AUGUST 2022
BxWP2022-12

BORDEAUX ECONOMICS WORKING PAPERS
CAHIERS D'ECONOMIE DE BORDEAUX

Regret aversion and information aversion

Emmanuelle GABILLON
Univ. Bordeaux, CNRS, BSE, UMR 6060, F-33600 Pessac, France

Bordeaux Sciences Economiques
Bordeaux School of Economics

BSE UMR CNRS 6060
Université de Bordeaux
Avenue Léon Duguit, Bât. H
33608 Pessac – France
Tel : +33 (0)5.56.84.25.75
http://bse.u-bordeaux.fr/

Abstract

Regret is a negative and counterfactual emotion that occurs when a decision maker believes her past decision, if changed, would achieve a better outcome. Regret is intrinsically related to the comparison of the chosen alternative outcome with the foregone alternative outcomes. The result of this comparison is influenced by the decision maker's information about the foregone alternative outcomes (feedback structure). In this paper, we use Gabillon (2020)'s model, which generalizes regret theory to any feedback structure. We show that a regretful decision maker exhibits information aversion. The anticipation of learning about the payoffs of the foregone alternatives decreases her expected utility. We use the concept of statistical sufficiency in order to classify the feedback structures according to their informational content. We show that the less informative the feedback structure is, the higher the utility of a regretful decision maker.

Keywords: Regret, Emotion, Information.

JEL: D03, D81, D82.

To cite this paper: **GABILLON Emmanuelle** (2022), Regret aversion and information aversion, Bordeaux Economics Working Papers, BxWP2022-12

https://ideas.repec.org/p/grt/bdxewp/2022-12.html

Regret aversion and information aversion

Emmanuelle Gabillon*

August 12, 2022

Abstract

Regret is a negative and counterfactual emotion that occurs when a decision maker believes her past decision, if changed, would achieve a better outcome. Regret is intrinsically related to the comparison of the chosen alternative outcome with the foregone alternative outcomes. The result of this comparison is influenced by the decision maker's information about the foregone alternative outcomes (feedback structure). In this paper, we use Gabillon (2020)'s model, which generalizes regret theory to any feedback structure. We show that a regretful decision maker exhibits information aversion. The anticipation of learning about the payoffs of the foregone alternatives decreases her expected utility. We use the concept of statistical sufficiency in order to classify the feedback structures according to their informational content. We show that the less informative the feedback structure is, the higher the utility of a regretful decision maker.
JEL classification D03 . D81 . D82

*BSE - UMR CNRS 6060, Bâtiment H, Université de Bordeaux, Avenue Léon Duguit, 33608 Pessac cedex, France. Email: emmanuelle.gabillon@u-bordeaux.fr.

Regret is a counterfactual emotion (Kahneman and Miller 1986), which can occur when a decision maker (DM) compares the result of her choice to what she would have obtained had she made another decision. Regret occurs when the DM concludes that things would have been better under a different choice.

In decision theory, anticipated regret was first considered by Savage (1951) and further explored by Luce & Raiffa (1956). Seminal contributions in regret modeling can be found in Bell (1982, 1983) and Loomes and Sugden (1982, 1987). Axiomatic foundations of preferences are provided by Fishburn (1989), Sugden (1993), Quiggin (1994) and, more recently, by Diecidue and Somasundaram (2017).

A large part of regret theory is established under perfect information, where the payoffs of the foregone alternatives are perfectly observable. Among the exceptions, Bell (1983) considers the choice between a sure thing and a risky lottery and asks whether the choice of the sure thing would not be more attractive if the foregone lottery were unresolved. More recently, Gabillon (2020) proposes a model in which a DM receives signals about the foregone alternative payoffs. This approach allows considering any level of information about the foregone payoffs (feedback structure). The feedback structure (FS) can be perfectly informative when signals perfectly reveal the payoffs of the foregone alternatives, non-informative when signals do not disclose any information, and imperfectly informative when signals partially reveals the payoffs of the foregone alternatives. Gabillon (2020) shows that anticipated regret does depend on anticipated feedback.

In this paper, we use the model of Gabillon (2020) to compare the different FSs according to the preferences of a regretful DM. We show that a regretful DM prefers to be as little informed as possible about the rejected alternative payoffs. Information about the foregone alternative payoffs makes anticipated regret more salient and decreases the DM expected utility. In order to obtain this result, we use Fisher (1920)'s statistical criteria of sufficiency in order to compare the FS informational contents. FS A is said to be more informative than FS B if signals in A are sufficient statistics for signals in B about the foregone alternative payoffs. We show that, if FS A is more informative than FS B, a regretful DM prefers FS B. Moreover, we show that, among all possible FS, a regretful DM always prefers the non-informative FS. Regret aversion leads to aversion to *ex-post* information, information which occurs after the choice. Furthermore, Gabillon (2020) shows that information received before the choice can also be harmful to a regretful DM, even though this information improves the DM's knowledge about the different alternatives among which she has to choose.

On the experimental side, our results about regret and information are consistent with the study of Zeelenberg *et al.* (1996), which shows that people tend to avoid having information about foregone alternatives. The authors performed an experiment where they set up two risky lotteries to which participants are indifferent. Indifference as regards the two lotteries is established when there is no feedback on the foregone lottery. Stated otherwise, people exclusively obtain feedback on the lottery of their choice. One of the two lotteries is relatively risky, the other relatively safe (the probability of winning is higher but the gain is lower). Zeelenberg *et al.* (1996) modify the feedback context and observe the behavioral consequences. When people know that the result of the risky lottery will be systematically revealed, they are no longer indifferent to the two lotteries, tending to prefer the risky one. They abandon the safe lottery because they try to protect themselves against the regret which may arise from having information about the foregone lottery (information about the risky lottery if they choose the safe lottery). Zeelenberg *et al.* (1996) show that regret aversion induces risk-seeking behavior (when people anticipate feedback on the risky lottery), or risk-avoiding behavior (when people anticipate feedback on the safe lottery). These types of behavior, which consist in avoiding information about the foregone lottery, are consistent with our result. Many other experimental studies (Josephs *et al.* 1992; Larrick and Boles 1995; Ritov 1996; Zeelenberg and Beattie 1997; Zeelenberg 1999) also reveal the sensitivity of choices to the feedback context, and demonstrate that people try to protect themselves against information about what they could have obtained by making a different choice.

In regret theory, Bell (1983) introduces the concept of cancellation price, which corresponds to the sure thing which makes a regretful DM indifferent about choosing the sure thing or choosing a risky lottery. Bell (1983) assumes that the foregone lottery is not resolved if the sure thing is selected. In our vocabulary, Bell (1983) defines the cancellation price under a non-informative FS. Gabillon (2020) generalizes Bell (1983)'s cancellation price to a large range of utility functions and refers to the cancellation price as the *regret certainty equivalent*.

In this paper, we generalize the regret certainty equivalent of a risky lottery to any FS. We show that the regret certainty equivalent of a risky lottery increases with the informativeness of the FS. The certainty equivalent is thus maximal when the FS is perfectly informative and minimal when the FS is non-informative. Under a non-informative FS, the choice of the sure thing fully protects the DM against anticipated regret. After the choice, since the lottery payoff is not observable, it cannot be compared to the sure thing and regret cannot be experienced. When, however, some information about the foregone choice is available after the choice, the sure thing no longer offers a full protection against regret and becomes less attractive. Consequently, the regret certainty equivalent of the risky lottery increases with the informativeness of the FS.

The paper is organized as follows. Sections 1 and 2 are dedicated to a short presentation of the model of Gabillon (2020): Section 1 presents the concept of FS and Section 2 presents a generalization of preferences to any FS. Section 3 introduces the concept of statistical sufficiency in regret theory. Section 4 is devoted to information aversion.

