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Against the Odds! The Tradeoff Between Risk and Incentives is Alive and Well

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Keywords:
Risk-Incentives Tradeoff, Rank-Dependent Utility, Mean-Variance-Skewness, Experiments

JEL codes:
C92, D23, D86, M54

Working Paper

Against the Odds! The Tradeoff Between Risk and Incentives is Alive and Well*

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March 2, 2023

Abstract

The risk-incentives tradeoff (RIT) is a fundamental result of principal-agent theory. Yet, empirical evidence has been elusive. This could be due to a lack of robustness of the theory outside of the standard expected utility framework (EUT) or to confounding factors in the empirical tests. First, we theoretically study the existence of RIT under alternative theories: Rank-Dependent Utility (RDU) and Mean-Variance-Skewness (MVS). We show that RIT is remarkably robust under RDU, but not under MVS. Second, we use a novel experimental design that eliminates confounding factors and find evidence for RIT even in the case of risk-seeking agents, which is a distinct prediction of RDU. Our results provide support for the risk-incentives tradeoff and suggest that it applies to a broad range of situations including cases in which agents are risk-seeking (e.g., executive compensation).

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1 Introduction

Principal-agent theory has played a key role in understanding human behavior across disciplines ranging from finance, accounting, strategy and political science to neuroeconomics (Jensen and Meckling, 1976; Lambert, 2001; Miller, 2005; Brocas and Carrillo, 2008; Dranove et al., 2017). In economics, the principal-agent framework is a cornerstone of numerous fields including the theory of incentives. A central result in this literature is the existence of a tradeoff between providing incentives to foster the effort of risk-averse agents and protecting them against risk

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(Borch, 1962; Mirrlees, 1974; Holmström, 1979; Shavell, 1979; Milgrom and Roberts, 1992; Bolton and Dewatripont, 2005; Laffont and Martimort, 2009; Gibbons and Roberts, 2013). The risk-incentives tradeoff (RIT, henceforth) emerges because providing steeper incentives implies strengthening the link between output and rewards which, in turn, exposes agents to a greater risk whenever output is a noisy measure of effort. As a result, the optimal contract typically incorporates a variable pay that incentivizes the agent to exert effort and a fixed pay that partially hedges the agent against output shocks. These types of contracts are widespread, and unsurprisingly RIT has been applied to a wide variety of economic settings ranging from sharecropping to medical insurance (e.g., Zeckhauser, 1970; Stiglitz, 1974) and compensation setting in firms (Gibbons and Roberts, 2013).

Although the rationale for RIT is appealing, empirical evidence remains scarce (Garen, 1994; Prendergast, 2002; Lazear and Oyer, 2013). A glimpse of hope has recently come from laboratory studies reporting some evidence for RIT (Corgnet and Hernan-Gonzalez, 2019; Chowdhury and Karakostas, 2020). These lab studies control for possible confounding factors such as organizational hierarchies, implicit incentives or tacit knowledge that are notoriously difficult to control for in the field. Yet, the size of the effect reported in Corgnet and Hernan-Gonzalez (2019) and Chowdhury and Karakostas (2020) remains small.[1] Furthermore, recent evidence from laboratory experiments by Dohmen et al. (2021) is not consistent with RIT since the presence of output risk does not lead agents to demand weaker incentive schemes, that is lower piece rates.

In this paper, we use theory and experiments to investigate whether the limited evidence for RIT is due to a lack of robustness of the underlying theory or to the confounding factors in empirical tests. Principal-agent models are notorious for their lack of tractability (Grossman and Hart, 1983; Rogerson, 1985) which has led researchers to focus on particular specifications such as the LEN (Linear Exponential Normal) model (see Milgrom and Roberts, 1992; Varian, 1992; Laffont and Martimort, 2002; Bolton and Dewatripont, 2005; Gibbons and Roberts, 2013; Besanko et al., 2017). In this model, the risk-neutral principal proposes the agent a linear contract composed of a fixed pay and a share of output. The risk-averse agent who maximizes expected utility (assumed to be exponential) then decides whether to accept the contact or not. In case of acceptance, the agent chooses a level of effort under the agreed-upon contract. Even though the principal cannot observe the level of effort, she can observe the final output, which is impacted by an additive (normally distributed) shock.

The classical version of RIT is derived assuming Expected Utility Theory (EUT, henceforth) and the LEN specification. Although the LEN model has often been discussed and defended by contract theorists on the basis of tractability and realism (Holmstrom and Milgrom, 1987; Diamond, 1998; Laffont and Martimort, 2002; Bolton and Dewatripont, 2005; Carroll, 2015; Holmström, 2017), little is known about the robustness of RIT in non-EUT settings. This led us to study the robustness of RIT to alternative theories that allow for distortions of probabilities (Rank-Dependent Utility theory, RDU, henceforth, Quiggin, 1982) and an explicit preference for skewness (Mean-Variance-Skewness, MVS, henceforth, Spiliopoulos and Hertwig, 2019). Risk attitudes have been traditionally characterized by the curvature of the utility function. However, non-EUT models characterize risk attitudes along different dimensions. For example, overall risk attitudes under RDU stem both from utility risk attitudes (i.e., the curvature of the utility function) and probability risk attitudes (i.e., probability weighting). Under MVS, overall risk attitudes depend on agents' preferences for variance and skewness.

We theoretically show that RIT is pervasive under RDU because it occurs not only when agents are overall risk-averse, but also when they are risk-neutral or risk-seeking. For example,

[1] Corgnet and Hernan-Gonzalez (2019) report a 8.1% (Cohen's d = 0.34) decrease in the piece rate value in their noise treatment as compared to a noise-free baseline. A similar decrease (12.7%) if also found by Chowdhury and Karakostas (2020), notwithstanding their EUT-based prediction of a one-third decrease.

RIT happens when overall risk-neutral or risk-seeking agents are moderately risk-seeking in the probability domain (i.e., they moderately overweight probabilities) and risk-averse in the utility domain (i.e., their utility function is concave). This result suggests that RIT might be more widespread than predicted by EUT. Yet, this observation contrasts with the limited empirical evidence for RIT.

In line with existing empirical evidence, MVS provides a setup in which RIT is less pervasive than under EUT. This happens because RIT does not occur for all risk-averse agents (as in EUT) and disappears for those that exhibit a preference for positive skewness. Furthermore, the optimal variable pay (fixed pay) can increase (decrease) with risk, which is what we refer to as reversed RIT. This occurs when the distribution of the shock is positively skewed and the aversion to variance is less pronounced than the value of skewness for a risk-averse agent exhibiting MVS preferences.

