the last state (Constellation 2).

Constellations 3–5 examine prominence by varying the placement of (sub-)states. Each includes, in addition to the unsplit baseline, a baseline with swapped state positions, a one-time simple split, and a one-time right split. We distinguish between symmetric splits (Constellation 3) and asymmetric splits. In the asymmetric case, we further vary whether the larger sub-state (Constellation 4) or the smaller sub-state (Constellation 5) is relocated to the right.

Finally, Constellation 6 varies granularity and prominence jointly. It includes a one-time simple split, a two-times split version in which one sub-state is shifted to the right, and a three-times split version in which two sub-states are shifted to the right.

In one of the six constellations, the options' downside is £2 rather than £0, allowing us to assess whether ESEs are driven by a particular aversion to zero outcomes. The order of the 24 binary choices is randomized ex ante such that consecutive choice problems never belong to the same constellation. Appendix B.1 provides an overview of all constellations and the corresponding choice problems. Across tasks, we also randomize whether the target option appears in the upper or lower row.

Before making the 24 choices, participants receive detailed instructions on the choice tasks, how to interpret the matrix display, and the payment procedure. The full instructions are provided in Appendix B.2. The experiment was preregistered on AsPredicted (available at `https://aspredicted.org/q9s5-4rwf.pdf`).[3]

4.2. Procedures

The experiment was computerized using the software oTree (Chen et al., 2016) and conducted online on Prolific in September 2024. We recruited 441 participants, of whom 400 (188 female, 208 male, 4 non-binary) completed the study and are included in our analysis. Before participants proceeded to the main tasks, we administered comprehension questions to ensure they understood the matrix display and the payment procedure. We also embedded two attention checks within the 24 choice problems, instructing participants

[3] IRB approval was given by the German Association for Experimental Economic Research e.V. (GfeW) and is available at `https://gfew.de/ethik/Wg3yT8cN`.

which option to select. The 41 excluded participants either answered a comprehension question incorrectly twice or failed an attention check.[4]

Across all 441 participants, average earnings were £8.41 (excluding Prolific VAT), including the fixed participation fee of £2.50. The median time participants spent on the experiment was 12.87 minutes. After the choice tasks, we elicited participants' general risk attitude using the survey item from Dohmen et al. (2011), their self-assessed mathematical ability, and the direction in which they typically read written text. We also collected standard socio-demographic variables (e.g., age, gender, education, employment status, and origin). Finally, we recorded decision times to obtain a proxy for attentiveness during the task.

5. Results

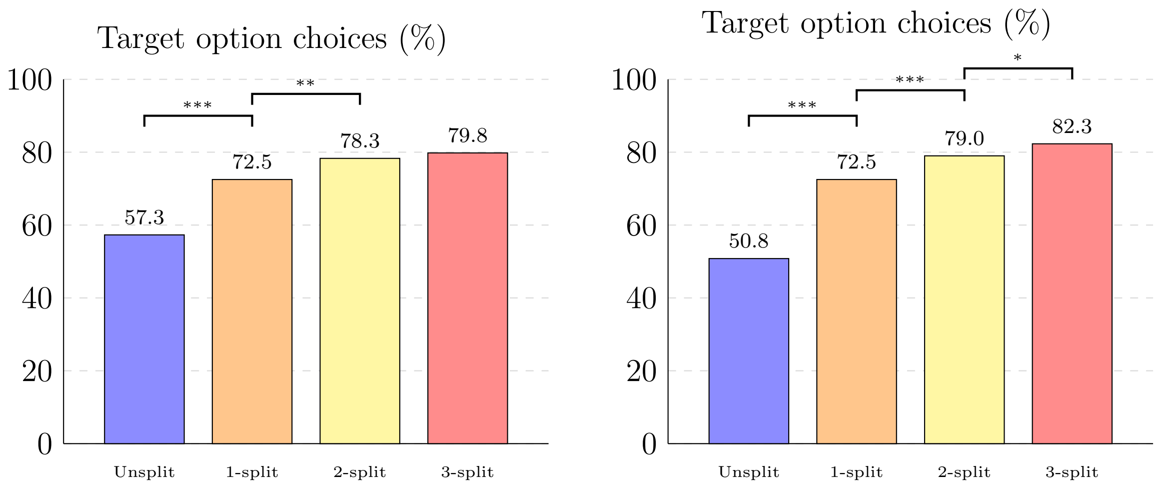
In this section, we report our main findings on the emergence of ESEs across different split types. We first examine how granularity, i.e., the number of simple splits, affects choice behavior. We then analyze the role of prominence, varying the placement of (sub-)states within the matrix. Finally, we study the joint variation of granularity and prominence to assess their relative importance for the occurrence of ESEs. For all non-parametric tests, the p-values of the changes in selection rates are calculated based on McNemar tests. We complement our non-parametric tests with regression analysis in Section 5.4.

5.1. Granularity: Number of Splits

Constellations 1 and 2 are designed to test how granularity affects choice by varying the number of simple splits. Each constellation comprises four versions of the same decision problem: an unsplit baseline and three split versions in which the advantageous state for the target option is partitioned into one, two, and three additional sub-states, respectively. The two constellations differ in where the advantageous state is located in the matrix: in Constellation 1, it is the first state, whereas in Constellation 2, it is the last. Figure 5 plots the corresponding shares of subjects choosing the target option across versions. Exact McNemar p-values for Constellations 1 and 2 are reported in Appendix C.1 (Tables 3–4).

In Constellations 1 and 2, we find the same qualitative pattern: increasing granularity raises the share of subjects choosing the target option. Relative to the unsplit baseline, the 1-, 2-, and 3-split versions all generate statistically significant increases in both constellations ($p < 0.01$). Moving from one to two splits produces an additional significant increase ($p < 0.05$ in Constellation 1; $p < 0.01$ in Constellation 2), and the difference

[4]Both the target sample size of 400 and the exclusion rule were preregistered. Excluded participants could still earn the fixed participation fee of £2.50 by completing the study.



(a) Splitting the first state.

(b) Splitting the last state.

Figure 5: Selection rates when performing simple splits one, two, or three times.

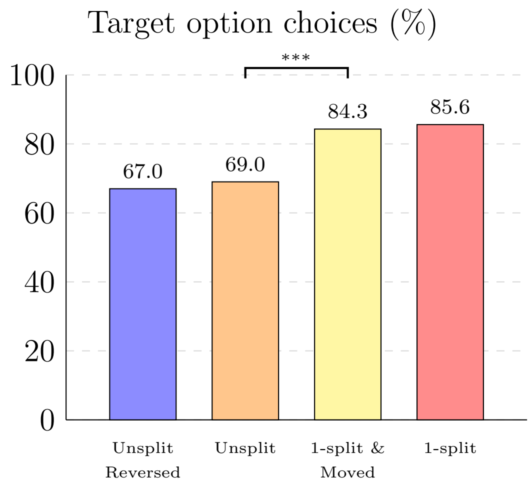
between one and three splits is significant in both cases ($p < 0.01$). By contrast, the step from two to three splits yields only a small further increase, which is not statistically significant in Constellation 1 ($p = 0.286$) and is only marginal in Constellation 2 ($p < 0.10$). Pooling both constellations likewise yields only a difference at the 10% significance level (see Figure 35 in Appendix C.2).

Taken together, simple splits imply a monotone but concave relationship between granularity and target choice: additional splits continue to raise selection rates, but with diminishing marginal impact. This pattern is consistent with our theoretical predictions and appears robust to whether the advantageous state is located first or last, provided that no sub-states are relocated within the matrix. We therefore view these findings as strong support for Hypotheses 1–3.

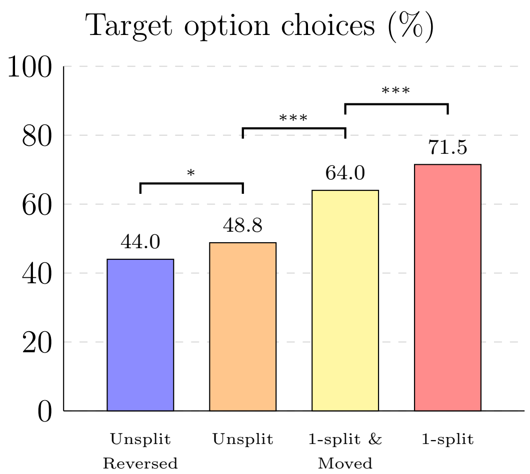
Result 1. *We find strong ESEs in Constellations 1 and 2. Increasing granularity through additional simple splits raises the share of subjects choosing the target option, but with diminishing marginal impact as the number of splits increases.*

5.2. Prominence: Position of States

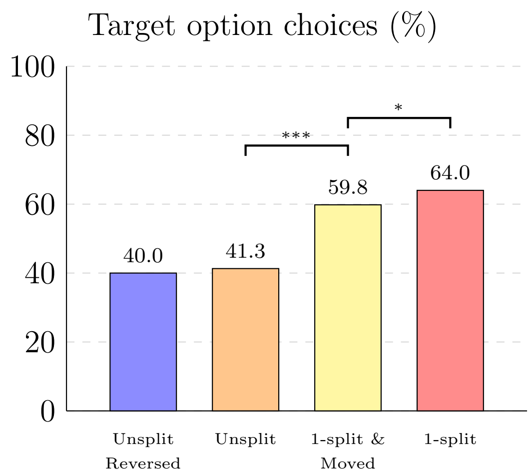
To study the role of prominence in the emergence of ESEs, we designed Constellations 3, 4, and 5. Each constellation comprises four versions of the same choice problem: an unsplit baseline, the same baseline with the two states reversed, a 1-split version featuring a simple split of the advantageous state for the target option, and a 1-split version featuring a right split. Comparing the two split versions to the reversed baseline allows us to evaluate splitting relative to a left placement of the split mass. Figure 6 displays the corresponding shares choosing the target option across versions. Exact McNemar p-values for Constellations 3–5 are reported in Appendix C.1 (Tables 5–7).



(a) Shifting the half-sized sub-state to the right.



(b) Shifting the larger sub-state to the right.



(c) Shifting the smaller sub-state to the right.

Figure 6: Selection rates when performing a one-time simple and a one-time right split.

Across Constellations 3–5, we observe a consistent pattern. In the unsplit baseline, the share choosing the target option is higher than in the reversed baseline, i.e., choices favor B more when the advantageous state is placed on the left (higher prominence). This baseline difference is marginal in Constellation 4 ($p < 0.10$) and not statistically significant in the other two constellations.