1 Feedback Structures

In this section, we briefly recall the concept of FS introduced in Gabillon (2020). Let $\Phi = \{Y_1, .., Y_{N+1}\}$ denote the set of $N+1$ risky alternatives. A risky alternative Y_n is a random variable, which takes its values on a set Ω, which contains a finite number of positive values. A risky alternative Y_n is characterized by a probability distribution on Ω, denoted by its generic term $p(y_n)$.

Without loss of generality, the chosen alternative is denoted by X and the foregone alternatives by $Y_1, .., Y_N$. In order to deal with any FS, we assume that, at the feedback stage (i.e., after the choice), a DM observes not only the chosen alternative's outcome x but also a realization m of a signal M_X about the foregone alternative outcomes $y_1, .., y_N$. Signal M_X is assumed to be a random variable (possibly multidimensional), which takes its values on a set M, which contains a finite number of elements. In order to shorten our notations, the foregone alternative outcomes $y_1, .., y_N$ will be denoted by θ_{-x}. The random variable M_X is a signal on the feedback stage's state of nature $\theta_{\ x}$ and is characterized by a conditional probability distribution on M, denoted by its generic term $p(m|\theta_{\ x}, x)$. This conditional probability distribution depends on the chosen alternative X, but can also differ according to the observed payoff x. Probability $p(m|\theta_{\ x}, x)$ represents the probability of observing signal m given that alternative X has been chosen, given payoff x and given foregone alternative payoffs θ_{-x}.

In what follows, we first introduce the concept of FS at the level of one alternative X and then, we define a FS associated with an entire choice set $\Phi = \{Y_1, .., Y_{N+1}\}$.

Let $FS_X = (X, M_X)$ denote the *alternative X FS*. FS_X contains all available information at the feedback stage, after alternative X has been selected.

Definition 1. *FS_X is said to be non-informative if the probability distribution of M_X is the same for all θ_{-x}: $\forall x \in \Omega, \forall\ \theta_{-x} \in \Omega^N$, $p(m|\theta_{-x}, x) = p(m|x)$. One cannot learn about θ_{-x} by observing from M_X.*

At the other end, FS_X is said to be perfectly informative if for every $x \in \Omega$, for every pair $\left(\theta^i_{-x}, \theta^j_{-x}\right) \in \Omega^N \times \Omega^N$, the intersection of the support sets on which $p\left(m\left|\theta^i_{-x}, x\right.\right)$ and $p\left(m\left|\theta^j_{-x}, x\right.\right)$ are strictly positive is an empty set. After observing M_X, the state of nature θ_{-x} that generated M_X can be identified with certainty.

FS_X is said to be imperfectly informative in all other situations.

We point out that, even when FS_X is non-informative, a DM can learn about $\theta_{\ x}$ by observing x. This happens when X and $Y_1, .., Y_N$ are not statistically independent, a situation that we do not exclude from our analysis.

In the rest of the paper, either $\{Y_1, .., Y_{N+1}\}$ or $\{X, Y_1, .., Y_N\}$ will refer to the choice set Φ depending on whether we need or not to distinguish the chosen alternative X from the other alternatives. Hereafter, we give the definition of a FS associated to a choice set Φ:

Definition 2. *The feedback structure FS, associated to the choice set $\Phi = \{Y_1, .., Y_{N+1}\}$, is the set of all alternative FSs:*

$FS = \left\{FS_{Y_1}, ..., FS_{Y_{N+1}}\right\}$

Definition 3. *A FS is said to be non-informative if FS_{Y_n} is non-informative for every $Y_n \in \Phi$.*

A FS is said to be perfectly informative if FS_{Y_n} is perfectly informative for every $Y_n \in \Phi$.

A FS is said to be imperfectly informative in all other situations.

2 Preferences

We use the preferences developed in Gabillon (2020). The regret utility function (r-utility) $u(x, r)$ depends on the payoff x of the chosen alternative X and on a reference point. The reference point represents the impact of anticipated regret on the DM's utility. When $r > x$, we will see in what follows that a foregone alternative performs better than the chosen alternative, and regret is anticipated[1]. In order to give a definition of the reference point, we need to define the concept of choiceless utility (c-utility):

Definition 4. *The c-utility function is defined as $v(x) = u(x, x)$ and measures the satisfaction generated by the consumption of payoff x, independently of any choice-related feeling.*

In Definition 4, the c-utility function represents preferences in which sensitivity to regret has been removed ($r = x$) and corresponds to the DM's preferences if she were not regret averse. The c-utility $v(x)$ represents the utility of x when the payoff x is evaluated in a no-choice setting. At the feedback stage, we assume that the $N + 1$ alternatives are evaluated with the c-utility function since the choice has already been made and cannot be modified.

Gabillon (2020) makes some assumptions about the r-utility function $u(x, r)$. Let $u_1(x, r)$ denote $\frac{\partial u(x,r)}{\partial x}$, $u_2(x, r)$ denote $\frac{\partial u(x,r)}{\partial r}$ and $v'(x)$ denote $\frac{\partial v(x)}{\partial x}$.

A0. The r-utility $u(x, r)$ is differentiable on $\mathbb{R}^{+2}$.

A1. $v'(x) = u_1(x, x) + u_2(x, x) > 0$.

A2. $u_1(x, r) > 0$.

A3. $u_2(x, r) < 0$.

[1] Gabillon (2020) shows that $r > x$ does not necessarily imply that regret is anticipated. A reference point greater than the chosen action payoff can also mean that the DM experiences a psychological opportunity cost. In this paper, we will, however, do not make the distinction, always referring to anticipated regret when $r > x$. See Gabillon (2020) for a formal distinction between anticipated regret and psychological opportunity cost.

Assumptions $A1$ and $A2$ state that utility increases with payoff x. Assumption $A3$ states that the r-utility decreases with the reference point and characterizes regret aversion. Given payoff x, anticipated regret increases with the reference point and utility decreases.

We assume that a DM has some priors about the foregone alternative payoffs denoted by $p(\theta_{-x})$. At the feedback stage, each foregone alternative Y_n is characterized by a posterior probability distribution $p(\theta_{-x}|x,m)$ after the information has been processed. The posterior probability distribution represents the DM's knowledge about Y_n at the feedback stage. We recall that, at the feedback stage, a DM evaluates the $N+1$ alternatives with the c-utility function. We can compute the posterior certainty equivalent of each alternative Y_n :

$$v\left(CE_{Y_n}^{v,FS_x}\right) = E\left[v(Y_n)|\, FS_x\right], \tag{1}$$

where $FS_x = \{x, m\}$ and where the operator $E[.|\, FS_x]$ represents the conditional expectation, given the realizations of X and M_X. The notation $CE_{Y_n}^{v,FS_x}$ indicates, in superscript, that the certainty equivalent is computed with the c-utility function $v(.)$, given information $FS_x = \{x, m\}$.

The posterior certainty equivalent of the chosen alternative is equal to the realization of the payoff itself.

$$CE_X^{v,x,m} = x. \tag{2}$$

We can now give the definition of a reference point which accommodates any FS.

Definition 5. *The reference point R^{FS_X} is the highest posterior certainty equivalent:*
$R^{FS_X} = Max\left\{X, CE_{Y_1}^{v,FS_X}, .., CE_{Y_N}^{v,FS_X}\right\}$ *where* $FS_X = (X, M_X)$.

The notation R^{FS_X} indicates, in superscript, the variables that a DM observes at the feedback stage. Under assumption $A1$, the reference point is the certainty equivalent of the alternative which maximizes the expected c-utility, given available information at the feedback stage[2]. In the event $R^{FS_X} > X$, the DM regrets her choice since, given her information, a foregone alternative proves to be more attractive than the chosen alternative.

We can rewrite the reference point (see Definition 5) as

$$R^{FS_X} = Max\left\{X, CE_{Max}^{v,FS_X}\right\}, \tag{3}$$

with $CE_{Max}^{v,FS_X} = Max\left\{CE_{Y_1}^{v,FS_X}, ..., CE_{Y_N}^{v,FS_X}\right\}$.