These theoretical results show that non-EUT models provide reasons for both hope and despair regarding the robustness of RIT. To test the predictions of the alternative theories, we develop a novel experimental testbed for RIT that eliminates confounding factors. We focus on agents' decisions by eliciting the minimum fixed pay they are willing to accept for different values of the variable pay. As principals do not make contractual decisions (see, e.g., Dohmen et al., 2021) we can discard confounding factors related to their risk attitudes. This design also eliminates any asymmetry of information between the principal and the agent whose preferences are unknown. We also use monetary effort instead of a real-effort task (see e.g., Anderhub et al., 2002; Keser and Willinger, 2007; Gächter and Königstein, 2009) to discard other confounding factors often present in experimental data such as social motives and reference points (see Corgnet and Hernan-Gonzalez, 2019), as well as more general ones such as organizational hierarchies, delegation, implicit incentives, tacit knowledge, uncertainty and market dynamics (Jensen and Meckling, 1995; Raith, 2008; Adams, 2005; DeVaro and Kurtulus, 2010; Edmans et al., 2012; He et al., 2014). We do not mean to underplay the importance of these factors but rather aim at implementing a testbed for the basic mechanism underlying RIT. It follows that a lack of evidence supporting RIT in our setup would be a definitive blow for the theory. To ensure that our design can be effectively used to study RIT, we analyze a BareBone (BB, henceforth) principal-agent model.

Our experiment shows that RIT is remarkably robust and more pervasive than predicted by EUT. In line with RDU but in contrast with EUT and MVS, RIT arises even when agents are risk-seeking. This finding has direct implications for various applications of the theory in which agents are risk-seeking, as is the case of executive compensation (Garen, 1994; Edmans and Gabaix, 2011; Edmans et al., 2012, 2017) and high-pay workers (Ma et al., 2019). Risk-seeking is likely to be pervasive in these cases because of selection effects (MacCrimmon and Wehrung, 1990; Brenner, 2015). Furthermore, executive packages are often positively skewed due to, for example, the use of stock options (Edmans et al., 2017). As a result, an agent who appears to be risk-averse when rewarded according to a linear contract might be risk-seeking when facing a skewed compensation package.

The remainder of the paper is organized as follows. Section 2 presents the theoretical models for RIT under EUT, RDU and MVS. In Section 3, we describe the experimental design. Section 4 presents the results of the experiment and Section 5 concludes.

2 Model

2.1 Standard setup and predictions

2.1.1 Assumptions

A risk-neutral principal offers a contract to an agent to perform a task. If the agent does not accept the contract, he receives an outside option y_0. If he accepts the contract, then he has to exert effort e to produce output $z = z(e)$, where $z = e + \tilde{\epsilon}$ and $\tilde{\epsilon}$ is a random variable. Thus, there is a noisy relationship between effort and output. The cost of effort function $C(e)$ is increasing and convex. The principal observes the level of output, but not the underlying level of effort. The principal maximizes her revenue θz, where $\theta > 0$ denotes the marginal product of effort. To ease exposition, we consider a binary shock model (see e.g., Milgrom and Roberts, 1992), which is often used in empirical tests of the theory (see Corgnet and Hernan-Gonzalez, 2019; Dohmen et al., 2021).[2] In Appendix C we further show that our predictions qualitatively hold if we consider a continuous shock. In particular, this includes the special case of the normally distributed shock used in the LEN model (see e.g., Milgrom and Roberts, 1992; Bolton and Dewatripont, 2005). Below, we outline our assumptions.

Assumption 0 (A0: Binary shock). The shock $\tilde{\epsilon}$ is a binary random variable defined as $\tilde{\epsilon} = \big(-\epsilon, \frac{1-p}{p}\epsilon; 1-p, p\big)$, $\epsilon \geq 0$ and $p \in (0,1]$ so that $E(\tilde{\epsilon}) = 0$ and $V(\tilde{\epsilon}) = \frac{1-p}{p}\epsilon^2$.[3]

Assumption 1 (A1: Risk-neutral principal). The principal is risk-neutral and maximizes the expected payoff.

Assumption 2 (A2: Linear contracts). The principal proposes to the agent a contract (α, β) that is linear in output and pays $y = \alpha + \beta\theta z$, where $\alpha \in \mathbb{R}$ is the fixed pay and $\beta > 0$ the variable pay.[4]

Assumption 3 (A3: CARA utility). The agent's utility function is $u(x) = \frac{1-exp(-rx)}{r}$ for $r \neq 0$ and $u(x) = x$ for $r = 0$.

With Assumption 3, we define utility risk attitudes in terms of the shape of the utility function. By contrast, the overall risk attitudes of the agent depend on his overall valuation of the contract which is only partly captured by the utility function. We define utility risk attitudes and overall risk attitudes as follows.

Definition 1 (Utility risk attitudes). Utility risk-aversion [risk-neutrality] (risk-seeking) corresponds to a concave, $r > 0$ [linear, $r = 0$] (convex, $r < 0$) utility function.

Definition 2 (Overall risk attitudes). An agent exhibits overall risk-aversion [risk-neutrality] (risk-seeking) whenever his risk premium for accepting the contract is positive [null] (negative).

Definition 2 is a general (model-free) definition of risk attitudes due to Pratt (1971) and Arrow (1964). Under EUT, overall risk attitudes and utility risk attitudes always coincide.

[2] Milgrom and Roberts (1992) and Laffont and Martimort (2002) derive fundamental results in the theory of incentives using a model with binary shocks.

[3] We consider continuous random shocks in Appendix C.

[4] We assume linear contracts because they are theoretical tractable and empirically relevant (e.g., Holmström, 2017). Also, we do not require $\beta \in [0,1]$ (e.g., Milgrom and Roberts, 1992; Laffont and Martimort, 2002). Principal could then set $\beta > 1$ and $\alpha < 0$, especially for risk-seeking agent.

However, this is not the case under RDU or MVS where utility risk-aversion (utility risk-seeking) does not necessarily imply overall risk-aversion (risk-seeking).

In this paper, we consider the standard assumption of a concave utility function (i.e., Assumption 3' which is equivalent to Assumption 3 with $r > 0$), unless stated otherwise.

Assumption 3' (A3': Utility risk-averse agent). The agent is utility risk-averse in the sense of $r > 0$.

For the sake of concision, hereafter we use the term risk attitudes (risk-aversion, risk-seeking or risk-neutrality) to refer to overall risk attitudes.

Assumption 3" (A3": Relative risk-aversion). The relative risk-aversion index evaluated at x is less than 1, that is $-\dfrac{u''(x)}{u'(x)}x = rx < 1$.

Assumption 4 (A4: Public knowledge of the agent's risk-attitudes). The principal knows the agent's risk attitudes.

Assumption 5 (A5: Quadratic cost). The cost of effort function is: $C(e) = \psi e^2$ with $\psi > 0$.

