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A New Approach to the Study of Editing of Repeated Lotteries*

Alessandra Cillo[†] Enrico De Giorgi[‡]

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Abstract

We propose a new theoretical approach to the study of editing rules applied by decision makers when dealing with repeated lotteries. Under the assumption that decision makers detect state-dominance among simply two-outcome lotteries and always prefer n draws of a dominating lottery to n draws of a dominated lottery, we study editing rules beyond the use of acceptance rates. We derive an appropriate experimental methodology based on loss and gain differences, which also allows us to quantify the strength of preferences. An experiment supports previous findings showing that editing might depend on the risk profile of the underlying lottery. Moreover, we provide evidence that acceptance rates could lead to different conclusions than our methodology, because they generally do not account for the strength of preferences.

Keywords: editing, segregation, aggregation, repeated lotteries.
JEL Classification: D81.

1 Introduction

Normative models of decision making assume that decision makers evaluate their choice alternatives according to their payoff distributions. However, there is growing experimental and empirical evidence showing that decision makers mentally transform payoff distributions to simplify their choice problem. To capture this observation, prospect theory (PT) of Kahneman and Tversky (1979) distinguishes two distinct phases in the choice process: an initial phase where choice alternatives are edited, the so-called *editing phase*, and a subsequent phase where edited choices are evaluated, the so-called *evaluation phase*. In the editing phase, decision makers mentally organize and reformulate their choice alternatives to simplify their decision problem. Kahneman and Tversky (1979) define the editing phase as a "preliminary analysis of the ordered prospects, which often yields to a different representation of these prospects", while the evaluation phase is the successive phase where people evaluate *edited* prospects and choose the one with the highest value. As a matter of fact, the payoff distributions of edited prospects often differ from those of the original choice alternatives people faced.

Editing is also related to the way a decision problem is framed, i.e., presented to the decision maker. For example, Benartzi and Thaler (1995) argue that stocks are more attractive to loss averters with

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longer evaluation periods, because they only assess the long-term aggregated payoff distribution. By contrast, loss averters with shorter evaluation periods tend to segregate short-term payoffs from the overall aggregated distribution, and thus are more frequently confronted with losses. Therefore, despite the underlying decision problem is identical for both investors, the different ways the problem is framed often lead to different investment decisions, as experimentally confirmed by Benartzi and Thaler (1999).

In many decision contexts, people face repeated choices. As discussed above, the way such repeated choices are edited often leads to different decisions. Kahneman and Lovallo (1993) argue that people tend to consider each choice as unique. As an example, when a choice alternative is presented as n independent draws of a given lottery, people tend to *narrowly bracket* it, i.e., evaluate each draw in isolation, disregarding the aggregated outcome distribution. This editing rule is called *segregation*. On the other hand, Samuelson (1963) and Redelmeier and Tversky (1992) provide evidence that the acceptance rate for n independent draws of a lottery is higher than the acceptance rate for the lottery considered alone, suggesting that people do not segregate. Finally, when the overall aggregated distribution is displayed, inducing this way the aggregated format (or, equivalently, an editing rule called *aggregation*), the acceptance rate increases compared to the case of n independent draws, an evidence against the assumption that only the aggregated outcome distribution matters, i.e., that people aggregate each draw into the overall outcome distribution. Indeed, Benartzi and Thaler (1999) show that when the overall distribution of repeated plays with a positive expected value is displayed, people tend to like it more. Klos, Weber, and Weber (2005) provide evidence that people seem to be unable to correctly infer the outcome distribution behind repeated-play of a lottery, to the point that they suggest, as Benartzi and Thaler (2002), that decision makers should be provided with the overall distribution. Moreover, Langer and Weber (2001) very interestingly find that the acceptance rate for n independent draws of a lottery can be higher or lower than when the overall aggregated distribution is displayed, depending on the risk profile of the lottery. This finding confirms that people do not seem to always aggregate, but also suggests that the editing process might depend on the risk profile of the underlying lottery.

Despite wide evidence on the fact that editing influences choices, many decision models assume that decisions only depend on preferences with respect to the proposed outcome distributions, i.e., either editing already occurred or it has no impact on choices. Most of these models only consider the evaluation phase of PT, while the literature on the editing phase is more limited. One difficulty to analyse the editing phase is to separate editing from evaluation when choices are observed. Indeed, most of the before mentioned studies on repeated choices are based on acceptance rates. As Langer and Weber (2001, page 731) write, this is "[...] another challenging area for further research in the experimental examination of evaluation differences for lotteries that do not allow a simple acceptance rate comparison. For these extremely (un)attractive lotteries the complex coding problems have to be analyzed, then an appropriate experimental method must be developed to provide a more general test for the empirical correctness of our theoretical predictions."

The main goal of this paper is to propose a new theoretical framework to study editing rules. In line with most of previous literature, we focus on editing of n independent draws of two-outcome lotteries. Under reasonable assumptions, we propose a theoretical model that separates editing from evaluation, and thus allows us to derive testable conditions for editing rules used by decision makers when facing repeated draws of a lottery. Our theoretical analysis assumes that decision makers detect state-dominance among two-outcome lotteries and always prefer n draws of a dominating lottery to n draws of a dominated lottery. An important implication of this assumption is that an observed preference reversal is uniquely caused by the editing rule. In this way, we isolate editing from evaluation and can study editing rules beyond the use of acceptance rates, which depend on both editing and evaluation. We derive, and justify using cumulative prospect theory (CPT) of Tversky and Kahneman (1992), an appropriate experimental methodology based on loss and gain differences between editing rules, which also allows us to quantify the strength of preferences. We apply our methodology in a experiment to analyse editing rules used by decision makers dealing with n independent draws of a lottery and how these rules differ from segregation and aggregation. Our results partially support previous findings based on acceptance rates. Specifically, we show that editing rules might depend on the risk profile of the underlying lottery, even though our findings differ from Langer and Weber (2001), as we do not show that aggregation is less attractive than segregation for lotteries with low probabilities of large losses. However, we provide evidence that acceptance rates could lead to different conclusions than our methodology, because they generally do not account for the strength of preferences.

The reminder of the paper is structured as follows. Section 2 presents our new theoretical framework to study editing and provides the foundation for the experimental methodology. Section 3 describes the experimental design, while Section 4 presents the results. Section 5 concludes with suggestions for further research.

2 Theoretical Framework

Let $L = (l, 1-p; g, p)$ be a two-outcome lottery, where $l, g \in \mathbb{R}$ ($l \leq 0 \leq g$) and $p \in [0,1]$. When $p \in \{0,1\}$ or $l = g$, then L is a "degenerated lottery" with a sure outcome. By $\mathcal{L}_2$ we denote the set of all two-outcome lotteries. We analyse choice problems where decision makers face n independent draws of two-outcome lotteries, where n is an integer greater than or equal to 1. For notational convenience, we denote the choice alternative "n independent draws of lottery L" for $L \in \mathcal{L}_2$ by nL and the set of all such choice alternatives by $n\mathcal{L}_2 = \{nL : L \in \mathcal{L}_2\}$ for $n \geq 1$. Note that $n\mathcal{L}_2$ is not a set of probability distributions on $\mathbb{R}$.

Following the description of Kahneman and Tversky (1979), we formally define two distinct phases in the choice process of a decision maker. The first phase is editing, which is performed according to an individual editing rule $e(\cdot)$, which is typically unobservable. An editing rule is formally defined as a map from the set $n\mathcal{L}_2$ to the set $\mathcal{L}$ of real-valued *simple* lotteries on $\mathbb{R}$, i.e.,

$$e : n\mathcal{L}_2 \to \mathcal{L}, \quad nL \mapsto e(nL),$$

where $e(nL)$ is the edited lottery, i.e., a probability distribution on $\mathbb{R}$ that corresponds to the decision maker's mental representation of nL. The second phase is the evaluation, which is performed according to a preference relation $\succsim$ on $\mathcal{L}$ and reflects the classical way to model the decision-making process. We assume that $\succsim$ satisfies the usual assumption, i.e., completeness, transitivity, and monotonicity.

The two phases induce a preference relation $\succsim_e$ on $n\mathcal{L}_2$, i.e.,

$$nL \succsim_e nL' \Leftrightarrow e(nL) \succsim e(nL').$$

We point out the decision maker's choices reveals her preference according to the preference relation $\succsim_e$. However, $\succsim_e$ combines her editing $e(\cdot)$ as well as her preferences $\succsim$. Our goal is to disentangle these two characteristics from observed choices.

Editing can take many different forms. Kahneman and Tversky (1979) list some of the major operations in the editing phase and our editing rule $e(\cdot)$ could be a combination of several of those operations and many others. In order to develop a theoretical framework to analyse editing, we make the following assumptions on editing rules:

Assumption. *An editing rule $e : n\mathcal{L}_2 \to \mathcal{L}$ satisfies the following assumptions:*

(i) $e(1L) \sim L$*, for all* $L \in \mathcal{L}_2$*;*

(ii) If $L \geq L'$ *for* $L, L' \in \mathcal{L}_2$*, then* $e(nL) \succsim e(nL')$*.*

Assumption (i) says that two-outcome lotteries in $\mathcal{L}_2$ are editing-free. This assumption is consistent with Kahneman and Tversky (1979), who also consider two-outcome lotteries and write "we discuss choice problems where it is reasonable to assume either that the original formulation of the prospects leaves no room for further editing, or that the edited prospects can be specified without ambiguity." Note that in Kahneman and Tversky (1979) two-outcome lotteries could also have positive or negative payoffs only, and in these cases editing is performed by segregating the common risk-less component. Those lotteries are excluded in our paper because $l \leq 0 \leq g$. Therefore, in our paper we only study two-outcome lotteries which are considered by Kahneman and Tversky (1979) as being editing-free, consistently with Assumption (i) above. Assumption (ii) implies that $e(nL)$ is (weakly) preferred to $e(nL')$ when L never pays off less than L'. Briefly, decision makers detect the state-dominance among two-outcome lotteries and never prefer n draws of a dominated lottery to n draws of the corresponding dominating lottery. We point out that two-outcome lotteries are relatively simple to compare and $L = (l, 1-p; g, p) \geq L' = (l', 1-p'; g', p')$ if and only if $p = p'$, $0 \geq l \geq l'$, and $g \geq g' \geq 0$.

Two well-known examples of editing rules are segregation (s) and aggregation (a). In Langer and Weber (2001) segregation is specified throughout a preference relation $\succsim_s$ on $n\mathcal{L}_2$, where $nL \succsim_s nL' \Leftrightarrow n\,V(L) \geq n\,V(L')$ and V corresponds to CPT. In our theoretical framework, the model of segregation proposed by Langer and Weber (2001) implicitly defines an editing rule $s(\cdot)$ such that:

$$nL \succsim_s nL' \Leftrightarrow s(nL) \succsim s(nL').$$

The preference relation $\succsim$ is represented by the CPT evaluation V and

$$V(s(nL)) = n\,V(L).$$

The editing rule $s(\cdot)$ satisfies Assumptions (i) and (ii), because $V(s(1L)) = 1 \cdot V(L) = V(L)$, i.e., $s(1L) \sim L$, and $V(s(nL)) = n\,V(L) \geq n\,V(L') = V(s(nL'))$ when $L \geq L'$. Unfortunately, the model of segregation of Langer and Weber (2001) does not allow for a separation of editing and preferences, because the editing rule is directly specified in terms of the preference relation $\succsim_s$. In our theoretical framework segregation could alternatively be described as follows:

$$s(nL) \sim n\,CE_{\succsim}(L), \tag{1}$$

where $CE_{\succsim}(L)$ is the certainty equivalent of $L \in \mathcal{L}_2$ with respect to the preference relation $\succsim$, i.e., $L \sim CE_{\succsim}(L)$. This model of segregation implies that segregation does not apply to sure outcomes, i.e., n times a sure payoff x is correctly aggregated to $n\,x$. This means that a decision maker, despite she segregates nL when L is a risky lottery, correctly aggregates repeated sure payoffs.

Aggregation can be specified as follows:

$$a(nL) \sim L_n, \tag{2}$$

where $L_n = \left(n\,l, (1-p)^n; \ldots; k\,l + (n-k)\,g, \binom{n}{k}(1-p)^k\,p^{n-k}; \ldots; n\,g, p^n\right)$ is the aggregated probability distribution of "n independent draws of L." Editing rule $a(\cdot)$ clearly satisfies Assumptions (i) and (ii), because $a(1L) \sim L$ and $L_n \succsim L'_n$ when $L \geq L'$.