[2] The definition of the reference point implies that R^{FS_X} cannot be lower than X, excluding the feeling of rejoicing, when a DM learns that the chosen alternative turns out to be the best choice.

We obtain the preferences of a regretful DM :

$$E\left[u\left(X, R^{FS_X}\right)\right] = E\left[u\left(X, Max\left\{X, CE_{Max}^{v,FS_X}\right\}\right)\right]. \tag{4}$$

The properties of these preferences are analyzed in Gabillon (2020).

In this paper, we introduce two additional assumptions about the r-utility function:

A4. $u_{22}(x,r) \leq 0$

A5. $v''(x) \leq 0$

Assumptions $A4$ and $A5$ are "concavity assumptions". Concavity does not need to be strict: our results are compatible with $u_{22}(x,r) = 0$ and $v"(x) = 0$. (see Example 1 in the next section).

3 Statistical Sufficiency and Feedback Structures

In this section, we compare the informativeness of different FSs. We begin our analysis at the level of one alternative X, by comparing the informational content of two different *alternative X FSs.* Then, we generalize our comparison to a choice set Φ, by comparing the informational content of two different FS. For this purpose, we use the concept of statistical sufficiency of Fisher (1920).

Consider two different *alternative X FSs,* $FS_X^a = (X, M_X^a)$ and $FS_X^b = \left(X, M_X^b\right)$. Let $p(m_a | \theta_{-x}, x)$ denote the conditional probability of signal M_X^a and $p(m_b | \theta_{-x}, x)$ denote the conditional probability of signal M_X^b.

Definition 6. *FS_X^a is sufficient for FS_X^b about the foregone alternative payoffs if, for every $x \in \Omega$, there exits a stochastic transformation $\pi(m_a | m_b, x)$ such that*

$\forall m_b \in M, \forall \theta_{-x} \in \Omega^N, p(m_b | \theta_{-x}, x) = \sum_{m_a \in M} \pi(m_b | m_a, x)\, p(m_a | \theta_{-x}, x)$

with $\sum_{m_b \in M} \pi(m_b | m_a, x) = 1.$

Definition 6 can be reformulated as follows: FS_X^a is sufficient for FS_X^b if there exists a joint probability distribution $\pi(m_a, m_b | \theta_{-x}, x)$ (possibly different from the real joint probability distribution $p(m_a, m_b | \theta_{-x}, x)$), whose marginal distributions coincide with the true marginal distributions:

$$\sum_{m_b \in M} \pi(m_a, m_b | \theta_{-x}, x) = p(m_a | \theta_{-x}, x) \text{ and } \sum_{m_a \in M} \pi(m_a, m_b | \theta_{-x}, x) = p(m_b | \theta_{-x}, x). \tag{5}$$

and which satisfies

$$\forall\theta_{-x} \in \Omega^N, \pi\left(m_b \left| m_a, \theta_{-x}, x\right.\right) = \pi\left(m_b \left| m_a, x\right.\right). \tag{6}$$

Given distribution $\pi\left(m_a, m_b \left|\theta_{-x}, x\right.\right)$, signal M_X^b is garbled from signal M_X^a in the sense of Blackwell (1951). In other words, we move from signal M_X^a to signal M_X^b by adding noise. A DM who observes M_X^a can generate M_X^b with the stochastic process $\pi\left(m_b \left| m_a, x\right.\right)$, which is independent of θ_{-x}.

In order to compare different FSs with the concept of sufficiency, we introduce the following definition:

Definition 7. *FS^a is sufficient for FS^b if, for at least one $Y_n \in \Phi$, $FS^a_{Y_n}$ is sufficient for $FS^b_{Y_n}$, other alternative FSs being identical.*

Let FS^{ni} denote a non-informative FS and FS^i a perfectly informative FS. We obtain the following proposition:

Proposition 1. *Any FS is sufficient for FS^{ni}.*
FS^i is sufficient for any FS.

Proof. See Appendix A. □

4 Information Aversion

In this Section, we show that a regretful DM exhibits feedback aversion or *ex-post* information aversion. *Ex-post* information refers to information about the foregone alternative payoffs, which arises after the choice has been made. In order to go further, we introduce the following definition:

Definition 8. *A regretful DM prefers FS^b to FS^a if her expected utility under FS^b is higher than under FS^a:*

$$\underset{Y_n\in\Phi}{Max} E\left[u\left(Y_n, Max\left(Y, CE_{Max}^{v,FS^b_{Y_n}}\right)\right)\right] \geq \underset{Y_n\in\Phi}{Max} E\left[u\left(Y_n, Max\left(Y_n, CE_{Max}^{v,FS^a_{Y_n}}\right)\right)\right].$$

We obtain the following Proposition, which characterizes information aversion:

Proposition 2. *If FS^a is sufficient for FS^b then a regretful DM prefers FS^b to FS^a.*

Proof. See Appendix B. □

Appendix B shows that the expected utility of each alternative Y_n is higher under FS^b. According to Proposition 2, a DM prefers to minimize her exposure to *ex-post* information in order to protect herself against future regret. Concavity assumptions $A4$ and $A5$, which include the case $u_{22}(x,r) = 0$ and $v"(x) = 0$, are sufficient conditions for *ex-post* information aversion[3].

[3] In an alternative setting, in which the reference point is defined as $R^{FS_X} = Max\left\{v(X), v\left(CE_{Y_1}^{v,FS_X}\right), .., v\left(CE_{Y_N}^{v,FS_X}\right)\right\}$,, assumption $A4$ alone leads to information aversion. There is no need to formulate assumption $A5$.

To give an intuition about information aversion, let us consider the following property, which is demonstrated when FS^a is sufficient for FS^b(see Equation B.15 in Appendix B):

$$\forall X \in \Phi, \forall Y_n \in \Phi / \{X\}, \forall x \in \Omega, \forall m_b \in M, v\left(CE_{Y_n}^{v,FS_x^b}\right) = \sum_{m_a \in M} k_{m_b m_a}^x v\left(CE_{Y_n}^{v,FS_x^a}\right), \tag{7}$$

with $\sum_{m_a \in M} k_{m_b m_a}^x = 1$.

Under FS^b, at the feedback stage, the expected c-utility derived from a foregone alternative Y_n is a convex combination of the expected c-utilities of Y_n under FS^a. In other words, expected c-utilities under FS^b are mean preserving contractions of expected c-utilities under FS^a.

To give an intuition about the information aversion result, let us consider a particular case where $v(x)$ is linear. Equation 7 becomes

$$\forall X \in \Phi, \forall Y_n \in \Phi / \{X\}, \forall x \in \Omega, \forall m_b \in M, CE_{Y_n}^{v,FS_x^b} = \sum_{m_a \in M} k_{m_b m_a}^x CE_{Y_n}^{v,FS_x^a}, \tag{8}$$

Given the chosen alternative payoff x, the reference point $R^{FS_x} = Max\left\{x, CE_{Y_1}^{v,FS_x}, .., CE_{Y_N}^{v,FS_x}\right\}$ is a convex function and the r-utility, which decreases with the reference point, is concave. Mean preserving contraction and concavity explain the information aversion result. This property of concavity is not related to the shape of the r-utility function. Information aversion exists as soon as the r-utility does not exhibit too much convexity, which could then counteract the concavity property. The same goes for the c-utility function. In particular, information aversion is compatible with $u_{22}(x,r) = 0$ and $v"(x) = 0$.