Introducing a split raises the share choosing the target option under both a simple split and a right split; relative to either baseline, these increases are significant at the 1% level ($p < 0.01$). Moreover, in all three constellations, selection rates are higher under the simple split than under the right split. This difference is significant in Constellation 4 ($p < 0.01$), marginal in Constellation 5 ($p < 0.10$), and not statistically significant in Constellation 3 ($p = 0.266$). Thus, right relocation attenuates the ESE relative to a simple split. The attenuation is more pronounced when the relocated sub-state is larger, although the relationship is not perfectly one-to-one, as the effect is small for the symmetric split. Overall, based on the pooled data, we find strong support for Hypothesis 5 and suggestive evidence for Hypothesis 4 (see Figure 36 in Appendix C.2).

Result 2. *We find strong ESEs in Constellations 3–5. Baseline choices already reflect prominence: holding payoffs and probabilities fixed, the share choosing the target option is higher when the advantageous state is placed on the left, although this difference is statistically significant only in Constellation 4. Under splitting, right relocation attenuates ESEs: relative to a simple split, the share choosing the target option is lower when one sub-state is shifted to the right. This attenuation is statistically significant for the asymmetric split, but not for the symmetric split.*

5.3. Combining Granularity and Prominence

We designed Constellation 6 to assess the relative importance of granularity and prominence. As in the previous constellations, it comprises four versions of the same choice problem: an unsplit baseline and three split versions. The 1-split version implements a single simple split of the advantageous state. The 2-split & Moved and 3-split & Moved versions increase granularity further (two or three splits, respectively) while simultaneously reducing prominence by relocating an additional sub-state to the right. Figure 7 shows the corresponding shares choosing the target option across versions. Exact McNemar p-values for Constellation 6 are reported in Appendix C.1 (Table 8).

Compared with the unsplit baseline, the 1-split version increases the share selecting the target option ($p < 0.01$). The initial effect is sizable, i.e., about 25 percentage points (pp). Increasing granularity from one to two splits while simultaneously reducing prominence through an additional right relocation still raises the selection rate ($p < 0.05$), suggesting that at low split counts the marginal benefit of further partitioning outweighs the attenuation from rightward relocation. This pattern reverses when moving from two to three splits: starting from the 2-split & Moved version, adding another split together with an additional right shift significantly reduces the selection rate ($p < 0.05$). Thus, at higher split counts, the attenuation from reduced prominence dominates the effect of additional sub-states. Moreover, selection rates in the 1-split and 3-split & Moved versions are nearly identical (75% vs. 76%, $p = 0.918$), indicating that a single simple split can have roughly the same behavioral impact as three splits combined with two right relocations.

Result 3. *We find strong ESEs in Constellation 6. At low levels of granularity, the marginal benefit of an additional split outweighs the attenuation from a right relocation: moving from one to two splits increases the share choosing the target option despite the*

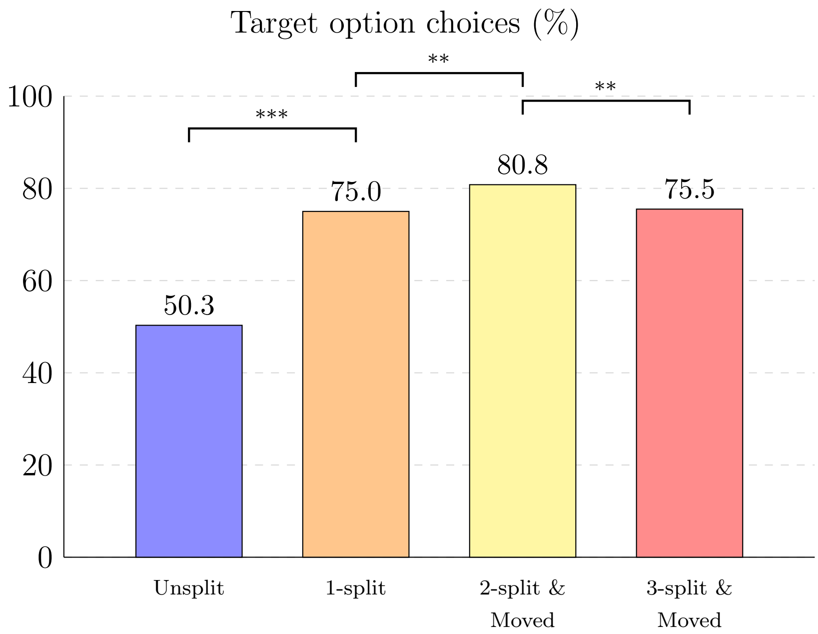


Figure 7: Selection rates when performing splits one, two, or three times while simultaneously shifting sub-states.

added right shift. This pattern reverses at higher split counts. When moving from two to three splits, the additional right relocation dominates, and the share choosing the target option falls.

5.4. Linear Probability Model

In addition to the non-parametric tests, we run the linear probability models (LPM) described in Section 3.2 to confirm our previous findings and gain a more nuanced picture regarding how granularity and prominence shape the occurrence of ESEs. The results are shown in Table 1.[5] See Appendix C.3 (Tables 11-17) for variable definitions, tie-coding robustness (Table 12), full-sample `selected` models (Table 15), and AMEs (Tables 16-17).

Table 1: Regression results with `ESE` as dependent variable

	(1)	(2)	(3)	(4)
Core regressors				
Constant	0.768***	0.877***	0.894***	0.999***
	(0.017)	(0.134)	(0.135)	(0.181)
number1	0.056***	0.087***	0.065***	0.076**

Continued on next page

[5]Since the R^2 of the main specification is low, we conduct an additional robustness check including individual fixed effects. The results remain qualitatively unchanged (see Table 13).

Table 1 (continued)

	(1)	(2)	(3)	(4)
	(0.017)	(0.022)	(0.022)	(0.035)
number2	0.012	-0.014	-0.007	0.004
	(0.016)	(0.020)	(0.021)	(0.029)
shifted	-0.112***	-0.106***	-0.092***	-0.075**
	(0.031)	(0.032)	(0.031)	(0.034)
shifted*number1				-0.115
				(0.174)
shifted*number2				0.002
				(0.148)
symmetric		0.076**	0.051	0.047
		(0.033)	(0.032)	(0.038)
back		-0.033	-0.027	-0.050
		(0.035)	(0.034)	(0.047)
upper		-0.010	-0.010	-0.010
		(0.017)	(0.017)	(0.017)
EV_dif		0.005	-0.007	-0.025
		(0.020)	(0.021)	(0.026)
time		-0.015	-0.013	-0.014
		(0.035)	(0.035)	(0.035)
position		0.007	0.007	0.007
		(0.007)	(0.007)	(0.007)
basis		-0.272	-0.353	-0.562
		(0.234)	(0.250)	(0.342)
downside			0.052	0.075*
			(0.037)	(0.041)
Model fit				
R^2	0.011	0.013	0.014	0.015
Adj. R^2	0.010	0.010	0.010	0.010
F-statistic	8.793	3.952	3.994	3.778
F-test p-value	<0.001	<0.001	<0.001	<0.001
Observations	2,416	2,416	2,416	2,416

Notes. Dependent variable `ESE` equals 1 if the subject switches toward the target option between a split version and its corresponding baseline; ties are excluded (coded 0 in robustness Table 12). For

Constellations 3, 4, and 5, we consistently use the baseline version rather than its reversed counterpart. `number1`/`number2` indicate additional splits; `shifted` equals the share of the original state moved to the right (sum across sub-states). See Appendix Table 11 for variable definitions and coding. Cluster-robust standard errors (CR2) in parentheses; clustering at the subject level.
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

A first notable finding is that our key design variables, i.e., `number1` (granularity) and `shifted` (prominence), are consistently statistically significant. Additional splitting has a positive effect: in the third specification in Table 1, increasing the number of splits from one to two raises the probability of observing an ESE by 6.5 pp ($p < 0.01$). By contrast, `number2` is close to zero, indicating little difference between two and three splits. Prominence matters in the opposite direction. The coefficient on `shifted` is negative, implying that moving all split mass to the far right reduces the likelihood of an ESE by 9.2 pp ($p < 0.01$). These patterns are robust in logit and probit specifications with clustered standard errors (AME; Appendix Tables 16–17). Using the full sample with `selected` as the dependent variable yields consistent results; in particular, a first split increases target selection by about 19.5 pp ($p < 0.01$; Appendix Table 15).

The coefficients on `number1` and `shifted` remain statistically significant even when controlling for the baseline selection rate of the target option (`basis`) and for whether the option's downside is zero (`downside`). We find no robust evidence that a zero downside affects the occurrence of ESEs: the `downside` coefficient is not stable across specifications (Tables 1 and 14). By contrast, in the full-sample `selected` regressions, `downside` is positive and significant, indicating that zero losses generally raise target selection with only a small impact on the ESE mechanism itself (Appendix Table 15).

Including interaction terms leaves the main `ESE` results largely unchanged: the coefficients on `number1` and `shifted` remain significant, while the interaction terms are not. However, in the full-sample `selected` regressions, the interaction term suggests that the effect of `shifted` is mainly driven by movements in the split versions (-0.059, $p < 0.01$), consistent with the results from Section 5.2. There is no evidence that this effect increases monotonically with additional splits.

Finally, we control for the socio-demographic characteristics collected in the post-experimental questionnaire.[6] Including these covariates leaves the main results unchanged. The coefficient on `symmetric` becomes weakly significant (0.054, $p < 0.10$), suggesting that symmetric splits may be somewhat more likely to trigger ESEs, consistent with the pattern documented in Section 5.2.

[6]For the corresponding regression table, see Appendix C.3, Table 14.

6. Discussion

Our findings support a two-dimensional view of event-splitting in matrix displays. When splitting is implemented as a pure increase in granularity (simple splits), choices shift robustly toward the option for which the split state is advantageous. At the same time, the marginal impact of additional splits declines. This pattern is consistent with a frequency mechanism: repeating the advantageous payoff across more displayed states matters, but the additional leverage from further refinements quickly becomes limited.

Prominence provides the second dimension. Even without splitting, changing where the advantageous state appears can affect choices, although these baseline differences are modest in our data. Once splitting is introduced, however, prominence becomes a systematic moderator of ESEs. Right relocation attenuates ESEs relative to a simple split. The attenuation is strongest when the larger sub-state is shifted to the right and smaller when the relocated piece is small; in contrast, under symmetric splits we do not detect a comparably sharp size-based pattern. These results point to an important role for positional weighting in matrix displays, while suggesting that prominence effects need not translate into a simple monotone "dose–response" relationship in every split configuration. This muted size-dependence under symmetric splits may reflect limited headroom in our data (baseline choice rates in these constellations are already high), leaving less scope for detectable differences. It may also indicate that symmetric splitting is processed differently, because partitioning into equal–sized pieces can be perceived as a more neutral or "balanced" decomposition. More broadly, our findings point to a potential source of variation in ESEs: even within a fixed display format, seemingly minor layout choices can shift which components are encountered early versus late, thereby amplifying or dampening the effect.