The formal framework we described above also allows us to compare the decision maker's editing rule e with some specific, well-defined editing rule e', e.g., $e' = s$ (segregation) or $e' = a$ (aggregation). We say that $e(\cdot)$ is *more attractive* than $e'(\cdot)$ for a given choice alternative nL if and only if

$$e(nL) \succsim e'(nL).$$

The comparison of the unknown editing rule e with a specific, well-defined editing rule e' is important, because it gives useful insights on decision makers' editing processes.

The following result holds:

Lemma 1. *Let $e(\cdot)$ and $e'(\cdot)$ be two editing rules. Suppose that $L, L' \in \mathcal{L}_2$ exist such that $L \geq L'$ and $e(nL) \sim e'(nL')$. It follows that:*

$$e'(nL) \succsim e(nL).$$

Proof. Because $L \geq L'$, then according to Assumption (ii) we have:

$$e'(nL) \succsim e'(nL') \sim e(nL).$$

Therefore, because $\succsim$ is transitive, we have:

$$e'(nL) \succsim e(nL).$$

□

The interpretation of Lemma 1 is straightforward. A well-defined editing rule $e'(\cdot)$ is more attractive than the unknown editing rule $e(\cdot)$ when the corresponding edited lotteries $e'(nL')$ and $e(nL)$ are equally preferred despite L dominates L' by state-dominance. Lemma 1 has an important implication if we want to quantify the attractiveness of the known editing rule e' with respect to the unknown editing rule e. To better illustrate this statement, suppose that the preference relation $\succsim$ has a utility representation V. In this case, the difference in value between editing rules $e'(\cdot)$ and $e(\cdot)$ for a given choice alternative nL can be computed as follows:

$$V(e'(nL)) - V(e(nL)) = V(e'(nL)) - V(e'(nL')) + \underbrace{V(e'(nL')) - V(e(nL))}_{=0} = V(e'(nL)) - V(e'(nL')).$$

We observe that the right-hand side only depends on the known editing rule e'. Specifically, suppose that $e'(\cdot)$ corresponds to either segregation or aggregation, then we can determine the attractiveness of the unknown editing rule $e(\cdot)$ with respect to segregation or aggregation by computing the difference $V(e'(nL)) - V(e'(nL'))$, which only refers to segregation or aggregation, but not to the unknown e. We also point out that when L and L' satisfy the conditions of Lemma 1 and $e'(\cdot)$ satisfies Assumption (ii), then the sign of $V(e'(nL)) - V(e'(nL'))$ does not depend on the specific functional form of V (as long the corresponding preference relation satisfies monotonicity). Therefore, to determine if a lottery is more attractive under e or under aggregation/segregation, the preference relation $\succsim$ and its corresponding utility representation V do not have to be elicited. [1]

The methodology we apply in the experimental part of the paper relies on Lemma 1. The condition $e(nL) \sim e'(nL')$ is achieved as follows: for $n > 1$, we either fix $g > 0$ and $p \in (0,1)$, and elicit l and l' such that:

(i) for $L = (l, 1-p; g, p)$ we have $e(nL) \sim 0$;

(ii) for $L' = (l', 1-p; g, p)$ we have $e'(nL') \sim 0$.

or we fix $l < 0$ and $q \in (0,1)$, and elicit g and g' such that:

(i) for $L = (l, q; g, 1-q)$ we have $e(nL) \sim 0$;

(ii) for $L' = (l, q; g', 1-q)$ we have $e'(nL') \sim 0$.

Clearly, we can order lotteries L and L' according to the state-dominance order and apply Lemma 1. The indifference to zero is imposed for the following reason. Suppose that for editing rules e and e' one has L and L' such that $e(nL) \sim X$ and $e'(nL') \sim X$ for a given fixed $X \in \mathcal{L}$. Because lottery X is also subject to editing, the edited choice problems are $e(nL) \sim e(X)$ and $e'(nL') \sim e'(X)$ and finally differ from $e(nL) \sim X$ and $e'(nL') \sim X$, i.e., the indifference condition of Lemma 1 is violated, as $e(X)$ is generally not indifferent to $e'(X)$. Therefore, one has to ensure that X is editing free, i.e., $X \in n\mathcal{L}$ such that $e'(X) \sim X$. According to Assumption (i), only $X = 0$ generally satisfies this condition. Indeed, not even a sure amount different from zero, e.g., $n\,x$ for $x \in \mathbb{R}$ is generally editing free, i.e., satisfies $e(n\,x) \sim n\,x$. This is clear from our discussion of the model of segregation proposed by Langer and Weber (2001), where $e(n\,x)$ is not indifferent to $n\,x$. Related to this, we must point out that the use of certainty equivalents (see Klos, Weber, and Weber 2005) could also be problematic in our framework, unless we impose the additional assumption that sure outcomes are always editing-free.

3 Experimental Design

3.1 Subjects and Incentives

The experiment has been run at Bocconi University in Milan with 156 subjects. These were students from different programmes (economics, management, law) at Bocconi University. Subjects were paid a

[1] This differs from Langer and Weber (2001), where the sign of their distance measure D depends on the parameters of CPT; see Langer and Weber (2001, page 730). Indeed, Langer and Weber (2001) finally rely on acceptance rates.

flat fee of 10 EUR. Individual responses were not played out for real because large losses were involved. The random-lottery procedure is often used in experiments (see Holt 1986, Starmer and Sugden 1991). However, the effect of real incentives varies across decision tasks (see Camerer and Hogarth 1999). When losses are involved, to avoid that participants lose their own money, one could endow them with an amount before the experiment starts and then allow for losing up to that amount in playing out for real at least one of the choices (see Etchart-Vincent and l'Haridon 2011). However, from a theoretical perspective, this procedure might have some problems (Thaler and Johnson 1990).

3.2 Procedure

The study was computer run in sessions with a maximum of 12 subjects. At each session there were two interviewers. Each session was lasting, on average, 25 minutes. After the instructions were read aloud, each subject inserted age, gender, and academic degree, and started the experiment. The experiment had three parts, each with its own instruction and a warm-up elicitation. Because editing might depend on the risk profile of the lottery, in our experiment we considered two types of lotteries: good (G) lotteries (lotteries with moderate-high probability of large gains)" and bad (B) lotteries (lotteries with very small probability of large losses). Since the experiment was quite long, some subjects only faced G lotteries, while others only faced B lotteries. For each subject facing G lotteries, we elicited, in three parts, loss values l^e, l^s and l^a, for fixed gain g and probability p, according to the following conditions:
Part 1: l^e such that 2 independent draws of $G^e = (l^e, 1-p; g, p) \sim 0$;
Part 2: l^s such that $G^s = (l^s, 1-p; g, p) \sim 0$;
Part 3: l^a such that $(G^a)_2 = (2\,l^a, (1-p)^2; l^a + g, 2\,p\,(1-p); 2\,g, p^2) \sim 0$.
In part 1 we elicited l^e such that "2 independent draws of G^e" were indifferent to 0, inducing this way subjects' unknown editing rule. In part 2 we elicited l^s such that G^s indifferent to 0, inducing this way segregation. In part 3 we elicited l^a such that $(G^a)_2$ were indifferent to zero, inducing this way aggregation. We considered 9 different combinations of gain g and probability p (see Table 1, Panel A), and thus a total of 9 loss values for each part were elicited.

Similarly, for each subject facing B lotteries, we elicited, in three parts, gain values g^e, g^s and g^a, for fixed loss l and probability q, according to the following conditions:
Part 1: g^e such that 2 independent draws of $B^e = (l, q; g^e, 1-q) \sim 0$;
Part 2: g^s such that $B^s = (l, q; g^s, 1-q) \sim 0$;
Part 3: g^a such that $(B^a)_2 = (2\,l, q^2; l + g^a, 2\,(1-q)\,q; 2\,g^a, (1-q)^2) \sim 0$.
We considered 9 different combinations of loss l and probability q (see Table 1, Panel B), and thus a total of 9 gain values for each part were elicited.

We elicited subjects' indifferent values via a choice task.[2] Despite the drawback of being long, the choice task is well known as being more reliable (less inconsistencies) than the matching task (see Attema and Brouwer 2013). Subjects had to choose between a lottery, Option A, and the sure amount 0, Option B. They were asked to confirm their choice, once they had clicked on the preferred option.

[2]Klos (2013) replicates Redelmeier and Tversky (1992) and finds that the elicitation procedure influences people choice. Indeed, the tendency to segregate multiple lotteries, while does persist in the binary choice task, is eliminated when subjects face certainty and probability equivalents tasks. In our experiment subjects only faced simple decision tasks, namely, they always had to choose between two alternatives. Hence, we believe that our experimental procedure did not affect subjects' editing rules.

Table 1: **Experimental design.** The table describes the experimental design. G lotteries (Panel A) have gains $g = 2000, 3000, 4000$ with probabilities $p = 0.4, 0.5, 0.6$. For each subject we elicit 27 loss values in three parts, corresponding to 2 independent draws (part 1), one single draw (part 2), and the overall distribution of 2 independent draws (part 3). B lotteries (Panel B) have losses $l = -3000, -2000, -1000$ with probabilities $q = 0.02, 0.04, 0.06$. For each subject we elicit 27 gain values in three parts, corresponding to 2 independent draws (part 1), one single draw (part 2), and the overall distribution of 2 independent draws (part 3).

A: G lotteries

gain probability	$g = 2000, 3000, 4000$ $p = 0.4, 0.5, 0.6$
Part 1	2 independent draws of $(l^e, 1-p; g, p) \sim 0$
Part 2	$(l^s, 1-p; g, p) \sim 0$
Part 3	$(2\,l^a, (1-p)^2; l^a + g, 2\,(1-p)\,p; 2\,g, p^2) \sim 0$

B: B lotteries

loss probability	$l = -3000, -2000, -1000$ $q = 0.02, 0.04, 0.06$
Part 1	2 independent draws of $(l, q; g^e, 1-q) \sim 0$
Part 2	$(l, q; g^s, 1-q) \sim 0$
Part 3	$(2\,l, q^2; l + g^a, 2\,(1-q)\,q; 2\,g^a, (1-q)^2) \sim 0$

Each choice represented an iteration of a bisection procedure (see Appendix for details). Figure 1 shows an example of how choices of part 1 were displayed to subjects during the experiment.

We randomized parts 1, 2, and 3, and, within each part, we randomized the order of the 9 combinations of gain/loss and probability. To avoid further complexity in the task, the order of the iterations for each elicitation was not randomized.

3.3 Validity

It is well known that subjects' choices might deviate from their true preferences. To check for response errors, 9 iterations were repeated, i.e., for three randomly selected elicitations the *third last iteration* was repeated at the end of each part. We selected the third last iteration because it is close to the indifference value, and thus response errors are more likely to occur. Moreover, subjects violating state-dominance or exhibiting extreme risk seeking behaviour were forced to immediately terminate the experiment.