Example 1. *The r-utility function is $u(x,r) = x - \frac{r}{2}$ and the c-utility function is $v(x) = u(x,x) = \frac{x}{2}$. We consider a choice set $\Phi = \{Y_1, Y_2\}$, containing two statistically independent alternatives. Each alternative takes its values on the set $\Omega = \{6, 8, 16, 18\}$. Alternative Y_1 is characterized by the probability distribution $\left(\frac{1}{2}, 0, \frac{1}{2}, 0\right)$ and alternative Y_2 by the probability distribution $\left(0, \frac{3}{4}, 0, \frac{1}{4}\right)$. Signals M_{Y_1} (signal on Y_2 when Y_1 is chosen) and M_{Y_2} (signal on Y_1 when Y_2 is chosen) take values on $M = \{0, 1\}$.*

We assume that FS^a is perfectly informative. Signals $M_{Y_1}^a$ and $M_{Y_2}^a$ are characterized by the following conditional probability distributions :

Signal $M_{Y_1}^a$	$y_2 = 8$	$y_2 = 18$
$m_a = 0$	$p(m_a = 0 \mid y_2 = 8) = 1$	$p(m_a = 0 \mid y_2 = 18) = 0$
$m_a = 1$	$p(m_a = 1 \mid y_2 = 8) = 0$	$p(m_a = 1 \mid y_2 = 18) = 1$

and

Signal $M_{Y_2}^a$	$y_1 = 6$	$y_1 = 16$
$m_a = 0$	$p(m_a = 0 \mid y_1 = 6) = 1$	$p(m_a = 0 \mid y_1 = 16) = 0$
$m_a = 1$	$p(m_a = 1 \mid y_1 = 6) = 0$	$p(m_a = 1 \mid y_1 = 16) = 1$

Under FS^b, signal probability distributions are the following:

Signal $M_{Y_1}^b$	$y_2 = 8$	$y_2 = 18$
$m_b = 0$	$p(m_b = 0 \mid y_2 = 8) = \frac{3}{4}$	$p(m_b = 0 \mid y_2 = 18) = \frac{1}{4}$
$m_b = 1$	$p(m_b = 1 \mid y_2 = 8) = \frac{1}{4}$	$p(m_b = 1 \mid y_2 = 18) = \frac{3}{4}$

and

Signal $M_{Y_2}^b$	$y_1 = 6$	$y_1 = 16$
$m_b = 0$	$p(m_b = 0 \mid y_1 = 6) = \frac{3}{4}$	$p(m_b = 0 \mid y_1 = 16) = \frac{1}{4}$
$m_b = 1$	$p(m_b = 1 \mid y_1 = 6) = \frac{1}{4}$	$p(m_b = 1 \mid y_1 = 16) = \frac{3}{4}$

First, we note that FS^a is sufficient for FS^b:

$$\forall m_b \in M = \{0,1\}, \forall \theta_{-x} \in \{6,16\} \text{ or } \{8,18\}, p(m_b \mid \theta_{-x}) = \sum_{m_a \in M} \pi(m_b \mid m_a)\, p(m_a \mid \theta_{-x}), \tag{9}$$

with

$\pi(m_b \mid m_a)$	$m_a = 0$	$m_a = 1$
$m_b = 0$	$\frac{3}{4}$	$\frac{1}{4}$
$m_b = 1$	$\frac{1}{4}$	$\frac{3}{4}$

and $\sum_{m_b \in M} \pi(m_b \mid m_a, x) = 1.$

Annexe C shows that the expected r-utilities of both alternatives are higher under FS^b.

From propositions 1 and 2, we obtain the following corollary, which also characterizes information aversion :

Corollary 1. *A regretful DM prefers a non-informative FS to any other FS. On the other hand, the perfectly informative FS is the worst FS for a regretful DM.*

While Proposition 2 is restricted to the comparison of FSs that can be ordered with the criteria of sufficiency, we stress the generality of Corollary 1. Among all FSs (without any restrictions), a regretful DM prefers the non-informative FS. Similarly, among all FS, the perfectly informative FS represents the least desirable FS.

In what follows, we generalize to any FS the definition of the regret certainty equivalent, which was developed under a non informative FS in Gabillon (2020) and first introduced by Bell (1983) under the name of cancellation price.

Definition 9. *The regret certainty equivalent $CE_Y^{u,FS}$ of a risky alternative Y corresponds to the sure payoff which makes the DM indifferent about choosing $CE_Y^{u,FS}$ or Y.*

The regret certainty equivalent $CE_Y^{u,FS}$ is the Z-solution of the following Equation:

$$E\left[u\left(Z, Max\left(Z, CE_Y^{v,FS_Z}\right)\right)\right] = E\left[u\left(Y, Max\left(Y, Z\right)\right)\right], \tag{10}$$

where $FS_Z = \{Z, M_Z\}$ contains a signal M_Z about lottery Y.

When a DM chooses Y, she observes the result of her choice (the result of the risky lottery Y) and she knows the result of the foregone choice (the value of the sure payoff). When she chooses the sure payoff, she obviously knows the result of her choice and she receives a signal M_Z on the result of the foregone risky alternative Y. In this setting, the informativeness of M_Z determines the level of informativeness of the FS.

Let $CE_Y^{u,ni}$ denote the regret certainty equivalent of Y under a non-informative FS (M_Z conveys no information). Gabillon (2020) shows that , $\underline{y} < CE_Y^{u,ni} < CE_Y^v$, where $\underline{y}$ denotes the minimum value that Y can take on its support Ω and CE_Y^v denotes the Arrow-Pratt certainty equivalent of Y, computed with the c-utility function[4]. Gabillon (2020) shows that, under a non-informative FS, the regret certainty equivalent is lower than the Arrow-Pratt certainty equivalent.This result is independent of the shape of the r-utility function. Under a non-informative FS, for a DM who chooses between a sure payoff and a risky lottery, the sure payoff is more attractive when anticipated regret is taken into account in decision-making. The sure payoff offers a protection against anticipated regret. When the sure payoff is chosen under a non-informative FS, the DM does not learn the result of the foregone risky alternative after her choice and regret cannot be felt. On the contrary, when she chooses the risky alternative Y, she can compare the obtained payoff to the sure payoff. The difference $\Pi_Y = CE_Y^v - CE_Y^u$ is a generalization to a large range of utility function $u(x, r)$ (satisfying $A0$ to $A3$) of the regret premium introduced by Bell (1983). Gabillon (2020) show that the regret premium is always positive when rejoicing is not taken into account. The author also proposes a new interpretation of the regret premium, as the maximum psychological opportunity cost a DM is willing to endure to avoid regret[5].

Proposition 3. *Whatever the FS, the regret certainty equivalent $CE_Y^{u,FS}$ exists and is unique.*

Proof. See Appendix D. □

Proposition 4. *If FS^a is sufficient for a FS^b then for any risky alternative Y, we have $CE_Y^{u,FS^b} \leq CE_Y^{u,FS^a}$.*

Proof. See Appendix D. □

When the FS becomes more informative, choosing the sure payoff offers less protection against feedback and anticipated regret. The attractiveness of the sure thing decreases with the informativeness of the FS. In order to remain as attractive as the lottery, the certainty equivalent must increase as the informativeness of the FS intensifies.

[4] Under a non-informative FS, the Arrow-Pratt certainty equivalent satisfies $v\left(CE_Y^v\right) = E\left[v\left(Y\right)\right]$.

[5] A psychological opportunity cost is defined as the negative emotional counterpart of a strategy of regret avoidance.

If CE_Y^{u,FS^i} denote the regret certainty equivalent under FS^i and $CE_Y^{u,FS^{ni}}$ the regret certainty equivalent under FS^{ni}, propositions 1 and 4 give :

Corollary 2. *For any FS and for any riky alternative* Y*, we have* $CE_Y^{u,FS^{ni}} \leq CE_Y^{u,FS} \leq CE_Y^{u,FS^i}$.