The interaction between granularity and prominence has two implications that go beyond documenting another display effect. First, it challenges the monotonicity intuition of standard subadditive (frequency-based) accounts: more splitting need not increase distortions. Once relocation is introduced, the effect of additional splitting can be neutralized or even reversed. In our combined manipulation, the net effect flips at higher split counts, and a single simple split can be comparable in magnitude to multiple splits combined with substantial right relocation. The results further suggest that the prominence effect changes with the number of splits. One possible explanation is that a larger number of displayed states increases cognitive effort when reading the choice problem, thereby strengthening the left-to-right mechanism. In our data, however, this appears to occur mainly when moving from no split to one split: for additional splits, we do not find a significant further change in the `shifted` variable, although this may partly reflect limited power since only one constellation combined multiple splits with shifted states.

Nevertheless, this trade-off suggests that ESEs should be analyzed as a multi-dimensional phenomenon—at least along granularity and prominence.

Second, the results speak to measurement in experimental work. When partitioning the state space—for instance, to study risk preferences or to implement display-based manipulations—this may inadvertently change additional features of the representation. In our setting, changes in partitioning can coincide with changes in prominence, which may matter for behavior. Even when the number of displayed branches is held fixed, differences in their placement may leave residual variation in how the display is processed. For this reason, it can be helpful for studies using matrix-like displays to report the ordering and placement of states alongside payoffs and probabilities, and to keep layout comparable across treatments whenever possible.

From an applied perspective, risk segmentation and layout function act as complementary design levers. In menus and comparison tables, increasing granularity can increase the attractiveness of the option that benefits in the split event, but prominence can either reinforce this (left shifts) or counteract it (right shifts). This suggests that institutions can affect choices without changing underlying probabilities or outcomes, simply by adjusting how finely risks are partitioned and where sub-items are placed. At the same time, the diminishing marginal returns to repeated splitting caution against ever finer segmentation: beyond a point, additional categories may add complexity without proportionate behavioral impact, and if placement cues run in the opposite direction, they may cancel out the intended effect.

Several limitations qualify the scope of our conclusions. First, our evidence is based on the matrix display and on a population that predominantly reads from left to right. Position effects may differ in other formats (lists, mobile views, collapsed menus) or under different scanning conventions. Second, while the results are consistent with a primacy mechanism, we do not directly measure visual attention (e.g., via eye tracking). Future work could use eye-tracking or interaction logs to separate attention from comprehension and to test whether reversing scan direction reverses the position channel. Third, our setting features binary choice without an opt-out option; in field environments with non-choice, granularity and prominence may shift some responses into non-participation rather than across alternatives.

Overall, the evidence suggests that ESEs are best understood as the outcome of interacting design choices. Treating granularity and prominence as separate levers improves both theory and identification and helps reconcile heterogeneous ESE magnitudes across implementations that differ subtly in layout.

7. Conclusion

This paper shows that ESEs in matrix displays can be multi-dimensional. In particular, choices respond not only to *granularity*—how finely a state is partitioned—but also to *prominence*—where the resulting sub-states are placed. We formalize this two-dimensional view in the Position-Adjusted Reference Utility (PARU) model and test its comparative statics in a preregistered, fully incentivized online experiment.

Empirically, simple splits generate large and robust ESEs: increasing granularity shifts choices toward the option for which the split state is advantageous, but with diminishing marginal impact as splitting becomes finer. Prominence systematically moderates these effects. Relative to simple splits, right relocation attenuates ESEs, and under combined manipulations the attenuation can be strong enough to neutralize or even reverse the gains from additional splitting. Together, these findings highlight a fundamental trade-off between granularity and prominence.

Beyond documenting another display effect, our results provide a framework for thinking about how segmented descriptions shape risky choice. They also suggest a practical takeaway for experimental and applied settings that rely on matrix-like representations: holding payoffs and objective probabilities fixed is not sufficient to pin down behavior if the placement of states and sub-states varies. A natural next step is to extend the analysis to other layouts and to combine experimental variation in prominence with direct process measures (e.g., attention and search) to better characterize the mechanisms through which positioning affects decision weights.

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A. Mathematical Appendix

Derivation of the specific position weighting function t:

1. **Shift Monotonicity:** For states $(a, b]$ with $p = b - a$ holds

$$t((a,b]) = (1-a)^{\alpha} - (1-[a+p])^{\alpha} = (1-a)^{\alpha} - (1-a-p)^{\alpha}$$

Thus, for the first derivative w.r.t. a follows

$$\frac{\partial t}{\partial a} = -\alpha(1-a)^{\alpha-1} + \alpha(1-a-p)^{\alpha-1}$$

Therefore, (MON) is fulfilled if and only if

$$\begin{aligned} & \frac{\partial t}{\partial a} < 0 \\ \Leftrightarrow \quad & (1-a-p)^{\alpha-1} < (1-a)^{\alpha-1} \\ \Leftrightarrow \quad & \left(\frac{1-a-p}{1-a}\right)^{\alpha-1} < 1 \\ \Leftrightarrow \quad & \alpha > 1. \end{aligned}$$

2. **Partition Additivity:** For $a < b < c$ and $(a, b], (b, c] \subset (0, 1]$, it follows

$$\begin{aligned} t((a,b]) + t((b,c]) &= (1-a)^{\alpha} - (1-b)^{\alpha} + (1-b)^{\alpha} - (1-c)^{\alpha} \\ &= (1-a)^{\alpha} - (1-c)^{\alpha} \\ &= t((a,c]). \end{aligned}$$

q.e.d

Proof of Proposition 1: First, note that for defining the state space $\mathcal{S} = \{s_1, ..., s_n\}$ on the unit intervall $(0, 1]$, it must be fulfilled $\bigcup_{i=1}^{n} s_i = (0,1]$ *and* $s_i \cap s_j = \emptyset$ for $s_i, s_j \in \mathcal{S}$, $i \neq j$ before and after splitting.

Furthermore, let $\mathcal{S}^{w_1} = \{s_1^{w_1}, ..., s_{n+w_1}^{w_1}\}$ be the state space after splitting state s_j $w_1 \geq 0$ times into $w_1 + 1$ sub-states $\{s_j^{w_1}, s_{n+1}^{w_1}, ..., s_{n+w_1}^{w_1}\}$ and $\mathcal{S}^{w_2} = \{s_1^{w_2}, ..., s_{n+w_2}^{w_2}\}$ be the state space after further splitting state $s_j^{w_1}$ for an additional $w_2 - w_1$ times into totally $w_2 + 1$ sub-states $\{s_j^{w_2}, s_{n+1}^{w_2}, ..., s_{n+w_2}^{w_2}\}$, where $w_2 > w_1$ and $\Delta_k^{w_1} = \Delta_k^{w_2}$ for all $k = n+1, ..., n+w_1$.

Then, the relative position weight difference $\mathcal{I}_k(\mathcal{S}^{w_1}, \mathcal{S}^{w_2})$ of a given state is defined as

$$\mathcal{I}_i(\mathcal{S}^{w_1}, \mathcal{S}^{w_2}) := \frac{t(s_i^{w_2})}{\sum_{k=1}^{n+w_2} t(s_k^{w_2})} - \frac{t(s_i^{w_1})}{\sum_{k=1}^{n+w_1} t(s_k^{w_1})}, \tag{A.1}$$

for any non-split state s_i, with $i \neq j$; for the split state s_j, it is given by

$$\mathcal{I}_j(\mathcal{S}^{w_1}, \mathcal{S}^{w_2}) := \frac{t(s_j^{w_2}) + \sum_{l=n+1}^{n+w_2} t(s_l^{w_2})}{\sum_{k=1}^{n+w_2} t(s_k^{w_2})} - \frac{t(s_j^{w_1}) + \sum_{l=n+1}^{n+w_1} t(s_l^{w_1})}{\sum_{k=1}^{n+w_1} t(s_k^{w_1})}. \tag{A.2}$$

W.l.o.g. let state s_1 be the state that is split w_1 times into w_1+1 sub-states and w_2 times into w_2+1 sub-states, $w_2 > w_1 \geq 0$, and suppose $[v(x_1^B) - v(x_1^A)] - [v(x_i^B) - v(x_i^A)] > 0$ for all $i \neq 1$. Further, verify that $\sum_{i=1}^n \mathcal{I}_i(\mathcal{S}^{w_1}, \mathcal{S}^{w_2}) = 0$. The PARU model predicts an ESE between the two situations if and only if