Given these assumptions, the compensation associated with the contract, which is the random wage net of the cost of effort, can be described as a lottery L:

$$L := \left(\alpha + \beta\theta\left(e + \frac{1-p}{p}\epsilon\right) - \psi e^2, \alpha + \beta\theta\left(e - \epsilon\right) - \psi e^2; p, 1-p\right) \tag{1}$$

where the first three moments (i.e., mean E, variance V and skewness S) are:

$$E(L) = \alpha + \beta\theta e - \psi e^2, \quad V(L) = \frac{1-p}{p}\beta^2\theta^2\epsilon^2 \quad \text{and} \quad S(L) = \frac{1-p}{p}\frac{1-2p}{p}\beta^3\theta^3\epsilon^3$$

Note that varying ϵ does not affect the expected value of the lottery ($E(L)$) but impacts variance ($V(L)$) and skewness ($S(L)$). By contrast, varying the fixed pay (α) impacts the expected value of the lottery without affecting the other two moments. Finally, the variable pay (β) impacts all three moments.

2.1.2 Model specification under EUT, RDU and MVS

We first determine how the agent evaluates lottery L based on three different specifications: EUT, RDU and MVS.

EUT

Under EUT, the agent values the contract by its expected utility:

$$EU(L) = pu\left(\alpha + \beta\theta\left(e + \frac{1-p}{p}\epsilon\right) - \psi e^2\right) + (1-p)u\left(\alpha + \beta\theta\left(e - \epsilon\right) - \psi e^2\right) \tag{2}$$

In this model, $\frac{\partial EU(L)}{\partial \epsilon} < 0$ as long as the utility function $u(.)$ is concave.[5]

[5] By contrast, (2) increases with (is unaffected by) the shock magnitude if $r < 0$ ($r = 0$).

RDU

Under RDU, the agent distorts probabilities using a probability weighting function $w(p)$, which is a strictly increasing function from $[0,1]$ to $[0,1]$ with $w(0) = 0$ and $w(1) = 1$. Hence, risk attitudes not only stem from utility curvature (as in EUT), but also from probability weighting. Below, we define probability risk-aversion, risk-neutrality and risk-seeking.

Definition 3 (Probability risk attitudes). Under RDU, an agent exhibits probability risk-aversion [risk-neutrality] (risk-seeking) for a specific probability p if $w(p) < p$ [$w(p) = p$] ($w(p) > p$).

The agent's valuation of the contract then becomes:

$$RDU(L) = w(p)u\left(\alpha + \beta\theta\left(e + \frac{1-p}{p}\epsilon\right) - \psi e^2\right) + (1 - w(p))u\left(\alpha + \beta\theta\left(e - \epsilon\right) - \psi e^2\right) \quad (3)$$

For a probability risk-seeking agent, the valuation of the contract in (3) has an inverted J-shape with respect to ϵ (see Figure 1). To grasp the intuition, consider an arbitrarily small shock (ϵ_0) making the agent approximately utility risk-neutral, thus exhibiting a linear utility function. In that case $\frac{\partial RDU(L)}{\partial \epsilon} = w(p)\beta\theta\frac{1-p}{p} - (1 - w(p))\beta\theta > 0 \iff w(p) > p$. Hence, for that level of shock the agent is necessarily risk-seeking because he is both utility risk-neutral and probability risk-seeking. That is, for small shocks, risk attitudes are driven by probability weighting rather than by the curvature of the utility function. As shown in Figure 1, the valuation of the lottery ($RDU(L)$) at ϵ_0 is above the utility of the expected value of the lottery ($u(E[L])$), implying a negative risk premium and hence a risk-seeking agent.

However, as the shock increases in magnitude, utility risk-aversion increases up to a point in which utility risk-aversion exactly offsets probability risk-seeking, making the agent risk-neutral. This level of shock (denoted ϵ_1 in Figure 1) corresponds to a null risk premium associated with the contract lottery (i.e., $RDU(L) = u(E[L])$). Between ϵ_0 and ϵ_1, there is also a level of shock (denoted ϵ^* in Figure 1) for which the negative effect of increasing the shock magnitude due to utility risk-aversion is exactly equal to the positive effect due to probability risk-seeking. For shocks greater than ϵ_1, a probability risk-seeking agent is risk-averse (i.e., $RDU(L) < u(E[L])$).

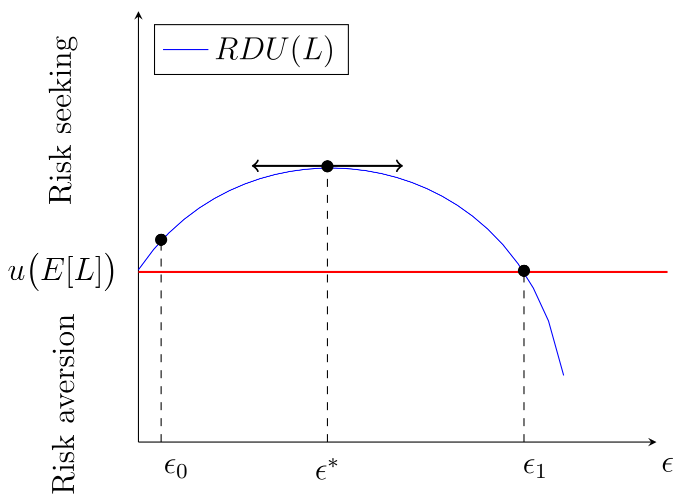


Figure 1: Valuation of the contract by a probability risk-seeking RDU agent (equation (3)) as a function of the shock magnitude.

MVS

Under MVS, the agent evaluates a lottery according to its mean, variance and skewness (Kraus and Litzenberger, 1976; Spiliopoulos and Hertwig, 2019) as follows:

$$MVS(L) = E(L) + a_v V(L) + a_s S(L) \tag{4}$$

where a_v is a parameter that captures attitudes towards variance and a_s captures attitudes towards skewness. In line with the LEN framework and with empirical evidence (Kraus and Litzenberger, 1976; Spiliopoulos and Hertwig, 2019), we assume that the agent is averse to variance (i.e., $a_v < 0$) and seeks positive skewness (i.e., $a_s > 0$). Furthermore, in contrast to EUT, we explicitly consider following the literature (e.g., Spiliopoulos and Hertwig, 2019; Mitton and Vorkink, 2007) that a_v and a_s are unrelated.[6]

An MVS agent exhibits risk-aversion for any negatively-skewed lottery. For positively-skewed lotteries, he is risk-seeking (risk-averse) [risk-neutral] if $-\frac{a_v}{a_s} < \tau_N(\beta, \epsilon)$ ($-\frac{a_v}{a_s} > \tau_N(\beta, \epsilon)$) [$-\frac{a_v}{a_s} = \tau_N(\beta, \epsilon)$], where $\tau_N(\beta, \epsilon) := \frac{S(L)}{V(L)} = \frac{1-2p}{p}\beta\theta\epsilon$. For any $p \geq 1/2$, we have $\tau_N(\beta, \epsilon) \leq 0$ so that the agent is systematically risk-averse since $-\frac{a_v}{a_s} > 0$.

