

# Regret theory and risk attitudes\*

Jeeva Somasundaram,<sup>†</sup> Enrico Diecidue<sup>‡</sup>

April 24, 2017

We examine risk attitudes under regret theory and derive analytical expressions for two components—the resolution and regret premiums—of the risk premium under regret theory. We posit that *regret-averse* decision makers are risk seeking (resp., risk averse) for low (resp., high) probabilities of gains and that feedback concerning the forgone option reinforces risk attitudes. We test these hypotheses experimentally and estimate empirically both the resolution premium and the regret premium. Our results confirm the predominance of regret aversion but not the risk attitudes predicted by regret theory; they also clarify how feedback affects attitudes toward both risk and regret.

*Keywords:* regret theory, resolution premium, regret premium

---

\*We thank Aurélien Baillon, Han Bleichrodt, Luc Wathieu, Klaus Wertenbroch, and Horst Zank for their helpful comments. We also gratefully acknowledge support from the People Programme (Marie Curie Actions) of the European Union’s Seventh Framework Programme FP7/2007-2013/ under REA grant agreement 290255.

<sup>†</sup>Decision Sciences, INSEAD, Boulevard de constance, 77305 Fontainebleau, France.

<sup>‡</sup>Decision Sciences, INSEAD, Boulevard de constance, 77305 Fontainebleau, France. Corresponding author, email: enrico.diecidue@insead.edu, phone: +33 160724447.

# 1 Introduction

In economics and management, the classic model of expected utility (von Neumann and Morgenstern 1947) is the benchmark for representing preferences under risk and uncertainty. Yet several models have been introduced since the 1970s to accommodate some of expected utility’s descriptive failures (for reviews see Starmer 2000, Wakker 2010). *Regret theory* (Bell 1982, Loomes and Sugden 1982) is one of the most popular alternatives to expected utility (EU). Regret theory is based on the intuition that a decision maker (DM)—when choosing among various risky objects (e.g., lotteries, gambles, and investments)—is concerned not only about the payoff he receives but also about the payoff had he chosen differently. The role of regret in decision making has been extensively investigated (Larrick 1993, Larrick and Boles 1995, Zeelenberg 1999, Connolly and Zeelenberg 2002, Connolly and Butler 2006). Regret theory has a simple structure: a utility function capturing attitudes toward outcomes and a function capturing the effect of regret. Despite this structural simplicity, regret theory can account for many of the empirical violations of EU. The key to explaining these violations is the psychological intuition that most decision makers are by nature regret averse. Regret theory’s intuitive content and explanatory power make it well suited to real-world applications. For example, Barberis et al. (2006), Gollier and Salanié (2006), Muermann and Volkman Wise (2006), Michenaud and Solnik (2008), and Qin (2015) have applied the notion of regret to financial and insurance decisions. Perakis and Roels (2008) reinterpreted the newsvendor model in terms of regret, and Filiz-Ozbay and Ozbay (2007) and Engelbrecht-Wiggans and Katok (2008) proposed models in auction theory that rely on regret. Diecidue et al. (2012), Nasiry and Popescu (2012), and Viefers and Strack (2014) focused on dynamic applications of regret.

More than 25 years after the introduction of regret theory, Bleichrodt et al. (2010) proposed the first method to quantitatively measure its parameters. Their method also allowed Diecidue and Somasundaram (2015) to develop the first complete behavioral foundation for regret theory. When combined with quantitative measurement, this behavioral foundation established the normative and descriptive validity of regret theory, further

increasing its appeal. The availability of a measurement method and a corresponding behavioral foundation allow us to deploy regret theory in the service of practical decision analysis.

To deploy a theory for decision analysis, the risk attitudes under that theory should be well understood. Under EU, risk attitudes are fully captured by “utility curvature” (Wakker 2010); in more complex models, such as prospect theory, risk attitudes are captured by the *interaction* between utility and a probability weighting function that yields a fourfold pattern of risk attitudes (Kahneman and Tversky 1979, Tversky and Kahneman 1992, Tversky and Wakker 1995). Under regret theory, however, it is not clear how the interaction between utility and regret is related to risk attitudes. Bell (1983) formalized the risk premium under regret theory and showed that it consists of two distinct components: a resolution premium and a regret premium. However, Bell (1982, 1983) did not suggest a empirical method suitable for measuring these two components of the risk premium (Anand 1985).

In this paper, we provide an analytical expression for both the resolution premium and the regret premium. These expressions enable—for the first time—a precise characterization of risk attitudes under regret theory and thus rigorous predictions about the risk attitudes of a regret-averse decision maker. We predict that regret-averse DMs will be risk seeking for low probabilities of gains and risk averse for high probabilities; we also postulate that risk attitudes are reinforced by feedback. We introduce a method to measure the risk premium under regret theory. This method allowed us then to compute both the resolution and regret premiums and thereby to understand the effect of feedback on regret attitudes. Finally, we design an experiment to estimate empirically the risk premium’s components and to test our predictions about risk attitudes. The experiment serves also as a descriptive test of regret theory.

The data support regret aversion as a robust empirical phenomenon. However, we find no significant support for the risk attitude predictions of regret theory. We also discover that immediate feedback polarizes regret attitudes: It increases the regret aversion of regret-averse subjects but it reduces the regret aversion within the entire subject pool.

The paper is organized as follows. Section 2 introduces the notation and our definition of regret theory; in Section 3, we first derive analytically the two components of the risk premium under regret theory and then introduce a measurement (based on trade-off consistency) that distinguishes the two components. Building on this new measurement, Section 4 derives formal predictions for the risk attitudes of a regret-averse decision maker; the experiment described in Section 5 tests those predictions. We discuss the experiment's results in Section 6 and then conclude in Section 7.

## 2 Notation and basic concepts

Consider a state space  $S$ . Subsets of  $S$  are events  $E$ . The outcome set is  $\mathbb{R}$ , with real numbers designating amounts of money. Prospects are state-contingent outcomes mapping the state space  $S$  to  $\mathbb{R}$ . Prospects are denoted by lower case letters ( $f, g, \dots$ ), and outcomes are usually denoted by Greek letters ( $\alpha, \beta, \gamma, \delta$ ) or by Roman letters with subscripts (e.g.,  $x_1$ ). Consider a preference relation  $\succeq$  over the set of prospects. Strict preference  $\succ$ , indifference (or equivalence)  $\sim$ , and reverse preferences  $\preceq$  and  $\prec$  are defined as usual. Let  $\mathbb{R}^n$  denote the set of all prospects. A prospect  $f$  is denoted by  $f = (E_1, f_1; \dots; E_n, f_n)$ , where  $f_1, \dots, f_n$  are outcomes under events  $E_1, \dots, E_n$ . For a prospect  $f$ , we use  $\alpha_{E_i}f$  to signify that the outcome of prospect  $f$  under event  $E_i$  is replaced by  $\alpha$ . The prospect  $f$  is also denoted by  $(p_1, f_1; \dots; p_n, f_n)$ , where  $p_1, \dots, p_n$  are the probabilities attached to events  $E_1, \dots, E_n$ .

Regret theory considers the utility of the outcomes associated with the selected prospect and also the regret or “rejoice” associated with comparisons between the selected and the forgone prospect. Before defining regret theory formally, we examine some of its basic formulations and properties. Consider the two-outcome prospects  $\alpha_E\beta$  and  $\gamma_E\delta$ . The general formulation of regret theory proposed by Loomes and Sugden (1987) postulates a real-valued function  $\psi$  such that

$$\alpha_E\beta \succeq \gamma_E\delta \iff p\psi(\alpha, \gamma) + (1-p)\psi(\beta, \delta) \geq 0. \quad (2.1)$$

The function  $\psi(\alpha, \gamma)$  can be interpreted as assigning a real-valued index to the net advantage of choosing  $\alpha_p\beta$  rather than  $\gamma_p\delta$  if event  $E$  obtains with subjective probability  $p$ . The function  $\psi$  is unique up to scale—that is, it can be replaced by any other function  $\psi' = a\psi$  without affecting preferences—and satisfies the following two restrictions.

1. The function  $\psi$  is *strictly increasing* (resp., *strictly decreasing*) in its first (resp., second) argument: for any outcome  $\gamma$ , if  $\alpha > \beta$  then  $\psi(\alpha, \gamma) > \psi(\beta, \gamma)$  and  $\psi(\gamma, \alpha) < \psi(\gamma, \beta)$ .
2. The function  $\psi$  is *skew symmetric*: for all  $\alpha$  and  $\beta$ ,  $\psi(\alpha, \beta) = -\psi(\beta, \alpha)$ .

Bell (1982) and Loomes and Sugden (1982) considered a restricted form of Eq. (2.1) in which

$$\psi(\alpha, \beta) = Q(u(\alpha) - u(\beta)), \quad (2.2)$$

where  $Q$  is the regret function and  $u$  is a von Neumann–Morgenstern utility function.<sup>1</sup> We use Eq. (2.2) to define regret theory formally as follows.

**Definition 1.** *Regret theory* holds if there exist both a continuous strictly increasing utility function  $u: \mathbb{R} \rightarrow \mathbb{R}$  and a continuous strictly increasing skew-symmetric regret function  $Q: \mathbb{R} \rightarrow \mathbb{R}$  such that

$$f \succeq g \iff \sum_{i=1}^n p_i \cdot Q(u(f_i) - u(g_i)) \geq 0; \quad (2.3)$$

here  $f = (E_1, f_1; \dots; E_n, f_n)$  and  $g = (E_1, g_1; \dots; E_n, g_n)$  are prospects and  $p_i$  is the subjective probability of event  $E_i$ .

Expected utility is the special case of Eq. (2.3) in which  $Q$  is the identity function. The convexity (resp., concavity) of the  $Q$ -function indicates regret aversion (resp., regret seeking). Regret aversion is responsible for the distinctive predictions of regret theory (see Loomes and Sugden 1982, Bleichrodt and Wakker 2015).

---

<sup>1</sup>Loomes and Sugden (1982) refer to  $u$  as a “choiceless utility function”.

Bleichrodt et al. (2010) presented the first quantitative measurement of regret, which built on the trade-off method (Wakker and Deneffe 1996) and allowed making regret theory observable for the first time. This two-stage measurement allows one to measure utility (in the first stage) and regret function (in the second stage) without imposing any parametric form. Appendix A describes the two stages in detail. In the next section, we use the Bleichrodt et al. (2010) method to derive and measure risk premium under regret theory.

### 3 Risk premium under regret: Derivation and measurement

The *risk premium* of a prospect is the monetary difference between its expected value (EV) and the sure amount concerning which the decision maker is indifferent to that prospect (this latter amount is known as the certainty equivalent, CE). The risk premium is widely used as a measure of risk aversion (Wakker 2010). Bell (1983) was the first to study risk premium under regret theory and showed that it is the sum of two components: the resolution premium and the regret premium. The *resolution premium* entails that the DM is not actually indifferent to “resolving” the forgone option (i.e., to discovering its true value); thus the premium is what a DM pays to avoid resolution of the forgone option. The *regret premium* is the extra—as compared with what an EU maximizer would pay—that a DM pays to avoid regret. The following example illustrates these two types of premiums.