3.4 Analysis of the Strength of Preferences

Our analysis in Section 4 will be based on elicited losses and gains for G and B lotteries, respectively. Specifically, to derive conclusions on the strength of preferences, for G lotteries we will consider the loss difference $\Delta^{e,k} = l^e - l^k$ for $k = s, a$ between the loss l^e elicited under the unknown editing rule e of the subject and the loss l^k for $k = s, a$ elicited under segregation and aggregation, respectively. Similarly,

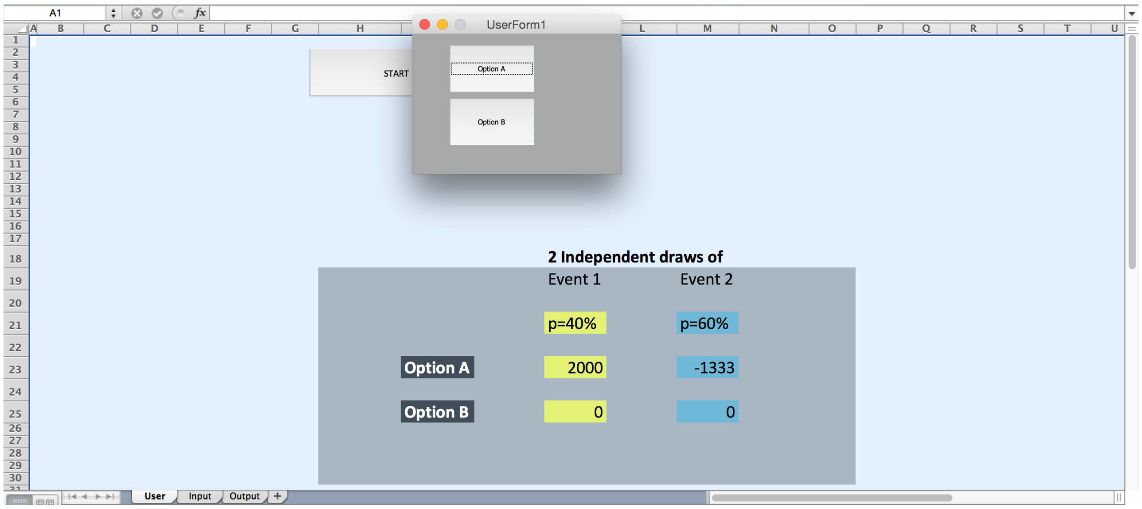

Figure 1: **Screenshot from the experiment.** The figure shows an example of how choice tasks were displayed to subjects. In this example, the subject faced 2 independent draws (part 1) of a G lottery with gain $g = 2000$ and corresponding probability $p = 0.4$.

for B lotteries we will consider the gain difference $\Delta^{e,k} = g^e - g^k$ for $k = s, a$ between the gain g^e elicited under the unknown editing rule e of the subject and the gain g^k for $k = s, a$ elicited under segregation and aggregation, respectively. We show that the use of loss/gains differences to measure the strength of preferences can be justified from the assumption that decision makers' preferences are well-described by CPT. More specifically, we now assume that the preference relation $\succsim$ possesses a CPT representation. For $L = (x_1, p_1; x_2, p_2; \ldots, x_n, p_n) \in \mathcal{L}$ with $x_1 < x_2 < \cdots < x_m \leq 0 < x_{m+1} < \cdots < x_n$, the CPT evaluation is:

$$V(L) = \sum_{i=1}^{n} v(x_i)\, \pi_i$$

where π_i are the decision weights, defined as follows:

$$\pi_i = \begin{cases} w^-(p_1) & \\ w^-(p_1 + \cdots + p_i) - w^-(p_1 + \cdots + p_{i-1}) & 2 \leq i \leq m \\ w^+(p_i + \cdots + p_n) - w^+(p_{i+1} + \cdots + p_n) & m < i < n \\ w^+(p_n) & \end{cases}$$

where w^+ and w^- are weighting functions defined for probabilities associated with gains and losses, respectively, v is assumed to be strictly increasing, differentiable on $\mathbb{R} \setminus \{0\}$, convex on losses and concave on gains, with $v(0) = 0$. The following results apply:

Lemma 2 (G lotteries)**.** *Let $G^e = (l^e, 1-p; g, p)$, $G^s = (l^s, 1-p; g, p)$, and $G^a = (l^a, 1-p; g, p)$.*

(i) ***Segregation****. Let $\underline{l} = \min\{l^e, l^s\}$. It follows that:*

$$|V(s(2G^e)) - V(e(2G^e))| \geq 2\, w^-(1-p)\, v'(\underline{l})\, |\Delta^{e,s}|, \tag{3}$$

where $\Delta^{e,s} = l^e - l^s$, and v' is the first derivative of value function v.

(ii) ***Aggregation***. *Let* $\underline{l} = \min\{l^e, l^a\}$ *and* $\bar{l} = \max\{l^e, l^a\}$*. Suppose that* $\underline{l} + g > 0$*. It follows that:*

$$|V(a(2G^e)) - V(e(2G^e))| \geq \left[2\, w^-((1-p)^2)\, v'(2\,\underline{l}) + \left(w^+(p\,(2-p)) - w^+(p^2)\right)\, v'(\bar{l} + g)\right]\, |\Delta^{e,a}|, \tag{4}$$

where $\Delta^{e,a} = l^e - l^a$*, and* v' *is the first derivative of value function* v*.*

Proof. See Appendix A.

□

Lemma 3 (B lotteries)**.** *Let* $B^e = (l, q; g^e, 1-q)$*,* $B^s = (l, q; g^s, 1-q)$*, and* $B^a = (l, q; g^a, 1-q)$*.*

(i) ***Segregation***. *Let* $\overline{g} = \max\{g^e, g^s\}$*. It follows that:*

$$|V(s(2B^e)) - V(e(2B^e))| \geq 2\, w^+(1-q)\, v'(\overline{g})\, |\Delta^{e,s}|, \tag{5}$$

where $\Delta^{e,s} = g^e - g^s$*, and* v' *is the first derivative of value function* v*.*

(ii) ***Aggregation***. *Let* $\underline{g} = \min\{g^e, g^a\}$ *and* $\overline{g} = \max\{g^e, g^a\}$*. Suppose that* $l + \overline{g} < 0$*. It follows that:*

$$|V(a(2B^e)) - V(e(2B^e))| \geq \left[\left(w^-(q(2-q)) - w^-(q^2)\right)\, v'(l + \underline{g}) + 2\, w^+((1-q)^2)\, v'(2\,\overline{g})\right]\, |\Delta^{e,a}|, \tag{6}$$

where $\Delta^{e,a} = g^e - g^a$*, and* v' *is the first derivative of value function* v*.*

Proof. Similar to Lemma 2, hence omitted.

□

Lemmas 2 and 3 show that the difference in utility between the editing rules applied by subjects and segregation/aggregation is bounded from below by the differences in elicited losses and gains for G and B lotteries, respectively, after multiplying by a factor reflecting subjects' preferences. The factor reflecting subjects' preferences ranges from 0.15 to 1.8 using typical parameters' values for CPT, and correspond to 0.7-0.9 when Tversky and Kahneman's (1992) parametrization of CPT is applied. Therefore, Lemmas 2 and 3 will support our choice in Section 4 to consider differences in elicited losses and gains as proxies for differences in utilities.

4 Results

Our results are based on 129 subjects. Indeed, 27 subjects either violated state-dominance or exhibited extreme risk seeking behavior and thus were forced to previously end the experiment. As discussed in Section 3, our analysis on the strength of preferences is based on loss and gain differences for G and B lotteries, respectively, which represent a valid proxy for differences in utility between editing rules.

4.1 G lotteries

63 subjects faced G lotteries. Consistency rates in the experiment are in line with those found in the literature (see Stott 2006). Indeed, 78% of the repeated iterations in part 1, 72% in part 2, and 71% in part 3 were consistent with the answers in the original questions.

Table 2 reports median elicited losses $\tilde{l}^e$ (2 independent draws), $\tilde{l}^s$ (one single draw), and $\tilde{l}^a$ (overall distribution of 2 independent draws) for the 9 elicitations with G lotteries. We observe that median losses elicited under aggregation are higher than median losses elicited under the editing rules used by subjects. By contrast, median losses elicited under segregation are generally lower (with two exceptions with elicitations 6 and 7, which correspond to $(g, p) = (3000, 0.6)$ and $(g, p) = (4000, 0.4)$, respectively) than under the editing rules applied by subjects. However, the differences in this case are rather small. Figures 2 and 3 graphically display the results of Table 2. Specifically, Figure 2 shows that, for fixed probabilities of gains, median losses increase as a function of the gain, while Figure 3 shows that, for fixed gains, median losses increase with the probability of a gain. Therefore, subjects seem to fulfil monotonicity, i.e., within each part, for a fixed probability of gain (gain), the higher the gain (probability of a gain), the higher the loss subjects are willing to take. A detailed analysis considers the 18 different triples of lotteries where either the probability of gains or the gain values are fixed (e.g., the triples (g, p) where $g = 2000$ and $p = 0.4, 0.5, 0.6$) and shows that consistency rates with respect to monotonicity ranges from a minimum of 43% to a maximum of 76%. Consistency rates with respect to monotonicity are similar in the three parts, but slightly higher in part 3.

Table 2: **Median losses for G lotteries.** Median elicited losses $\tilde{l}^e$ (2 independent draws), $\tilde{l}^s$ (one single draw), and $\tilde{l}^a$ (overall distribution of 2 independent draws).

	probability p	gain g	editing $\tilde{l}^e$	segregation $\tilde{l}^s$	aggregation $\tilde{l}^a$
1	0.40	2000	-745	-720	-996
2	0.50	2000	-1012	-987	-1587
3	0.60	2000	-1387	-1262	-1837
4	0.40	3000	-1012	-987	-1562
5	0.50	3000	-1512	-1512	-2412
6	0.60	3000	-1562	-1812	-2512
7	0.40	4000	-1104	-1179	-1879
8	0.50	4000	-2037	-1987	-3112
9	0.60	4000	-2812	-2587	-4012

Table 3 reports median elicited loss *differences* between editing rules applied by subjects and segregation/aggregation, for each of the 9 elicitations. We observe that editing rules applied by subjects do not seem to differ much from segregation and aggregation, with the only exceptions being with aggregation when the probability of a gain is $p = 0.4$. The statistical analysis confirms this observation. Specifically, we perform one-side Wilcoxon rank tests with null hypotheses that used editing rules correspond to segregation (median loss difference equal zero, i.e., $\tilde{\Delta}^{e,s} = 0$) or aggregation (median loss difference equal zero, i.e., $\tilde{\Delta}^{e,a} = 0$), against the alternatives $\tilde{\Delta}^{e,s} < 0$ or $\tilde{\Delta}^{e,s} > 0$, respectively. We use the Bonferroni correction for multiple testing in order to compute p-values. We cannot reject that used editing rules are segregation. For aggregation, we have mixed findings. Specifically, in 2 elicitations, when the probability of gains is $p = 0.4$ and gain values are rather large ($g = 3000, 4000$), we can reject aggregation in favor of the alternative that used editing rules are *less* attractive than aggregation. I.e., when the probability associated to high gains is 40%, then the overall distribution appears as being more attractive to our subjects compared to their own editing of 2 independent draws. We must point out that in 6 out of 9 elicitations we can reject at the 5% confidence level the hypothesis that median loss differences between segregation and aggregation are equal to zero; see Table 6. This implies that