In the presence of aversion to variance ($a_v < 0$) and preference for positive skewness ($a_s > 0$), the valuation function (4) is J-shaped with respect to ϵ when $p < 1/2$ (see Figure 2). The intuition behind Figure 2 follows from the fact that for small (large) levels of the shock, the variance of L is larger (smaller) than its skewness. Hence, for a small level of shock (say ϵ_0), the agent is necessarily risk-averse since the aversion to variance outbalances the preference for positive skewness. This gives rise to a positive risk premium: the valuation of the lottery (MVS(L)) lies below its expected value. For a sufficiently high level of shock magnitude ($\forall \epsilon > \epsilon_1$ in Figure 2), the agent necessarily exhibits risk-seeking since the preference for positive skewness outbalances the aversion to variance. At some level of the shock (denoted ϵ_1 in Figure 2), the two effects cancel out so that the agent is risk-neutral with a null risk premium (MVS(L)=E[L]). Finally, Figure 2 also features a level of shock ϵ^* for which the negative effect of increasing the shock magnitude due to aversion to variance is exactly equal to the positive effect of increasing the shock magnitude due to the preference for positive skewness.

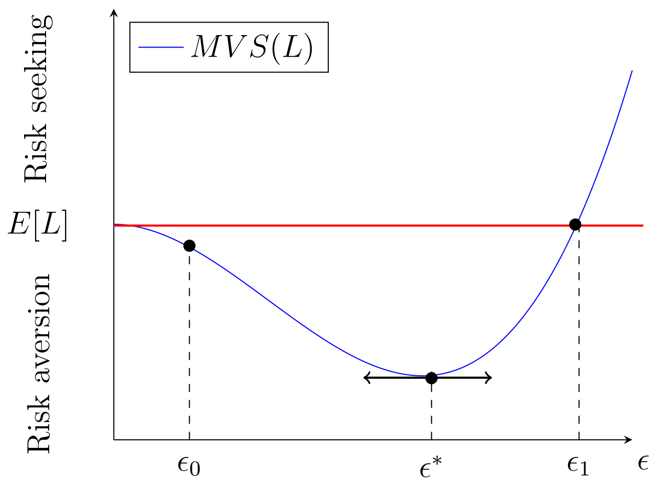


Figure 2: Valuation of the contract by an averse-to-variance ($a_v < 0$) and preference-for-positive-skewness ($a_s > 0$) MVS agent (equation (4)) as a function of the shock magnitude when $p < 1/2$.

[6]Under EUT, a_v and a_s are linked via utility function. The third order Taylor approximation of the certainty equivalent incorporates attitudes towards variance and skewness due to the second and third derivatives of the utility function.

2.1.3 RIT predictions

For each theory, we can characterize the optimal contract: the fixed pay (α^*) and the variable pay (β^*) proposed by the principal, as well as the optimal level of effort e^* provided by the agent. We provide the corresponding proofs in Appendix A. Here, we focus on characterizing the conditions of existence of RIT for the optimal contract. Definition 4 below characterizes RIT and reversed RIT. RIT occurs when increasing the variable pay generates a trade-off between desirable and undesirable consequences, thus forcing the principal to set a compensation contract with an intermediate intensity of incentives (i.e., $0 < \beta^* < 1$). On the positive side, increasing the variable pay incentivizes the agent to exert more effort. On the negative side, it increases the level of risk faced by the agent because it makes his pay more sensitive to output shocks. It follows that under RIT an increase in the magnitude of the output shock requires the principal to set a contract that limits the agent's exposure to the shock. This is achieved by decreasing the variable pay while increasing the fixed pay to ensure the agent is willing to accept the contract (see Definition 4i).

Definition 4 (RIT and Reversed RIT)
i) RIT corresponds to the case in which the optimal variable pay (fixed pay) decreases (increases) in the output shock ϵ for a given p.
ii) Reversed RIT corresponds to the case in which the optimal variable pay (fixed pay) increases (decreases) in the output shock ϵ for a given p.
iii) No RIT corresponds to the case in which there is no relationship between the optimal pay and the output shock ϵ for a given p

Under EUT, RIT always occurs for risk-averse agents (Assumption 3'). For risk-neutral agents, there is no RIT because fixed pay and variable pay do not vary with the shock (see Definition 4iii). For risk-seeking agents, RIT is reversed because the optimal variable (fixed) pay increases (decreases) with the shock size. These results are standard in the LEN model (see e.g., Milgrom and Roberts, 1992). Yet, we provide the details of the proofs in Appendix A (Proposition A1) for the case of a binary shock and for the case of a general utility function and a continuous shock (see Propositions B1 to B3 and Proposition C1 in Appendices B and C).

Under RDU, RIT is even more pervasive than under EUT. As in EUT, it occurs whenever agents are risk-averse (see Proposition A2 in Appendix A) given that the valuation function (3) is decreasing in the shock magnitude. In contrast to EUT, it can also occur when agents are risk-neutral or risk-seeking (see Proposition A3 in Appendix A). In the case of a risk-seeking agent who overweighs probabilities, the value of the contract in (3) increases with fixed pay α (irrespective of risk attitudes) and is inverse J-shaped with respect to the shock size (see Figure 1). For a small shock (ϵ_0 in Figure 1), (3) is increasing in the shock magnitude. In that case, the principal can offer the agent a lower fixed pay while keeping his utility equal to the outside option (y_0). As in EUT, this situation corresponds to reversed RIT. However, for an intermediate shock ($\epsilon^* < \epsilon < \epsilon_1$ in Figure 1), the risk-seeking RDU agent's contract valuation is decreasing in the shock. This implies that the principal needs to offer the agent a higher fixed pay to keep his level of utility constant in response to a larger shock. Hence, for a risk-seeking RDU agent RIT emerges at an intermediate shock level. Example 1 provides a numerical illustration of RIT for a (moderately) risk-seeking RDU agent.

Example 1 (RIT for a risk-seeking agent under RDU). We consider $r = 0.1$, $(\psi, \theta, y_0) = (0.5, 1, 4)$. In the absence of shock (i.e., $\epsilon = 0$), the optimal variable pay is $\beta^* = 1$ and the optimal fixed pay is $\alpha^* = 3.5$. In the presence of a shock ($\epsilon = 1$) and given a RDU agent who overweights probability 0.1 such that $w(p) = 0.15$, we obtain $\beta^* = 0.76$ and $\alpha^* = 3.64$.