Consider a decision maker who must choose between \$8,000 for sure and the prospect  $(0.5, \$20,000; 0.5, \$0)$ ; this is our notation for “receiving \$20,000 with a 50% chance and receiving \$0 otherwise”. Suppose the DM chooses the prospect and receives nothing after the uncertainty is resolved. Then the DM will regret her decision: not only did she receive \$0, she also lost the opportunity to earn a sure amount of \$8,000. The premium a DM is willing to pay in order to avoid regret is the *regret premium*. Suppose that the decision

maker chooses not between a prospect and a sure monetary amount but rather between two prospects:  $f = (0.05, \$40,000; 0.95, \$0)$  and  $g = (0.1, \$20,000; 0.9, \$0)$ . Now suppose that the DM chooses prospect  $f$  and then—after resolution of the uncertainty—receives nothing. The DM might (or might not) like to hear about the outcomes of prospect  $g$ . The amount of money a DM will pay to avoid (hearing about) resolution of the forgone prospect is the *resolution premium*.<sup>2</sup>

Although Bell (1982, 1983) introduced the notions of a regret and a resolution premium, he did not suggest an empirical method suitable for measuring these two components of the risk premium (Anand 1985). Yet measuring them accurately is necessary for sound practical applications of regret theory, such as pricing the uncertainty in stocks and insurance contracts (Michenaud and Solnik 2008). Only a method that can make the regret function  $Q$  observable and measurable at the individual level can provide useful information about the risk premium under regret theory. The “trade-off consistency” approach of Bleichrodt et al. (2010) is the only method known to be capable of measuring the  $Q$ -function at the individual level. In this section we show how that method can be adapted to isolate the two components of the risk premium under regret theory. For simplicity we limit the exploration to prospects with only two outcomes and to events for which the probabilities can be specified. However, the same method can be extended to prospects with a larger number of outcomes. Details of the measurement method are given next.

In the first stage, the utility function is elicited as in Bleichrodt et al. (2010); in the second stage, the regret function  $Q$  is elicited under two different conditions: condition 1, when there is feedback about resolution of the forgone option ( $Q_1$ ); and condition 2, when there is no such feedback ( $Q_2$ ). The elicited values of  $u$ ,  $Q_1$ , and  $Q_2$  are fitted using power functions as in Bleichrodt et al. (see Appendix A of this paper). Larrick and Boles (1995) and Zeelenberg (1999) showed that resolving the forgone option increases regret aversion; we therefore expect  $Q_1$  to be more convex than  $Q_2$  (Bleichrodt et al. 2010).

In the rest of this section we derive analytical expressions for both the resolution

---

<sup>2</sup>If instead the DM does want to hear about (resp., is indifferent to) the forgone prospect’s payoffs, then the resolution premium is negative (resp., zero).

premium and the regret premium.

## Resolution premium

Consider prospects of the form  $x = (p, x_k; 1 - p, x_0)$ ; here  $p \in (0, 1)$ ,  $x_0$  is the starting outcome of the standard sequence for the elicitation of utility as in Bleichrodt et al. (2010), and  $x_k$  is any outcome such that  $x_k \geq x_0 \geq 0$  (for details see Appendix A). We indicate the CE of prospect  $x$  under condition 1 by  $y_1$  and under condition 2 by  $y_2$ ; then the resolution premium is the difference between  $y_2$  and  $y_1$ . The resolution premium (ResP) of a prospect  $x$  is derived in Appendix C and is given by

$$\text{ResP}(x) = y_2 - y_1 = u^{-1} \left( u(x_k) \left( \frac{Q_2^{-1}\left(\frac{p}{1-p}\right)}{1 + Q_2^{-1}\left(\frac{p}{1-p}\right)} \right) \right) - u^{-1} \left( u(x_k) \left( \frac{Q_1^{-1}\left(\frac{p}{1-p}\right)}{1 + Q_1^{-1}\left(\frac{p}{1-p}\right)} \right) \right). \quad (3.1)$$

Replacing  $Q_1$  and  $Q_2$  in Eq. (3.1) with the power function specifications  $Q_1(\alpha) = \alpha^{\theta_1}$  and  $Q_2(\alpha) = \alpha^{\theta_2}$ , we obtain

$$\text{ResP}(x) = y_2 - y_1 = u^{-1} \left( u(x_k) \left( \frac{\left(\frac{p}{1-p}\right)^{1/\theta_2}}{1 + \left(\frac{p}{1-p}\right)^{1/\theta_2}} \right) \right) - u^{-1} \left( u(x_k) \left( \frac{\left(\frac{p}{1-p}\right)^{1/\theta_1}}{1 + \left(\frac{p}{1-p}\right)^{1/\theta_1}} \right) \right).$$

Here  $\theta$  captures the convexity of  $Q$  function, and thereby regret aversion. The power function parameters of  $u$ ,  $Q_1$ , and  $Q_2$  can be estimated using the measurement method described previously in this section.

## Regret premium

Consider prospects of the form  $x = (p, x_k; 1 - p, x_0)$ ; again  $p \in (0, 1)$ ,  $x_0$  is the starting outcome of the standard sequence, and  $x_k$  is any outcome such that  $x_k \geq x_0 \geq 0$ . The regret premium (RegP) for prospect  $x$  is the difference between the certainty equivalent



under EU and the CE under regret, where the latter is derived in Appendix C. Hence we can write the regret premium (RegP) of prospect  $x$  as

$$\text{RegP}(x) = u^{-1}(u(x_k) \cdot p) - u^{-1}\left(u(x_k) \left(\frac{Q_2^{-1}\left(\frac{p}{1-p}\right)}{1 + Q_2^{-1}\left(\frac{p}{1-p}\right)}\right)\right). \quad (3.2)$$

Replacing  $Q_2$  in Eq. (3.2) with the power function specification  $Q_2(\alpha) = \alpha^{\theta_2}$ , we obtain

$$\text{RegP}(x) = u^{-1}(u(x_k) \cdot p) - u^{-1}\left(u(x_k) \left(\frac{\left(\frac{p}{1-p}\right)^{1/\theta_2}}{1 + \left(\frac{p}{1-p}\right)^{1/\theta_2}}\right)\right).$$

The power function parameters of  $u$  and  $Q_2$  are elicited using the measurement method described previously in this section. We remark that, for any two-outcome prospect  $x = (p, x_k; 1 - p, x_0)$ , the term  $u(x_0)$  can be scaled to 0 and Eqs. (3.1) and (3.2) can be used to compute (respectively) the resolution and regret premiums.

## 4 Risk attitudes under regret

According to the results presented in Section 3, the risk premium of prospect  $x$  under regret is the sum of resolution and regret premiums ( $\text{ResP}(x) + \text{RegP}(x)$ ). Larrick and Boles (1995) and Zeelenberg et al. (1996) provided experimental evidence that a regret-averse decision maker could be both risk averse and risk seeking. However, these studies were unable to establish precise boundary conditions for the risk attitudes of a regret-averse DM. Now that we have derived expressions for the components of risk premium under regret, in this section we present a result that characterizes the risk attitude of a regret-averse DM—that is, a decision maker described by a convex  $Q$ -function. Under regret theory, a DM's risk attitude is reflected mainly by the regret function  $Q$  while the utility function  $u$  captures his attitude toward money. To extract the pure effect of

regret on risk attitude, in the following analysis we shall assume that  $u$  is linear. Previous literature (Fox et al. 1996, Lopes and Oden 1999, Rabin 2000) has documented a linear utility function when the amounts of money involved are moderate. The assumption of linear utility under regret theory was also validated empirically by the estimates of Bleichrodt et al. (2010). Under linear utility, the expressions for resolution premium (ResP) and regret premium (RegP) in Eq. (3.1) and Eq. (3.2) can be simplified as follows (scaling  $U(x_0) = 0$  yields  $U(x_k) = x_k - x_0$ ):

$$\text{ResP}(x) = (x_k - x_0) \cdot \left( \left( \frac{Q_2^{-1}\left(\frac{p}{1-p}\right)}{1 + Q_2^{-1}\left(\frac{p}{1-p}\right)} \right) - \left( \frac{Q_1^{-1}\left(\frac{p}{1-p}\right)}{1 + Q_1^{-1}\left(\frac{p}{1-p}\right)} \right) \right), \quad (4.1)$$

$$\text{RegP}(x) = (x_k - x_0) \cdot \left( p - \left( \frac{Q_2^{-1}\left(\frac{p}{1-p}\right)}{1 + Q_2^{-1}\left(\frac{p}{1-p}\right)} \right) \right); \quad (4.2)$$

Consider a prospect of the form  $x = (p, x_k; 1 - p, x_0)$ , where  $x_k \geq x_0 \geq 0$ . The following proposition uses Eq. (4.1) and Eq. (4.2) to characterize the risk attitudes of a regret-averse decision maker.

**Proposition 1.** *Suppose regret theory holds with a linear utility function  $u$ . Then a regret-averse DM is risk seeking for probabilities  $p \in (0, 1/2)$ , is risk averse for probabilities  $p \in (1/2, 1)$ , and is risk neutral for probability  $p = 1/2$ .*

*Proof.* The proof (see Appendix D) relies on analyzing the resolution and regret premiums for all possible values of probability  $p$  (i.e.,  $p = 1/2$ ,  $p \in (0, 1/2)$ , and  $p \in (1/2, 1)$ ). We prove the proposition by showing that both the resolution premium and the regret premium are negative for probabilities  $p \in (0, 1/2)$  yet are positive for probabilities  $p \in (1/2, 1)$ .  $\square$

Under condition 2—the case of a regret-averse DM with *no* feedback about resolution of the forgone option—the resolution premium (ResP) is zero and hence the risk premium

coincides with the regret premium (RegP). It follows from Proposition 1 that the regret premium is negative for probability  $p \in (0, 1/2)$  and positive for probability  $p \in (1/2, 1)$ . So even in the absence of feedback, a regret-averse DM is risk seeking for  $p < 1/2$  and risk averse for  $p > 1/2$ . These risk attitudes are reinforced (because of the resolution premium) when there is feedback, as described in Proposition 1.<sup>3</sup>

If the utility function  $u$  is not linear, then the regret-averse DM is still risk seeking for low probabilities of gains and risk averse for high probabilities; however, the risk neutrality cutoff point is no longer  $p = 1/2$ . In particular, if  $u$  is concave (resp., convex) then the DM is risk seeking for probabilities  $(0, m)$ ,  $m < 1/2$  (resp.,  $m > 1/2$ ).

## Resolution and regret premiums: An example

To illustrate the intuition behind Proposition 1, we calculate resolution and regret premiums for a specific example. Following the empirical estimates of Bleichrodt et al. (2010), we assume that  $u(\alpha) = \alpha^{0.96}$  for the utility function and that  $Q_2(\alpha) = \alpha^{1.73}$ . Because  $Q_1$  is expected to be more convex than  $Q_2$ , we assume  $Q_1(\alpha) = \alpha^{3.26}$  — a value in the top decile of the estimates in Bleichrodt et al (2010). While assuming  $u(0) = 0$ , we compute the resolution and regret premiums of the prospect  $(p_j, 100; 1 - p_j, 0)$  for different probabilities  $p_j$ .

Probability	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
Resolution premium	-11.68	-8.53	-5.56	-2.75	0	2.77	5.65	8.75	12.16
Regret premium	-11.5	-19.32	-13.52	-6.94	0	7.01	13.83	20.04	24.49
CE (EU)	9.09	18.70	28.53	38.50	48.58	58.74	68.97	79.26	89.61
CE (condition 2)	20.58	39.32	42.87	45.83	48.58	51.33	54.31	57.91	63.14
CE (condition 1)	32.27	46.56	47.62	48.19	48.58	48.95	49.48	50.47	52.95
Total risk premium	-23.18	-27.85	-19.09	-9.69	0	9.78	19.48	28.79	36.66

Table 1: Resolution premium and regret premium for a specific example

Table 1 reports the resolution and regret premiums computed using (respectively) Eq. (3.1) and Eq. (3.2). The certainty equivalent under condition 2 is computed by adding

---

<sup>3</sup>In our set-up, note that the resolution premium is computed independently from the regret premium. So our set-up allows a regret averse DM to even be resolution seeking.

the regret premium to the CE under EU; we obtain the CE under condition 1 by adding the resolution premium to the CE under condition 2. The risk premium, resolution premium, and regret premium are negative for low probabilities and are positive for high probabilities of gains. This relation indicates that a regret-averse DM is risk seeking for low probabilities of gains and risk averse for high probabilities (in condition 2) and that this attitude is reinforced in the presence of feedback (condition 1) owing to the resolution premium. The intuition for this result is as follows. If a DM is choosing between a prospect and its expected value, then for low probabilities—say, a choice between  $(0.05, 100; 0.95, 0)$  and 5—the DM prefers the prospect because the anticipated regret of *not* choosing the prospect and losing out on larger amount (here, of 100) is greater. Yet for high probabilities—say, a choice between  $(0.95, 100; 0.05, 0)$  and 95—the DM prefers the EV because the anticipated regret of choosing the prospect, receiving nothing, and losing out on the sure amount (here, of 95) is greater. Figure 4.1 plots the CE under conditions 1 and 2 as well as the expected value.