$$
\begin{aligned}
& V_{PARU}^{\mathcal{S}^{w_2}}(B) - V_{PARU}^{\mathcal{S}^{w_2}}(A) > V_{PARU}^{\mathcal{S}^{w_1}}(B) - V_{PARU}^{\mathcal{S}^{w_1}}(A) \\
\Leftrightarrow \quad & \gamma \sum_{i=1}^{n+w_2} \frac{t(s_i^{w_2})}{\sum_{k=1}^{n+1} t(s_k^{w_2})}[v(x_i^B) - v(x_i^A)] + (1-\gamma)\frac{1}{n+w_2}\sum_{i=1}^{n+w_2}[v(x_i^B) - v(x_i^A)] \\
& > \gamma \sum_{i=1}^{n+w_1} \frac{t(s_i^{w_1})}{\sum_{k=1}^{n} t(s_k^{w_1})}[v(x_i^B) - v(x_i^A)] + (1-\gamma)\frac{1}{n+w_1}\sum_{i=1}^{n+w_1}[v(x_i^B) - v(x_i^A)] \\
\Leftrightarrow \quad & \gamma\frac{t(s_1^{w_2}) + \sum_{j=n+1}^{n+w_2} t(s_j^{w_2})}{\sum_{k=1}^{n+w_2} t(s_k^{w_2})}[v(x_1^B) - v(x_1^A)] + (1-\gamma)\frac{w_2+1}{n+w_2}[v(x_1^B) - v(x_1^A)] \\
& + \gamma \sum_{i=2}^{n} \frac{t(s_i^{w_2})}{\sum_{k=1}^{n+w_2} t(s_k^{w_2})}[v(x_i^B) - v(x_i^A)] + (1-\gamma)\frac{1}{n+w_2}\sum_{i=2}^{n}[v(x_i^B) - v(x_i^A)] \\
& > \gamma\frac{t(s_1^{w_1}) + \sum_{j=n+1}^{n+w_1} t(s_j^{w_1})}{\sum_{k=1}^{n+w_1} t(s_k^{w_1})}[v(x_1^B) - v(x_1^A)] + (1-\gamma)\frac{w_1+1}{n+w_1}[v(x_1^B) - v(x_1^A)] \\
& + \gamma \sum_{i=2}^{n} \frac{t(s_i^{w_1})}{\sum_{k=1}^{n+w_1} t(s_k^{w_1})}[v(x_i^B) - v(x_i^A)] + (1-\gamma)\frac{1}{n+w_1}\sum_{i=2}^{n}[v(x_i^B) - v(x_i^A)] \\
\Leftrightarrow \quad & \gamma\left(\frac{t(s_1^{w_2}) + \sum_{j=n+1}^{n+w_2} t(s_j^{w_2})}{\sum_{k=1}^{n+w_2} t(s_k^{w_2})} - \frac{t(s_1^{w_1}) + \sum_{j=n+1}^{n+w_1} t(s_j^{w_1})}{\sum_{k=1}^{n+w_1} t(s_k^{w_1})}\right)[v(x_1^B) - v(x_1^A)] \\
& \quad + (1-\gamma)\frac{(n-1)(w_2-w_1)}{(n+w_1)(n+w_2)}[v(x_1^B) - v(x_1^A)] \\
& > \sum_{i=2}^{n}\left[\gamma\left(\frac{t(s_i^{w_1})}{\sum_{k=1}^{n+w_1} t(s_k)^{w_1}} - \frac{t(s_i^{w_2})}{\sum_{k=1}^{n+w_2} t(s_k^{w_2})}\right) + (1-\gamma)\frac{w_2-w_1}{(n+w_1)(n+w_2)}\right][v(x_i^B) - v(x_i^A)] \\
\Leftrightarrow \quad & \left[-\gamma\sum_{i=2}^{n}\mathcal{I}_i(\mathcal{S}^{w_1}, \mathcal{S}^{w_2}) + (1-\gamma)\frac{(n-1)(w_2-w_1)}{(n+w_1)(n+w_2)}\right][v(x_1^B) - v(x_1^A)] \\
& > \sum_{i=2}^{n}\left[-\gamma\mathcal{I}_i(\mathcal{S}^{w_1}, \mathcal{S}^{w_2}) + (1-\gamma)\frac{w_2-w_1}{(n+w_1)(n+w_2)}\right][v(x_i^B) - v(x_i^A)] \\
\Leftrightarrow \quad & -\frac{(n+w_1)(n+w_2)}{(n-1)(w_2-w_1)}\frac{\gamma}{1-\gamma}\sum_{i=2}^{n}\mathcal{I}_i(\mathcal{S}^{w_1}, \mathcal{S}^{w_2})[v(x_1^B) - v(x_1^A)] + v(x_1^B) - v(x_1^A) \\
& > -\frac{(n+w_1)(n+w_2)}{(n-1)(w_2-w_1)}\frac{\gamma}{1-\gamma}\sum_{i=2}^{n}\mathcal{I}_i(\mathcal{S}^{w_1}, \mathcal{S}^{w_2})[v(x_i^B) - v(x_i^A)] + \frac{1}{n-1}\sum_{i=2}^{n}[v(x_i^B) - v(x_i^A)] \\
\Leftrightarrow \quad & (1-\gamma)\frac{w_2-w_1}{(n+w_1)(n+w_2)}\sum_{i=2}^{n}\left(v(x_1^B) - v(x_1^A) - [v(x_i^B) - v(x_i^A)]\right) \\
& > \gamma\sum_{i=2}^{n}\mathcal{I}_i(\mathcal{S}^{w_1}, \mathcal{S}^{w_2})\left(v(x_1^B) - v(x_1^A) - [v(x_i^B) - v(x_i^A)]\right) \qquad (\star)
\end{aligned}
$$

Rearranging Inequality ($\star$) yields

$$\mathcal{M}(w_2)-\mathcal{M}(w_1)=(1-\gamma)\frac{w_2-w_1}{(n+w_1)(n+w_2)}\sum_{i=2}^{n}\big(v(x_1^B)-v(x_1^A)-[v(x_i^B)-v(x_i^A)]\big)$$
$$-\gamma\sum_{i=2}^{n}\mathcal{I}_i(\mathcal{S}^{w_1},\mathcal{S}^{w_2})\big(v(x_1^B)-v(x_1^A)-[v(x_i^B)-v(x_i^A)]\big)$$

As (MON) and (ADD) imply $\mathcal{I}_i(\mathcal{S}^{w_1},\mathcal{S}^{w_2})=0$ for all $i=1,...,n$ and $[v(x_1^B)-v(x_1^A)]-[v(x_i^B)-v(x_i^A)]>0$ for all $i\neq 1$, it follows $\mathcal{M}(w_2)-\mathcal{M}(w_1)>0$, such that, for simple splits, PARU always predicts an ESE, and (i) holds. Please note that for $w_1=0$, it follows $\mathcal{M}(0)=0$, such that this special case corresponds exactly to implication (i) in the proposition.

Furthermore, holding w_1 fixed, $\mathcal{M}(w_2)-\mathcal{M}(w_1)$ is strictly increasing in w_2 as the fraction $\frac{w_2-w_1}{(n+w_1)(n+w_2)}$ strictly increases in w_2, showing (ii).

On the other hand, for fixed $w_2-w_1=c$, the fraction is strictly decreasing in w_2, implying (iii).

q.e.d

Proof of Proposition 2: Recall

$$\mathcal{M}(w_2)-\mathcal{M}(w_1)=(1-\gamma)\frac{w_2-w_1}{(n+w_1)(n+w_2)}\sum_{i=2}^{n}\big(v(x_1^B)-v(x_1^A)-[v(x_i^B)-v(x_i^A)]\big)$$
$$-\gamma\sum_{i=2}^{n}\mathcal{I}_i(\mathcal{S}^{w_1},\mathcal{S}^{w_2})\big(v(x_1^B)-v(x_1^A)-[v(x_i^B)-v(x_i^A)]\big).$$

In case of right splits, (MON) and (ADD) imply $\mathcal{I}_i(\mathcal{S}^{w_1},\mathcal{S}^{w_2})\geq 0$ for all $i\neq 1$, such that $\mathcal{M}(w_2)-\mathcal{M}(w_1)$ is smaller than in the case of an otherwise identical simple split and (iii) is fulfilled.

Furthermore, rearranging ($\star$) yields

$$\begin{aligned}&\mathcal{M}(w_2)-\mathcal{M}(w_1)>0\\ \Longleftrightarrow\ &\gamma<\tilde{\gamma}:=\frac{1}{1+\frac{(n+w_1)(n+w_2)}{w_2-w_1}\frac{\sum_{i=2}^{n}\mathcal{I}_i(\mathcal{S}^{w_1},\mathcal{S}^{w_2})\left\{[v(x_j^B)-v(x_j^A)]-[v(x_i^B)-v(x_i^A)]\right\}}{\sum_{i=2}^{n}\left\{[v(x_j^B)-v(x_j^A)]-[v(x_i^B)-v(x_i^A)]\right\}}}.\end{aligned} \tag{A.3}$$

For $\mathcal{S}=\{s_1,s_2\}$, $\tilde{\gamma}$ simplifies to

$$\tilde{\gamma}=\frac{1}{1+\frac{(n+w_1)(n+w_2)}{w_2-w_1}\cdot\frac{t(s_2^{w_2})-t(s_1^{w_1})}{t((0,1])}}, \tag{A.4}$$

such that (i) holds.

Lastly, in case of left splits, (MON) and (ADD) imply $\mathcal{I}_i(\mathcal{S}^{w_1},\mathcal{S}^{w_2})\leq 0$ for all $i\neq 1$, such that $\mathcal{M}(w_2)-\mathcal{M}(w_1)$ is larger than in the case of an otherwise identical simple split and (ii) is fulfilled.

q.e.d

B. Appendix: Details on the Experiment

B.1. Choice Problems used in the Experiment

	1 70	71 100
○	**£0**	**£25**
○	**£9**	**£0**
	70%	30%

Figure 8: Problem 1, Unsplit Version

	1 40	41 70	71 100
○	**£0**	**£0**	**£25**
○	**£9**	**£9**	**£0**
	40%	30%	30%

Figure 9: Problem 1, 1-split Version

	1 20	21 40	41 70	71 100
○	**£0**	**£0**	**£0**	**£25**
○	**£9**	**£9**	**£9**	**£0**
	20%	20%	30%	30%

Figure 10: Problem 1, 2-split Version

	1 20	21 40	41 55	56 70	71 100
○	**£0**	**£0**	**£0**	**£0**	**£25**
○	**£9**	**£9**	**£9**	**£9**	**£0**
	20%	20%	15%	15%	30%

Figure 11: Problem 1, 3-split Version

	1 40	41 100
○	**£0**	**£6**
○	**£10**	**£0**
	40%	60%

Figure 12: Problem 2, Unsplit Version

	1 40	41 70	71 100
○	**£0**	**£6**	**£6**
○	**£10**	**£0**	**£0**
	40%	30%	30%

Figure 13: Problem 2, 1-split Version

	1 40	41 55	56 70	71 100
○	**£10**	**£0**	**£0**	**£0**
○	**£0**	**£6**	**£6**	**£6**
	40%	15%	15%	30%

Figure 14: Problem 2, 2-split Version

	1 40	41 55	56 70	71 85	86 100
○	**£10**	**£0**	**£0**	**£0**	**£0**
○	**£0**	**£6**	**£6**	**£6**	**£6**
	40%	15%	15%	15%	15%

Figure 15: Problem 2, 3-split Version

	1 60	61 100
○	**£0**	**£20**
○	**£15**	**£0**
	60%	40%

Figure 16: Problem 3, Unsplit Version

	1 40	41 100
○	**£20**	**£0**
○	**£0**	**£15**
	40%	60%

Figure 17: Problem 3, Unsplit Reversed Version

	1 30	31 60	61 100
○	**£0**	**£0**	**£20**
○	**£15**	**£15**	**£0**
	30%	30%	40%

Figure 18: Problem 3, 1-split Version

	1 30	31 70	71 100
○	**£0**	**£20**	**£0**
○	**£15**	**£0**	**£15**
	30%	40%	30%

Figure 19: Problem 3, 1-split & Moved Version

	1 – 55	56 – 100
○	**£2**	**£13**
○	**£10**	**£2**
	55%	45%

Figure 20: Problem 4, Unsplit Version

	1 – 45	46 – 100
○	**£2**	**£10**
○	**£13**	**£2**
	45%	55%

Figure 21: Problem 4, Unsplit Reversed Version

	1 – 10	11 – 55	56 – 100
○	**£2**	**£2**	**£13**
○	**£10**	**£10**	**£2**
	10%	45%	45%

Figure 22: Problem 4, 1-split Version

	1 – 10	11 – 55	56 – 100
○	**£10**	**£2**	**£10**
○	**£2**	**£13**	**£2**
	10%	45%	45%

Figure 23: Problem 4, 1-split & Moved Version

	1 – 65	66 – 100
○	**£5**	**£0**
○	**£0**	**£16**
	65%	35%

Figure 24: Problem 5, Unsplit Version

	1 – 35	36 – 100
○	**£16**	**£0**
○	**£0**	**£5**
	35%	65%

Figure 25: Problem 5, Unsplit Reversed Version

	1 – 50	51 – 65	66 – 100
○	**£0**	**£0**	**£16**
○	**£5**	**£5**	**£0**
	50%	15%	35%