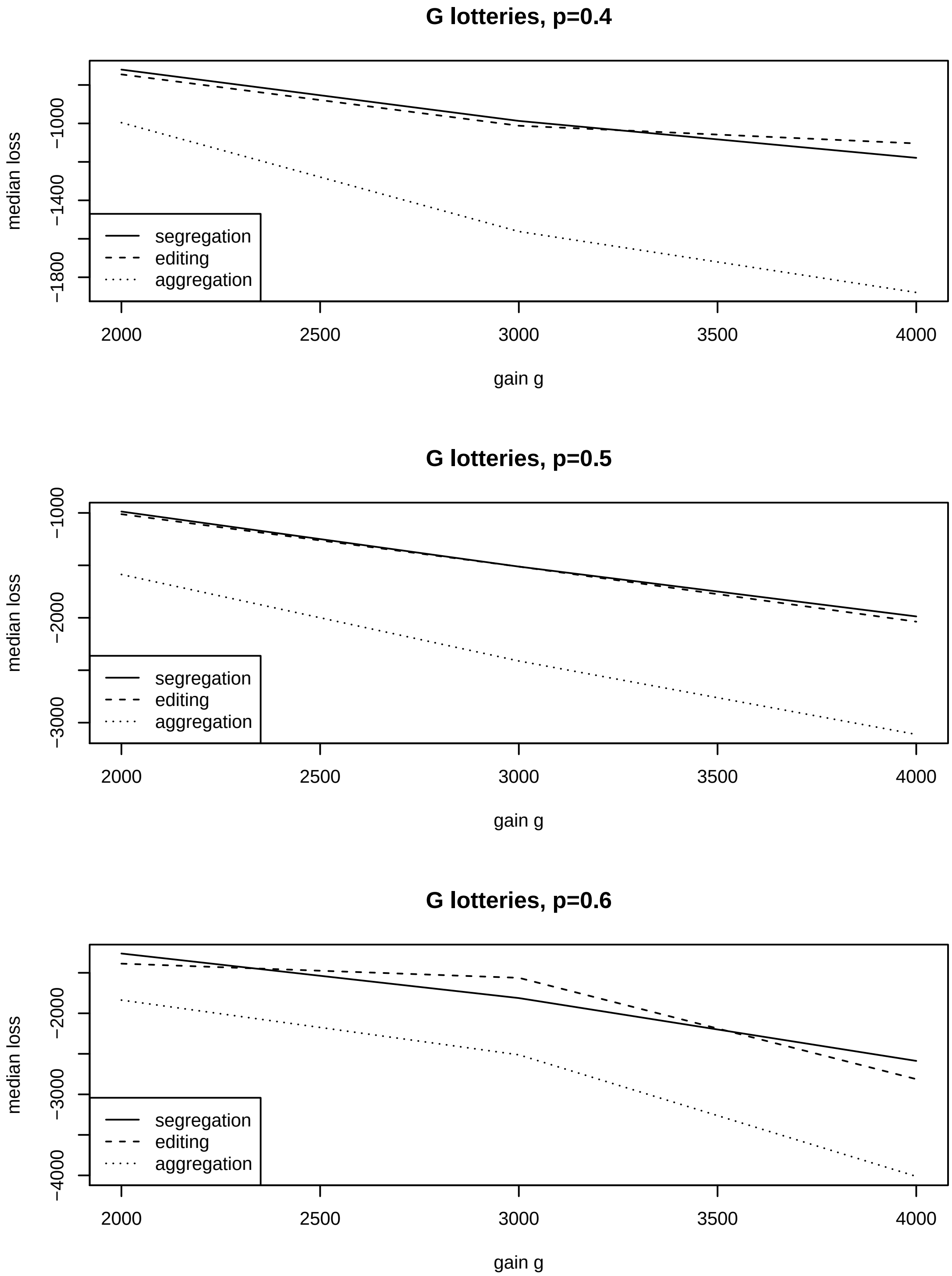

Figure 2: **Median losses for G lotteries.** Median elicited losses $\tilde{l}^e$ (2 independent draws), $\tilde{l}^s$ (one single draw), and $\tilde{l}^a$ (overall distribution of 2 independent draws). In each panel, we fix the probability of gain and show the median losses as function of the corresponding gain value.

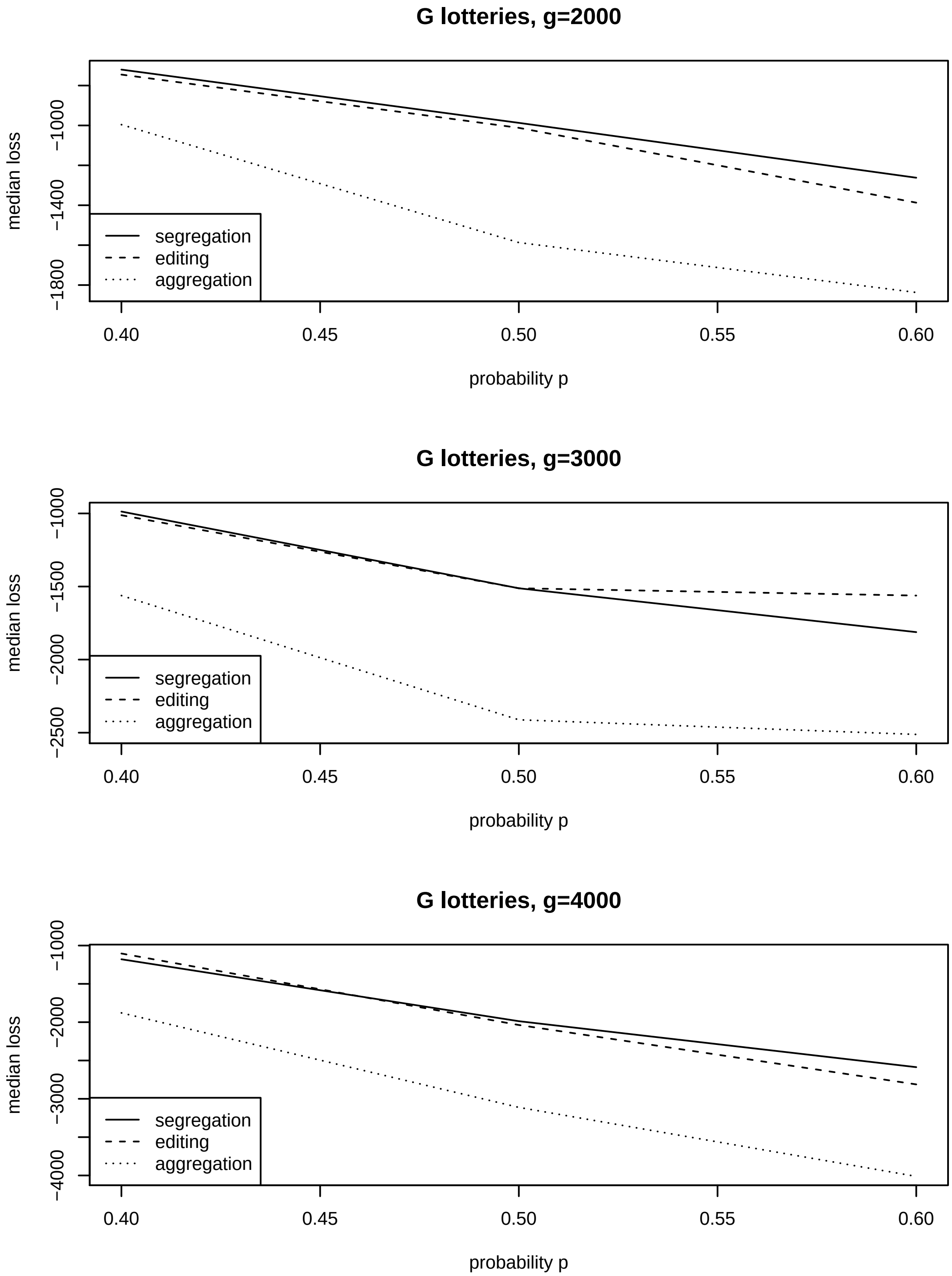

Figure 3: **Median losses for G lotteries.** Median elicited losses $\tilde{l}^e$ (2 independent draws), $\tilde{l}^s$ (one single draw), and $\tilde{l}^a$ (overall distribution of 2 independent draws). In each panel, we fix the gain value and show the median losses as function of the corresponding probability of gain.

for our lotteries segregation and aggregation generally differ and lead to different results in terms of elicited losses. Specifically, aggregation is generally more attractive than segregation for our G lotteries.

Table 3: **Median loss differences for G lotteries.** Median elicited loss differences $\tilde{\Delta}^{e,s}$ (2 independent draws versus segregation), and $\tilde{\Delta}^{e,a}$ (2 independent draws versus aggregation) for G lotteries. In brackets we report test results. We applied the one-side Wilcoxon rank test to test the null hypotheses that $\tilde{\Delta}^{e,k} = 0$, for $k = s, a$, against the alternatives that $\tilde{\Delta}^{e,s} < 0$ and $\tilde{\Delta}^{e,a} > 0$ for segregation and aggregation, respectively. p-values are adjusted for multiple-testing according to the Bonferroni correction method.

	probability p	loss g	segregation $\tilde{\Delta}^{e,s}$	aggregation $\tilde{\Delta}^{e,a}$
1	0.40	2000	0	26
			(1.000)	(0.072)
2	0.50	2000	0	0
			(0.163)	(0.104)
3	0.60	2000	0	0
			(1.000)	(0.071)
4	0.40	3000	0	375
			(0.289)	(0.000)***
5	0.50	3000	0	0
			(0.672)	(0.382)
6	0.60	3000	75	25
			(1.000)	(0.100)
7	0.40	4000	-25	225
			(0.250)	(0.001)**
8	0.50	4000	0	0
			(0.086)	(0.277)
9	0.60	4000	0	50
			(0.688)	(0.245)

Figure 4 graphically summarises our results for median differences. For our discussion we refer to two-dimensional Figures 5 and 6. Specifically, in Figure 5 (Figure 6) we fix the probability of gain (gain value) and show median loss differences as function of gain values (probabilities of gain). In line with our discussion above, median elicited loss differences $\tilde{\Delta}^{e,s}$ and $\tilde{\Delta}^{e,a}$ are mostly flat and around 0, except for $p = 0.4$ and $g = 3000, 4000$ (first panel in Figure 5 and second and third panels in Figure 6), where median differences $\tilde{\Delta}^{e,a}$ are significantly larger than 0.

4.2 B lotteries

66 subjects faced B lotteries. Consistency rates are similar to those observed for G lotteries: 76%, 78%, and 78% of the repeated iterations in parts 1, 2, and 3, respectively, were consistent with the answers in the original questions.

Table 4 shows median elicited gains $\tilde{g}^e$, $\tilde{g}^s$ and $\tilde{g}^a$ for the 9 elicitations. We observe that the median elicited gains under both aggregation and segregation are smaller than under the editing rules applied by subjects (except for elicitation 2, i.e., $(l, q) = (-1000, 0.04)$, in case of segregation). Figures 7 and

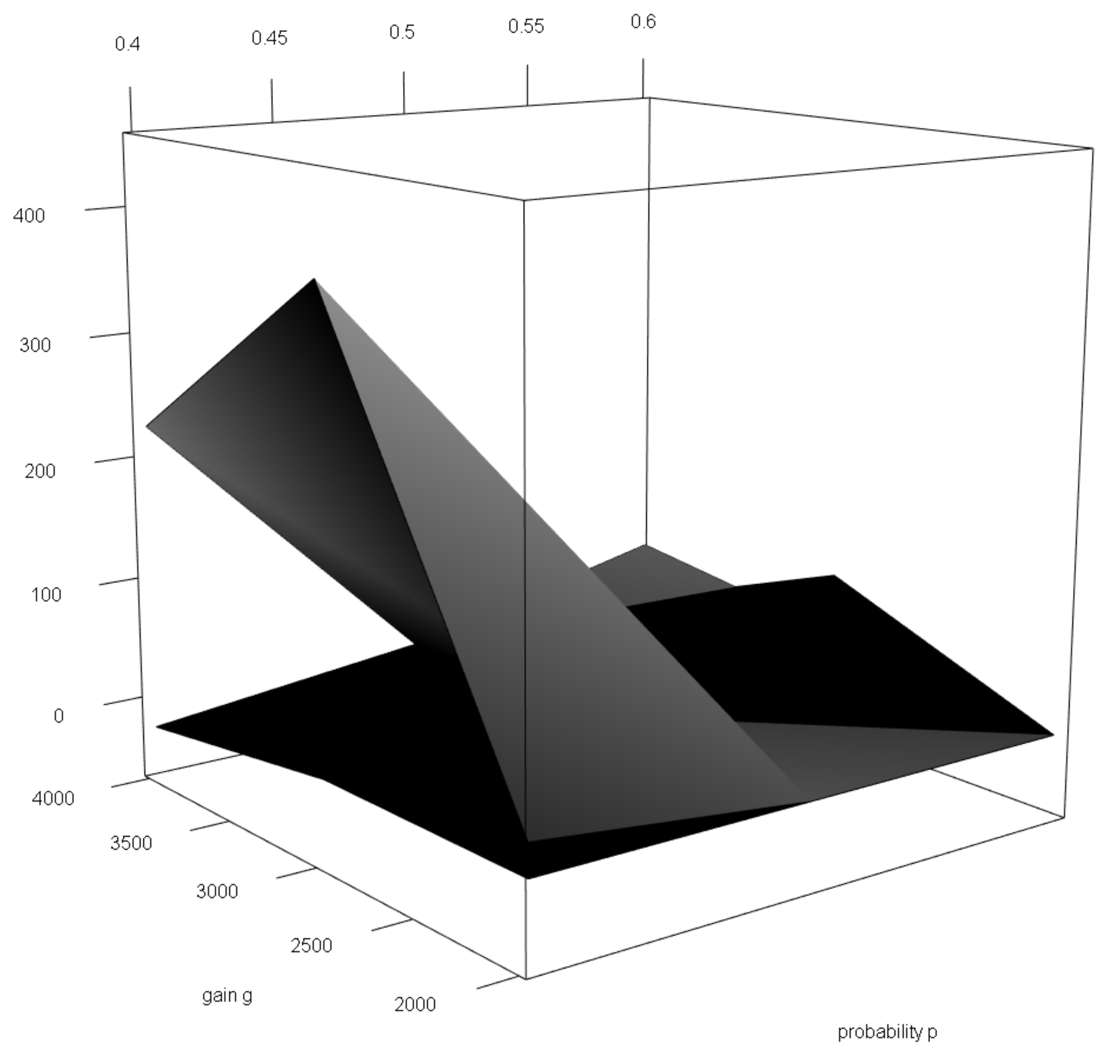

Figure 4: **Median loss differences for G lotteries.** Median elicited loss differences differences $\tilde{\Delta}^{e,s}$ (2 independent draws versus segregation, black surface), and $\tilde{\Delta}^{e,a}$ (2 independent draws versus aggregation, grey surface).