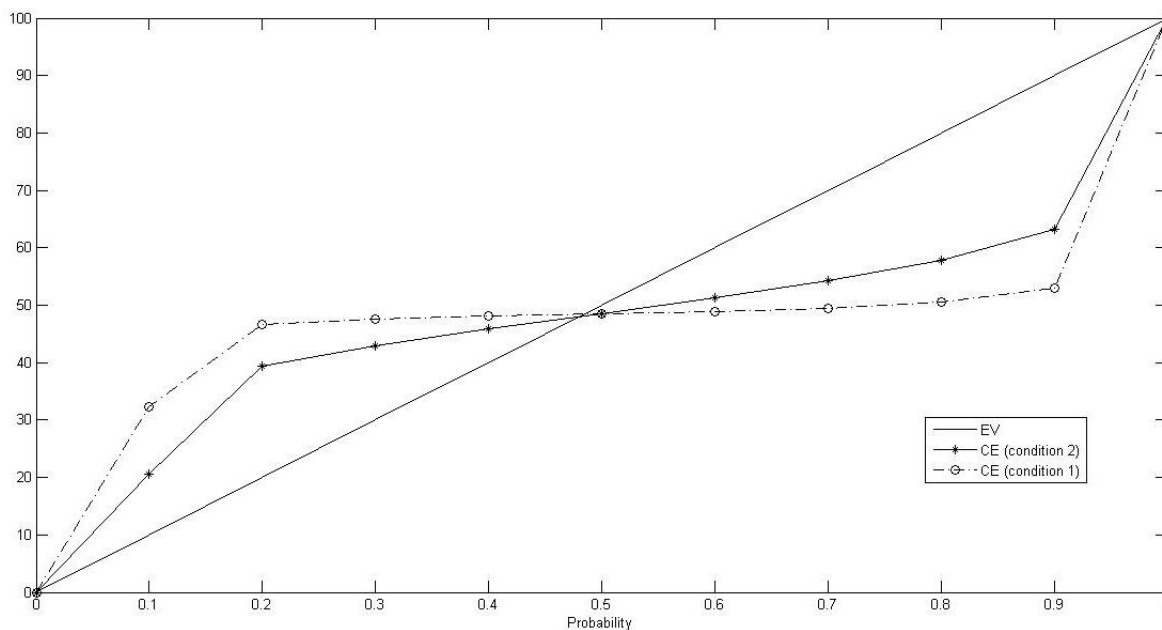


Figure 4.1: Expected value, CE (condition 1), CE(condition 2)

Our example illustrates Proposition 1 and predicts an inverse-S curve for the certainty

equivalents of the prospects under consideration. Because of the resolution premium, this curve is less linear when there is feedback. Given this example and Proposition 1, we make two summary predictions as follows. (i) When evaluating prospect  $x = (p, x_k; 1 - p, x_0)$ , a regret-averse decision maker is risk seeking for low probabilities of gains ( $p < 1/2$ ) and risk averse for high probabilities ( $p > 1/2$ ); (ii) the risk attitude of a regret-averse DM is reinforced in the presence of feedback owing to the resolution premium.

We tested these predictions in an experimental study. The next section is devoted to reporting the results of that study.

## 5 The experiment

Our experiment consisted of choices between prospects and was divided into two sections. Section I involved 24 questions devised for identifying regret-averse decision makers. The questions amounted to choices between two (three-outcome) prospects whose outcomes were determined by rolling a 6-sided die. Of these two prospects, one is clearly preferable to—and so should be chosen by—a regret-averse DM. In section II of the experiment, another 26 questions were used to assess the risk attitudes of the regret-averse DMs identified in section I. These latter questions were also choices between two prospects, but at this stage the outcomes were determined by rolling a 20-sided die. Much as in section I, we expect that a particular one of the two prospects would be chosen by (and only by) a risk-averse decision maker. Each section of the experiment featured two conditions: with feedback (condition 1) and without feedback (condition 2). The experimental subjects were randomly assigned (in equal numbers) to one of these two conditions, both of which employed the exact same questions. In condition 1, these participants received immediate feedback about their payoff after each choice by rolling a 6- or 20-sided die (depending on the experiment's section). Immediately after the subject chose one of the prospects, a computer-simulated die was rolled and the subject was informed of the outcome. In condition 2, participants received no feedback after their choices.

We tested our predictions in terms of the following hypotheses.

- H1: *Regret-averse subjects are risk seeking for low probabilities ( $p < 1/2$ ) and risk averse for high probabilities ( $p > 1/2$ ) in conditions 1 and 2 both.*
- H2: *The risk attitudes of regret-averse subjects are reinforced more under condition 1 than under condition 2.*

The outcomes of prospects used in the experiment were small (€0–€99) and therefore within the domain of a decision maker’s linear evaluation. This presumption allowed us to test both H1 and H2 for  $p < 1/2$  and for  $p > 1/2$ .

## 5.1 Subjects and stimuli

The experiment was conducted at the INSEAD–Sorbonne lab in Paris. The 107 subjects (71 female), of mean age 23, were university students in Paris. The stimuli used in each of the sections are shown in Appendix E (Figure E.1). The section I stimuli correspond to the monetary outcomes received under both prospects—outcomes that are determined by rolling a 6-sided die. In section II of the experiment, the stimuli (see Figure E.2) again correspond to the monetary outcomes received under both prospects, but now those outcomes are determined by rolling a 20-sided die. The subjects were asked to express their preferences when comparing two prospects. Figure E.3 depicts a (condition 1) feedback value as indicated by the feedback device (6-sided die).

## 5.2 Incentives

Each subject participating in the study was paid, at the very least, a flat fee of €8. To supplement that amount we instituted a randomized incentive procedure: subjects were informed that they might be able to play one of their randomly selected choices for real and win a cash amount of as much as €99. At the end of the experiment, 8 of the 107 subjects were randomly selected to play one of their choices for real. The selected subjects were asked to draw a question number from a box that consisted of all the questions used in the experiment. If the subject was in the feedback condition, then she was paid the

outcome originally given as immediate feedback for that particular question; if the subject was in the no-feedback condition, then she rolled a 6- or 20-sided die. Thus the extra payouts were based on the subjects' original choices and a roll of the die. The average extra amount earned by these eight randomly selected subjects was €25.

### 5.3 Procedures

The experiment was conducted via computer in the lab. Participants were randomly assigned to one of the two experimental conditions and were informed that the experiment would take about 45 minutes to complete. The subjects were then given detailed instructions regarding the stimuli and the experiment, and they were also briefed about the incentive system. The instructions in both conditions were identical except that, in condition 1, the subjects were told that they would know their payoff immediately after each choice. Both conditions used the same questions; the only difference between them was the feedback manipulation.<sup>4</sup> The order of questions was randomized once, after which the same order was presented to all subjects.

The questions in section I consisted of a choice between two prospects. In each such pair, the “RA” prospect is the one that should be chosen by a truly regret-averse decision maker. Figure E.1 (in Appendix E) shows the stimuli used in section I, which consists of the outcomes received for each prospect as indicated by the roll of a 6-sided die. Subjects were allowed to choose one of the two prospects or to express indifference; they were also informed that, if they expressed indifference between two prospects, then the computer would select one of them (with equal probability) on their behalf. In section I, the subjects' responses to 16 of the 24 questions were used to identify regret-averse individuals. Of those 16 questions, 8 were choices between what we set up to be a regret-averse (RA) and a regret-seeking (RS) prospect of the same EV; the remaining 8 were choices between a RA and a RS prospect of different expected values. Six additional questions were used to estimate the  $Q$ -function parametrically; the section I questions also included one to

---

<sup>4</sup>The full list of questions is given in Appendix F (the instructions are available at [goo.gl/jKOT3R](http://goo.gl/jKOT3R) and [goo.gl/3ftKzu](http://goo.gl/3ftKzu)).

assess dominance and one to check for consistency. After answering the 24 questions in section I of the experiment, all subjects proceeded to section II.

In section II of the experiment, participants were required to choose between a less risky and a more risky prospect having the same expected value. The presentation of less risky and more risky prospects was counterbalanced across questions. Monetary outcomes in section II ranged from €0 to €50. Figure E.2 shows the stimuli used in section II—namely, the outcomes associated with the roll of a 20-sided die. Subjects were allowed to choose one of the prospects or to express indifference. The subjects' responses to 26 questions in section II were used to identify risk attitudes. After answering the questions in sections I and II, subjects were asked to provide personal and demographic information.

## 5.4 Validity of measurement

To ensure valid responses, we included dominance and consistency checks. These checks are detailed in what follows.

### Dominance checks

There were two dominance checks, one in each section of the experiment. The dominance checks were a choice between two prospects, one of which stochastically dominates the other. This check was included as question 11 in section I and as question 14 in section II.

### Consistency checks

These checks were included in the experiment to ensure consistent responses. One of the questions in each section was repeated (i.e., asked twice); thus, questions 8 and 17 (in section I) were identical and questions 3 and 16 (in section II) were identical.

## 5.5 Analyses

We first present data for the classification of subjects according to regret attitudes, after which we analyze the risk attitudes of regret-averse subjects. Differences between



proportions were tested via binomial and multinomial methods, and the significance of differences was tested parametrically.

### 5.5.1 Analysis for section I

We classified subjects based on their regret attitudes. Removing the dominance and consistency checks left 22 questions, of which 16 allowed us to classify subjects according to their regret attitudes. For each of those 16 questions, a subject could choose the RA or the RS prospect or could express indifference. A subject who expressed indifference for the majority of questions was classified as regret neutral; one who chose the RA (resp., RS) prospect for the majority of questions was classified as regret averse (resp., regret seeking). All subjects with no majority choice were classified as “mixed”. As mentioned previously, in half of the 16 questions the RA prospect’s EV was lower than that of the RS prospect. The reason for including such questions is as follows. For comparable payoff levels, Bleichrodt et al. (2010) and ? find that subjects have a linear utility function at the aggregate level. At the individual level, however, some subjects have a concave and others a convex utility function. A subject with a concave or convex utility function might prefer the RA prospect despite not being regret averse. Thus the aim of these eight questions was to identify regret-averse subjects while controlling for the utility function’s curvature.<sup>5</sup>

The remaining six questions in section I allowed us to estimate parametrically the regret function  $Q$  under conditions 1 and 2 at the aggregate level. We assume a linear utility function and a power function specification for the  $Q$ :  $Q(\alpha) = \alpha^\theta$  if  $\alpha \geq 0$  and  $Q(\alpha) = -|\alpha|^\theta$  if  $\alpha < 0$ . The results of Bleichrodt et al. (2010) and ? report values for the exponent  $\theta$  in the range  $[0.8, 2.4]$ . Hence we chose these six questions in such a way that a subject with  $\theta = 0.8, 1, 1.3, 1.6, 1.95, 2.41$  would be indifferent between the RA and

---

<sup>5</sup>For instance, consider a choice between prospects  $a = (E_1, 20; E_2, 70; E_3, 30)$  and  $b = (E_1, 45; E_2, 25; E_3, 50)$  when all three events are equally likely. Prospect  $a$  is a RA prospect because if  $Q$  is convex and  $u$  is linear then  $Q(45) > Q(25) + Q(20)$ , in which case  $a \succeq b$ . If instead  $u$  is convex and  $Q$  is linear, we still have still  $a \succeq b$ . Similar cases occur also when  $u$  is concave and  $Q$  is linear. To avoid classifying such subjects as regret averse, we included eight questions in which the RA prospect’s EV was *lower* than that of the RS prospect.