Figure 26: Problem 5, 1-split Version

	1 50	51 85	86 100
○	**£5**	**£0**	**£5**
○	**£0**	**£16**	**£0**
	50%	35%	15%

Figure 27: Problem 5, 1-split & Moved Version

	1 55	56 100
○	**£18**	**£0**
○	**£0**	**£23**
	55%	45%

Figure 28: Problem 6, Unsplit Version

	1 25	26 55	56 100
○	**£0**	**£0**	**£23**
○	**£18**	**£18**	**£0**
	25%	30%	45%

Figure 29: Problem 6, 1-split Version

	1 25	26 40	41 85	86 100
○	**£0**	**£0**	**£23**	**£0**
○	**£18**	**£18**	**£0**	**£18**
	25%	15%	45%	15%

Figure 30: Problem 6, 2-split & Moved Version

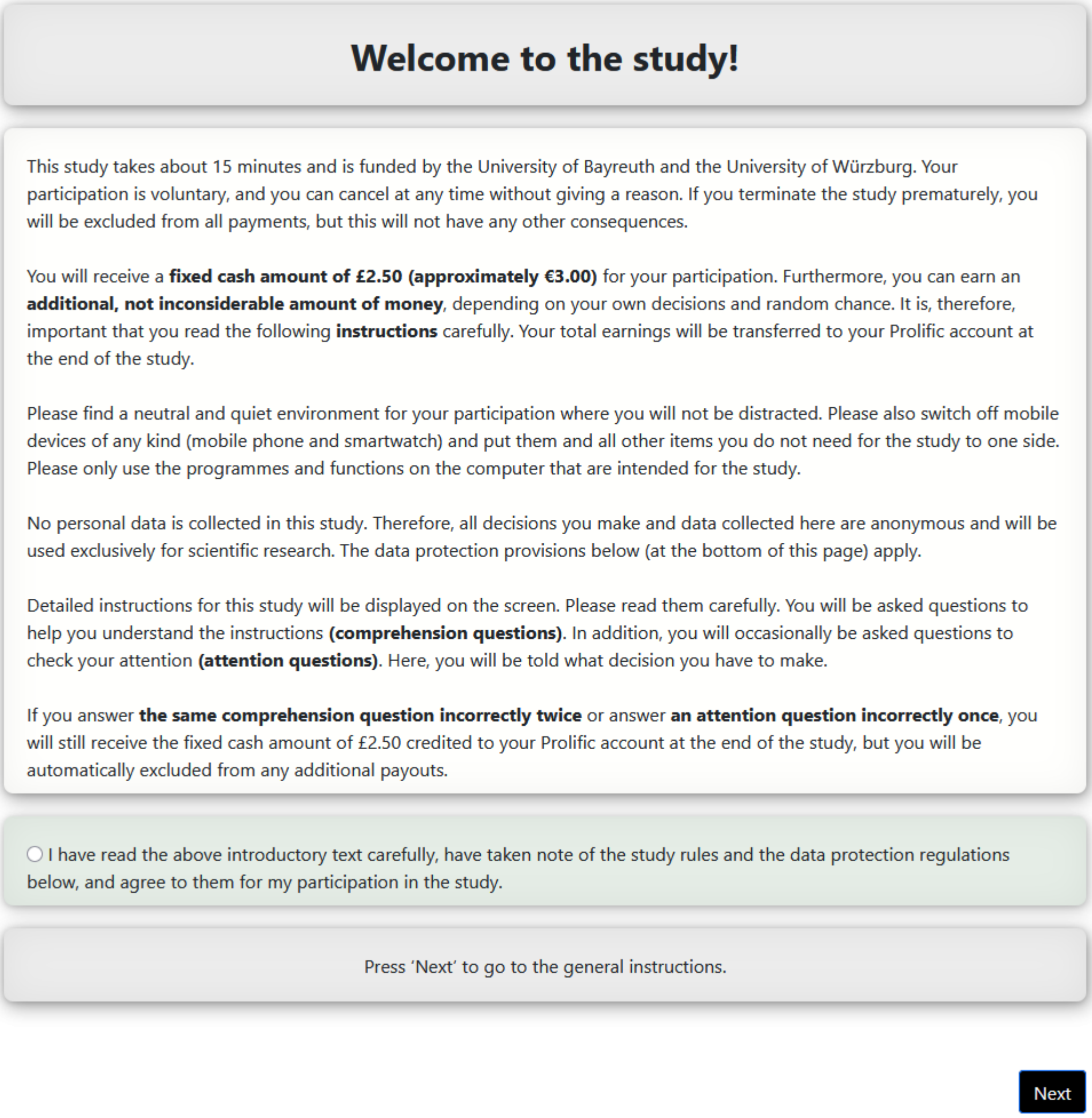
	1 10	11 25	26 70	71 85	86 100
○	**£0**	**£0**	**£23**	**£0**	**£0**
○	**£18**	**£18**	**£0**	**£18**	**£18**
	10%	15%	45%	15%	15%

Figure 31: Problem 6, 3-split & Moved Version

Problem	Version	s_1	s_2	s_3	s_4	s_5	x_1^A	x_2^A	x_3^A	x_4^A	x_5^A	x_1^B	x_2^B	x_3^B	x_4^B	x_5^B	$E[A]$	$E[B]$
1	unsplit	$(0, 0.7]$	$(0.7, 1]$				9	0				0	25				6.3	7.5
1	1 split	$(0, 0.4]$	$(0.4, 0.7]$	$(0.7, 1]$			9	9	0			0	0	25			6.3	7.5
1	2 splits	$(0, 0.2]$	$(0.2, 0.4]$	$(0.4, 0.7]$	$(0.7, 1]$		9	9	9	0		0	0	0	25		6.3	7.5
1	3 splits	$(0, 0.2]$	$(0.2, 0.4]$	$(0.4, 0.55]$	$(0.55, 0.7]$	$(0.7, 1]$	9	9	9	9	0	0	0	0	0	25	6.3	7.5
2	unsplit	$(0, 0.4]$	$(0.4, 1]$				0	6				10	0				3.6	4
2	1 split	$(0, 0.4]$	$(0.4, 0.7]$	$(0.7, 1]$			0	6	6			10	0	0			3.6	4
2	2 splits	$(0, 0.4]$	$(0.4, 0.55]$	$(0.55, 0.7]$	$(0.7, 1]$		0	6	6	6		10	0	0	0		3.6	4
2	3 splits	$(0, 0.4]$	$(0.4, 0.55]$	$(0.55, 0.7]$	$(0.7, 0.85]$	$(0.85, 1]$	0	6	6	6	6	10	0	0	0	0	3.6	4
3	unsplit	$(0, 0.6]$	$(0.6, 1]$				15	0				0	20				9	8
3	unsplit reversed	$(0, 0.4]$	$(0.4, 1]$				0	15				20	0				9	8
3	1 split	$(0, 0.3]$	$(0.3, 0.6]$	$(0.6, 1]$			15	15	0			0	0	20			9	8
3	1 split & shift	$(0, 0.3]$	$(0.3, 0.7]$	$(0.7, 1]$			15	0	15			0	20	0			9	8
4	unsplit	$(0, 0.55]$	$(0.55, 1]$				10	2				2	13				6.4	6.95
4	unsplit reversed	$(0, 0.45]$	$(0.45, 1]$				2	10				13	2				6.4	6.95
4	1 split	$(0, 0.1]$	$(0.1, 0.55]$	$(0.55, 1]$			10	10	2			2	2	13			6.4	6.95
4	1 split & shift	$(0, 0.1]$	$(0.1, 0.55]$	$(0.55, 1]$			10	2	10			2	13	2			6.4	6.95
5	unsplit	$(0, 0.65]$	$(0.65, 1]$				5	0				0	16				3.25	5.6
5	unsplit reversed	$(0, 0.35]$	$(0.35, 1]$				0	5				16	0				3.25	5.6
5	1 split	$(0, 0.5]$	$(0.5, 0.65]$	$(0.65, 1]$			5	5	0			0	0	16			3.25	5.6
5	1 split & shift	$(0, 0.5]$	$(0.5, 0.85]$	$(0.85, 1]$			5	0	5			0	16	0			3.25	5.6
6	unsplit	$(0, 0.55]$	$(0.55, 1]$				18	0				0	23				9.9	10.35
6	1 split	$(0, 0.25]$	$(0.25, 0.55]$	$(0.55, 1]$			18	18	0			0	0	23			9.9	10.35
6	2 splits & shift	$(0, 0.25]$	$(0.25, 0.4]$	$(0.4, 0.85]$	$(0.85, 1]$		18	18	0	18		0	0	23	0		9.9	10.35
6	3 splits & shift	$(0, 0.1]$	$(0.1, 0.25]$	$(0.25, 0.7]$	$(0.7, 0.85]$	$(0.85, 1]$	18	18	0	18	18	0	0	23	0	0	9.9	10.35

Table 2: Overview of Choice Problems and Versions

B.2. Instructions and Comprehension Questions



Welcome to the study!

This study takes about 15 minutes and is funded by the University of Bayreuth and the University of Würzburg. Your participation is voluntary, and you can cancel at any time without giving a reason. If you terminate the study prematurely, you will be excluded from all payments, but this will not have any other consequences.

You will receive a **fixed cash amount of £2.50 (approximately €3.00)** for your participation. Furthermore, you can earn an **additional, not inconsiderable amount of money**, depending on your own decisions and random chance. It is, therefore, important that you read the following **instructions** carefully. Your total earnings will be transferred to your Prolific account at the end of the study.

Please find a neutral and quiet environment for your participation where you will not be distracted. Please also switch off mobile devices of any kind (mobile phone and smartwatch) and put them and all other items you do not need for the study to one side. Please only use the programmes and functions on the computer that are intended for the study.

No personal data is collected in this study. Therefore, all decisions you make and data collected here are anonymous and will be used exclusively for scientific research. The data protection provisions below (at the bottom of this page) apply.

Detailed instructions for this study will be displayed on the screen. Please read them carefully. You will be asked questions to help you understand the instructions **(comprehension questions)**. In addition, you will occasionally be asked questions to check your attention **(attention questions)**. Here, you will be told what decision you have to make.

If you answer **the same comprehension question incorrectly twice** or answer **an attention question incorrectly once**, you will still receive the fixed cash amount of £2.50 credited to your Prolific account at the end of the study, but you will be automatically excluded from any additional payouts.

◯ I have read the above introductory text carefully, have taken note of the study rules and the data protection regulations below, and agree to them for my participation in the study.

Press 'Next' to go to the general instructions.