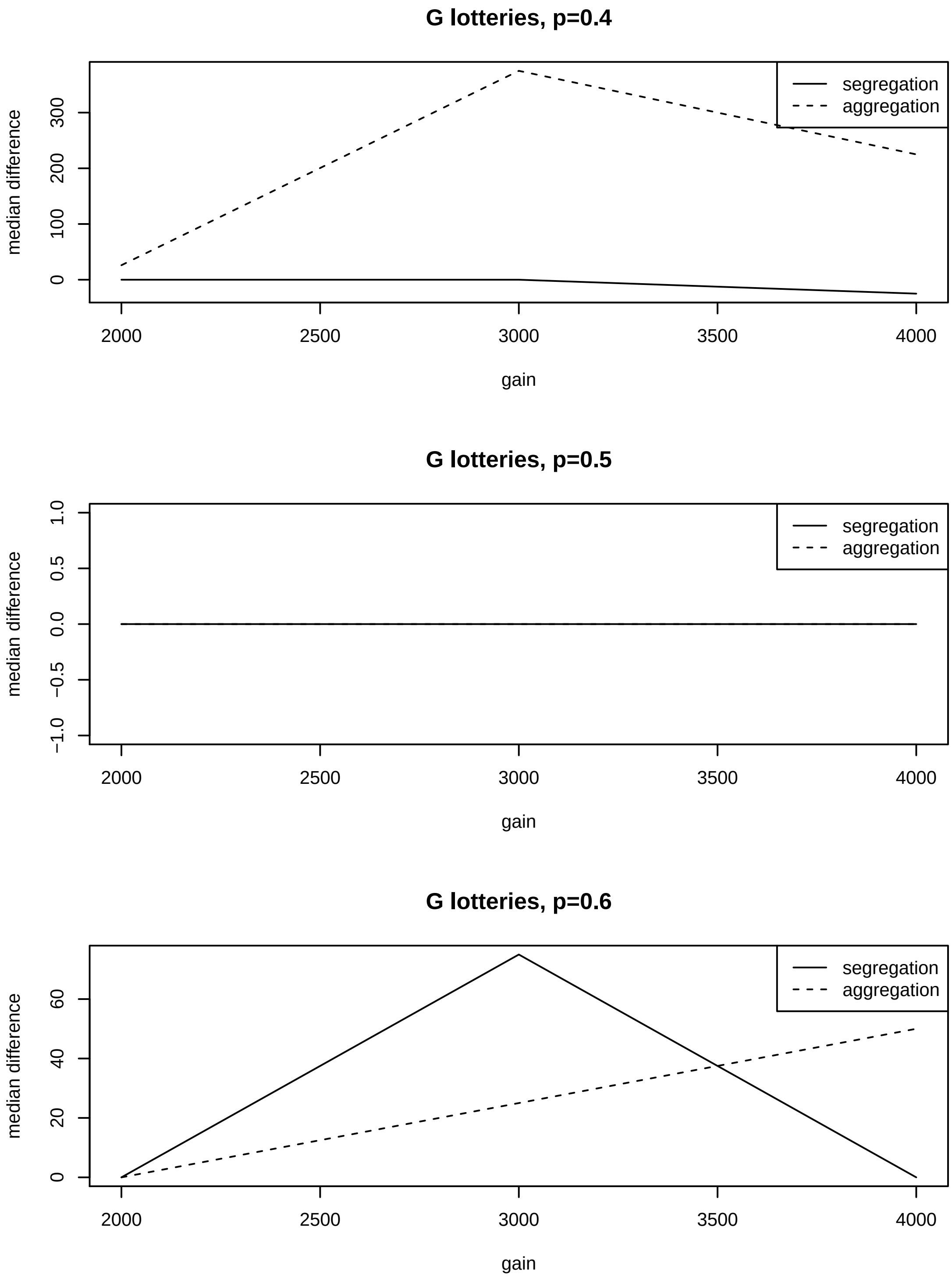

Figure 5: **Median loss differences for G lotteries.** Median elicited loss differences differences $\tilde{\Delta}^{e,s}$ (2 independent draws versus segregation), and $\tilde{\Delta}^{e,a}$ (2 independent draws versus aggregation). In each panel, we fix the probability of gain and show the median loss differences as a function of the corresponding gain values.

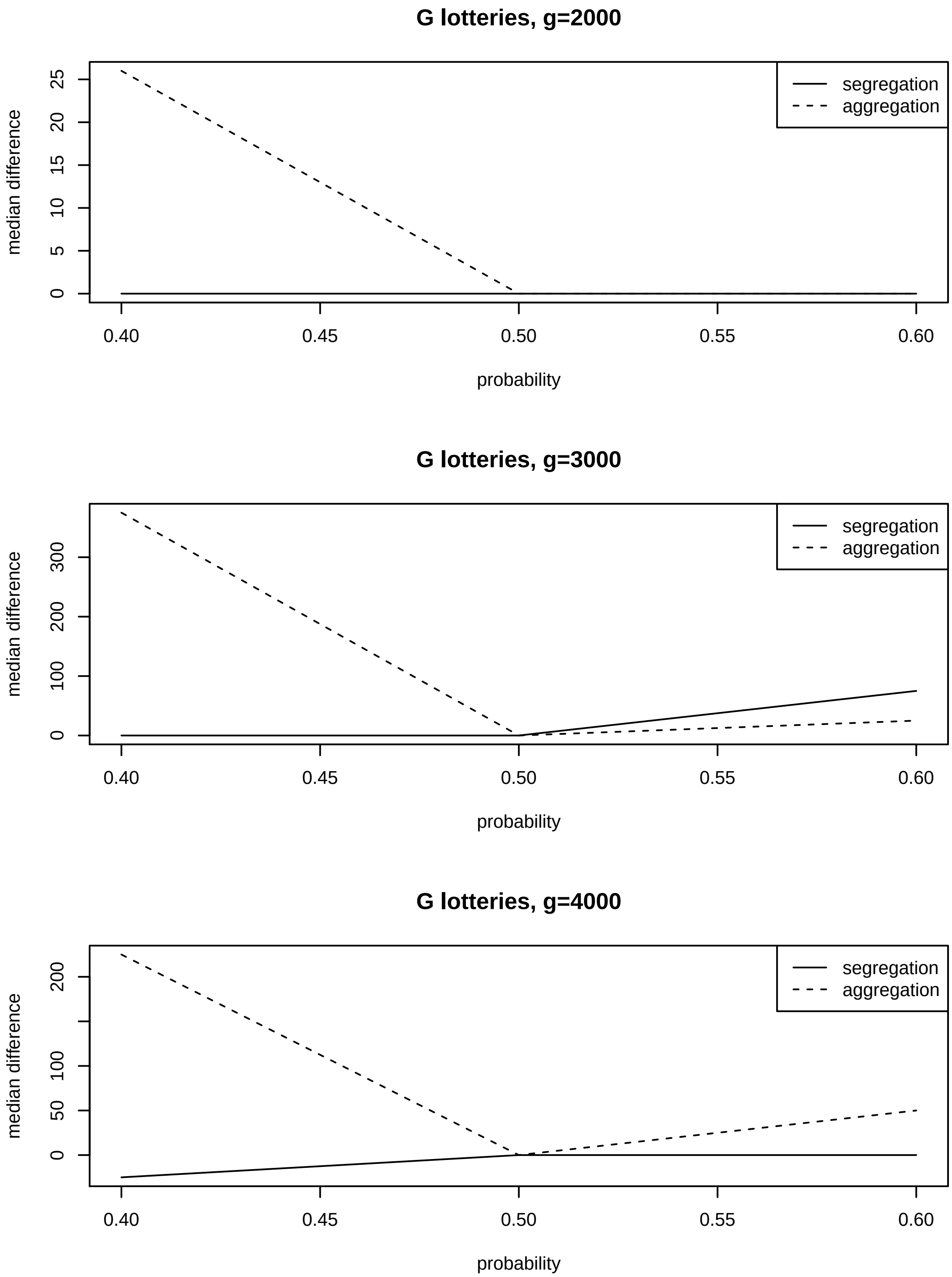

Figure 6: **Median loss differences for G lotteries.** Median elicited loss differences differences $\tilde{\Delta}^{e,s}$ (2 independent draws versus segregation), and $\tilde{\Delta}^{e,a}$ (2 independent draws versus aggregation). In each panel, we fix the gain value and show the median losses as function of the corresponding probability of gain.

8 graphically report the results of Table 4. Specifically, Figure 7 shows that, for fixed probabilities of loss, median gains increase as the loss increases, while Figure 8 shows that, for fixed loss values, median gains increase as the probability of the loss increases. Hence, subjects seem to fulfil monotonicity in B lotteries, as well. A detailed analysis shows that within each triple of lotteries where either the probability of losses or the loss values are fixed, the consistency rates with respect to monotonicity ranges from 23% to 74%. Consistency rates with respect to monotonicity are similar in the three parts, but again slightly higher in part 3.

Table 4: **Median gains for B lotteries.** Median elicited gains $\tilde{g}^e$ (2 independent draws), $\tilde{g}^s$ (one single draw), and $\tilde{g}^a$ (overall distribution of 2 independent draws).

	probability q	loss l	editing $\tilde{g}^e$	segregation $\tilde{g}^s$	aggregation $\tilde{g}^a$
1	0.02	-1000	408	283	283
2	0.04	-1000	405	418	279
3	0.06	-1000	440	402	352
4	0.02	-2000	504	442	454
5	0.04	-2000	696	509	559
6	0.06	-2000	691	529	653
7	0.02	-3000	699	599	474
8	0.04	-3000	813	688	638
9	0.06	-3000	1029	854	854

Table 5 reports the median elicited gain differences $\tilde{\Delta}^{e,k}$ for $k = s, a$ between the editing rules used by subjects and segregation/aggregation, for each of the 9 elicitations. While we observe that editing rules used by subjects do not differ much from segregation, the difference between editing rules and aggregation is strictly positive in each of the 9 elicitations, which implies that editing rules used by subjects tend to make 2 independent draws less attractive than aggregation. A statistical analysis confirms this observation. We perform one-side Wilcoxon rank tests to test the null hypotheses that the used editing rules correspond to segregation (median gain difference equals zero, i.e., $\tilde{\Delta}^{e,s} = 0$) and aggregation (median gain difference equals zero, i.e., $\tilde{\Delta}^{e,a} = 0$), with alternatives $\tilde{\Delta}^{e,s} > 0$ and $\tilde{\Delta}^{e,a} > 0$, respectively. We use the Bonferroni correction for multiple testing in order to compute p-values, which are reported in parenthesis in Table 5. The test results suggest that we cannot reject the null hypothesis that used editing rules are segregation, but we generally reject the null hypothesis that used editing rules are aggregation, with one single exception when $q = 0.06$ and $l = -2000$.

Figure 9 graphically summarises our results for median differences. For our discussion we refer to two-dimensional Figures 10 and 11. Specifically, in Figure 10 (Figure 11) we fix the probability of loss (loss value) and show median gain differences as function of the loss values (probabilities of loss). Median elicited gain differences between the editing rules and segregation, namely, $\tilde{\Delta}^{e,s}$, is always constant and zero. The median elicited gain differences between the editing rules and aggregation, namely, $\tilde{\Delta}^{e,a}$ are strictly positive and increase as the loss increases. Such differences are still strictly positive as the probabilities of losing increase, but they tend to be more stable.