RS prospects for exactly one of the six questions. We then identified the question whose  $\theta$  value is the one at which the majority choice shifts from the RA to the RS prospect. This approach allowed us to estimate  $\theta$  at the aggregate level. We could then use the aggregate  $\theta$  estimated under conditions 1 and 2 to compute the resolution and regret premiums via (respectively) Eq. (4.1) and (4.2).

### 5.5.2 Analysis for section II

Following the classification derived in section I, we restricted our focus to regret-averse subjects. So in the results and analysis for section II of the experiment, the term “subjects” refers to regret-averse subjects. After removal of the dominance and consistency checks there remained 23 questions, of which 16 were a choice between a risky prospect and a sure outcome. These 16 questions allowed us to classify subjects based on their risk attitudes. Just as with regret attitudes in Section I, a subject who expressed indifference for the majority of questions was classified as risk neutral; one who chose the safe (resp., risky) prospect for majority of questions was classified as risk averse (resp., risk seeking). As before, subjects with no majority choice were classified as “mixed”. Because the 16 questions asked subjects to choose between a risky prospect and a sure outcome, the certainty effect (Kahneman and Tversky 1979, Cohen and Jaffray 1988) could affect their choices. To control for this effect, the remaining 7 questions in section II were a choice between two risky prospects: a “low probability of a large outcome” prospect and a “high probability of a small outcome” prospect of the same expected value. These 7 questions allowed us to test H1 while controlling for the certainty effect. For each question, a subject could choose one of the risky prospects or express indifference. Note that the prospects we included in Section II, had probability of positive outcomes in the range  $(0 - 0.3]$  or  $[0.7, 1)$ . We did not include the intermediate range of probabilities to control for utility curvature (see discussion after Proposition 1 for details).

We divide the rest of our analysis of section II into three levels: subject, question, and aggregate. Hypotheses H1 and H2 were tested at all three levels. For the first two levels, we classified (respectively) subjects’ choices and the questions themselves as being either

“consistent with H1”, “inconsistent with H1”, or “unclassified”.

In the *subject-level* analysis, we tested for whether the subjects’ choices were consistent with H1. For this analysis we ignored the choices of subjects expressing indifference, since a subject who expresses indifference between the two prospects can reasonably be supposed to have chosen either one of them with equal probability.<sup>6</sup> If more than (resp., less than, exactly) 50% of a subject’s choices were consistent with H1, then we classified her as “consistent with H1” (resp., “inconsistent with H1”, “unclassified”). We sought to establish that more subjects behaved consistently than inconsistently with H1 and thereby to validate that hypothesis. Toward the end of validating H2, we tested for whether the proportion of subjects consistent with H1 was larger in condition 1 than in condition 2.

In the *question-level analysis*, for each question we computed the proportion of subjects behaving consistently with the predictions of H1. For each question, if the majority (resp., minority) of the subjects chose according to H1 then we classified that question as “consistent with H1” (resp., “inconsistent with H1”); if there was no majority then the question remained unclassified. For each question we also tested whether the proportion of subjects choosing the prospect consistent with H1 is larger than the proportion choosing the other prospect.

In the *aggregate-level* analysis, we considered all choices made by all subjects. We checked for whether most choices are consistent with H1 in both conditions and for both low and high probabilities. To validate H2, we tested for whether the proportion of choices consistent with H1 in condition 1 is greater than that in condition 2.

## 5.6 Results

Of the 54 subjects in condition 1, three violated the dominance check; in condition 2 there was no dominance violation. We performed the analysis both with and without those subjects and, since no significant differences were found, we include all the subjects in the following analysis.

---

<sup>6</sup>Subjects expressed indifference for 5.6% of the questions under condition 1, for 6.1% of the questions under condition 2, and for 5.8% of the questions in total.

### 5.6.1 Section I

Table 2 shows, for each condition, the number (and percentage) of subjects classified in terms of their regret attitudes.

	Condition 1: With feedback	Condition 2: Without feedback
Regret averse	36 (67%)	49 (92%)
Regret seeking	14 (26%)	3 (6%)
Regret neutral	3 (6%)	—
Mixed	1 (2%)	1 (2%)

Table 2: Classification of experimental participants based on regret attitudes

In both conditions, the majority of the subjects were regret averse: 67% in condition 1 and 92% in condition 2. The proportion of regret-averse subjects was greater than the proportion of mixed subjects ( $p < 0.001$ ) and regret-seeking subjects ( $p < 0.001$ ) in both conditions, which indicates that—as one would expect—regret aversion is the dominant phenomenon. We also measured the proportion of regret-averse choices made by subjects: 67.5% in condition 1 and 82.8% in condition 2. The difference is significant ( $p < 0.001$ ), so section I of the experiment offers solid evidence that feedback reduces regret aversion.

#### **Estimation of regret and resolution premium: The role of feedback**

Six questions in section I allowed for estimating the regret function  $Q$  under conditions 1 and 2. In Table 3 we list the aggregate-level choices of subjects under both conditions for the six questions, where MRA denotes the more regret-averse prospect (on the left) and LRA the less regret-averse prospect (on the right). For each question, the exponent  $\theta$  that renders a decision maker indifferent between the MRA and LRA prospects is reported in the second column. The percentage of subjects choosing MRA and LRA under each condition is reported in the last four columns of the table.

Questions (MRA vs. LRA)	Indifference $\theta$	Condition 1		Condition 2	
		% MRA	% LRA	% MRA	% LRA
(22, 96, 43) vs. (67, 1, 78)	0.8	78	17	96	4
(99, 23, 35) vs. (9, 73, 75)	1	56	37	67	25
(27, 32, 83) vs. (69, 78, 8)	1.3	<b>56</b>	<b>39</b>	75	25
(89, 32, 18) vs. (9, 71, 73)	1.6	<b>37</b>	<b>52</b>	<b>48</b>	<b>40</b>
(25, 93, 22) vs. (69, 18, 73)	1.95	33	50	<b>27</b>	<b>58</b>
(35, 32, 73) vs. (79, 75, 15)	2.41	13	78	25	73

Table 3: Estimating  $\theta$  at the aggregate level—all experimental subjects  
*Notes:* MRA = more regret-averse prospect; LRA = less regret-averse prospect.  
 Boldface values indicate the switching point.

Table 3 shows that, at the aggregate level, the majority choice shifts from MRA to LRA for a value of  $\theta$  between 1.3 and 1.6 under feedback and between 1.6 and 1.95 under no feedback. We use this information to derive an aggregate  $\theta$  value of 1.45 (i.e., the midpoint between 1.3 and 1.6) under condition 1; under condition 2, we have  $\theta = 1.78$  (midpoint between 1.6 and 1.95). Hence the corresponding  $Q$ -functions under condition 1 and condition 2 are  $Q_1(\alpha) = \alpha^{1.45}$  and  $Q_2(\alpha) = \alpha^{1.78}$ , respectively. We observe that the  $Q$ -function under feedback ( $Q_1$ ) is *less* convex than the  $Q$ -function under no feedback ( $Q_2$ ); overall, then, immediate feedback *reduces* subjects' level of regret aversion. The estimated  $Q$ -function under condition 2,  $Q_2(\alpha) = \alpha^{1.78}$ , is consistent with Bleichrodt et al. (2010).

Next we shall estimate the  $Q$ -function of regret-averse subjects only. Table 4 lists the proportion of these subjects choosing MRA and LRA under conditions 1 and 2. We observe that the majority choice shifts from MRA to LRA for  $\theta$  between 1.95 and 2.41 under feedback and between 1.6 and 1.95 under no feedback. Given this majority choice, we can write the  $Q$ -functions under conditions 1 and 2 as  $Q_1(\alpha) = \alpha^{2.16}$  and  $Q_2(\alpha) = \alpha^{1.78}$ , respectively. For these regret-averse subjects we observe that the  $Q$ -function under feedback ( $Q_1$ ) is *more* convex than the  $Q$ -function under no feedback ( $Q_2$ ); hence immediate feedback *increases* the regret aversion of subjects who are already regret averse.

Questions (MRA vs. LRA)	Indifference $\theta$	Condition 1		Condition 2	
		% MRA	% LRA	% MRA	% LRA
(22, 96, 43) vs. (67, 1, 78)	0.8	89	8	98	2
(99, 23, 35) vs. (9, 73, 75)	1	75	19	72	21
(27, 32, 83) vs. (69, 78, 8)	1.3	69	25	77	23
(89, 32, 18) vs. (9, 71, 73)	1.6	56	33	<b>56</b>	<b>33</b>
(25, 93, 22) vs. (69, 18, 73)	1.95	<b>44</b>	<b>39</b>	<b>28</b>	<b>58</b>
(35, 32, 73) vs. (79, 75, 15)	2.41	<b>19</b>	<b>72</b>	26	74

Table 4: Estimating  $\theta$  at the aggregate level—regret-averse subjects only  
*Note:* See Notes to Table 3.

From the results reported in Tables 2 and 3, we inferred that immediate feedback leads to less regret aversion (i.e., a less convex  $Q$ -function). For regret-averse subjects, however, the regret function is more convex under feedback than under no feedback (see Table 4). We also estimated  $Q$ -functions for regret-*seeking* subjects, which were the same in condition 2 as in condition 1.<sup>7</sup> Thus feedback increases the number of regret-seeking subjects and thereby reduces the subject pool’s overall regret aversion. At the same time, feedback increases the regret aversion of regret-averse subjects. In short, feedback polarizes regret attitudes: subjects who are regret averse or regret seeking become even more so when feedback is given.

In the analysis that follows, we once again focus solely on regret-averse subjects. Our previous estimates of the exponent  $\theta$  for regret-averse subjects enables measurement of the two components of risk premium under regret theory. As a concrete example, in Table 5 we report the resolution and regret premiums of the prospect  $(p_j, 50; 1 - p_j, 0)$  computed for different probabilities  $p_j$  using Eqs. (4.1) and (4.2), respectively.

In Figure 5.1 we plot the estimated certainty equivalent under condition 1 and condition 2. We predict that—under both conditions—a decision maker is risk seeking for low probabilities of gains ( $p < 0.5$ ) and risk averse for high probabilities ( $p > 0.5$ ); this is

<sup>7</sup>The estimated regret functions of regret-seeking subjects are identical under conditions 1 and 2:  $Q_1(\alpha) = Q_2(\alpha) = \alpha^{0.9}$ . However, feedback increases the number of regret-seeking subjects. In particular, the number (14) of regret-seeking subjects in condition 1 is significantly larger than the number (3) of regret-seeking subjects in condition 2. Feedback therefore decreases the entire subject pool’s regret aversion. The extremely few regret-seeking subjects under condition 2 precludes any meaningful comparison with their counterparts under condition 1.

Probability	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
Resolution premium	-2	-1.51	-0.99	-0.49	0	0.49	0.99	1.51	2
Regret premium	-6.27	-5.72	-4.15	-2.16	0	2.16	4.15	5.72	6.27
Expected value	5	10	15	20	25	30	35	40	45
CE (condition 2)	11.27	15.72	19.16	22.16	25	27.83	30.84	34.27	37.83
CE (condition 1)	13.27	17.23	20.15	22.65	25	27.34	29.85	32.76	35.83
Total risk premium	-8.27	-7.23	-4.16	-2.65	0	2.65	4.16	7.23	8.27

Table 5: Resolution premium and regret premium under conditions 1 and 2

hypothesis H1. Since immediate feedback increases the regret aversion of a regret-averse DM (makes his  $Q$ -function more convex), it follows that the DM should be more risk seeking (resp., risk averse) for low (resp., high) probabilities in condition 1 than in condition 2; this is hypothesis H2. Thus our results from section I validate the assumptions about regret attitudes that underlie our hypotheses. We next discuss the validity of H1 and H2 in section II of the experiment.