5 Conclusion

In this paper, we show that perfect feedback corresponds to the most unfavorable informational background for a regretful DM. It is under perfect feedback that anticipated regret is the most harmful to the decision maker. In Gabillon (2020), the singularity of perfect feedback is also highlighted as the author shows that *statewise stochastic dominance,* an apparently natural property of preferences, is satisfied under perfect feedback, but cannot be generalized to any other FS. Gabillon (2020) also shows that perfect feedback represents the unique FS under which the author's concept of psychological opportunity cost[6] is irrelevant. Given the particularity of its implications, we believe that the assumption of perfect feedback should be used with caution when drawing general conclusions about decision-making under regret aversion.

Appendix *A*

Let FS be any feedback structure and let $p\left(m\,|\theta_{-x},x\right)$ denote the conditional probability of signal M_X under FS. Let $p\left(m_{ni}\,|\theta_{-x},x\right)$ denote the conditional probability of signal M_X^{ni} under FS^{ni}.

FS^{ni} is non-informative if

$$\forall X \in \Phi, \forall x \in \Omega, \forall m_{ni} \in M, \forall \theta_{-x} \in \Omega^N, p\left(m_{ni}\,|\theta_{-x},x\right) = p\left(m_{ni}\,|x\right). \quad \text{(A.1)}$$

We notice that

$$p\left(m_{ni}\,|\theta_{-x},x\right) = \sum_{m \in M} p\left(m_{ni}\,|x\right) p\left(m\,|\theta_{-x},x\right), \quad \text{(A.2)}$$

with $\sum\limits_{m_{ni} \in M} p\left(m_{ni}\,|x\right) = 1$.

Taking $\pi\left(m_{ni}\,|m,x\right) = p\left(m_{ni}\,|x\right)$, we can conclude that $\forall X \in \Phi, FS_X$ is sufficient for FS_X^{ni} about the foregone alternative payoffs. Since M_X^{ni} is non-informative, the conditional probability $\pi\left(m_{ni}\,|m,x\right)$ does not depend on m. This ends the proof of the first part of Proposition 1.

Let $p\left(m_i\,|\theta_{-x},x\right)$ denote the conditional probability of signal M_X^i under FS^i.

[6] A negative emotional counterpart of a strategy of regret avoidance.

FS^i is perfectly informative if $\forall X \in \Phi, \forall x \in \Omega$, for each $\theta_{-x} \in \Omega^N$, there exist a subset $F_{\theta_{-x}} \sqsubset M$ such that

$$\forall m_i \in F_{\theta_{-x}}, p\left(m_i \left|\theta_{-x}, x\right.\right) > 0 \text{ and } \sum_{F_{\theta_{-x}}} p\left(m_i \left|\theta_{-x}, x\right.\right) = 1. \tag{A.7}$$

Observing M_X^i is equivalent to observing θ_{-x} and thus $p\left(m \left|m_i, \theta_{-x}, x\right.\right) = p\left(m \left|m_i, x\right.\right)$. A DM who observes the value m_i taken by signal M_X^i knows the state of nature $\theta_{-x}\left(m_i\right)$ and can generate signal M_X with the stochastic process $p\left(m \left|\theta_{-x}\left(m_i\right), x\right.\right)$ and obtain a result equivalent to the result of observing both M_X^i and M_X. Observing M_X^i is sufficient.

We have

$$p\left(m \left|\theta_{-x}, x\right.\right) = \sum_{m_i \in M} p\left(m \left|m_i, \theta_{-x}, x\right.\right) p\left(m_i \left|\theta_{-x}, x\right.\right) = \sum_{m_i \in M} p\left(m \left|m_i, x\right.\right) p\left(m_i \left|\theta_{-x}, x\right.\right) \tag{A.8}$$

This ends the proof of the second part of Proposition 1.

Appendix B

Let $p\left(\theta_{\ x} \left|x\right.\right)$ the posterior probability of θ_{-x} given the observation of the chosen alternative payoff. Definition 6 gives:

$$\begin{aligned} \forall x \quad &\in \quad \Omega, \forall m_b \in M, \forall \theta_{-x} \in \Omega^N, p\left(m_b \left|\theta_{-x}, x\right.\right) p\left(\theta_{-x} \left|x\right.\right) \\ &= \sum_{m_a \in M} \pi\left(m_b \left|m_a, x\right.\right) p\left(m_a \left|\theta_{-x}, x\right.\right) p\left(\theta_{-x} \left|x\right.\right), \end{aligned} \tag{B.1}$$

with $\sum_{m_b \in M} \pi\left(m_b \left|m_a, x\right.\right) = 1$.

By summing over θ_{-x}, we have

$$\begin{aligned} \forall x \quad &\in \quad \Omega, \forall m_b \in M, \sum_{\theta_{-x} \in \Omega^N} p\left(m_b \left|\theta_{-x}, x\right.\right) p\left(\theta_{-x} \left|x\right.\right) \\ &= \sum_{\theta_{-x} \in \Omega^N} \sum_{m_a \in M} \pi\left(m_b \left|m_a, x\right.\right) p\left(m_a \left|\theta_{-x}, x\right.\right) p\left(\theta_{-x} \left|x\right.\right), \end{aligned} \tag{B.2}$$

with $\sum_{m_b \in M} \pi\left(m_b \left|m_a, x\right.\right) = 1$.

Which gives

$$\forall x \in \Omega, \forall m_b \in M,\ p\left(m_b \left|x\right.\right) = \sum_{m_a \in M} \pi\left(m_b \left|m_a, x\right.\right) p\left(m_a \left|x\right.\right), \tag{B.3}$$

with $\sum_{m_b \in M} \pi(m_b | m_a, x) = 1$.

Besides, Equation (B.1) can be rewritten as follows:

$$\forall x \in \Omega, \forall m_b \in M, \forall \theta_{-x} \in \Omega^N, p(m_b, \theta_{-x} | x) = \sum_{m_a \in M} \pi(m_b | m_a, x) p(m_a, \theta_{-x} | x), \tag{B.4}$$

with $\sum_{m_b \in M} \pi(m_b | m_a, x) = 1$.

Or else

$$\begin{aligned} \forall x &\in \Omega, \forall m_b \in M, \forall \theta_{-x} \in \Omega^N, p(\theta_{-x} | m_b, x) p(m_b | x) \\ &= \sum_{m_a \in M} \pi(m_b | m_a, x) p(\theta_{-x} | m_a, x) p(m_a | x). \end{aligned} \tag{B.5}$$

with $\sum_{m_b \in M} \pi(m_b | m_a, x) = 1$.

We obtain

$$\begin{aligned} \forall x &\in \Omega, \forall m_b \in M, \forall \theta_{-x} \in \Omega^N, p(\theta_{-x} | m_b, x) \\ &= \sum_{m_a \in M} \frac{\pi(m_b | m_a, x) p(m_a | x)}{p(m_b | x)} p(\theta_{-x} | m_a, x). \end{aligned} \tag{B.6}$$

with $\sum_{m_b \in M} \pi(m_b | m_a, x) = 1$.

Let us introduce a new variable:

$$k^x_{m_b m_a} = \frac{\pi(m_b | m_a, x) p(m_a | x)}{p(m_b | x)} \tag{B.7}$$

Equation (B.3) implies that

$$\sum_{m_a \in M} k^x_{m_b m_a} = \frac{\sum_{m_a \in M} \pi(m_b | m_a, x) p(m_a | x)}{p(m_b | x)} = \frac{p(m_b | x)}{p(m_b | x)} = 1. \tag{B.8}$$

Equations (B.6), (B.7) and (B.8) give

$$\forall x \in \Omega, \forall m_b \in M, \forall \theta_{-x} \in \Omega^N, p(\theta_{-x} | m_b, x) = \sum_{m_a \in M} k^x_{m_b m_a} p(\theta_{-x} | m_a, x), \tag{B.9}$$

with $\sum_{m_a \in M} k^x_{m_b m_a} = 1$.