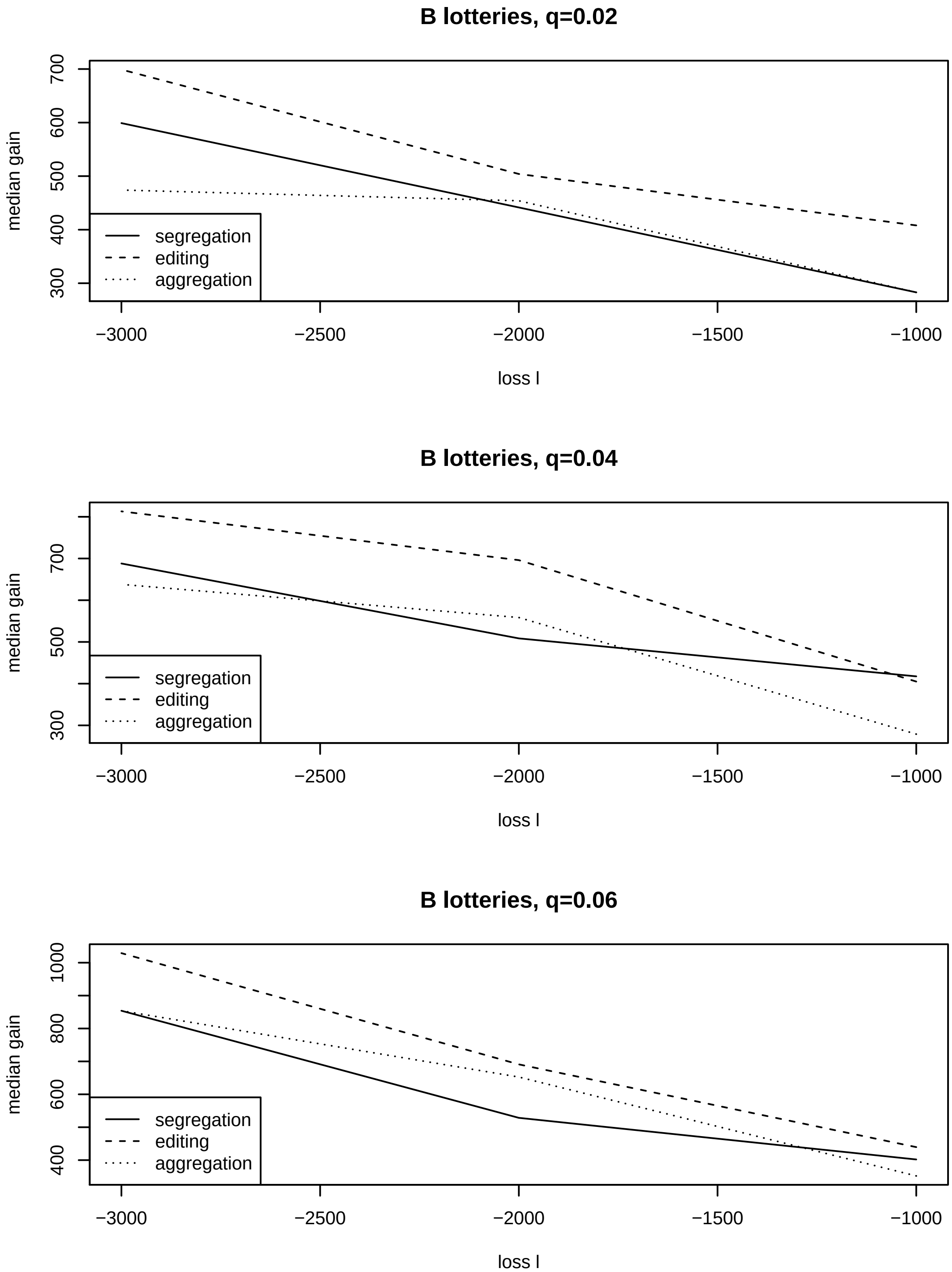

Figure 7: **Median gains for B lotteries.** Median elicited gains $\tilde{g}^e$ (2 independent draws), $\tilde{g}^s$ (one single draw), and $\tilde{g}^a$ (overall distribution of 2 independent draws). In each panel, we fix the probability of loss and show median gains as function of the corresponding loss value.

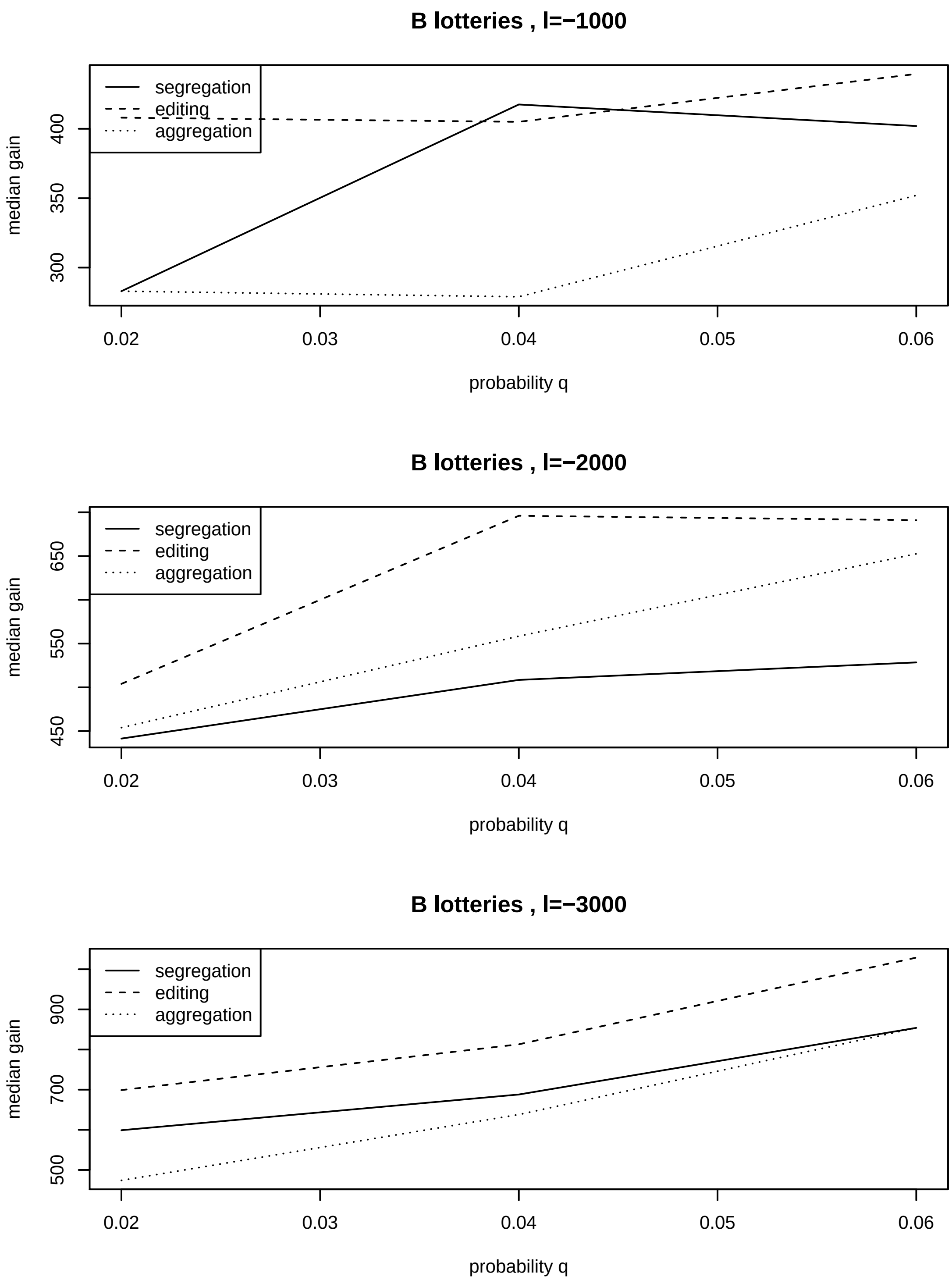

Figure 8: **Median gains for B lotteries.** Median elicited gains $\tilde{g}^e$ (2 independent draws), $\tilde{g}^s$ (one single draw), and $\tilde{g}^a$ (overall distribution of 2 independent draws). In each panel, we fix the loss value and show median gains as function of the corresponding probability of loss.

Table 5: **Median gain differences for B lotteries.** Median elicited gain differences $\tilde{\Delta}^{e,s}$ (2 independent draws versus segregation), and $\tilde{\Delta}^{e,a}$ (2 independent draws versus aggregation) for B lotteries. In bracket we report test results. We applied the one-side Wilcoxon rank test with the null hypotheses that $\tilde{\Delta}^{e,k} = 0$, for $k = s, a$, against the alternative that $\tilde{\Delta}^{e,k} > 0$, for $k = s, a$. p-values are adjusted for multiple-testing according to the Bonferroni correction method.

	probability q	loss l	segregation $\tilde{\Delta}^{e,s}$	aggregation $\tilde{\Delta}^{e,a}$
1	0.02	-1000	12	38
			(1.000)	(0.007)**
2	0.04	-1000	0	14
			(0.987)	(0.002)**
3	0.06	-1000	0	25
			(1.000)	(0.030)*
4	0.02	-2000	0	25
			(1.000)	(0.005)**
5	0.04	-2000	0	75
			(1.000)	(0.017)*
6	0.06	-2000	0	38
			(1.000)	(0.132)
7	0.02	-3000	0	100
			(1.000)	(0.026)*
8	0.04	-3000	0	100
			(1.000)	(0.005)**
9	0.06	-3000	12	112
			(1.000)	(0.026)*

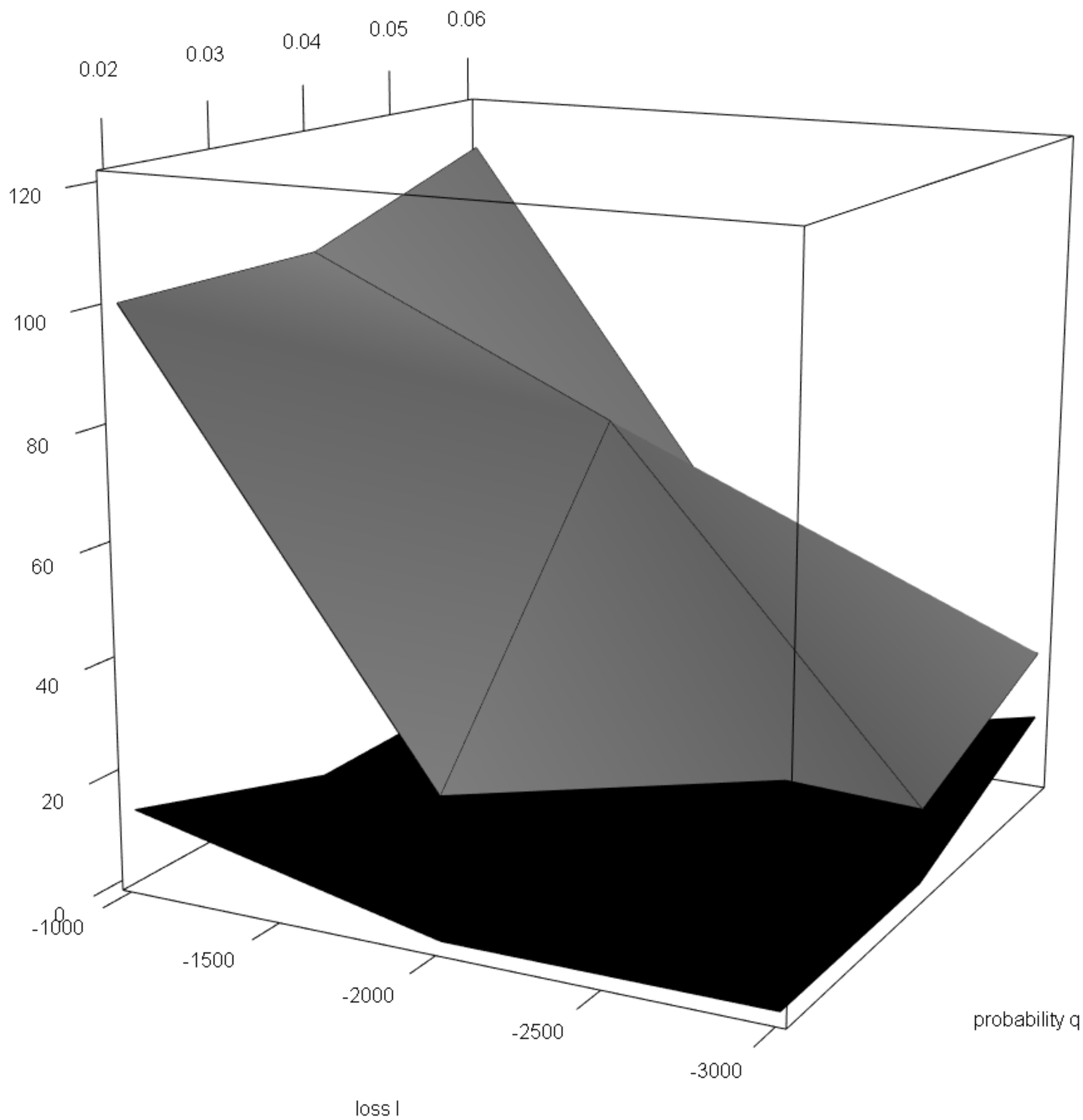

Figure 9: **Median loss differences for G lotteries.** Median elicited loss differences differences $\tilde{\Delta}^{e,s}$ (2 independent draws versus segregation, black surface), and $\tilde{\Delta}^{e,a}$ (2 independent draws versus aggregation, grey surface).