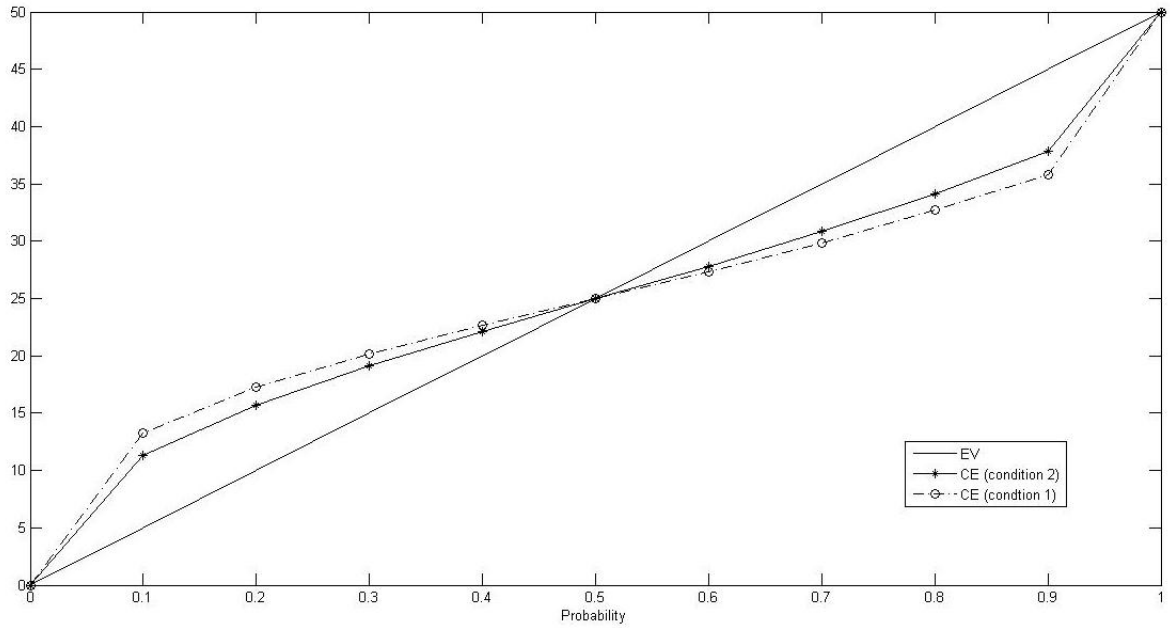


Figure 5.1: Certainty equivalent under conditions 1 and 2 for the estimated value of  $\theta$

### 5.6.2 Section II

We now present results concerning the risk attitudes of regret-averse participants. There were 36 (67%) such subjects in condition 1 and 49 (92%) in condition 2. As before, we present results at the subject level, the question level, and the aggregate level. In the following, all considered subjects are regret averse.

#### Classification of regret-averse subjects based on their risk attitudes

Table 6 reveals that the proportion of risk-averse subjects decreases when regret is made more prominent by feedback ( $p < 0.05$ ). In both conditions, the proportion of risk-averse subjects was compared with the proportion of subjects exhibiting other risk attitudes; we found the proportion of risk-averse subjects to be greater than the proportion of risk-seeking ( $p < 0.001$ ), risk-neutral ( $p < 0.001$ ), and mixed subjects ( $p < 0.001$ ). Risk aversion is the dominant finding in both conditions.

	Condition 1: With feedback	Condition 2: Without feedback
Risk averse	25 (69%)	44 (89%)
Risk seeking	10 (27%)	4 (8%)
Risk neutral	—	—
Mixed	1 (4%)	1 (2%)

Table 6: Classification of regret-averse subjects based on risk attitudes

#### Subject-level results

We employed two sets of questions for the measurement of risk attitude. In questions from the first set we provided each subject the choice between a risky prospect and its expected value. For this first set of questions, Table 7 reports the number (and percentage) of subjects who are—with respect to H1—consistent, inconsistent, and unclassified. The proportion of subjects consistent with H1 was 56% in condition 1 and 63% in condition 2, but that difference is not significant. We observe that, in both conditions, a higher percentage of subjects are consistent than inconsistent with H1. However, this difference is not significant either in condition 1 ( $p = 0.24$ ) or in condition 2 ( $p = 0.06$ ).



	Condition 1: With feedback	Condition 2: Without feedback
Consistent with H1	20 (56%)	31 (63%)
Inconsistent with H1	13 (36%)	18 (37%)
Unclassified	3 (8%)	0 (0%)

Table 7: Classification of subjects based on consistency with H1—first set of questions

In questions from the second set we provided subjects with a choice between two risky prospects: a “low probability of a large outcome” prospect and a “high probability of a small outcome” prospect of the same expected value. According to H1, a regret-averse subject should prefer the “low probability of a large outcome” prospect. For this second set of questions, Table 8 reports the number of subjects who are consistent or inconsistent with H1 (or unclassified). The proportion of subjects whose choices were consistent with H1 was only 22% in condition 1 and 12.2% in condition 2—significantly smaller, in both conditions, than those of the subjects who are *inconsistent* with H1. Clearly, then, participant responses to the second set of questions run counter to that hypothesis.

	Condition 1: With feedback	Condition 2: Without feedback
Consistent with H1	8 (22%)	6 (12.2%)
Inconsistent with H1	27 (75%)	41 (83.6%)
Unclassified	1 (3%)	2 (4%)

Table 8: Classification of subjects based on consistency with H1—second set of questions

### Question-level results

As just discussed, we used two sets of questions to measure risk attitudes. Table 9 lists the proportion of subjects choosing between a risky prospect and its expected value. For each of the 16 questions, Table 9 gives the choice predicted by H1, the majority choice, and the proportion of subjects choosing the prospect that is consistent with H1. Table 10 summarizes results concerning the number of questions for which the majority of subject responses is consistent with H1. For 9 out of 16 questions the majority choice was consistent with H1 in condition 2 (no feedback); in condition 1 (with feedback), the

majority choice was consistent with H1 for 11 out of 16 questions. The other questions were all inconsistent with H1.

Question choices	Prediction of H1	Condition 1		Condition 2	
		Proportion choosing Prospect A	Proportion choosing Prospect B	Proportion choosing Prospect A	Proportion choosing Prospect B
(0.8, 40; 0) vs. 32	B	31%	<b>67%**</b>	14%	<b>84%**</b>
(0.95, 50;0) vs. 47.5	B	42%	<b>56%</b>	27%	<b>69%**</b>
(0.05, 50;0) vs. 2.5	A	<b>53%</b>	42%	37%	57%
(0.3, 40; 0) vs. 12	A	19%	<b>78%**</b>	6%	<b>88%**</b>
(0.1, 40; 0) vs. 4	A	47%	53%	24%	<b>67%**</b>
(0.7, 50; 0) vs. 35	B	36%	<b>58%</b>	84%	14%**
(0.15, 40; 0) vs. 6	A	22%	<b>72%**</b>	22%	<b>68%**</b>
(0.75, 40; 0) vs. 30	B	14%	<b>81%**</b>	8%	<b>92%**</b>
(0.2, 50; 0) vs. 10	A	19%	<b>75%**</b>	14%	<b>78%**</b>
(0.85, 50; 0) vs. 42.5	B	28%	<b>72%**</b>	16%	<b>82%**</b>
(0.9, 40; 0) vs. 36	B	36%	<b>64%*</b>	14%	<b>84%**</b>
(0.25, 50; 0) vs. 12.5	A	19%	<b>78%**</b>	18%	<b>78%**</b>
(0.9, 50; 0) vs. 4.5	B	13%	<b>87%**</b>	11%	<b>86%**</b>
(0.05, 8; 0) vs. 0.4	A	<b>61%**</b>	29%	<b>69%**</b>	14%
(0.1, 5; 0) vs. 0.5	A	<b>65%**</b>	29%	<b>75%**</b>	14%
(0.95, 8; 0) vs. 7.6	B	26%	<b>74%**</b>	14%	<b>81%**</b>

Table 9: Percentage of subjects making, with and without feedback, choices that are consistent versus inconsistent with H1—risky prospects versus their expected values

*Notes:* Payoffs for responses to questions (i.e., subjects' choices) are denominated in euros (€). Boldface indicates that the majority of responses to that question were consistent with H1.

\*significant at  $\alpha = 10\%$ , \*\*significant at  $\alpha = 5\%$ , \*\*\*significant at  $\alpha = 1\%$

	Condition 1: With feedback	Condition 2: Without feedback
Consistent with H1	11	9
Inconsistent with H1	5	7
Unclassified	0	0

Table 10: Classification of questions based on majority choices with respect to H1

For each question, we tested whether the proportion of choices consistent with H1 is different from the proportion of choices inconsistent with H1; Table 11 presents the results. At the 95% confidence level, under condition 1 we found that 7 questions were consistent with H1, 4 were inconsistent with H1, and the other 5 questions were unclassified; under condition 2, 9 (resp. 6) questions were consistent (resp. inconsistent) with H1 and the remaining question was unclassified. So overall, subject responses to the first set of questions support H1 under condition 2 and—even more strongly—under condition 1.<sup>8</sup>

	Condition 1: With feedback		Condition 2: Without feedback	
	$\alpha = 0.05$	$\alpha = 0.1$	$\alpha = 0.05$	$\alpha = 0.1$
Consistent with H1	7	8	9	9
Inconsistent with H1	4	4	6	6
Unclassified	5	4	1	1

Table 11: Classification of questions based on consistency with H1 and significance of proportions

We also tested hypothesis H1 using the second set of questions, which asked subjects to choose between two risky prospects: a “low probability of a large outcome” prospect and a “high probability of a small outcome prospect” of the same expected value. To be consistent with H1, subjects should prefer the “low probability of a large outcome” prospect. Table 12 lists the prospects and the proportion of subjects choosing each. Except for one question in condition 1, we find no support for H1 in the responses to these questions.

---

<sup>8</sup>If the certainty effect influenced our result, then the subjects would have been more consistent with respect to H1 for the *second* set of questions (since both prospects are risky). However, our evidence points in the opposite direction.

Question choices	H1 prediction	Condition 1		Condition 2	
		Proportion choosing		Proportion choosing	
		Prospect A	Prospect B	Prospect A	Prospect B
(0.3, 40; 0) vs. (0.8, 15; 0)	A	17%	72%**	8%	80%**
(0.1, 45; 0) vs. (0.9, 5; 0)	A	42%	56%	18%	73%**
(0.1, 40; 0) vs. (0.8, 5; 0)	A	33%	58%	20%	63%**
(0.05, 50; 0) vs. (0.85, 3; 0)	A	<b>50%</b>	42%	33%	55%
(0.15, 50; 0) vs. (0.75, 10; 0)	A	22%	78%**	10%	80%**
(0.2, 40; 0) vs. (0.8, 10; 0)	A	14%	78%**	10%	78%**
(0.25, 40; 0) vs. (0.8, 12.5; 0)	A	22%	69%**	14%	73%**

Table 12: Percentage of subjects making, with and without feedback, choices that are consistent versus inconsistent with H1—two risky prospects (less probable high payoff versus more probable low payoff)

*Note:* See Notes to Table 11.