Thus, the optimal variable (fixed) pay in the presence of a shock is smaller (larger) than in its absence, which means RIT holds. Because the expected value of the contract ($E(L^*) = 3.93$) is lower than its certainty equivalent (which is equal to the outside option $y_0 = 4$ due to the participation constraint), the agent is risk-seeking for the optimal contract (α^*, β^*)=(3.64,0.76). As a result, RIT is observed for a risk-seeking agent.

Under MVS, we show that RIT may not hold when agents are risk-averse which stands in stark contrast with EUT predictions. In particular, when the shock is positively skewed ($p < 1/2$), RIT may not hold (and may even reverse) for risk-averse agents who value positive skewness (see Appendix A, Propositions A4 and A5). This happens because the MVS-based valuation of the contract in (4) increases with fixed pay α (irrespective of risk attitudes) and is J-shaped in the shock magnitude (see Figure 2). For a small shock (ϵ_0 in Figure 2) and a risk-averse agent, the valuation (4) is decreasing in the shock size. In that case, the principal must offer the agent a higher fixed pay to maintain utility equal to the outside option (y_0). As in EUT, this situation corresponds to RIT.

However, for an intermediate shock (see $\epsilon^* < \epsilon < \epsilon_1$ in Figure 2) the value function of the risk-averse MVS agent is increasing in the shock size. This implies that the principal can offer the agent a lower fixed pay while maintaining his level of utility equal to the outside option. Unlike EUT, this situation corresponds to reversed RIT for a risk-averse agent. Finally, in line with EUT, a risk-seeking MVS agent systematically exhibits reversed RIT given that his valuation in (4) is increasing in the shock magnitude. Example 2 provides a numerical illustration of a situation in which reversed RIT occurs for a risk-averse agent under MVS.

Example 2 (Reversed RIT for a risk-averse agent under MVS). We consider $(\psi, \theta, y_0) = (0.5, 1, 20)$ and $a_v = -0.0229$ and $a_s = 0.0037$ following the estimates provided in Spiliopoulos and Hertwig (2019). In the absence of shock (i.e., $\epsilon = 0$), the optimal variable pay is $\beta^* = 1$ and the optimal fixed pay is $\alpha^* = 19.5$. In the presence of a shock $(\epsilon, p) = (1, 0.32)$, we obtain $\beta^* = 1.02$ and $\alpha^* = 9.70$. Thus, the optimal variable (fixed) pay in the presence of a shock is larger (smaller) than in the absence of shock implying reversed RIT. Because the expected value of contract (E[L^*]=20.09) is higher than its certainty equivalent (20), the agent is risk-averse for the optimal contract $(\alpha^*, \beta^*) = (9.70, 1.02)$. As a result, we observe reversed RIT for a risk-averse agent.

We summarize our theoretical RIT predictions for EUT, RDU and MVS in Table 1. For each type of agent risk attitudes, we report the three theories (EUT, MVS and RDU) for which RIT is present (left column), absent (middle column), or reversed (right column).

Table 1: RIT and risk-attitudes

Agent's risk attitudes	RIT	No RIT	Reversed RIT
Risk-averse	RDU-EUT-MVS	MVS	MVS
Risk-neutral	RDU	RDU-EUT-MVS	MVS
Risk-seeking	RDU	RDU	RDU-EUT†-MVS

† With Assumption 3', an agent cannot be risk-seeking under EUT. To consider risk-seeking agents, we need to consider convex utility giving rise to reversed RIT.

2.2 The BareBone model

Our aim is to test RIT in a BareBone (BB) experimental design that is robust to commonly observed deviations from standard Assumptions 1-5. In practice, the risk-neutrality of the principal cannot be ensured so that Assumption 1 does not necessarily hold in the lab. In addition, principals do not know the risk preferences of agents notwithstanding Assumption 4. To alleviate these issues, we adopt an empirical approach that directly elicits the minimum fixed pay (α_m) agents are ready to accept given a preset value of the variable pay (β). This approach allows us to focus on agents' decisions abstracting away from principals' contractual decisions. In our BB approach, RIT can be defined as follows.

Definition 5 (RIT and Reversed RIT in the BB model). RIT (Reversed RIT) [No RIT] corresponds to the case in which the minimum fixed pay accepted by an agent (α_m) increases (decreases) [does not change] in the output shock ϵ for given values of β and p.

Under EUT, we can derive Proposition 1 stating that a risk-averse agent demands a higher fixed pay when the shock magnitude increases, giving rise to RIT. This behavior boils down to an enhanced demand for insurance when facing greater risk. Proposition 1ii states that RIT holds under EUT for risk-averse agents in line with Table 1. In Appendix D, we provide the proof of Proposition 1 and show its connection with Propositions A1 (Appendix A), B1 (Appendix B) and C1 (Appendix C). In line with the diagonal entries in Table 1, we can also show that RIT is absent (reversed) under EUT when the agent is risk-neutral (risk-seeking) (see Appendix D).

Proposition 1 *(RIT with EUT).*
i) The minimum fixed pay increases in utility risk-aversion.
ii) For risk-averse agents, the minimum fixed pay increases in ϵ and β.

Under RDU, we show that RIT holds whenever the agent is probability risk-averse (see Proposition 2ii). By Assumption 3', this implies that the agent is also overall risk-averse. Furthermore, Proposition 2iii states that RIT also holds for a probability risk-seeking agent as long as the index of absolute risk aversion (r) is above a certain threshold ($r_{to}(\beta,\epsilon)$) such that his level of utility risk-aversion is sufficiently high. Interestingly, this threshold is lower than the value of the index of absolute risk aversion ($r_N(\beta,\epsilon)$) for which a probability risk-seeking agent exhibits risk-neutrality given the contract (α_m,β) (see Proposition 2iv). As a result, for any value of the index of absolute risk aversion $r \in (r_{to}(\beta,\epsilon), r_N(\beta,\epsilon))$, the agent is risk-seeking and exhibits RIT. Finally, Proposition 2v implies that the agent is more likely to exhibit RIT when the shock magnitude and the variable pay are large. It also implies that the agent is more likely to exhibit risk-seeking attitudes for a small shock and a low variable pay. In Appendix D, we provide the proof of Proposition 2 and show its connection with Propositions A2-A3 (Appendix A), B2-B3 (Appendix B) and C1 (Appendix C).