Next

Figure 32: Instructions

Instructions: Gamble decisions

In the study, you are shown **24 decisions between two gambles**, one after the other.

Example of a gamble decision:

	1 – 50	51 – 80	81 – 100
○	**£5**	**£4**	**£2**
○	**£1**	**£9**	**£2**
	50%	30%	20%

A gamble assigns an amount of money to each number between 1 and 100. Number ranges are summarised in the top row of the table shown. The chance that the randomly drawn number falls within a specific number range is shown in the bottom row of the table.

In this example, the upper gamble pays out £5 for a number between 1 and 50 (50% chance), £4 for a number between 51 and 80 (30% chance) and £2 for a number between 81 and 100 (20% chance). The lower gamble pays out £1 for a number between 1 and 50 (50% chance), £9 for a number between 51 and 80 (30% chance) and £2 for a number between 81 and 100 (20% chance).

Decision

Your **task in this study** is to **select the gamble that you personally prefer.** You select your favourite gamble by clicking in the circle in front of the respective alternative.

Payment

At the end of the study, the computer randomly selects **one gamble decision as being payout-relevant**. Each gamble decision has the same probability of being selected. After that, the computer will draw a random number between 1 and 100 and you will receive the amount of money that the gamble you have chosen in the payout-relevant decision assigns to the random number.

Assume that you have selected the upper gamble in the example above. If the random number is between 1 and 50, you will receive £5. If the random number is between 51 and 80, you will receive £4, and if the random number is between 81 and 100, you will receive £2.

Figure 33: Instructions

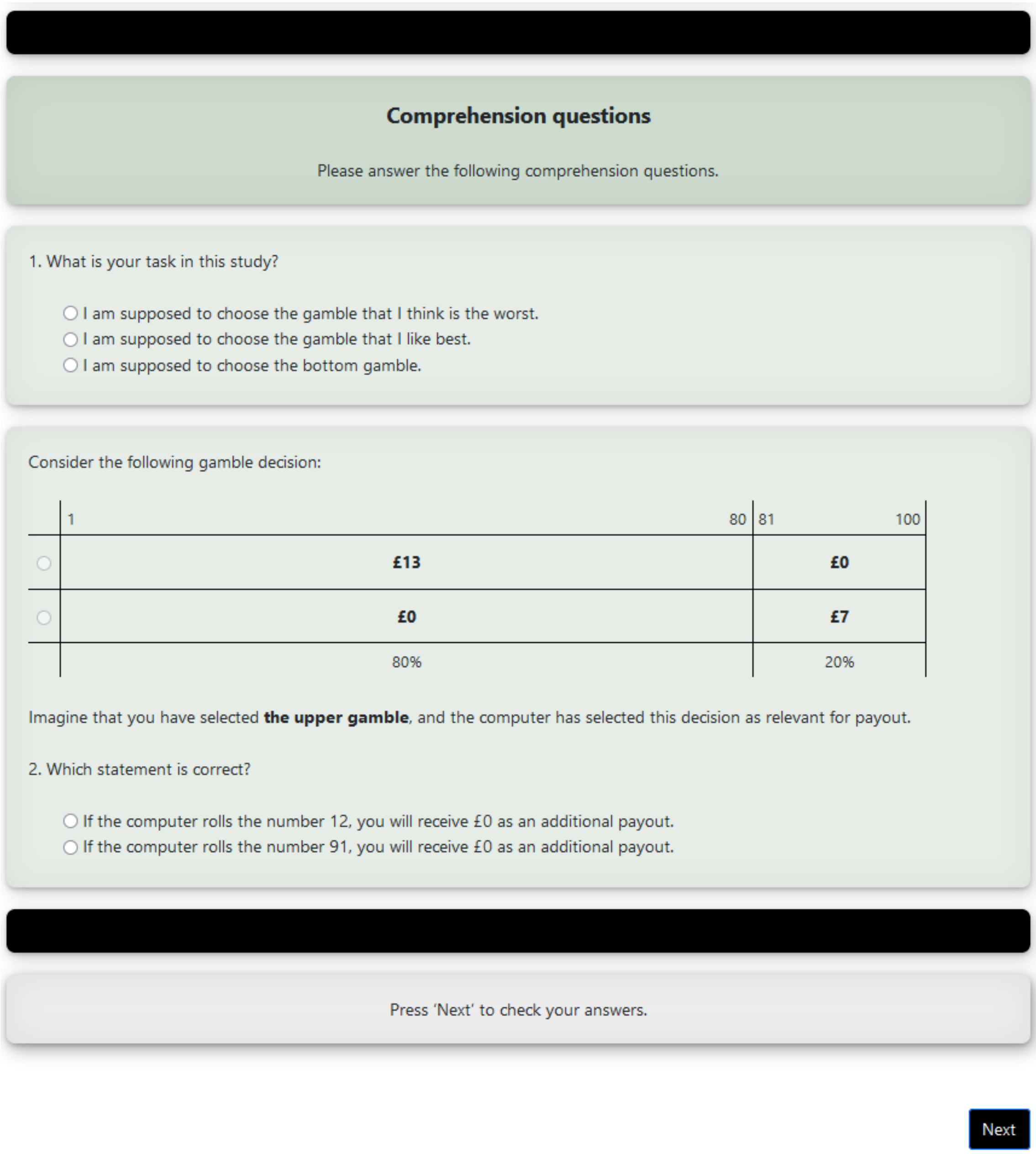


Figure 34: Comprehension questions

C. Appendix: Experimental Results and Additional Regressions

C.1. Frequency Tables

C.1.1. Constellation 1

	Number of subjects choosing target option when display is:		
Problem pair	**Unsplit**	**(Additionally) Split**	**p-value**
Unsplit, 1-split	229	290	$p < 0.01$
Unsplit, 2-split	229	313	$p < 0.01$
Unsplit, 3-split	229	319	$p < 0.01$
1-split, 2-split	290	313	$p = 0.010$
1-split, 3-split	290	319	$p < 0.01$
2-split, 3-split	313	319	$p = 0.286$

Table 3: p-values of testing the increases in choices by splitting the first state one, two, or three times. The p-values are based on one-sided exact McNemar tests.

C.1.2. Constellation 2

	Number of subjects choosing target option when display is:		
Problem pair	**Unsplit**	**(Additionally) Split**	**p-value**
Unsplit, 1-split	203	290	$p < 0.01$
Unsplit, 2-split	203	316	$p < 0.01$
Unsplit, 3-split	203	329	$p < 0.01$
1-split, 2-split	290	316	$p < 0.01$
1-split, 3-split	290	329	$p < 0.01$
2-split, 3-split	316	329	$p = 0.077$

Table 4: p-values of testing the increases in choices by splitting the last state one, two, or three times. The p-values are based on one-sided exact McNemar tests.

C.1.3. Constellation 3

	Number of subjects choosing target option when display is:		
Problem pair	**Unsplit/Not-moved**	**Split/Moved**	**p-value**
Unsplit, Unsplit Reversed	276	268	$p = 0.267$
Unsplit, 1-split	276	343	$p < 0.01$
Unsplit, 1-split & Moved	276	337	$p < 0.01$
Unsplit Reversed, 1-split	268	343	$p < 0.01$
Unsplit Reversed, 1-split & Moved	268	337	$p < 0.01$
1-split, 1-split & Moved	343	337	$p = 0.266$

Table 5: p-values of testing the increases in choices by splitting one state into two sub-states of equal size and moving one sub-state. The p-values are based on one-sided exact McNemar tests.

C.1.4. Constellation 4

	Number of subjects choosing target option when display is:		
Problem pair	**Unsplit/Not-moved**	**Split/Moved**	**p-value**
Unsplit, Unsplit Reversed	195	176	$p = 0.058$
Unsplit, 1-split	195	286	$p < 0.01$
Unsplit, 1-split & Moved	195	256	$p < 0.01$
Unsplit Reversed, 1-split	176	286	$p < 0.01$
Unsplit Reversed, 1-split & Moved	176	256	$p < 0.01$
1-split, 1-split & Moved	286	256	$p < 0.01$

Table 6: p-values of testing the increases in choices by splitting one state into two sub-states and moving the bigger one. The p-values are based on one-sided exact McNemar tests.

C.1.5. Constellation 5

	Number of subjects choosing target option when display is:		
Problem pair	**Unsplit/Not-moved**	**Split/Moved**	**p-value**
Unsplit, Unsplit Reversed	165	160	$p = 0.357$
Unsplit, 1-split	165	256	$p < 0.01$
Unsplit, 1-split & Moved	165	239	$p < 0.01$
Unsplit Reversed, 1-split	160	256	$p < 0.01$
Unsplit Reversed, 1-split & Moved	160	239	$p < 0.01$
1-split, 1-split & Moved	256	239	$p = 0.064$

Table 7: p-values of testing the increases in choices by splitting one state into two sub-states and moving the smaller one. The p-values are based on one-sided exact McNemar tests.

C.1.6. Constellation 6

	Number of subjects choosing target option when display is:		
Problem pair	**Unsplit**	**(Additionally) Split**	**p-value**
Unsplit, 1-split	201	300	$p < 0.01$
Unsplit, 2-split & Moved	201	323	$p < 0.01$
Unsplit, 3-split & Moved	201	302	$p < 0.01$
1-split, 2-split & Moved	300	323	$p = 0.028$
1-split, 3-split & Moved	300	302	$p = 0.918$
2-split & Moved, 3-split & Moved	323	302	$p = 0.042$

Table 8: p-values of testing the increases in choices by splitting the last state one, two, or three times and moving sub-states at the end. The p-values are based on McNemar tests. We performed two-sided tests to determine the differences between 1-split, 2-split, and 3-split.

C.2. Pooling Constellations

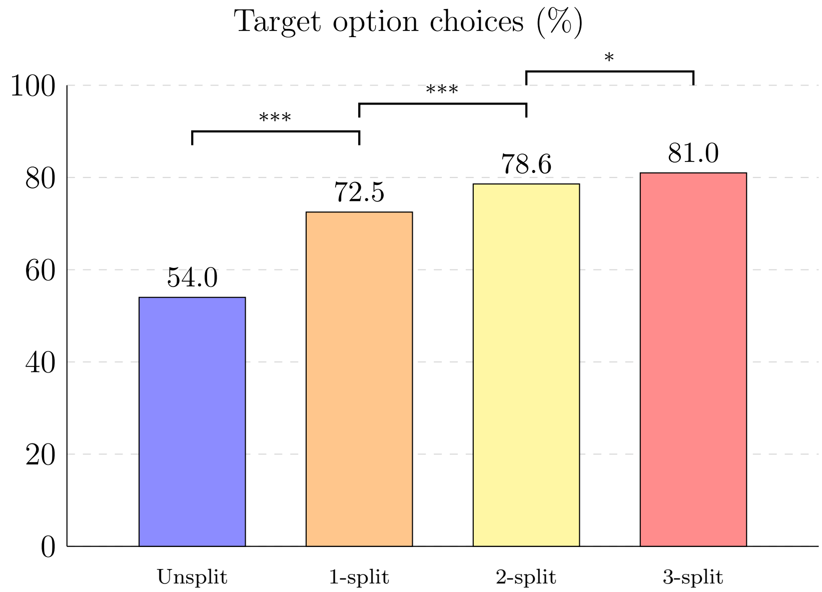


Figure 35: Selection rates when performing simple splits one, two, or three times and pooling Constellation 1 and 2.