Much as with the subject-level results, we observe that majority choices for most of the questions are consistent with H1 when subjects are asked to choose between a risky prospect and its expected value. However, if subjects are asked to choose between two risky projects—one offering a less probable high payoff and the other a more probable low payoff—then participant choices are inconsistent with H1. We conclude that there is no evidence in favor of H1 at the question level of analysis.

### Aggregate-level results

Table 13 shows that the majority of choices were consistent with H1—both in condition 1 (53.4%) and in condition 2 (56.5%). We found that in both conditions the subjects were risk averse for both low and high probabilities of gains. We conclude that, although more than 50% of the choices were consistent with H1, we do not find evidence of risk seeking for small probabilities.

Questions	Choices consistent with H1	Risk attitude
Condition 1: With feedback		
$p < 1/2$	104 out of 278 (37.4% <sup>***</sup> )	Risk aversion
$p > 1/2$	193 out of 278 (69.4% <sup>***</sup> )	Risk aversion
Total	297 out of 556 (53.4% <sup>*</sup> )	Consistent with H1
Condition 2: Without feedback		
$p < 1/2$	112 out of 366 (30.6% <sup>***</sup> )	Risk aversion
$p > 1/2$	302 out of 366 (82.5% <sup>***</sup> )	Risk aversion
Total	414 out of 732 (56.5% <sup>***</sup> )	Consistent with H1

Table 13: Choices consistent with H1 at the aggregate level  
<sup>\*</sup>significant at  $\alpha = 10\%$ , <sup>\*\*\*</sup>significant at  $\alpha = 1\%$

We also tested H1 by comparing the proportion of subjects choosing the “low probability of a large outcome” prospect over the “high probability of a small outcome” prospect. Table 14 reveals that the choices of most subjects were inconsistent with H1. Thus we find no evidence in favor of H1 at the aggregate level, either.

Conditions	Consistent with H1	Inconsistent with H1
Condition 1	26%	66% <sup>***</sup>
Condition 2	16%	71% <sup>***</sup>

Table 14: Aggregate-level choices between less probable high payoffs and more probable low payoffs

<sup>\*\*\*</sup>significant at  $\alpha = 1\%$

To validate H2, we compared the proportion of choices consistent with H1 in condition 1 versus condition 2. Table 15 presents the results, which indicate that—in line with our prediction—regret-averse subjects are more risk seeking for *low* probabilities under feedback. Yet for high probabilities also we find that, contrary to our prediction, increased risk seeking under feedback. When all questions are considered, the evidence in favor of H2 is neither significant nor persuasive. The subjects become uniformly more risk seeking under condition 1 ( feedback) than condition 2 (no feedback).

Proportion consistent with H1				
Choice	Condition 1	Condition 2	Difference	Effect of feedback
$p < 1/2$	37.4%	30.6%	6.8%*	Increased risk seeking
$p > 1/2$	69.4%	82.5%	-13.1%**	Reduced risk aversion
Total	53.4%	56.5%	-3.1%	Reduced consistency with H1

Table 15: Effect of feedback (resolution premium) at the aggregate level and across all choices—regret-averse subjects

\*significant at  $\alpha = 10\%$ , \*\*significant at  $\alpha = 5\%$

## 5.7 Summary of results

Our results from section I of the experiment showed that a significant proportion of subjects were regret averse in both conditions, confirming that regret aversion is a dominant phenomenon. We also estimated the power function parameters for the regret function  $Q$  under conditions 1 and 2. We observe that feedback increases the regret aversion of regret-averse subjects but reduces regret aversion for the entire subject pool. In other words, feedback polarizes regret attitudes by making regret-averse (resp., regret-seeking) subjects more regret averse (resp., more regret seeking).<sup>9</sup> In section II of the experiment, we find support for H1 at the subject level, the question level, and the aggregate level when subjects were asked to choose between a risky prospect and a sure outcome. However, when H1 is tested by asking subjects to choose between two risky prospects, we do not find support for H1. We find that H2 holds for low probabilities of gains but do not find evidence for high probabilities. In fact, feedback uniformly increases risk seeking for both low and high probabilities.

Finally, we conducted an extensive online pilot study (on the Socialsci platform). The 121 subjects (64 female, mean age = 31.6) were Americans representing all income levels. Results of the lab experiment reported in this paper replicated, by and large, those of the pilot. In both studies: (i) regret aversion was the dominant phenomenon under both conditions; (ii) there was support for H1 at the subject, question, and aggregate level for the first set of questions under both conditions; and (iii) feedback increased the risk-

<sup>9</sup>When subjects whose responses in section II were inconsistent with regret theory are removed and the  $Q$ -function is then recomputed, we still find that feedback polarizes regret attitudes.

seeking attitudes of regret-averse subjects for both small and large probabilities. In the pilot we were able to check the robustness of results to payoff levels lower than those used in section II of this experiment. The detailed pilot results are available upon request.

## 6 Discussion

Our data showed that regret aversion is a robust phenomenon and supported regret theory as a valid model for describing the emotion of regret. The estimates for the parameter of the regret function  $Q$  were also in accordance with findings reported in Bleichrodt et al. 2010. Our consistent results across two experiments (online pilot and lab study) for a total of 228 subjects, lend credence to regret theory and to our experimental methodology.

The experiment described in Section 5 enabled us to develop a better understanding of how feedback affects attitudes toward regret. It is assumed in most of the psychology literature (Josephs et al. 1992, Larrick 1993, Larrick and Boles 1995, Ritov and Baron 1995, Ritov 1996, Zeelenberg et al. 1996) that people are generally regret averse and that feedback about forgone options increases regret aversion. In contrast, our results indicate that a significant number of subjects were actually regret seeking when there is feedback about payoffs. We also observed that, although feedback increases the regret aversion of regret-averse subjects, it *reduces* the entire subject pool's level of regret aversion. Thus the effect of feedback on anticipated regret is less straightforward than its treatment in the psychology literature suggests. Because our study does not employ a within-subject design, we cannot ascertain precisely how feedback influences subjects exhibiting various degrees of regret aversion. Nonetheless, the results presented here provide the first evidence that feedback may affect subjects differently depending on their prior attitude towards regret. Future research should provide more insights on how prior regret attitude moderates the effect of feedback on regret attitudes.

We were also able to quantify and measure the effect of feedback for the first time in the literature: We empirically estimated the resolution premium and thereby quantified the psychological pain (and pleasure) of immediate feedback. In other words, we were

able to estimate precisely how much more a decision maker would pay for a risky prospect when she expects to receive immediate feedback. This precise estimation allows us then to deploy regret theory for applications in public policy, marketing, and investment. For example, the resolution premium accounts for why a regret-averse investor prefers betting on the underdog in a sport competition (i.e., feedback) to investing in a start-up venture of equal worth (delayed or no feedback).

We also observe that our results in section II for the first set of questions are consistent with H1. However we do not find support for H1 in section II responses to the second set of questions—that is, when subjects must choose between two prospects of the same expected value (a “low probability of a large outcome” prospect and a “high probability of a small outcome” prospect). Because responses to the second set of questions could not be confounded by a certainty effect (since there was no sure outcome), we expected them to offer more support for H1. However, we found almost no support for H1 in the second set of questions under either condition: irrespective of feedback, subjects preferred (to a significant degree) a more probable low payoff over a less probable high payoff. The support for H1 in the first set of questions and the absence of that support in the second set is surprising, and it suggests that a different mechanism could be operating in responses to the two sets of questions. For example, subjects could have attended more to probabilities in the second than in the first set of questions; that emphasis could have triggered a comparison (regret versus rejoice) on the probability scale rather than on the outcome scale, resulting in choices that are inconsistent with H1. The role of probability attention and probability transformation has been extensively studied in decision theory (Quiggin 1982; Tversky and Kahneman 1992). Since regret theory captures comparisons only on the outcome scale and ignores comparisons on the probability scale, it may not always predict risk attitudes accurately. Therefore, further development and investigation is needed of models that can capture anticipated regret on both probability and outcome scales; one example is the perceived relative argument model, or PRAM (Loomes 2010).

The other explanation for the lack of support for regret theory’s risk attitude predictions is that we used three-outcome prospects to identify regret averse DMs (section



I), but two-outcome prospects to test their risk attitudes (section II). Theoretically this should not matter, but decreasing the number of outcomes changes the state space and could have made outcome comparisons difficult (? also face a similar issue). Additionally, in section II stimuli (for both set of questions), we were not able to make outcome comparisons distinct. For example to trigger outcome comparisons in the first set of questions, we were not able to split the single outcome of the safe prospect into two separate outcomes coinciding with the risky prospect’s state space — as event splitting effect (Starmer and Sugden 1993) could affect the results.

The results reported in this paper also help us understand the effect of feedback on the risk attitudes of regret-averse DMs. Regret theory predicts that if feedback increases an individual’s regret aversion then it should reinforce his risk attitude (H2). Although the regret aversion of regret-averse subjects did increase under feedback in our experiment, we do not find statistical support for H2. In our experiment (and also in the pilot study), regret-averse subjects are significantly more risk-seeking for both low and high probabilities of gains. Thus it seems that feedback affects risk attitudes through a mechanism other than anticipated regret. The literature on decision from experience (Barron and Erev 2003, Hertwig et al. 2004, Erev et al. 2015) provides additional evidence concerning the effect of feedback on attitudes toward risk. In a recent paper, consistent with our results, Erev et al. (2015) find that feedback instigates regret minimizing choices, but increases risk seeking for gains. They suggest different mechanisms (like the change in shape of probability weighting function, reliance on a small sample) that could mediate the effect of feedback on risk attitudes. Future research should compare such alternatives with the mechanism (explored in this paper) of anticipated regret. Doing so would increase still further our knowledge about the role of immediate feedback in affecting risk attitudes.

## 7 Conclusions

The paper presents an analysis of risk attitudes under regret theory. We derive analytical expressions for the risk premium's two components under that theory: the resolution premium and the regret premium. We also empirically estimate those two components and characterize the risk attitude of a regret-averse decision maker. That characterization yields two predictions that we test in an experiment. We find that regret aversion is a robust phenomenon. However we do not find sufficient support for the risk attitude predictions of regret theory—in particular, that regret-averse decision makers are not risk seeking (resp., risk averse) for low (resp., high) probabilities of gains. We discuss possible reasons for these divergent findings and offer directions for future research. Our experiment also provides new insights regarding the effect of feedback on regret and risk attitudes. Namely, we find that feedback polarizes the regret attitudes of all experimental participants and also increases risk seeking among those who are regret averse. We posit that there may exist mechanisms other than anticipated regret that mediate the effect of immediate feedback on risk attitudes.

By modeling the risk attitudes under regret theory and measuring resolution and regret premium empirically, we show that regret theory is a simple yet powerful framework to describe the pervasive emotion of regret and the risk attitudes associated. However our experimental results suggest that regret theory provides a partial account of risk attitudes as it captures the regret-rejoice trade-offs on the outcome scale only. As a consequence, decision analysts can effectively use regret theory to understand the effects of anticipated regret and feedback on the outcome scale. Decision theorists should target their efforts in developing new models to capture the regret-rejoice trade-offs also on the probability scale.

# Appendices

## Appendix A

The two stages of the Bleichrodt et al. (2010) method are described next.

### Stage 1

The first stage follows the same procedure described by Wakker and Deneffe (1996) and enables measurement of the utility function. The subject is asked to choose the outcome  $x_1$  that would make him indifferent between the prospects  $(p, x_1; 1 - p, g_1)$  and  $(p, x_0; 1 - p, g_2)$ ; here  $g_1$  and  $g_2$  are fixed “gauge” outcomes,  $x_0$  is the (fixed) starting outcome, and  $p \in [0, 1]$  is a given (fixed) probability. The method is based on a choice task: each subject is asked to choose between two prospects,  $(p, x_1; 1 - p, g_1)$  and  $(p, x_0; 1 - p, g_2)$ , for different values of  $x_1$  until indifference is reached (see Appendix B for an example of this choice task).