Proposition 2 *(RIT with RDU).*
i) The minimum fixed pay increases in utility risk-aversion and probability risk-aversion.
ii) Under probability risk-aversion ($w(p) < p$), the minimum fixed pay increases in ϵ.
iii) Under probability risk-seeking ($w(p) > p$), there exists a threshold $r_{to}(\beta,\epsilon) > 0$ such that the minimum fixed pay increases (decreases) in ϵ if and only if $r > r_{to}(\beta,\epsilon)$.
iv) We have $r_{to}(\beta,\epsilon) < r_N(\beta,\epsilon)$, where $r_N(\beta,\epsilon)$ is the level of absolute risk aversion such that a probability risk-seeking agent exhibits risk-neutrality for the contract (α_m,β).
v) The two thresholds $r_{to}(\beta,\epsilon)$ and $r_N(\beta,\epsilon)$ decrease in ϵ and β.

Under MVS, we show that RIT holds whenever the shock is negatively skewed ($p \geq 1/2$) in which case the agent is risk-averse (see Proposition 3ii). Furthermore, Proposition 3iii shows that for a positively skewed shock ($p < 1/2$), RIT [reversed RIT] holds as long as the value of the ratio , $\tau := -\frac{a_v}{a_s}$, between aversion to variance and preference for positive skewness is above [below] a certain threshold ($\tau_{to}(\beta,\epsilon)$), that is as long as the agent has a sufficiently high [low] aversion to variance relative to his preference for positive skewness. Given that $\tau_{to}(\beta,\epsilon)$ is higher than the ratio ($\tau_N(\beta,\epsilon)$) for which an MVS agent exhibits risk-neutrality given the contract (α_m,β) (see Proposition 3iv), a risk-averse MVS agent exhibits reversed RIT for any $-\frac{a_v}{a_s} \in (\tau_N(\beta,\epsilon),\tau_{to}(\beta,\epsilon))$.[7] Finally, Proposition 3v implies that a MVS agent is more likely to exhibit reversed RIT when the shock magnitude and the variable pay are large. It also implies that the agent is more likely to exhibit risk-seeking attitudes for a high shock magnitude and a high level of variable pay. In Appendix D, we provide the proof for Proposition 3 and show its connection with Propositions A4-A5 (Appendix A).

Proposition 3 *(RIT under MVS).*
i) The minimum fixed pay increases in the aversion to variance a_v. In addition, if $p < 1/2$ ($p > 1/2$), the minimum fixed pay decreases (increases) in the preference for positive skewness a_s.
ii) If the shock is negatively skewed ($p \geq \frac{1}{2}$) then the minimum fixed pay increases in ϵ.
iii) If the shock is positively skewed ($p < \frac{1}{2}$), there exists a threshold $\tau_{to}(\beta,\epsilon) := \frac{3}{2}\frac{1-2p}{p}\beta\theta\epsilon$ such that the minimum fixed pay increases (decreases) in ϵ if and only if $-\frac{a_v}{a_s} > \tau_{to}(\beta,\epsilon)$.
iv) We have $\tau_{to}(\beta,\epsilon) > \tau_N(\beta,\epsilon) := \frac{1-2p}{p}\beta\theta\epsilon$, where $\tau_N(\beta,\epsilon)$ is the level of $-\frac{a_v}{a_s}$ such that the agent exhibits risk-neutrality for the contract (α_m,β).
v) The two thresholds $\tau_{to}(\beta,\epsilon)$ and $\tau_N(\beta,\epsilon)$ increase in ϵ and β.

Propositions 1, 2 and 3 show that our BB model can be used to study RIT. Predictions in Table 1 thus carry on to the BB model. The next section provides details of the experimental test of the BB model predictions.

3 Experimental design

In line with the BB model, we study RIT using the minimum fixed pay (α_m) accepted by the agent.

3.1 Elicitation of minimum fixed pay

We elicit the minimum fixed pay (α_m) an agent is willing to accept given the incentive contract (β), as well as the magnitude and the probability of occurrence of the shock (ϵ, p). We thus elicit α_m for various combinations of (β,ϵ,p) based on the following indifference condition:

$$L(\alpha_m|\beta,\epsilon,p) \sim y_0$$

where y_0 is the riskless outside option and $L(.)$ is the lottery associated with a given incentive contract (β) and a given shock (ϵ, p) as defined in (1). We vary the triplet (β,ϵ,p) while fixing the parameters of the cost of effort function ($\psi = 2.5$), the marginal product of effort ($\theta = 100$), and the outside option ($y_0 = 1,000$). We consider 30 combinations of $(\beta,\epsilon,p) \in \{0.3, 0.5, 0.7\} \times \{3, 4\} \times \{0.1, 0.25, 0.33, 0.5, 0.75\}$.[8] For each combination, we also assume that

[7] From Definition 2 (overall risk attitudes) and equation (4) of MVS, the risk premium in MVS is equal to $a_vV(L)+a_sS(L)$. Risk neutrality corresponds to $a_vV(L)+a_sS(L) = 0$ or equivalently to $-\frac{a_v}{a_s} = \frac{S(L)}{V(L)} := \tau_N(\beta,\epsilon)$ and risk-aversion (risk-seeking) corresponds to $a_vV(L)+a_sS(L) > 0$ (< 0) or equivalently to $-\frac{a_v}{a_s} < (>)\ \tau_N$.

[8] We do not consider the trivial case of $\epsilon = 0$ for which the task boils down to picking the highest value in a table of numbers.

the agent implements the optimal level of effort e^* that maximizes the value of the lottery so that we elicit α_m as follows:

$$L(\alpha_m \big| \beta, \epsilon, p; e^*) \sim y_0$$

Where $e^* = \frac{\beta\theta}{2\psi}$. In the experiment, we automatically implement the optimal level of effort because it is a trivial decision for the agent. This allows us to focus on the choice of α_m. For each combination (β, ϵ, p), we elicit α_m using a multiple price list á la Holt and Laury (2002) in which we vary the fixed pay of a contract in increments of 50 between 0 and 1,000 for a total of 21 possible values. We set an upper bound equal to the value of the outside option (1,000).[9] Figure 3 provides an example of a decision screen for the combination (β, ϵ, p)=(0.7,3,0.5), where Option A corresponds to the sure payoff associated with the outside option and Option B represents all the possible payments associated with lottery $L(\alpha_i \big| 0.7, 3, 0.5; e^*)$. The value of fixed pay is such that $\alpha_i = (i-1) \times 50$, where i is the row number between 1 and 21. For (β, ϵ, p)=(0.7,3,0.5), we have that $e^* = \frac{\beta\theta}{2\psi} = 14$. Thus, for row $i = 1$, Option B displays the two possible payments associated with $L(0 \big| 0.7, 3, 0.5; 14)$: 280 if the shock is negative and 700 otherwise. The likelihood of a given payment is visually represented by the frequency of cells in which it appears. Different amounts appear in different colors to facilitate the reading of the table. In total, participants face 30 tables, each corresponding to a different combination of (β, ϵ, p). All amounts in tables are in euro cents. To avoid hedging issues (Charness et al., 2016), one of the 30 tables is selected at random for payment upon a successful completion of the experiment.