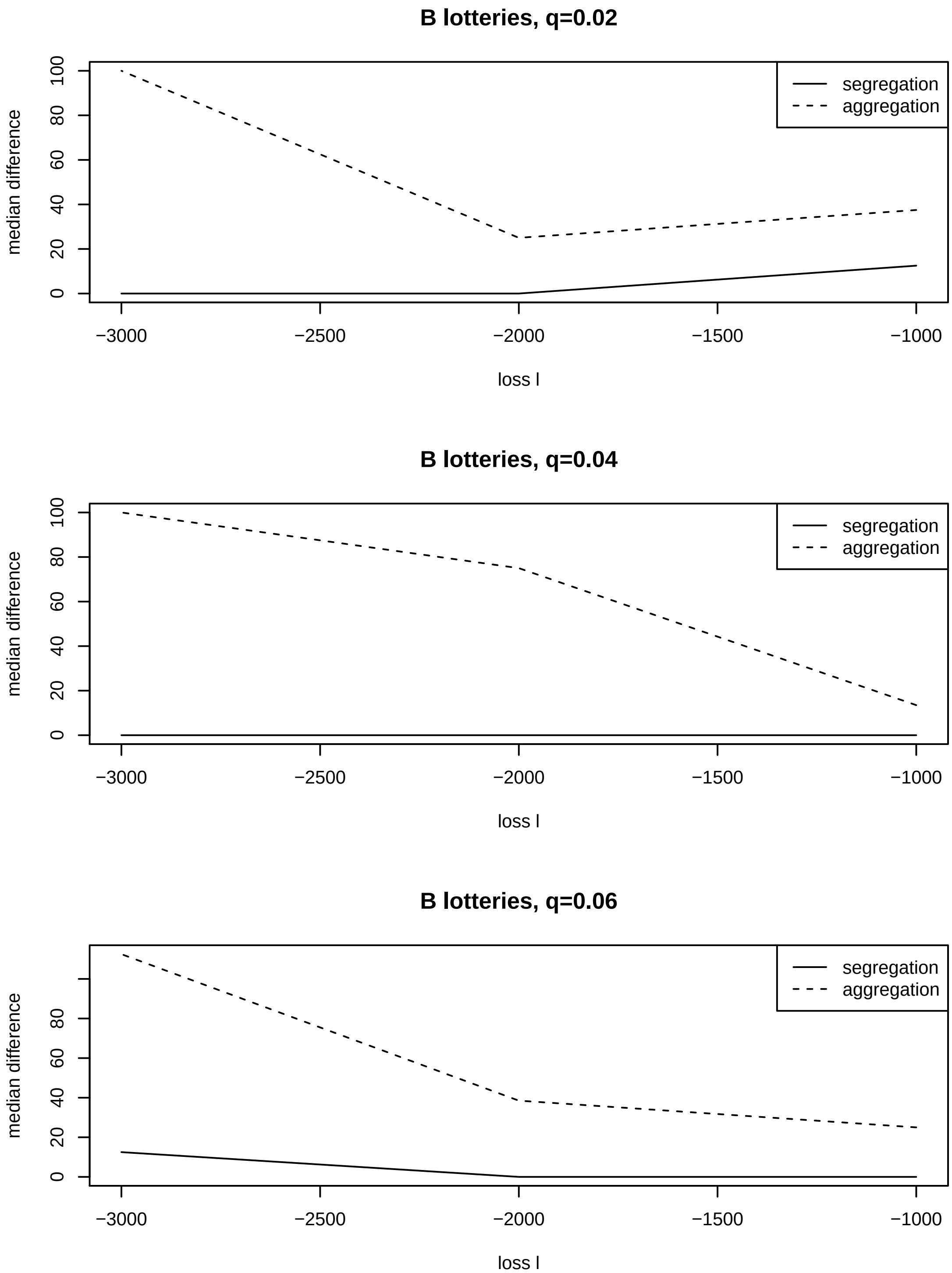

Figure 10: **Median gain differences for B lotteries.** Median elicited gain differences $\tilde{\Delta}^{e,s}$ (2 independent draws versus segregation), and $\tilde{\Delta}^{e,a}$ (2 independent draws versus aggregation) for B lotteries. In each panel, we fix the probability of loss and show median gain differences as function of the corresponding loss values.

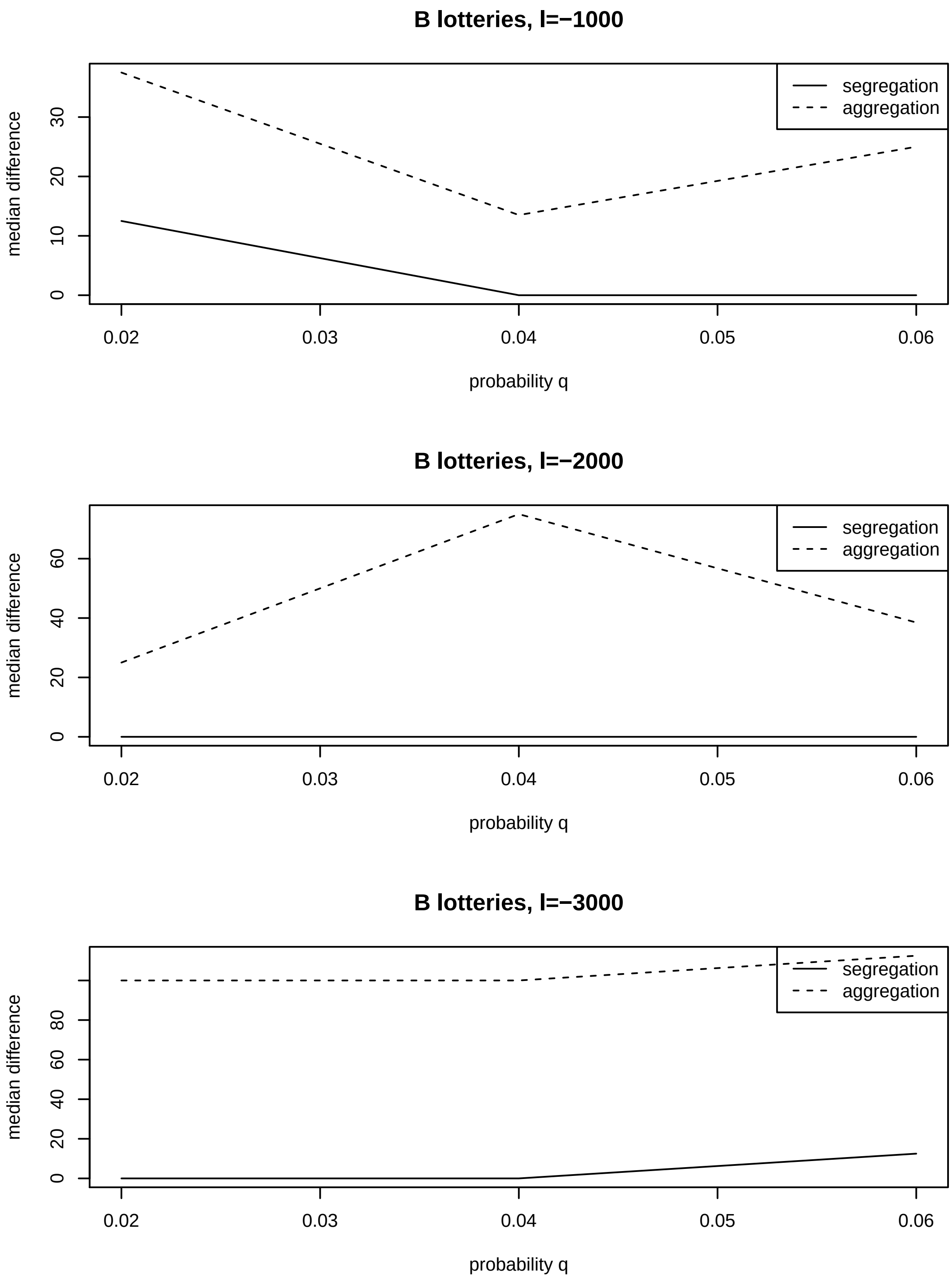

Figure 11: **Median gains differences for B lotteries.** Median elicited gain differences $\tilde{\Delta}^{e,s}$ (2 independent draws versus segregation), and $\tilde{\Delta}^{e,a}$ (2 independent draws versus aggregation) for B lotteries. In each panel, we fix the loss value and show median gain differences as a function of the corresponding probabilities of loss.

4.3 Loss/Gain Differences and Acceptance Rates

As discussed in the Introduction, most of previous results in the literature on editing of repeated lotteries refer to acceptance rates. Acceptance rates do not describe the strength of preferences, i.e., decision makers could strongly prefer a choice alternative when edited according to a given editing rule compared to another editing rule, but nevertheless accept to play the choice alternative under both editing rules. Specifically, when a choice alternative is generally unattractive under any editing rule, acceptance rates do not provide any evidence to compare different editing rules. By contrast, the new approach proposed in this paper allows to measure the strength of preferences, as it directly relates to gain and loss differences, as discussed in Section 3.

To obtain further insights on how the two approaches (loss/gain differences and acceptance rates) differ when comparing editing rules, we analyse the observed differences in our experiment between segregation and aggregation. To compute acceptance rates for G and B lotteries, we consider elicited losses and gains, respectively. For segregation, we assume that lottery $G^e = (l^e, 1-p; g, p)$ ($B^e = (l, q; g^e, 1-q)$) is accepted if and only if $l^e > l^s$ ($g^e > g^s$). Similarly, for aggregation, we assume that lottery $(G^e)_2 = (2\,l^e, (1-p)^2; l^e + g, 2\,p\,(1-p); 2\,g, p^2)$ ($(B^e)_2 = (2\,l, q^2; l + g^e, 2\,(1-q)\,q; 2\,g^e, (1-q)^2)$) is accepted if and only if $l^e > l^a$ ($g^e > g^a$). These assumptions directly follow from the definition of l^s (g^s) and l^a (g^a), which implies indifference to zero under the corresponding editing rule, and the monotonicity of preferences. We compute acceptance rates λ^s and λ^a according to the proportion of subjects that accept G^e (B^e) under segregation and aggregation, respectively.

Tables 6 and 7 report the results on our comparison between segregation and aggregation for G and B lotteries, respectively. We observe that our methodology based on loss and gain differences generally leads to results that are consistent with the use of acceptance rates. However, we also observe that our methodology could lead to different conclusions than the use of acceptance rates. For example, for the G lottery with $(g, p) = (2000, 0.4)$, the test based on loss differences does not allow to reject the hypothesis of equality between segregation and aggregation, while acceptance rates lead to the opposite result. Acceptances in this case are mainly driven by small differences $\Delta^{e,s}$ and $\Delta^{e,a}$. By contrast, for the G lottery with $(g, p) = (4000, 0.6)$, the test based on loss differences does allow to reject the hypothesis of equality between segregation and aggregation, while acceptance rates lead to the opposite result. Acceptances in this case are mainly driven by large differences $\Delta^{e,s}$ and $\Delta^{e,a}$. Similar conclusions apply to B lotteries. Therefore, we observe that in general our methodology based on loss and gain difference mainly differ from acceptance rates by the fact that it also consider the strength of preferences when comparing different editing rules.