Given that $\theta_{-x} = \{y_1, ..., y_N\}$, it is easy to obtain from Equation (B.9) that

$$\forall x \in \Omega, \forall m_b \in M, \forall Y_n \in \Phi / \{X\}, \forall y_n \in \Omega, p(y_n | m_b, x) = \sum_{m_a \in M} k^x_{m_b m_a} p(y_n | m_a, x), \tag{B10}$$

with $\sum_{m_a \in M} k^x_{m_b m_a} = 1$.

Besides (see Equation 1), we recall that $\forall Y_n \in \Phi / \{X\}$

$$\forall x \in \Omega, \forall m_b \in M, v\left(CE^{v, FS^b_x}_{Y_n}\right) = E\left[v(y_n) | FS^b_x \right], \tag{B.11}$$

where $FS^b_x = \{x, m_b\}$.
Or, equivalently

$$\forall x \in \Omega, \forall m_b \in M, v\left(CE^{v,x,m_b}_{Y_n}\right) = \sum_{y_n \in \Omega} v(y_n) p(y_n | m_b, x). \tag{B.12}$$

From Equation (B10) and Equation (B.12), we obtain

$$\forall x \in \Omega, \forall m_b \in M, v\left(CE^{v,x,m_b}_{Y_n}\right) = \sum_{y_n \in \Omega} v(y_n) \sum_{m_a \in M} k^x_{m_b m_a} p(y_n | m_a, x). \tag{B.13}$$

Or, equivalently

$$\forall x \in \Omega, \forall m_b \in M, v\left(CE^{v,x,m_b}_{Y_n}\right) = \sum_{m_a \in M} k^x_{m_b m_a} \sum_{y_n \in \Omega} v(y_n) p(y_n | m_a, x). \tag{B.14}$$

We obtain the following relationship between $CE^{v,x,m_a}_{Y_n}$ and $CE^{v,x,m_b}_{Y_n}$:

$$\forall X \in \Phi, \forall Y_n \in \Phi / \{X\}, \forall x \in \Omega, \forall m_b \in M, v\left(CE^{v,x,m_b}_{Y_n}\right) = \sum_{m_a \in M} k^x_{m_b m_a} v\left(CE^{v,x,m_a}_{Y_n}\right), \tag{B.15}$$

with $\sum_{m_a \in M} k^x_{m_b m_a} = 1$.

We thus have

$$\forall X \in \Phi, \forall Y_n \in \Phi / \{X\}, \forall x \in \Omega, \forall m_b \in M, v\left(CE_{Y_n}^{v,x,m_b}\right) \leq \sum_{m_a \in M} k_{m_b m_a}^{x} v\left(CE_{Max}^{v,x,m_a}\right), \tag{B.16}$$

with $CE_{Max}^{v,x,m_a} = Max\left\{CE_{Y_1}^{v,x,m_a}, ..., CE_{Y_N}^{v,x,m_a}\right\}$.

And thus, we also have

$$\forall X \in \Phi, \forall x \in \Omega, \forall m_b \in M, v\left(CE_{Max}^{v,x,m_b}\right) \leq \sum_{m_a \in M} k_{m_b m_a}^{x} v\left(CE_{Max}^{v,x,m_a}\right), \tag{B.17}$$

with $CE_{Max}^{v,x,m_b} = Max\left\{CE_{Y_1}^{v,x,m_b}, ..., CE_{Y_N}^{v,x,m_b}\right\}$.

Under assumption $A5$, equations (B.8) and (B.17) imply

$$\forall X \in \Phi, \forall x \in \Omega, \forall m_b \in M, v\left(CE_{Max}^{v,x,m_b}\right) \leq v\left(\sum_{m_a \in M} k_{m_b m_a}^{x} CE_{Max}^{v,x,m_a}\right). \tag{B.18}$$

Which implies, under $A1$,

$$\forall X \in \Phi, \forall x \in \Omega, \forall m_b \in M, CE_{Max}^{v,x,m_b} \leq \sum_{m_a \in M} k_{m_b m_a}^{x} CE_{Max}^{v,x,m_a}. \tag{B.19}$$

Which implies, under $A3$,

$$\forall X \in \Phi, \forall x \in \Omega, \forall m_b \in M, u\left(x, Max\left(x, \sum_{m_a \in M} k_{m_b m_a}^{x} CE_{Max}^{v,x,m_a}\right)\right) \leq u\left(x, Max\left(x, CE_{Max}^{v,x,m_b}\right)\right). \tag{B.20}$$

Moreover, since the Max function is convex, we have

$$Max\left(\sum_{m_a \in M} k_{m_b m_a}^{x} x, \sum_{m_a \in M} k_{m_b m_a}^{x} CE_{Max}^{v,x,m_a}\right) \leq \sum_{m_a \in M} k_{m_b m_a}^{x} Max\left(x, CE_{Max}^{v,x,m_a}\right). \tag{B.21}$$

Given equations (B.20) and (B.21), we obtain, under $A3$,

$$\forall X \in \Phi, \forall x \in \Omega, \forall m_b \in M, u\left(x, \sum_{m_a \in M} k_{m_b m_a}^{x} Max\left(x, CE_{Max}^{v,x,m_a}\right)\right) \leq u\left(x, Max\left(x, CE_{Max}^{v,x,m_b}\right)\right). \tag{B.22}$$

Which implies, under $A4$,

$$\forall X \in \Phi, \forall x \in \Omega, \forall m_b \in M, \sum_{m_a \in M} k^x_{m_b m_a} u\left(x, Max\left(x, CE^{v,x,m_a}_{Max}\right)\right) \leq u\left(x, Max\left(x, CE^{v,x,m_b}_{Max}\right)\right). \tag{B.23}$$

Equations (B.7) and (B.23) give

$\forall X \in \Phi, \forall x \in \Omega, \forall m_b \in M,$

$$\sum_{m_a \in M} \pi\left(m_b \left| m_a, x\right.\right) p\left(m_a \left| x\right.\right) u\left(x, Max\left(x, CE^{v,x,m_a}_{Max}\right)\right) \leq p\left(m_b \left| x\right.\right) u\left(x, Max\left(x, CE^{v,x,m_b}_{Max}\right)\right). \tag{B.24}$$

Which implies that

$\forall X \in \Phi, \forall x \in \Omega,$

$$\sum_{m_b \in M} \sum_{m_a \in M} \pi\left(m_b \left| m_a, x\right.\right) p\left(m_a \left| x\right.\right) u\left(x, Max\left(x, CE^{v,x,m_a}_{Max}\right)\right) \leq \sum_{m_b \in M} p\left(m_b \left| x\right.\right) u\left(x, Max\left(x, CE^{v,x,m_b}_{Max}\right)\right). \tag{B.25}$$

Or, equivalently

$\forall X \in \Phi, \forall x \in \Omega,$

$$\sum_{m_a \in M} p\left(m_a \left| x\right.\right) u\left(x, Max\left(x, CE^{v,x,m_a}_{Max}\right)\right) \sum_{m_b \in M} \pi\left(m_b \left| m_a, x\right.\right) \leq \sum_{m_b \in M} p\left(m_b \left| x\right.\right) u\left(x, Max\left(x, CE^{v,x,m_b}_{Max}\right)\right). \tag{B.26}$$

Given that $\sum_{m_b \in M} \pi\left(m_b \left| m_a, x\right.\right) = 1$, we obtain

$\forall X \in \Phi, \forall x \in \Omega,$

$$\sum_{m_a \in M} p\left(m_a \left| x\right.\right) u\left(x, Max\left(x, CE^{v,x,m_a}_{Max}\right)\right) \leq \sum_{m_b \in M} p\left(m_b \left| x\right.\right) u\left(x, Max\left(x, CE^{v,x,m_b}_{Max}\right)\right). \tag{B.27}$$