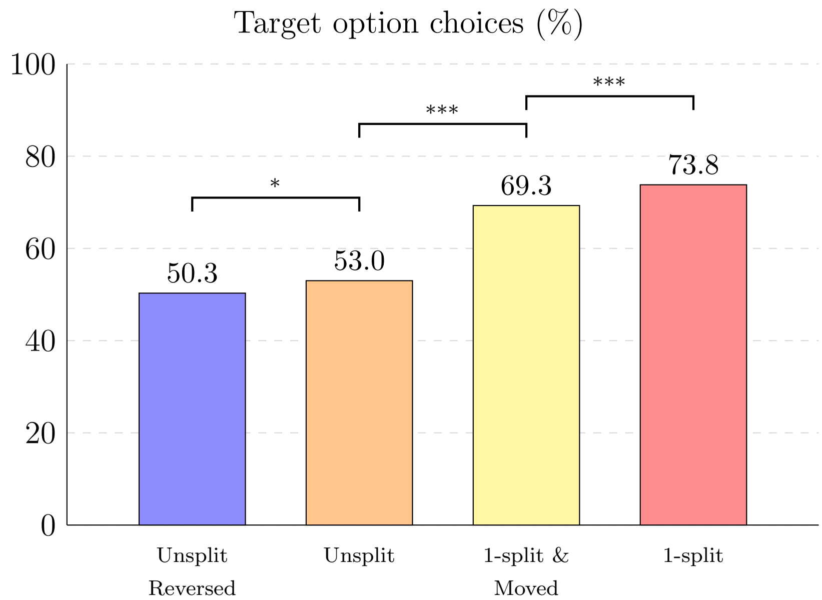


Figure 36: Selection rates when comparing the reversed unsplit version, the unsplit version, the one-time right split, and the one-time simple split and pooling Constellations 3, 4, and 5.

C.3. Regression Analyses

To assess participants' math skills, we included the question "How do you rate your math skills?" in the post-experimental questionnaire. Responses were recorded on an ordinal scale (A=excellent, B=good, C=average, D=slightly below average, E=poor) and subsequently transformed into a metric variable ranging from 0 to 4 (0=poor, 4=excellent). Thus, higher values reflect higher self-assessed math skills.

Participants' general risk attitudes were measured using a question adapted from Dohmen et al. (2011), asking subjects to indicate their general willingness to take risks. Responses were provided on a scale from 1 (not at all willing) to 10 (very willing), with higher values indicating a greater propensity for risk-taking.

In addition to the measures for math skills and risk attitudes, we asked participants whether they read lines from left to right in their native language (`reading` variable). Individuals accustomed to reading in a different direction may approach spatial structures differently, which could affect the occurrence of ESEs when performing left or right splits.

Finally, we control for a range of demographic characteristics collected in the questionnaire. An overview of subjects' responses to these post-experimental questions is provided in Tables 9 and 10.

Variable	**Min.**	**Median**	**Mean**	**Std. Dev.**	**Max.**
Age	18.00	30.00	32.43	9.81	75.00
Math skills	0.00	3.00	2.75	0.81	4.00
General risk attitude	1.00	6.00	6.03	2.25	10.00

Table 9: Overview of metric variables included in the ex-post questionnaire.

The linear probability model (LPM) discussed in section 5.4 (Tables 1 and 14) identifies factors that influence the occurrence of ESEs. As an alternative specification, we estimate a similar regression in which the dependent variable is a binary indicator for whether the safer option was chosen (`selected` variable). Since our design consistently promotes the safer option, this variable reflects whether subjects followed that intended direction.

This alternative approach offers two main advantages. First, it allows us to include all observations, whereas the `ESE` variable requires calculating the difference between a choice in a split problem and its corresponding unsplit counterpart, thus limiting the sample. Second, the regression serves as a robustness check for the initial findings.

As the set of independent variables largely overlaps with the previous specification, we do not discuss them in detail again. However, we exclude the variables `symmetric`, `back`,

Variable	**Categories**	**# observations**
Gender	Female	188
	Male	208
	non-binary	4
		Total = 400
Origin	Europe	202
	North, Central, and South America	18
	Australia and Oceania	7
	Arabia	3
	None of the above	170
		Total = 400
Education	University degree	286
	Master craftsman	7
	A-levels	37
	Secondary school leaving certificate	65
	None of the above	5
		Total = 400
Occupation	Education and research	29
	Public administration and justice	16
	Office work	128
	Medical work	23
	Craft worker	11
	Pupil or student	44
	Pensioner	5
	Not employed	42
	None of the above	102
		Total = 400
Reading	From left to right	392
	Other directions	8
		Total = 400

Table 10: Overview of categorical variables included in the ex-post questionnaire.

and `basis` in this model, as they pertain specifically to comparisons between pre- and post-split decisions, which are not the focus here. It is also important to note that the number variables continue to capture the effect of an additional split. However, while the baseline situation in the ESE model already involves one split, the current model starts from a scenario without any split. Consequently, `number1` in this model reflects the effect of a first split, whereas in the previous model, it captured the effect of a second split.

In the following, we analyze the results of this regression (Table 15) and compare them to the results discussed in section 5.4.

Examining the coefficients for one-time, two-time, and three-time splitting reveals that a single split increases the probability of choosing the safer option by approximately 19.5 pp ($p < 0.01$), while an additional split raises this probability by around 5.7 pp ($p < 0.01$). However, a third split does not produce a statistically significant effect. These findings largely mirror the differences in selection rates observed across the various levels of splitting. Moreover, the difference between one split and two or three splits closely aligns with the estimates obtained from the `ESE` model, thereby reinforcing the results presented earlier.

The coefficient of the `shifted` variable is approximately -3.4 pp ($p < 0.01$), and thus slightly smaller than in the previous model. This reduction is likely due to the inclusion of all observations, where the extent of shifting was lower in cases without a split. The `duration` variable turns out to be statistically insignificant.

The `EV_dif` variable now emerges as statistically significant. This makes sense as the expected value of the riskier option increases, fewer individuals should select the safer alternative. This is reflected in the negative sign of the coefficient (-0.07, $p < 0.01$).

Notably, the `downside` variable also has a significant effect in this linear probability model. This suggests that zero outcomes generally influence choice behavior. However, they do not appear to be a decisive factor in the emergence of ESEs, as their effect becomes smaller and statistically insignificant when we focus solely on preference switches in the `ESE` model.

We also find that older participants were more likely to choose the safer option (estimate for `age`: 0.002, $p < 0.1$), although age does not appear to influence the occurrence of ESEs in the `ESE` model. In contrast, male participants exhibited significantly more ESEs than female participants (estimate for `male`: 0.074, $p < 0.05$), while no such gender difference is observed in the `selected` model.

With regard to occupational status, we observe weakly significantly fewer ESEs among individuals in craft occupations compared to students (estimate `craft_job`: -0.257, $p < 0.1$).

Interestingly, participants from Australia and Oceania appear to be more risk-averse than their European counterparts (estimate for `australia_origin`: 0.118, $p < 0.1$). When focusing on preference switches in the `ESE` model, however, these origin-related effects become smaller and statistically insignificant, suggesting that they do not systematically influence the occurrence of ESEs.

Furthermore, we find no systematic differences in educational backgrounds. Finally, the estimate for risk aversion in the selected model is negative (-0.017, $p < 0.01$). This makes sense as individuals with a greater willingness to take risks are less likely to choose the safer option.

Table 11: Included Variables for regression analysis

Variable	Description
ESE	Binary variable; 1 if there was a preference switch in the predicted direction
selected	Binary variable; 1 if the safer option was chosen
number1	Binary variable; 1 if there was at least one additional split
number2	Binary variable; 1 if there were at least two additional splits
number3	Binary variable; 1 if there were at least three additional splits
shifted	Proportion of the advantageous state of the target option at the end of the matrix
symmetric	Binary variable; 1 if state was split into sub-states of equal size
back	Binary variable; 1 if the last state was split
upper	Binary variable; 1 if the target gamble was the upper option in the matrix
EV_dif	Expected value difference between target option and alternative option
time	Seconds an individual spent on a specific questions
position	Position at which the question was asked within the four related questions; 1 if it was the first question, 4 if it was the last one
basis	Selection rate in the basic unsplit problem
downside	Binary variable; 1 if the downside of both options was 0
age	Age of subject
male	Binary variable; 1 if male was stated as gender
female	Binary variable; 1 if female was stated as gender
non-binary	Binary variable; 1 if non-binary was stated as gender
teaching_job	Binary variable; 1 if employment in education or research was stated
public_job	Binary variable; 1 if employment in public administration or justice was stated
office_job	Binary variable; 1 if office work was stated
medical_job	Binary variable; 1 if medical work was stated
craft_job	Binary variable; 1 if craft work was stated
student_job	Binary variable; 1 if pupil or student status was stated
pensioner_job	Binary variable; 1 if pensioner status was stated
unemployed_job	Binary variable; 1 if unemployment status was stated
other_job	Binary variable; 1 if none of the other alternatives applied
europe_origin	Binary variable; 1 if Europe was stated as region of origin
america_origin	Binary variable; 1 if North, Central, or South America was stated as region of origin
australia_origin	Binary variable; 1 if Australia or Oceania was stated as region of origin
arabia_origin	Binary variable; 1 if Arabia was stated as region of origin
other_origin	Binary variable; 1 if none of the other alternatives applied
uni_edu	Binary variable; 1 if a university degree was stated as the highest level of education
craft_edu	Binary variable; 1 if a craft qualification was stated as the highest level of education
alevel_edu	Binary variable; 1 if A-levels was stated as the highest level of education
second_edu	Binary variable; 1 if a secondary school leaving certificate was stated as the highest level of education
other_edu	Binary variable; 1 if none of the other alternatives applied
reading	Binary variable; 1 if it was stated that the native language is not read from left to right
math_skills	Self-assessed math-skills on a scale from 0 ("awful") to 4 ("excellent")
risk_aversion	Self-assessed risk attitude on a scale from 1 ("fully risk-averse") to 10 ("very risk-loving")

Table 12: Regression results with `ESE` as dependent variable and `ESE` = 0 if no switch observed

	(1)	(2)	(3)
Core regressors			
Constant	0.288***	0.864***	0.858***
	(0.012)	(0.107)	(0.109)
number1	0.057***	0.050***	0.060***
	(0.011)	(0.014)	(0.012)
number2	-0.004	0.010	0.007
	(0.010)	(0.012)	(0.012)
shifted	0.014	-0.053**	-0.060***
	(0.022)	(0.021)	(0.020)
symmetric		-0.022	-0.010
		(0.022)	(0.020)
back		-0.023	-0.025
		(0.029)	(0.028)
upper		-0.010	-0.010
		(0.012)	(0.012)
EV_dif		-0.073***	-0.067***
		(0.015)	(0.017)
time		-0.034	-0.035
		(0.032)	(0.033)
position		0.002	0.002
		(0.005)	(0.004)
basis		-0.945***	-0.907***
		(0.181)	(0.197)
downside			-0.025
			(0.027)
Model fit			
R^2	0.003	0.013	0.013
Adj. R^2	0.003	0.011	0.011
F-statistic	9.942	7.020	7.352
F-test p-value	<0.001	<0.001	<0.001
Observations	6,000	6,000	6,000

Notes. Dependent variable `ESE` equals 1 if the subject switches toward the target option between a split version and its corresponding baseline; ties are included and coded as 0. For Constellations 3, 4, and 5, we consistently use the baseline version rather than its reversed counterpart. `number1`/`number2` indicate additional splits; `shifted` equals the share of the original state moved to the right (sum across sub-states). See Appendix Table 11 for variable definitions and coding. Cluster-robust standard errors (CR2) in parentheses; clustering at the subject level.