For each table, participants pick a single row corresponding to their switching point, i.e., the point beyond which they prefer Option B over Option A. Participants cannot select multiple switching points. In the example presented in Figure 3, the participant picked Option A for the first 10 rows and switched to Option B afterwards (see orange cells on the left of the table). This implies that the minimum fixed pay (α_m) the participant is willing to accept for this contract is in the interval (450,500). In that example, we estimate α_m to be the midpoint of the interval, that is 475 (e.g., Abdellaoui et al., 2008; Gonzalez and Wu, 1999).

[9]The lower bound of 0 does not appear to be restrictive in our experiment as only 1.1% of the decisions revealed a minimum fixed pay that is less or equal to 0.

TABLE #6

Option A		Option B										
1000	A1	B1	280	280	280	280	280	700	700	700	700	700
1000	A2	B2	330	330	330	330	330	750	750	750	750	750
1000	A3	B3	380	380	380	380	380	800	800	800	800	800
1000	A4	B4	430	430	430	430	430	850	850	850	850	850
1000	A5	B5	480	480	480	480	480	900	900	900	900	900
1000	A6	B6	530	530	530	530	530	950	950	950	950	950
1000	A7	B7	580	580	580	580	580	1000	1000	1000	1000	1000
1000	A8	B8	630	630	630	630	630	1050	1050	1050	1050	1050
1000	A9	B9	680	680	680	680	680	1100	1100	1100	1100	1100
1000	A10	B10	730	730	730	730	730	1150	1150	1150	1150	1150
1000	A11	B11	780	780	780	780	780	1200	1200	1200	1200	1200
1000	A12	B12	830	830	830	830	830	1250	1250	1250	1250	1250
1000	A13	B13	880	880	880	880	880	1300	1300	1300	1300	1300
1000	A14	B14	930	930	930	930	930	1350	1350	1350	1350	1350
1000	A15	B15	980	980	980	980	980	1400	1400	1400	1400	1400
1000	A16	B16	1030	1030	1030	1030	1030	1450	1450	1450	1450	1450
1000	A17	B17	1080	1080	1080	1080	1080	1500	1500	1500	1500	1500
1000	A18	B18	1130	1130	1130	1130	1130	1550	1550	1550	1550	1550
1000	A19	B19	1180	1180	1180	1180	1180	1600	1600	1600	1600	1600
1000	A20	B20	1230	1230	1230	1230	1230	1650	1650	1650	1650	1650
1000	A21	B21	1280	1280	1280	1280	1280	1700	1700	1700	1700	1700

Figure 3: Example of the decision screen for $(\beta, \epsilon, p) = (0.7, 3, 0.5)$. In this example, the participant selected Option A for the first 10 rows (cells A1 to A10 in orange) and selected Option B from the last 11 rows (cells B11 to B21 in orange). Therefore, this participant switched from Option A in row 10 to Option B in row 11. This switching point corresponds to a fixed pay between $450 = (10 - 1) \times 50$ and $500 = (11 - 1) \times 50$.

Prior to the 30 decisions, participants completed an incentivized training phase to get accustomed to the graphical representation of lottery payments. The probability training phase starts with a graphical simulation of the outcomes of a lottery in which the value 100 appears twice in the table while the value 400 appears 7 times. Participants learn that after a sufficient number of draws the frequency of occurrence of 100 (400) equals the underlying probability of 0.22 (0.78). A sequence of random draws is visually presented to the participants for at least 5 seconds. In the next 7 tables, participants estimate the frequency of occurrence of a given value after 100,000 random draws. These frequencies are calibrated to cover all the relevant frequencies used in the main experimental task: 0.1, 0.25, 0.33, 0.50, and 0.75. An answer within a 5% range of the actual frequency is worth 10 cents. Our design simplifies previous RIT experiments in two ways. First, we focus on the agent's decision to accept or reject a contract that is exogenously set by the experimenter (see e.g., Dohmen et al., 2021). As previously mentioned, this allows us to leave aside issues related to unknown risk preferences and asymmetric information between the agent and the principal. Furthermore, it allows us to discard fairness motives that can affect the principal's offer and the agent's acceptance decision. As observed in other principal-agent experiments, an equal split of revenues is often a modal response (see e.g., Anderhub et al., 2002; Keser and Willinger, 2007; Gächter and Königstein, 2009; Corgnet and Hernan-Gonzalez, 2019).

In contrast to Corgnet and Hernan-Gonzalez (2019) and Dohmen et al. (2021) who implement a real-effort task, our design relies on a monetary measure of effort (as in Chowdhury and Karakostas, 2020). Not using a real-effort task to elicit effort allows us to specify the cost of effort function and focus on the agent's acceptance decision. In our design, providing effort consists in making a money transfer at a monetary cost to the agent. The optimal effort decision turns out to be trivial to calculate and is automatically computed by our experimental software. The use of monetary effort allows us to present agent's choices in a payoff table (see Figure 3). We expect this layout contributes to downplaying the role of reference points so that we can center our analysis of RIT under non-EUT models on probability distortions (RDU) and attitudes towards variance and skewness (MVS).[10] In RIT setups using a real-effort task, reference dependence appears to play a role in explaining the impact of output shocks on effort (Corgnet and Hernan-Gonzalez, 2019; Dohmen et al., 2021).[11] The rationale is that people may exert higher effort in the presence of a shock than in its absence in order to offset any potential monetary loss. In our monetary effort design, this simple mechanism does not apply because the agent cannot hedge against monetary losses by increasing monetary effort. Indeed, monetary effort implies a monetary cost and thus perceived as a loss by the agent. This argument also reflects the fact that the increase in effort due to output shock observed in real-effort tasks (Sloof and Van Praag, 2010; Corgnet and Hernan-Gonzalez, 2019; Dohmen et al., 2021) is not observed when monetary effort is used (Chowdhury and Karakostas, 2020).[12]

3.2 Preliminary survey session

Two days before completing the main experimental task (as discussed in Section 3.1), participants completed a series of individual tests and questionnaires. This preliminary set of tasks includes a numeracy test (Schwartz et al., 1997; Cokely et al., 2012), a probability weighting elicitation task (Kpegli et al., 2022) for the relevant set of probabilities (i.e., 0.1, 0.25, 0.33, 0.5 and 0.75), probability training mimicking the setup used in the main experimental session, loss aversion measurement (Brink and Rankin, 2013), risk attitude measurement (Holt and Laury, 2002) and a 7-item modified version of the cognitive reflection test (Frederick, 2005; Toplak et al., 2014).