We thus have

$\forall X \in \Phi,$

$$\sum_{x \in \Omega} p\left(x\right) \sum_{m_a \in M} p\left(m_a \left| x\right.\right) u\left(x, Max\left(x, CE^{v,x,m_a}_{Max}\right)\right) \leq \sum_{x \in \Omega} p\left(x\right) \sum_{m_b \in M} p\left(m_b \left| x\right.\right) u\left(x, Max\left(x, CE^{v,x,m_b}_{Max}\right)\right). \tag{B.28}$$

Which allows us to conclude that

$$\forall X \in \Phi, E\left[u\left(X, Max\left(X, CE_{Max}^{v,FS_X^a}\right)\right)\right] \leq E\left[u\left(X, Max\left(X, CE_{Max}^{v,FS_X^b}\right)\right)\right]. \quad \text{(B.29)}$$

And thus

$$\underset{Y_n \in \Phi}{Max} E\left[u\left(Y_n, Max\left(Y_n, CE_{Max}^{v,FS_{Y_n}^a}\right)\right)\right] \leq \underset{Y_n \in \Phi}{Max} E\left[u\left(Y_n, Max\left(Y, CE_{Max}^{v,FS_{Y_n}^b}\right)\right)\right] \quad \text{(B.30)}$$

Appendix *C*

We compute the certainty equivalents of Y_1 and Y_2 under FS^a (see equations 1 and 2) :

	Y_1	Y_2
When Y_1 is chosen, given $m_a = 0$	$CE_{Y_1}^{v,y_1,m_a=0} = y_1$	$CE_{Y_2}^{v,y_1,m_a=0} = 8$
When Y_1 is chosen, given $m_a = 1$	$CE_{Y_1}^{v,y_1,m_a=1} = y_1$	$CE_{Y_2}^{v,y_1,m_a=1} = 18$
When Y_2 is chosen, given $m_a = 0$	$CE_{Y_1}^{v,y_1,m_a=0} = 6$	$CE_{Y_2}^{v,y_2,m_a=0} = y_2$
When Y_2 is chosen, given $m_a = 1$	$CE_{Y_1}^{v,y_1,m_a=1} = 16$	$CE_{Y_2}^{v,y_2,m_a=1} = y_2$

Easy computations give the probability distribution of $M_{Y_1}^a$ ($p(m_a = 0) = \frac{3}{4}$ and $p(m_a = 1) = \frac{1}{4}$) and the probability distribution of $M_{Y_2}^a$ ($p(m_a = 0) = \frac{1}{2}$ and $p(m_a = 1) = \frac{1}{2}$). We use these probability distributions and the certainty equivalents of Y_1 and Y_2 to compute the expected r-utilities (see Equation 4):

$$\begin{aligned}
E\left[u\left(Y_1, R^{FS_{Y_1}^a}\right)\right] &= E\left[u\left(Y_1, Max\left\{Y_1, CE_{Y_2}^{v,y_1,m_a}\right\}\right)\right] \\
&= \frac{1}{2}\left[\frac{3}{4}u\left(6, \underbrace{Max\{6,8\}}_{\text{regret}}\right) + \frac{1}{4}u\left(6, \underbrace{Max\{6,18\}}_{\text{regret}}\right)\right] \\
&\quad + \frac{1}{2}\left[\frac{3}{4}u(16, Max\{16,8\}) + \frac{1}{4}u\left(16, \underbrace{Max\{16,18\}}_{\text{regret}}\right)\right] \\
&= \frac{17}{4} = 4,25.
\end{aligned}$$

$$
\begin{aligned}
E\left[u\left(Y_2, R^{FS^a_{Y_2}}\right)\right] &= E\left[u\left(Y_2, Max\left\{Y_2, CE^{v,y_2,m_a}_{Y_1}\right\}\right)\right] \\
&= \frac{3}{4}\left[\frac{1}{2}u\left(8, Max\left\{8,6\right\}\right) + \frac{1}{2}u\left(8, \underbrace{Max\left\{8,16\right\}}_{\text{regret}}\right)\right] \\
&\quad + \frac{1}{4}\left[\frac{1}{2}u\left(18, Max\left\{18,6\right\}\right) + \frac{1}{2}u\left(18, Max\left\{18,16\right\}\right)\right] \\
&= \frac{15}{4} = 3,75.
\end{aligned}
$$

We also compute the certainty equivalents of Y_1 and Y_2 under FS^b(see equations 1 and 2) :

	Y_1	Y_2
When Y_1 is chosen, given $m_b = 0$	$CE^{v,y_1,m_b=0}_{Y_1} = y_1$	$CE^{v,y_1,m_b=0}_{Y_2} = 9$
When Y_1 is chosen, given $m_b = 1$	$CE^{v,y_1,m_b=1}_{Y_1} = y_1$	$CE^{v,y_1,m_b=1}_{Y_2} = 13$
When Y_2 is chosen, given $m_b = 0$	$CE^{v,y_1,m_b=0}_{Y_1} = \frac{17}{2}$	$CE^{v,y_2,m_b=0}_{Y_2} = y_2$
When Y_2 is chosen, given $m_b = 1$	$CE^{v,y_1,m_b=1}_{Y_1} = \frac{27}{2}$	$CE^{v,y_2,m_b=1}_{Y_2} = y_2$

Easy computations give the probability distribution of $M^b_{Y_1}$ ($p\left(m_b = 0\right) = \frac{10}{16}$ and $p\left(m_b = 1\right) = \frac{6}{16}$) and the probability distribution of $M^b_{Y_2}$ ($p\left(m_b = 0\right) = \frac{1}{2}$ and $p\left(m_b = 1\right) = \frac{1}{2}$). We compute the expected r-utilities under FS^b:

$$
\begin{aligned}
E\left[u\left(Y_1, R^{FS^b_{Y_1}}\right)\right] &= E\left[u\left(Y_1, Max\left\{Y_1, CE^{v,y_1,m_b}_{Y_2}\right\}\right)\right] \\
&= \frac{1}{2}\left[\frac{10}{16}u\left(6, \underbrace{Max\left\{6,9\right\}}_{\text{regret}}\right) + \frac{6}{16}u\left(6, \underbrace{Max\left\{6,13\right\}}_{\text{regret}}\right)\right] \\
&\quad + \frac{1}{2}\left[\frac{10}{16}u\left(16, Max\left\{16,9\right\}\right) + \frac{6}{16}u\left(16, Max\left\{16,13\right\}\right)\right] \\
&= \frac{35}{8} = 4,375.
\end{aligned}
$$

$$
\begin{aligned}
E\left[u\left(Y_2, R^{FS^b_{Y_2}}\right)\right] &= E\left[u\left(Y_2, Max\left\{Y_2, CE^{v,y_2,m_b}_{Y_1}\right\}\right)\right] \\
&= \frac{3}{4}\left[\frac{1}{2}u\left(8, \underbrace{Max\left\{8, \frac{17}{2}\right\}}_{\text{regret}}\right) + \frac{1}{2}u\left(8, \underbrace{Max\left\{8, \frac{27}{2}\right\}}_{\text{regret}}\right)\right] \\
&\quad + \frac{1}{4}\left[\frac{1}{2}u\left(18, Max\left\{18, \frac{17}{2}\right\}\right) + \frac{1}{2}u\left(18, Max\left\{18, \frac{27}{2}\right\}\right)\right] \\
&= \frac{33}{8} = 4,125.
\end{aligned}
$$

Expected r-utilities are higher under FS^bthan under FS^a.

Appendix D

Proof of Proposition 3 :

First, let us show that the solution of Equation 10 exists and is unique. In order to do that, let $\underline{y}$ and $\overline{y}$ respectively denote the minimum value and the maximum value of Y.