Once  $x_1$  is elicited, the procedure similarly finds an  $x_2$  such that the subject is indifferent between the prospects  $(p, x_2; 1 - p, g_1)$  and  $(p, x_1; 1 - p, g_2)$ . Repeated application of the same procedure allow us to elicit a sequence of outcomes  $x_0, \dots, x_k$ . For  $x_k$  the last outcome elicited,  $u(x_k)$  is scaled to 1 and  $u(x_0)$  is scaled to 0. The outcomes  $x_0, \dots, x_k$  are equally spaced in utilities (i.e.,  $u(x_i) = 1/k$  for all  $i \leq k$ ) and are called a *standard sequence* of outcomes. Although the method is nonparametric, the standard sequence of outcomes can be fitted with a parametric utility function—for example, a power function of the form  $u(\alpha) = \alpha^\theta$ —to build the utility function  $u$  under regret theory.

### Stage 2

The second stage of this method measures the regret function  $Q$ . The outcomes  $z_j$  are elicited such that the subject is indifferent between the prospects  $(p_j, x_k; 1 - p_j, x_0)$  and  $(p_j, x_{k-1}; 1 - p_j, z_j)$ , where  $x_k$  and  $x_{k-1}$  are (respectively) the last and the penultimate standard sequence outcomes. As in the first stage, a choice task is used to elicit the

values of  $z_j$  for the different probabilities  $p_j$ . The utility of  $z_j$  is then calculated by linear interpolation of the standard sequence of outcomes. The value of the  $Q$ -function is computed via  $Q(u(z_j)) = p_j/(1 - p_j)$  and by scaling  $u(x_0) = 0$ ,  $u(x_k) = 1$ , and  $Q(x_k - x_{k-1} = 1/k) = 1$ ; here  $k$  is the total number of standard sequence outcomes elicited. The method is nonparametric, but the values of  $Q$  can again be fitted with a power function of the form  $Q(\alpha) = \alpha^\theta$ ; in that way we can build the regret function  $Q$ . Hence this method facilitates accurate measurement of both the utility function ( $u$ ) and the regret function ( $Q$ ) at the individual level. The method was validated by an experiment reported in Bleichrodt et al. (2010).

## Appendix B

### Choice task

We present the choice task (bisection) following Bleichrodt et al. (2010). In the measurement of  $u$ ,  $x_{j+1}$  was elicited through choices between  $a = x_{j_p}g_1$  and  $b = x_{j+1_p}g_2$  ( $j = 0, \dots, 4$ ). The initial value of  $x_{j+1}$  was a random integer in the interval  $[x_j, x_j + 5(g_1 - g_2)]$ . There were two possible scenarios as follows. (i) If  $a$  was chosen then  $x_{j+1}$  was increased in increments of  $d = 5(g_1 - g_2)$  until  $b$  was chosen; then  $x_{j+1}$  was decreased by  $d/2$ . If  $a$  (resp.  $b$ ) was subsequently chosen then  $x_{j+1}$  was increased (resp. decreased) by  $d/4$ , and so forth. (ii) If  $b$  was chosen, then  $x_{j+1}$  was reduced in increments of  $d = (x_{j+1} - x_j)/2$  until  $a$  was chosen; then  $x_{j+1}$  was increased by  $d/4$ . If  $a$  (resp.  $b$ ) was subsequently chosen, then  $x_{j+1}$  was increased (resp. decreased) by  $d/8$ , and so forth. The elicitation was stopped when the difference—between the lowest value of  $x_{j+1}$  for which  $b$  was chosen and the highest value of  $x_{j+1}$  for which  $a$  was chosen—did not exceed 2. The indifference we recorded was the midpoint between two values. Table 16 presents an example of the procedure for eliciting  $x_1$  through comparison between  $a = (20)_{0.5}17$  and  $b = (x_1)_{0.5}13$ . In this example, the initial random value of  $x_1$  was 26 and the indifference value was 35 (i.e., midway between 34 and 36). The bisection method just described for stage 2 is similar.

Iteration	$x_1$	Choice
1	26	$a$
2	46	$b$
3	36	$b$
4	31	$a$
5	34	$a$

Table 16: Example of bisection method ( $p = 0.5$ )

## Appendix C

### Deriving the resolution premium

Consider prospects of the form  $x = (p, x_k; 1 - p, x_0)$  for  $p \in (0, 1)$  and such that  $x_k \geq x_0 \geq 0$ . We indicate the certainty equivalents of prospect  $x$  under conditions 1 and 2 by  $y_1$  and  $y_2$ , respectively; thus the resolution premium is the difference between  $y_2$  and  $y_1$ . Under condition 1, we have  $y_1 \sim (p, x_k; 1 - p, x_0)$ .

According to regret theory,

$$pQ_1(u(x_k) - u(y_1)) + (1 - p)Q_1(u(x_0) - u(y_1)) = 0.$$

Because  $x_0$  is the first outcome of the standard sequence, we scale  $U(x_0) = 0$ ; this yields

$$pQ_1(u(x_k) - u(y_1)) + (1 - p)Q_1(-u(y_1)) = 0,$$

$$\frac{p}{1 - p} = \frac{Q_1(u(y_1))}{Q_1(u(x_k) - u(y_1))}.$$

Assuming a power function specification for  $Q_1$ , we obtain

$$\frac{p}{1 - p} = Q_1\left(\frac{u(y_1)}{u(x_k) - u(y_1)}\right).$$

Since  $\frac{p}{1-p}$  is increasing, it follows that

$$Q_1^{-1}\left(\frac{p}{1 - p}\right) = \frac{u(y_1)}{u(x_k) - u(y_1)},$$

$$u(y_1) = U(x_k) \frac{Q_1^{-1}\left(\frac{p}{1-p}\right)}{1 + Q_1^{-1}\left(\frac{p}{1-p}\right)},$$

$$y_1 = u^{-1} \left( u(x_k) \frac{Q_1^{-1}\left(\frac{p}{1-p}\right)}{1 + Q_1^{-1}\left(\frac{p}{1-p}\right)} \right). \quad (7.1)$$

Similarly, the value of  $y_2$  is elicited as  $y_2 = u^{-1} \left( u(x_k) \frac{Q_2^{-1}\left(\frac{p}{1-p}\right)}{1 + Q_2^{-1}\left(\frac{p}{1-p}\right)} \right)$ . Hence the resolution premium of prospect  $x$  may be written as

$$\text{ResP}(x) = y_2 - y_1 = u^{-1} \left( u(x_k) \left( \frac{Q_2^{-1}\left(\frac{p}{1-p}\right)}{1 + Q_2^{-1}\left(\frac{p}{1-p}\right)} \right) \right) - u^{-1} \left( u(x_k) \left( \frac{Q_1^{-1}\left(\frac{p}{1-p}\right)}{1 + Q_1^{-1}\left(\frac{p}{1-p}\right)} \right) \right). \quad (7.2)$$

## Appendix D

### Proof of Proposition 1

We prove Proposition 1 by using Eqs. (4.1) and (4.2) to analyze the risk premium ( $\text{ResP} + \text{RegP}$ ) for three possible cases.

*Case 1: Probability  $p = 1/2$ .* Substituting  $p = 0.5$  in Eq. (4.1) and Eq. (4.2) yields  $\text{ResP}(x) = \text{RegP}(x) = 0$  because  $Q_1(1) = Q_2(1) = 1$ . Hence the risk premium is equal to zero. Therefore, when utility  $u$  is linear, a regret-averse decision maker (convex  $Q$ ) is risk neutral toward prospect  $x$  when the probability of positive outcome  $p = 1/2$ .

*Case 2: Probability  $p \in (0, 1/2)$ .*

(a) First we analyze the resolution premium ( $\text{ResP}$ ). Since  $Q_2$  is less convex than  $Q_1$ , it follows that  $Q_1^{-1}\left(\frac{p}{1-p}\right) > Q_2^{-1}\left(\frac{p}{1-p}\right)$ . Then  $\frac{Q_2^{-1}\left(\frac{p}{1-p}\right)}{1 + Q_2^{-1}\left(\frac{p}{1-p}\right)} < \frac{Q_1^{-1}\left(\frac{p}{1-p}\right)}{1 + Q_1^{-1}\left(\frac{p}{1-p}\right)}$  and so, by Eq.

(4.1) and since  $x_k \geq x_0$ , we have  $\text{ResP}(x) < 0$ .

(b) In order to analyze the regret premium ( $\text{RegP}$ ), in Eq. (4.2) we put  $p = 0.5 - l$ ; then for  $l \in (0, 1/2)$  we obtain  $\text{RegP}(x) = x_k \left( 0.5 - l - \left( \frac{Q_2^{-1} \left( \frac{0.5-l}{0.5+l} \right)}{1+Q_2^{-1} \left( \frac{0.5-l}{0.5+l} \right)} \right) \right)$ . The fraction

$\frac{Q_2^{-1} \left( \frac{0.5-l}{0.5+l} \right)}{1+Q_2^{-1} \left( \frac{0.5-l}{0.5+l} \right)}$  is increasing in the concavity of  $Q_2^{-1}$  (i.e., of  $1/Q_2$ ) and in the convexity of  $Q_2$ ; hence its lowest value occurs when  $Q_2$  is linear. Thus  $\text{RegP}(x) = 0$  for linear  $Q_2$ , so for convex  $Q_2$  we must have  $\text{RegP}(x) < 0$ .

Since  $\text{ResP}(x) < 0$  and  $\text{RegP}(x) < 0$ —as just established in (a) and (b), respectively—it follows that the risk premium is  $\text{ResP}(x) + \text{RegP}(x) < 0$ . Therefore, a regret-averse DM (convex  $Q$ ) is risk seeking for probabilities  $p \in (0, 1/2)$ .

*Case 3 : Probability  $p \in (1/2, 1)$ .*

(a) For  $p > 0.5$  we have  $\frac{p}{1-p} > 0$ ; therefore, since  $Q_2$  is less convex than  $Q_1$ , we must have  $Q_1^{-1} \left( \frac{p}{1-p} \right) < Q_2^{-1} \left( \frac{p}{1-p} \right)$ . Hence  $\frac{Q_2^{-1} \left( \frac{p}{1-p} \right)}{1+Q_2^{-1} \left( \frac{p}{1-p} \right)} > \frac{Q_1^{-1} \left( \frac{p}{1-p} \right)}{1+Q_1^{-1} \left( \frac{p}{1-p} \right)}$  and so, again by Eq. (4.1) and because  $x_k \geq x_0$ , in this case  $\text{ResP}(x) > 0$ .

(b) To analyze  $\text{RegP}$ , in Eq. (4.2) we put  $p = 0.5 + l$ ; then for  $l \in (0, 1/2)$  we obtain  $\text{RegP}(x) = x_k \left( 0.5 + l - \left( \frac{Q_2^{-1} \left( \frac{0.5+l}{0.5-l} \right)}{1+Q_2^{-1} \left( \frac{0.5+l}{0.5-l} \right)} \right) \right)$ . The fraction  $\frac{Q_2^{-1} \left( \frac{0.5+l}{0.5-l} \right)}{1+Q_2^{-1} \left( \frac{0.5+l}{0.5-l} \right)}$  decreases as the concavity of  $Q_2^{-1}$  increases and also as the convexity of  $Q_2$  increases. As before, then, it follows that this fraction's highest value occurs when  $Q_2$  is linear. For linear  $Q_2$  we have  $\text{RegP}(x)=0$  and so  $\text{RegP}(x) > 0$  for convex  $Q_2$ .

So given that (a)  $\text{ResP}(x) > 0$  and (b)  $\text{RegP}(x) > 0$ , the risk premium must be  $\text{ResP}(x) + \text{RegP}(x) > 0$ . As a consequence, a regret-averse DM (convex  $Q$ ) is risk averse for probabilities  $p \in (1/2, 1)$ .