5 Conclusion

Langer and Weber (2001) were the first to apply CPT to predict that an increase or a decrease of acceptance rates for independent draws of a lottery, when the overall distribution (aggregation) is displayed, depends on the risk profile of the lottery. More specifically, they show that consistently with their prediction, acceptance rates for independent draws of lottery $R = (0.5, -500; 2000, 0.5)$ are generally higher when the overall distribution is displayed, while the opposite holds for acceptance rates

Table 6: **Comparison of loss differences and acceptance rates for G lotteries.** Median elicited loss differences $\tilde{\Delta}^{s,a}$ (segregation versus aggregation) and acceptance rates $\hat{\lambda}^k$ for $k = s, a$. In brackets we report test results. We applied the one-side Wilcoxon rank test to test the null hypothesis that $\tilde{\Delta}^{s,a} = 0$ against the alternatives that $\tilde{\Delta}^{s,a} > 0$. We applied the Z-test to test the null hypothesis that $\hat{\lambda}^s = \hat{\lambda}^a$ against the alternative that $\hat{\lambda}^s < \hat{\lambda}^a$.

	probability	loss	loss differences	acceptance rates	
	p	g	$\tilde{\Delta}^{s,a}$	$\hat{\lambda}^s$ (%)	$\hat{\lambda}^a$ (%)
1	0.40	2000	76	43	60
			(0.072)	(0.025)*	
2	0.50	2000	25	32	60
			(0.013)*	(0.050)*	
3	0.60	2000	25	49	49
			(0.599)	(0.500)	
4	0.40	3000	375	40	67
			(0.000)***	(0.001)***	
5	0.50	3000	50	37	46
			(0.013)*	(0.139)	
6	0.60	3000	75	59	54
			(0.248)	(0.705)	
7	0.40	4000	325	35	59
			(0.000)***	(0.004)**	
8	0.50	4000	25	29	48
			(0.013)*	(0.014)*	
9	0.60	4000	25	37	51
			(0.0166)*	(0.053)	

Table 7: **Comparison of loss differences and acceptance rates for B lotteries.** Median elicited gain differences $\tilde{\Delta}^{s,a}$ (segregation versus aggregation) and acceptance rates $\hat{\lambda}^k$ for $k = s, a$. In brackets we report test results. We applied the one-side Wilcoxon rank test to test the null hypotheses that $\tilde{\Delta}^{s,a} = 0$ against the alternatives that $\tilde{\Delta}^{s,a} > 0$. We applied the Z-test to test the null hypotheses that $\hat{\lambda}^s = \hat{\lambda}^a$ against the alternative that $\hat{\lambda}^s < \hat{\lambda}^a$.

	probability q	loss l	gain differences $\tilde{\Delta}^{s,a}$	acceptance rates $\hat{\lambda}^s$ (%)	$\hat{\lambda}^a$ (%)
1	0.02	-1000	0	50	55
			(0.396)	(0.301)	
2	0.04	-1000	38.5	42	70
			(0.001)***	(0.000)***	
3	0.06	-1000	12.5	39	55
			(0.107)	(0.148)	
4	0.02	-2000	50	39	55
			(0.022)**	(0.041)*	
5	0.04	-2000	37.5	45	61
			(0.063)	(0.041)*	
6	0.06	-2000	1	48	62
			(0.723)	(0.058)	
7	0.02	-3000	62.5	44	58
			(0.003)*	(0.059)	
8	0.04	-3000	62.5	39	59
			(0.037)*	(0.012)*	
9	0.06	-3000	50	50	62
			(0.176)	(0.080)	

of independent draws of lottery $K = (0.04, -2100; 400, 0.96)$, which displays a small probability of a large loss.

In this paper, we propose a new theoretical approach to the study of editing rules of repeated lotteries, which is based on loss and gain differences instead of acceptance rates and allows to disentangling preferences from editing. Moreover, loss and gain differences capture the strength of preferences for one editing rule compared to another one. An experiment based on our new theoretical setup confirms Langer and Weber's (2001) prediction that editing depends on the risk profile of the underlying lottery. Specifically, when lotteries display low probabilities of large losses, we cannot reject that decision makers segregate repeated lotteries. Differently from Langer and Weber (2001) we always observe that repeated lotteries appear as being more attractive under aggregation compared to segregation. However, the set of lotteries considered in our paper differ from Langer and Weber (2001), and, as also Langer and Weber (2001) emphasize, their experimental results are "very sensitive to small changes of the lottery parameters".

Our theoretical approach is based on reasonable assumptions. The experimental methodology we propose is based on loss/gain differences and can be applied to compare different editing rules. For example, one could test if decision makers apply specific heuristics when editing different choice alternatives. Moreover, one could also analyse if and how editing changes with experience, generating, e.g., dynamically inconsistent choices (see Barkan and Busemeyer 2003). Another interesting question would be to test if the use of real incentives influences subjects' editing rules. Finally, our methodology can be easily extended to more than two independent draws, allowing for a more general analysis of editing rules for repeated lotteries. In this context, an interesting hypothesis has been formulated by Wedell and Böckenholt (1994), who state that a higher number of draws increases the application of quantitative tools and reduces the behavioral anomalies. From a theoretical perspective, future research could address possible generalizations of our experimental methodology, e.g., extending its foundation to include other decision models.

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Appendix

A. Proof of Lemma 2

(i) We have:

$$
\begin{aligned}
&V(s(2G^e)) - V(e(2G^e)) = \\
&\quad = \; V(s(G^e)) - V(s(2G^s)) \\
&\quad = \; 2\,V(G^e) - 2\,V(G^s) \\
&\quad = \; 2\,\big(w^-(1-p)\,v(l^e) + w^+(p)\,v(g)\big) - 2\,\big(w^-(1-p)\,v(l^s) + w^+(p)\,v(g)\big) \\
&\quad = \; 2\,w^-(1-p)\,\left(v(l^e) - v(l^s)\right).
\end{aligned}
$$

Because $l^k < 0$ for $k = e, s$ and v is convex on $\mathbb{R}_-$, then

$$|v(l^e) - v(l^s)| \geq v'(\underline{l})\,|\Delta^{e,s}|$$

where $\underline{l} = \min\{l^e, l^s\}$ and $\Delta^{e,s} = l^e - l^s$. It follows that:

$$|V(s(2G^e)) - V(e(2G^e))| \geq 2\,w^-(1-p)v'(\underline{l})\,|\Delta^{e,s}|.$$

(ii) We have:

$$
\begin{aligned}
&V(a(2G^e)) - V(e(2G^e)) = \\
&\quad = \quad V(s(G^e)) - V(a(2G^a)) \\
&\quad \overset{\underline{l}+g>0}{=} \quad w^-((1-p)^2)\,v(2\,l^e) + \big(w^+(p\,(2-p)) - w^+(p^2)\big)\;v(l^e+g) + w^+(p^2)\,v(2\,g) \\
&\qquad\qquad - \big(w^-((1-p)^2)\,v(2\,l^a) + \big(w^+(p\,(2-p)) - w^+(p^2)\big)\;v(l^a+g) + w^+(p^2)\,v(2\,g)\big) \\
&\quad = \quad w^-((1-p)^2)\;\left(v(2\,l^e) - v(2\,l^a)\right) + \big(w^+(p\,(2-p)) - w^+(p^2)\big)\;\left(v(l^e+g) - v(l^a+g)\right).
\end{aligned}
$$

Because $l^k < 0$ for $k = e, a$ and v is convex on $\mathbb{R}_-$, then

$$|v(2\,l^e) - v(2\,l^a)| \geq 2\,v'(2\,\underline{l})\,|\Delta^{e,a}|$$

where $\underline{l} = \min\{l^e, l^a\}$ and $\Delta^{e,a} = l^e - l^a$. Moreover, because $l^k + g > 0$ for $k = e, a$ and v is concave on $\mathbb{R}_+$, then

$$|v(l^e+g) - v(l^a+g)| \geq v'(\bar{l}+g)\,|\Delta^{e,a}|$$

where $\bar{l} = \max\{l^e, l^a\}$. It follows that:

$$|V(a(2G^e)) - V(e(2G^e))| \geq \big[2\,w^-((1-p)^2)\,v'(2\,\underline{l}) + \big(w^+(p\,(2-p)) - w^+(p^2)\big)\;v'(\bar{l}+g)\big]\;|\Delta^{e,a}|.$$

B. Bisection Procedure for Eliciting the Indifference Value for G lotteries

We used the bisection procedure to elicit the 9 losses that made each of the 9 combinations of gain g and probability p indifferent to zero.

Part 1. We have to elicit the loss l^e such that 2 independent draws of $G^e = (l^e, 1-p; g, p)$ were indifferent to 0. In order to do so, we used a bisection procedure. Subjects had to choose between options $A = G^e$ and option $B = 0$. The initial value of l^e, call it x, was such that A and B were equal in expected value terms. Then two different steps could realize:

(i) If A was initially chosen we decreased x by adding -800 until B was chosen. We then halved the step size and increased x by adding 400. If A [B] was subsequently chosen we once again halved the step size and decreased [increased] x by adding -200 [200], etc.

(ii) If B was initially chosen we increased x by adding 800 Euro until A was chosen. We then halved the step size and decreased x by adding -400. If A [B] was subsequently chosen we once again halved the step size and decreased [increased] x by adding -200 [200], etc.

The elicitation ended when the interval was of 25: the recorded indifferent point was the midpoint within this interval. If the subject kept choosing A at the beginning: after adding 5 times -800 (clicking consecutively 6 times on A), the computer stopped and the experiment ended for that subject. If the subject kept choosing B at the beginning: when x became strictly positive, and the subject again chose B, then the computer stopped and the experiment ended.

Part 2. For the elicitation of the loss l^s such that $G^s = (l^s, 1-p; g, p)$ was indifferent to 0, the procedure was the same as for the elicitation of l^e.

Part 3. We had to elicit the loss l^a such that $(G^a)_2 = (2\,l^a, (1-p)^2; l^a + g, 2\,p\,(1-p); 2\,g, p^2)$ was indifferent to zero. The initial value of l^a, was such that A and B were equal in expected value terms, as before. The only difference here is that l^a appeared in two out of three possible outcomes. Moreover, given that we dealt with 2 $l^{2,a}$, the elicitation ended when the interval was of 50: the recorded indifferent point was the midpoint within this interval.

C. Bisection Procedure for Eliciting the Indifference Value for B lotteries

The approach was similar to the one used for G lotteries.

Part 1. We have to elicit the gain g^e such that 2 independent draws of $B^e = (l, q; g^e, 1-q)$ were indifferent to 0. In order to do so, we used a bisection procedure. Subjects had to choose between options $A = B^e$ and option $B = 0$. The initial value of g^e, call it x, was such that A and B were equal in expected value terms. Then two things could happen:

(i) If A was initially chosen we decreased x by adding -800 until B was chosen. We then halved the step size and increased x by adding 400. If A [B] was subsequently chosen we once again halved the step size and decreased [increase] x by adding -200 [200], etc.

(ii) If B was initially chosen we increased x by adding 800 Euro until A was chosen. We then halved the step size and decreased x by adding -400. If A [B] was subsequently chosen we once again halved the step size and decrease [increase] x by adding -200 [200], etc.

The elicitation ended when the interval was of 25: the recorded indifferent point was the midpoint within this interval. If the subject kept choosing A at the beginning: when x became strictly negative, and the subject again chose A, then the computer stopped and the experiment ended. If the subject kept choosing B at the beginning: after adding 10 times 800 (clicking consecutively 11 times on B), the computer stopped and the experiment ended for that subject.

Part 2. For the elicitation of the gain g^s such that $B^s = (l, q; g^s, 1-q)$ was indifferent to 0, the procedure was the same as for the elicitation of g^e .

Part 3. We had to elicit the gain g^a such that $(B^a)_2 = (2\,l, q^2; l + g^a, 2\,(1-q)\,q; 2\,g^a, (1-q)^2)$ was indifferent to 0. The initial value of g^a, was such that A and $B = 0$ were equal in expected value terms, as before. The only difference here is that g^a appeared in two out of three events. Moreover, given that we dealt with 2 $g^{2,a}$, the elicitation ended when the interval was of 50: the recorded indifferent point was the midpoint within this interval.