If $Z = \underline{y}$ then the left-hand side of Equation 10 is

$$E\left[u\left(Z, Max\left(Z, CE^{v,FS_Z}_{Y}\right)\right)\right] = E\left[u\left(\underline{y}, Max\left(\underline{y}, CE^{v,FS_Z}_{Y}\right)\right)\right]. \tag{D.1}$$

The right-hand side is

$$E\left[u\left(Y, Max\left(Y, Z\right)\right)\right] = E\left[u\left(Y, Y\right)\right] = E\left[v\left(y\right)\right]. \tag{D.2}$$

Equation 10 is not satisfied since, under $A1$ and $A3$, we have

$$E\left[u\left(\underline{y}, Max\left(\underline{y}, CE^{v,FS_Z}_{Y}\right)\right)\right] < u\left(\underline{y}, \underline{y}\right) = v\left(\underline{y}\right) < E\left[v\left(y\right)\right]. \tag{D.3}$$

The right-hand side of Equation 10 is greater than the left-hand side.

If $Z = \overline{y}$ then the left-hand side of Equation 10 is

$$E\left[u\left(Z, Max\left(Z, CE^{v,FS_Z}_{Y}\right)\right)\right] = u\left(\overline{y}, \overline{y}\right). \tag{D.4}$$

The right-hand side is

$$E\left[u\left(Y, Max\left(Y, Z\right)\right)\right] = E\left[u\left(Y, \overline{y}\right)\right]. \tag{D.5}$$

Equation 10 is not satisfied since, under $A2$, $u(\overline{y},\overline{y}) > E[u(Y,\overline{y})]$. The left-hand side of Equation 10 is now greater than the right-hand side.

Moreover, under $A1$, function $E\left[u\left(Z, Max\left(Z, CE_Y^{v,FS_Z}\right)\right)\right]$ increases with Z and under $A3$, function $E[u(Y, Max(Y,Z))]$ decreases with Z. Under $A0$, the solution of Equation 10 exists, is unique and belongs to $\left[\underline{y},\overline{y}\right]$.

Proof of Proposition 4 :

If Z_a and Z_b respectively denote the Z-solution of Equation 10 under FS^a and under FS^b, let us show that $Z_b \leq Z_a$.

Proposition 1 states that if FS^a is sufficient for a FS^b then we have

$$\forall Y \in \Phi, E\left[u\left(Y, Max\left(Y, CE_{Max}^{v,FS_Y^a}\right)\right)\right] \leq E\left[u\left(Y, Max\left(Y, CE_{Max}^{v,FS_Y^b}\right)\right)\right]. \tag{D.6}$$

This property also holds for a sure thing Z:

$$E\left[u\left(Z, Max\left(Z, CE_Y^{v,FS_Z^a}\right)\right)\right] \leq E\left[u\left(Z, Max\left(Z, CE_Y^{v,FS_Z^b}\right)\right)\right]. \tag{D.7}$$

The left-hand side of Equation 10 is greater under FS^b than under FS^a.

The right-hand side of Equation 10, $[u(Y, Max(Y,Z))]$, is independent of the FS and, under A3, decreases with Z. We thus have $Z_b \leq Z_a$.

References

Bell, D. E., 1982. Regret in decision making under uncertainty. Operations Research 30(5), 961-981.

Bell, D. E. 1983. Risk premiums for decision regret. *Management Science*, 29 (10), 1156-1166.

Blackwell, D. 1951. Comparison of experiments. *In Proceedings of the second Berkeley symposium on mathematical statistics and probability. Berkeley: University of California Press.*

Diecidue, E., Somasundaram, J., 2017. Regret theory: A new foundation. Journal of Economic Theory 172, 88-119.

Fishburn, P. C., 1989. Non-transitive measurable utility for decision under uncertainty. Journal of Mathematical Economics 18(2), 187-207.

Fisher, R. A. 1920. A mathematical examination of the methods of determining the accuracy of an observation by the mean error, and by the mean square error, Monthly Notices R. Astr. Soc. 80, 759-770.

Gabillon, E. 2020. *When choosing is painful: Anticipated regret and psychological opportunity cost*. Journal of Economic Bahevior and Organization, 178, 644-659.

Josephs, R., Larrick, R., Steele, C. M., & Nisbett, R. 1992. Protecting the self from the negative consequences of risky decisions. *Journal of Personality and Social Psychology*, 62 (1), 26-37.

Kahneman, D., & Miller, D. T. 1986. Norm theory: Comparing reality to its alternatives. *Psychological Review*, 93 (2), 136–153.

Larrick, R., & Boles, T. 1995. Avoiding regret in decisions with feedback: A negotiation example. *Organizational Behavior and Human Decision Processes*, 63 (1), 87-97.

Loomes, G., & Sugden, R. 1982. Regret theory: an alternative theory of rational choices under uncertainty. *Economic Journal*, 63 (368), 805-824.

Loomes, G., Sugden, R., 1987. Some implications of a more general form of regret. Journal of Economic Theory 41(2), 270-287.

Luce, R. D. & Raiffa, H. 1956. Games and decisions: introduction and critical survey. New York: John Wiley & Co., 1956.

Quiggin, J., 1994. Regret theory with general choice sets. Journal of Risk and Uncertainty 8(2), 153–165.

Ritov, I. 1996. Probability of regret: Anticipation of uncertainty resolution in choice. *Organizational Behavior and Human Decision Processes*, 66 (2), 228-236.

Savage, L. J. 1951. The theory of statistical decision. Journal of the American Statistical Association, 46, 55–67.

Sugden, R., 1993. An axiomatic foundation for regret theory. Journal of Economic Theory 60(1), 159-180.

Zeelenberg, M., Beattie, J., Pligtand, J. van der, & Vries, N. de. (1996). Consequences of regret risk aversion : Effects of expected feedback on risky decision making. *Organizational, Behavior and Human Decision Processes*, 65 (2), 148-158.

Zeelenberg, M., & Beattie, J. 1997. Consequences of regret aversion 2: Additional evidence of the effects of feedback on decision making. *Organizational Behavior and Human Decision Processes*, 72(1) , 63-78.

Zeelenberg, M. 1999. Anticipated regret, expected feedback, and behavioral decision making. *Journal of Behavioral Decision Making*, 12: 93-106.

BSE UMR CNRS 6060

Université de Bordeaux
Avenue Léon Duguit,
Bât. H
33608 Pessac,
France

Tel : +33 (0)5.56.84.25.75
http://bse.u-bordeaux.fr/

Derniers numéros – Last issues

- 2022-11 **How Patent Rights Affect University Science** *by Laurent BERGE & Thorsten DOHERR & Katrin HUSSINGER*
- 2022-10 **From fork to fish: The role of consumer preferences on the sustainability of fisheries** *by Coralie KERSULEC & Luc DOYEN*
- 2022-09 **Navigating the well-being effects of monetary policy: Evidence from the European Central Bank** *by Mehdi EL HERRADI & Aurélien LEROY*
- 2022-08 **Modeling the Impact of Non-Tariff Barriers in Services on Intra-African Trade: Global Trade Analysis Project Model** *by Lukman OYELAMI & Amara ZONGO*
- 2022-07 **Failure of Gold, Bitcoin and Ethereum as safe havens during the Ukraine-Russia war** *by Alhonita YATIE*
- 2022-06 **The impact of the Ukraine-Russia war on world stock market returns** *by Whelsy BOUNGOU & Alhonita YATIE*
- 2022-05 **Instability of preferences due to Covid-19 Crisis and emotions: a natural experiment from urban Burkina Faso** *by Delphine Boutin & Larène Petifour & Haris MEGRAZI*
- 2022-04 **Intensification or Diversification: Responses by Anti Health-PassEntrepreneurs to French Government Announcements** *by Christophe LEVEQUE & Haris MEGRAZI*

Ernest MIGUELEZ is the scientific coordinators of the Bordeaux Economics Working Papers. The layout and distribution are provided by Cyril MESMER.