# Appendix E

## Experimental stimuli

Question 2: Choose between A and B (Note that the numbers 1,2,.....,6 in the figure below are obtained by rolling the six sided dice)

Choice	1	2	3	4	5	6
A	\$ 30		\$ 50		\$ 5	
B	\$ 10		\$ 30		\$ 45	

Which one do you choose? \*

- Option A
- Option B
- Equally prefer option A and B

Figure E.1: Screenshot of section I stimuli

Question 1: Choose between A and B (Note that the numbers 1,2,.....,20 in the figure below are obtained by rolling the twenty sided dice)

Choice	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	
A	\$ 20																				\$ 0
B																					\$ 1

Which do you choose? \*

- Option A
- Option B
- Equally prefer option A and B

Figure E.2: Screenshot of section II stimuli

The dice below was rolled and it showed "3", so you receive \$80. You would have received \$8 if you had chosen option B.



Figure E.3 Screenshot of feedback



## Appendix F

### Questions used in sections I and II of the lab experiment

Three-outcome prospects (each outcome equally likely)	Choice of regret-averse DM (RA prospect)	Question design
(35, 80, 40) vs. (75, 8, 72)	Option A	Same EV
(30, 50, 5) vs. (10, 30, 45)	Option B	Same EV
(64, 6, 60) vs. (20, 90, 20)	Option B	Same EV
(15, 55, 65) vs. (80, 25, 30)	Option B	Same EV
(58, 55, 40) vs. (3, 80, 70)	Option A	Same EV
(9, 70, 75) vs. (99, 30, 25)	Option B	Same EV
(30, 40, 50) vs. (20, 30, 35)	Dominance	
(5, 50, 45) vs. (55, 25, 20)	Option B	Same EV
(20, 25, 80) vs. (55, 69, 1)	Option A	Same EV
(50, 6, 55) vs. (20, 64, 25)	Option B	Different EV
(62, 40, 45) vs. (3, 71, 75)	Option A	Different EV
(74, 81, 4) vs. (30, 42, 86)	Option B	Different EV
(6, 76, 61) vs. (60, 48, 33)	Option B	Different EV
(34, 75, 23) vs. (69, 7, 58)	Option A	Different EV
(23, 18, 46) vs. (43, 38, 8)	Option A	Different EV
(53, 29, 25) vs. (4, 49, 55)	Option A	Different EV
(70, 50, 2) vs. (30, 20, 71)	Option B	Different EV
(6, 76, 61) vs. (60, 48, 33)	Option B	Consistency check
(99, 23, 35) vs. (9, 73, 75)	Indiff. for $\theta = 1$	Measure $Q$ function
(22, 96, 43) vs. (67, 1, 78)	Indiff. for $\theta = 0.8$	Measure $Q$ function
(27, 32, 83) vs. (69, 78, 8)	Indiff. for $\theta = 1.3$	Measure $Q$ function
(89, 32, 18) vs. (9, 71, 73)	Indiff. for $\theta = 1.6$	Measure $Q$ function
(25, 93, 22) vs. (69, 18, 73)	Indiff. for $\theta = 1.95$	Measure $Q$ function
(79, 75, 15) vs. (35, 32, 73)	Indiff. for $\theta = 2.41$	Measure $Q$ function

Table 17: Questions used in section I of the lab experiment

*Notes:* Payoffs for responses to questions (i.e., subjects' choices) are denominated in euros (€). EV = expected value.

Question choices	Prediction of H1
(0.8, 40;0) vs. 32	B
(0.95, 50;0) vs. 47.5	B
(0.05, 50;0) vs. 2.5	A
(0.3, 40; 0) vs. 12	A
(0.1, 40; 0) vs. 4	A
(0.7, 50; 0) vs. 35	B
(0.15, 40; 0) vs. 6	A
(0.75, 40; 0) vs. 30	B
(0.2, 50; 0) vs. 10	A
(0.85, 50; 0) vs. 42.5	B
(0.9, 40; 0) vs. 36	B
(0.25, 50; 0) vs. 12.5	A
(0.9, 5; 0) vs. 4.5	B
(0.05, 8; 0) vs. 0.4	A
(0.1, 5; 0) vs. 0.5	A
(0.95, 8; 0) vs. 7.6	B
(0.3, 40; 0) vs. (0.8, 15; 0)	A
(0.1, 45; 0) vs. (0.9, 5; 0)	A
(0.1, 40; 0) vs. (0.8, 5; 0)	A
(0.05, 50; 0) vs. (0.85, 3; 0)	A
(0.15, 50; 0) vs. (0.75, 10; 0)	A
(0.2, 40; 0) vs. (0.8, 10; 0)	A
(0.25, 40; 0) vs. (0.8, 12.5; 0)	A

Table 18: Questions used in section II of the lab experiment to identify attitudes toward risk

*Note:* Payoffs for responses to questions (i.e., subjects' choices) are denominated in euros (€).

## References

- P. Anand. Testing regret. *Management Science*, 31(1):114–116, 1985.
- N. Barberis, H. Ming, and R. Thaler. Individual preferences, monetary gambles, and stock market participation: A case for narrow framing. *The American Economic Review*, 96(4):1069–1090, 2006.
- G. Barron and I. Erev. Small feedback-based decisions and their limited correspondence to description-based decisions. *Journal of Behavioral Decision Making*, 16(3):215–233, 2003.
- D. E. Bell. Regret in decision making under uncertainty. *Operations Research*, 30(5):961–981, 1982.
- D. E. Bell. Risk premiums for decision regret. *Management Science*, 29(10):1156–1166, 1983.
- H. Bleichrodt, A. Cillo, and E. Diecidue. A quantitative measurement of regret theory. *Management Science*, 56(1):161–175, 2010.
- H. Bleichrodt and P. P. Wakker. Regret theory: A bold alternative to the alternatives. *The Economic Journal*, 125(583):493–532, 2015.
- M. Cohen and J.-Y. Jaffray. Certainty effect versus probability distortion: An experimental analysis of decision making under risk. *Journal of Experimental Psychology: Human Perception and Performance*, 14(4):554, 1988.
- T. Connolly and D. Butler. Regret in economic and psychological theories of choice. *Journal of Behavioral Decision Making*, 19(2):139–154, 2006.
- T. Connolly and M. Zeelenberg. Regret in decision making. *Current directions in psychological science*, 11(6):212–216, 2002.

- E. Diecidue, N. Rudi, and W. Tang. Dynamic purchase decisions under regret: Price and availability. *Decision Analysis*, 9(1):22–30, 2012.
- E. Diecidue and J. Somasundaram. Regret theory: A new foundation. *Working paper, INSEAD*, 2015.
- R. Engelbrecht-Wiggans and E. Katok. Regret and feedback information in first-price sealed-bid auctions. *Management Science*, 54(4):808–819, 2008.
- I. Erev, E. Ert, O. Plonsky, D. Cohen, and O. Cohen. From anomalies to forecasts: A choice prediction competition for decisions under risk and ambiguity. *Working paper*, 2015.
- E. Filiz-Ozbay and E. Y. Ozbay. Auctions with anticipated regret: Theory and experiment. *The American Economic Review*, pages 1407–1418, 2007.
- C. R. Fox, B. A. Rogers, and A. Tversky. Options traders exhibit subadditive decision weights. *Journal of Risk and Uncertainty*, 13(1):5–17, 1996.
- C. Gollier and B. Salanié. Individual decisions under risk, risk sharing and asset prices with regret. *Working paper*, 2006.
- R. Hertwig, G. Barron, E. U. Weber, and I. Erev. Decisions from experience and the effect of rare events in risky choice. *Psychological Science*, 15(8):534–539, 2004.
- R. A. Josephs, R. P. Larrick, C. M. Steele, and R. E. Nisbett. Protecting the self from the negative consequences of risky decisions. *Journal of personality and social psychology*, 62(1):26, 1992.
- D. Kahneman and A. Tversky. Prospect theory: An analysis of decision under risk. *Econometrica*, pages 263–291, 1979.
- R. P. Larrick. Motivational factors in decision theories: The role of self-protection. *Psychological Bulletin*, 113:440–450, 1993.

- R. P. Larrick and T. L. Boles. Avoiding regret in decisions with feedback: A negotiation example. *Organizational Behavior and Human Decision Processes*, 63(1):87–97, 1995.
- G. Loomes. Modeling choice and valuation in decision experiments. *Psychological review*, 117(3):902, 2010.
- G. Loomes and R. Sugden. Regret theory: An alternative theory of rational choice under uncertainty. *The Economic Journal*, 92(368):805–824, 1982.
- G. Loomes and R. Sugden. Some implications of a more general form of regret theory. *Journal of Economic Theory*, 41(2):270–287, 1987.
- L. L. Lopes and G. C. Oden. The role of aspiration level in risky choice: A comparison of cumulative prospect theory and SP/A theory. *Journal of Mathematical Psychology*, 43(2):286–313, 1999.
- S. Michenaud and B. Solnik. Applying regret theory to investment choices: Currency hedging decisions. *Journal of International Money and Finance*, 27(5):677–694, 2008.
- A. Muermann and J. Volkman Wise. Regret, pride, and the disposition effect. *Working paper*, 2006.
- J. Nasiry and I. Popescu. Advance selling when consumers regret. *Management Science*, 58(6):1160–1177, 2012.
- G. Perakis and G. Roels. Regret in the newsvendor model with partial information. *Operations Research*, 56(1):188–203, 2008.
- J. Qin. A model of regret, investor behavior, and market turbulence. *Journal of Economic Theory*, 160:150–174, 2015.
- J. Quiggin. A theory of anticipated utility. *Journal of Economic Behavior & Organization*, 3(4):323–343, 1982.

- M. Rabin. Risk aversion and expected-utility theory: A calibration theorem. *Econometrica*, 68(5):1281–1292, 2000.
- I. Ritov. Probability of regret: Anticipation of uncertainty resolution in choice. *Organizational Behavior and Human Decision Processes*, 66(2):228–236, 1996.
- I. Ritov and J. Baron. Outcome knowledge, regret, and omission bias. *Organizational Behavior and Human Decision Processes*, 64(2):119–127, 1995.
- C. Starmer. Developments in non-expected utility theory: The hunt for a descriptive theory of choice under risk. *Journal of Economic Literature*, pages 332–382, 2000.
- C. Starmer and R. Sugden. Testing for juxtaposition and event-splitting effects. *Journal of Risk and Uncertainty*, 6(3):235–254, 1993.
- A. Tversky and D. Kahneman. Advances in prospect theory: Cumulative representation of uncertainty. *Journal of Risk and Uncertainty*, 5(4):297–323, 1992.
- A. Tversky and P. Wakker. Risk attitudes and decision weights. *Econometrica*, pages 1255–1280, 1995.
- P. Viefers and P. Strack. Too proud to stop: Regret in dynamic decisions. *Working paper*, 2014.
- J. von Neumann and O. Morgenstern. *Theory of Games and Economic Behavior*. Princeton University Press, 1947.
- P. Wakker. *Prospect Theory for Risk and Ambiguity*. Cambridge University Press, 2010.
- P. Wakker and D. Deneffe. Eliciting von Neumann-Morgenstern utilities when probabilities are distorted or unknown. *Management Science*, 42(8):1131–1150, 1996.
- M. Zeelenberg. Anticipated regret, expected feedback and behavioral decision making. *Journal of Behavioral Decision Making*, 12(2):93–106, 1999.

M. Zeelenberg, J. Beattie, J. Van der Pligt, and N. K. de Vries. Consequences of regret aversion: Effect of expected feedback on risky decision making. *Organizational Behavior and Human Decision Processes*, 65:148–158, 1996.