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table 13: Regression results with `ESE` as dependent variable and individual fixed effects

	(1)	(2)	(3)
Core regressors			
number1	0.034**	0.049***	0.041**
	(0.014)	(0.018)	(0.016)
number2	0.018	0.004	0.007
	(0.013)	(0.016)	(0.016)
shifted	-0.077***	-0.070**	-0.065**
	(0.027)	(0.027)	(0.026)
symmetric		0.041	0.033
		(0.029)	(0.028)
back		-0.006	-0.005
		(0.034)	(0.033)
upper		-0.004	-0.004
		(0.013)	(0.013)
EV_dif		-0.002	-0.006
		(0.018)	(0.020)
time		-0.018	-0.017
		(0.025)	(0.025)
position		-0.001	-0.001
		(0.005)	(0.005)
basis		-0.209	-0.243
		(0.214)	(0.232)
downside			0.020
			(0.037)
Model fit			
Within R^2	0.010	0.012	0.012
Observations	2,391	2,391	2,391

Notes. Dependent variable `ESE` equals 1 if the subject switches toward the target option between a split version and its corresponding baseline; ties are excluded (coded 0 in robustness Table 12). For Constellations 3, 4, and 5, we consistently use the baseline version rather than its reversed counterpart. number1/number2 indicate additional splits; shifted equals the share of the original state moved to the right (sum across sub-states). See Appendix Table 11 for variable definitions and coding. Cluster-robust standard errors (CR2) in parentheses; clustering at the subject level. Subject fixed effects are included in all specifications.

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table 14: Regression results with ESE as dependent variable and including demographics

	(1)	(2)	(3)	(4)
Core regressors				
Constant	0.768***	0.877***	0.894***	0.765***
	(0.017)	(0.134)	(0.135)	(0.165)
number1	0.056***	0.087***	0.065***	0.062***
	(0.017)	(0.022)	(0.022)	(0.021)
number2	0.012	-0.014	-0.007	-0.004
	(0.016)	(0.020)	(0.021)	(0.021)
shifted	-0.112***	-0.106***	-0.092***	-0.098***
	(0.031)	(0.032)	(0.031)	(0.031)
symmetric		0.076**	0.051	0.054*
		(0.033)	(0.032)	(0.032)
back		-0.033	-0.027	-0.025
		(0.035)	(0.034)	(0.034)
upper		-0.010	-0.010	-0.006
		(0.017)	(0.017)	(0.017)
EV_dif		0.005	-0.007	-0.006
		(0.020)	(0.021)	(0.021)
time		-0.015	-0.013	-0.004
		(0.035)	(0.035)	(0.034)
position		0.007	0.007	0.006
		(0.007)	(0.007)	(0.007)
basis		-0.272	-0.353	-0.325
		(0.234)	(0.250)	(0.250)
downside			0.052	0.059

Continued on next page

Table 14 (continued)

	(1)	(2)	(3)	(4)
			(0.037)	(0.037)
Demographics and controls (Model 4 only)				
age				0.000
				(0.002)
male				0.074**
				(0.036)
nonbinary				-0.060
				(0.162)
teaching_job				-0.060
				(0.076)
public_job				-0.176*
				(0.098)
office_job				-0.049
				(0.047)
medical_job				-0.060
				(0.083)
craft_job				-0.257*
				(0.122)
pensioner_job				0.055
				(0.104)
unemployed_job				-0.007
				(0.058)
none_job				-0.086
				(0.055)
america_origin				0.015
				(0.068)
australia_origin				0.067
				(0.114)
arabia_origin				-0.228
				(0.431)
none_origin				-0.068*
				(0.041)
uni_edu				0.057

Continued on next page

Table 14 (continued)

	(1)	(2)	(3)	(4)
				(0.046)
craft_edu				0.096
				(0.123)
alevel_edu				0.043
				(0.068)
none_edu				-0.138
				(0.177)
reading				-0.044
				(0.165)
math_skills				0.009
				(0.022)
risk_aversion				0.013
				(0.009)
Model fit				
R^2	0.011	0.013	0.014	0.047
Adj. R^2	0.010	0.010	0.010	0.034
F-statistic	8.793	3.952	3.994	2.846
F-test p-value	<0.001	<0.001	<0.001	<0.001
Observations	2,416	2,416	2,416	2,416

Notes. Dependent variable `ESE` coded as in Table 1. `number1`/`number2` indicate additional splits; `shifted` equals the share of the original state moved to the right (sum across sub-states). See Appendix Table 11 for variable definitions and coding. Cluster-robust standard errors (CR2) in parentheses; clustering at the subject level.

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table 15: Regression results with `selected` as dependent variable and including demographics

	(1)	(2)	(3)	(4)
Core regressors				
Constant	0.532***	0.525***	0.523***	0.576***
	(0.016)	(0.021)	(0.021)	(0.072)
number1	0.196***	0.196***	0.209***	0.195***
	(0.015)	(0.015)	(0.015)	(0.015)
number2	0.069***	0.057***	0.055***	0.057***
	(0.011)	(0.012)	(0.011)	(0.012)
number3	0.001	0.002	0.005	0.002
	(0.012)	(0.012)	(0.012)	(0.012)
shifted	-0.034***	-0.034***	-0.017	-0.034***
	(0.013)	(0.013)	(0.016)	(0.013)
shifted*split			-0.059***	
			(0.026)	
upper		0.004	0.004	0.006
		(0.009)	(0.009)	(0.009)
position		0.000	0.000	0.000
		(0.004)	(0.004)	(0.004)
time		-0.005	-0.005	-0.004
		(0.002)	(0.002)	(0.001)
EV_dif		-0.070***	-0.071***	-0.070***
		(0.006)	(0.006)	(0.006)
downside		0.065***	0.060***	0.065***
		(0.014)	(0.014)	(0.014)
Demographics and controls (Model 4 only)				
age				0.002*
				(0.001)
male				-0.002
				(0.021)
nonbinary				-0.100
				(0.171)
teaching_job				-0.027

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Table 15 (continued)

	(1)	(2)	(3)	(4)
				(0.048)
public_job				-0.080
				(0.059)
office_job				-0.037
				(0.037)
medical_job				-0.010
				(0.050)
craft_job				0.081
				(0.055)
pensioner_job				-0.102
				(0.118)
unemployed_job				0.017
				(0.043)
none_job				-0.014
				(0.037)
america_origin				-0.064
				(0.055)
australia_origin				0.118*
				(0.053)
arabia_origin				-0.110
				(0.058)
none_origin				0.009
				(0.024)
uni_edu				0.018
				(0.031)
craft_edu				0.012
				(0.044)
alevel_edu				0.017
				(0.041)
none_edu				0.008
				(0.056)
reading				0.033
				(0.041)

Continued on next page

Table 15 (continued)

	(1)	(2)	(3)	(4)
math_skills				-0.008
				(0.013)
risk_aversion				-0.017***
				(0.005)
Model fit				
R^2	0.059	0.084	0.084	0.099
Adj. R^2	0.059	0.083	0.083	0.096
F-statistic	60.20	42.98	39.61	15.74
F-test p-value	<0.001	<0.001	<0.001	<0.001
Observations	9,600	9,600	9,600	9,600

Notes. Dependent variable `selected` equals 1 if the safer option is chosen. All observations included. `number1`/`number2`/`number3` indicate first, second, and third split; `shifted` equals the share of the original state moved to the right (sum across sub-states). See Appendix Table 11 for variable definitions and coding. Cluster-robust standard errors (CR2) in parentheses; clustering at the subject level.

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table 16: Average marginal effects for `ESE` (logit with clustered SEs)

Variable	AME
number1	0.067***
	(0.023)
number2	-0.007
	(0.022)
shifted	-0.081***
	(0.026)
symmetric	0.055
	(0.034)
back	-0.022
	(0.036)
upper	-0.010
	(0.017)
EV_dif	-0.004
	(0.022)
time	-0.013
	(0.001)
position	0.031
	(0.007)
basis	-0.331
	(0.255)
downside	0.041
	(0.034)
Model info	
Observations	2,416

Notes. Average marginal effects (AME) from a logit model; dependent variable `ESE` coded as in Table 1. `number1`/`number2` indicate additional splits; `shifted` equals the share of the original state moved to the right (sum across sub-states). See Appendix Table 11 for variable definitions and coding. Cluster-robust (CR2) standard errors in parentheses; clustering at the subject level.

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table 17: Average marginal effects for `ESE` (probit with clustered SEs)

Variable	AME
number1	0.067***
	(0.023)
number2	-0.006
	(0.022)
shifted	-0.084***
	(0.027)
symmetric	0.054
	(0.033)
back	-0.024
	(0.036)
upper	-0.009
	(0.017)
EV_dif	-0.005
	(0.021)
time	-0.014
	(0.032)
position	0.007
	(0.007)
basis	-0.339
	(0.253)
downside	0.043
	(0.034)
Model info	
Observations	2,416

Notes. Average marginal effects (AME) from a probit model; dependent variable `ESE` coded as in Table 1. `number1`/`number2` indicate additional splits; `shifted` equals the share of the original state moved to the right (sum across sub-states). See Appendix Table 11 for variable definitions and coding. Cluster-robust (CR2) standard errors in parentheses; clustering at the subject level.

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.