3.3 Procedure

The design has been approved by the local ethical committee at the GATE research institute and pre-registered on the AsPredicted website (#82616). We recruited a total of 237 participants from a pool of more than 2,000 students at a major experimental economic laboratory in France.[13] All sessions were conducted online using Qualtrics. The average duration was 23 (29) minutes for the main (survey) sessions. The average earnings for the two sessions were 18.54 euros including a 4 euro flat fee paid for completing both sessions. The complete set of instructions is available in Appendix H.

[10] Despite experiencing a potential negative shock, agents were typically not shown any losses. In very few instances, a small loss of 30 appeared in the first row when the shock was 4, the fixed pay was 0, and the variable pay was 0.3. This occurred in less than 0.5% of the cells presented to participants. Furthermore, these rows involved trivial decisions and were not critical switching points between Options A and B.

[11] See Appendix E for an analysis of RIT under reference-dependence.

[12] Extensive data confirming this claim is also available from the authors upon request.

[13] This is 20% less than the pre-registered target number (300) due to lower response rate than expected. This can be explained by the sudden increase in COVID cases at that specific time and location. Only 4 participants dropped out between the main experimental task and the survey sessions.

4 Results

4.1 Risk attitude parameters and classification of agents

The aim of this section is twofold. First, we test the assumptions about risk attitude components (utility function, probability weighting function, attitudes towards variance and skewness) underlying our theoretical predictions. That is, we aim to empirically check if agents exhibit a concave utility function ($r > 0$) under EUT, and overweight small probabilities ($w(p) > p$) and underweight intermediate and high probabilities ($w(p) < p$) under RDU. For MVS, we also check whether people exhibit an aversion to variance ($a_v < 0$) and a preference for skewness ($a_S > 0$) (MVS). Second, using these three models we classify participants into types by identifying the specification that best fits their decisions.

4.1.1 Risk attitude parameters

We use agents' switching points in the minimum fixed pay elicitation task to determine their certainty equivalents for binary lotteries with various probabilities. In addition to the 30 certainty equivalents from agents' switching points elicited in the main sessions, we also use 15 additional certainty equivalents obtained in the probability weighting elicitation task in the preliminary survey session. With 45 certainty equivalents per subject, we can estimate the probability weighting function and utility curvature at the individual level under RDU following Kpegli et al. (2022), as well as utility curvature for EUT and attitudes towards variance and skewness under MVS. Appendix F provides details of the estimation procedure.

Tables 2 to 4 summarize the results obtained at the individual level. Under EUT, Table 2 indicates that 192 participants (81.01%) have concave utility under EUT ($r > 0$). Under RDU, Table 3 indicates that 209 participants (88.19%) exhibit a concave utility function. In addition, the number of participants who overweight probabilities 0.1, 0.25, 0.33, 0.5 and 0.75 are 215 (90.72%), 178 (75.11%), 142 (59.92%), 92 (38.82%) and 46 (19.41%), respectively. In total, the number of participants who exhibit both concave utility and overweighting of small probabilities 0.1, 0.25 and 0.33 are 201 (84.81%), 163 (68.78%) and 133 (56.12%). Finally, the number of participants who exhibit both concave utility and underweighting of probabilities 0.5 and 0.75 equal 126 (53.16%) and 164 (69.20%). These average results are in line with the typical concave utility function and inverse S-shaped probability weighting found in the literature. Under MVS, Table 4 indicates that 193 (80.59%) and 191 participants (81.43%) exhibit an aversion to variance and a preference for skewness, respectively. In total, 187 participants (78.90%) exhibit both characteristics.

Table 9 in Appendix F summarizes aggregate estimates for the whole sample. Under EUT, the estimate of the CARA coefficient of absolute risk aversion r is 0.0038 (p-value < 0.001, t-test). This value indicates concavity of the utility function, which implies risk aversion under EUT. Under RDU, the estimate of r is 0.0023 (p-value < 0.001). This value indicates concave utility pointing to utility risk-aversion. The estimated probability weighting function (see Figure ??) is inverse S-shaped with overweighting for $p \leq 0.33$ (probability risk-seeking) and underweighting for $p \geq 0.5$ (probability risk-aversion). Our estimation results are consistent with the empirical literature on RDU (e.g., Tversky and Kahneman, 1992; Gonzalez and Wu, 1999; Bleichrodt and Pinto, 2000; Bruhin et al., 2010). Under MVS, the coefficients of attitudes towards variance and skewness are $a_v = -0.00097$ (p-value < 0.001) and $a_s = 4.8 \times 10^{-7}$ (p-value < 0.001). These estimates indicate an aversion to variance and a preference for positive skewness and once again stand in line with previous studies (e.g., Spiliopoulos and Hertwig, 2019).

Overall, the basic assumptions underlying our three models are validated by our experimental data on certainty equivalents. On average, participants exhibit a positive CARA coefficient that is below 1 (for both EUT and RDU), an inverse S-shaped probability weighting function (for RDU), and an aversion to variance and a preference for skewness (for MVS).

Table 2: Utility curvature under EUT

	Number	Percentage
Concave	192	81.01 %
Convex	45	18.99 %
Total	237	100 %

Table 3: Utility curvature and probability weighting under RDU

Number (%)	Underweighting	Overweighting	Total
Probability	$p = 0.1$		
Concave	8 (3.38%)	201 (84.81%)	209 (88.19%)
Convex	14 (5.91%)	14 (5.91%)	28 (11.81%)
Total	22 (9.28%)	215 (90.72%)	237 (100%)
Probability	$p = 0.25$		
Concave	46 (19.41%)	163 (68.78%)	209 (88.19%)
Convex	13 (5.49%)	15 (6.33%)	28 (11.81%)
Total	59 (24.89%)	178 (75.11%)	237 (100%)
Probability	$p = 0.33$		
Concave	76 (32.07%)	133 (56.12%)	209 (88.19%)
Convex	19 (8.02%)	9 (3.80%)	28 (11.81%)
Total	95 (40.08%)	142 (59.92%)	237 (100%)
Probability	$p = 0.50$		
Concave	126 (53.16%)	83 (35.02%)	209 (88.19%)
Convex	19 (8.02%)	9 (3.80%)	28 (11.81%)
Total	145 (61.18%)	92 (38.82%)	237 (100%)
Probability	$p = 0.75$		
Concave	164 (69.20%)	45 (18.99%)	209 (88.19%)
Convex	27 (11.39%)	1 (0.42%)	28 (11.81%)
Total	191 (80.59%)	46 (19.41%)	237 (100%)

Table 4: Attitudes towards variance and skewness under MVS

Number (%)	Aversion to skewness	Preference for skewness	Total
Preference for variance	40 (16.88%)	4 (1.69%)	44 (18.57%)
Aversion to variance	6 (2.53%)	187 (78.90%)	193 (81.43%)
Total	46 (19.41 %)	191 (80.59 %)	237 (100%)

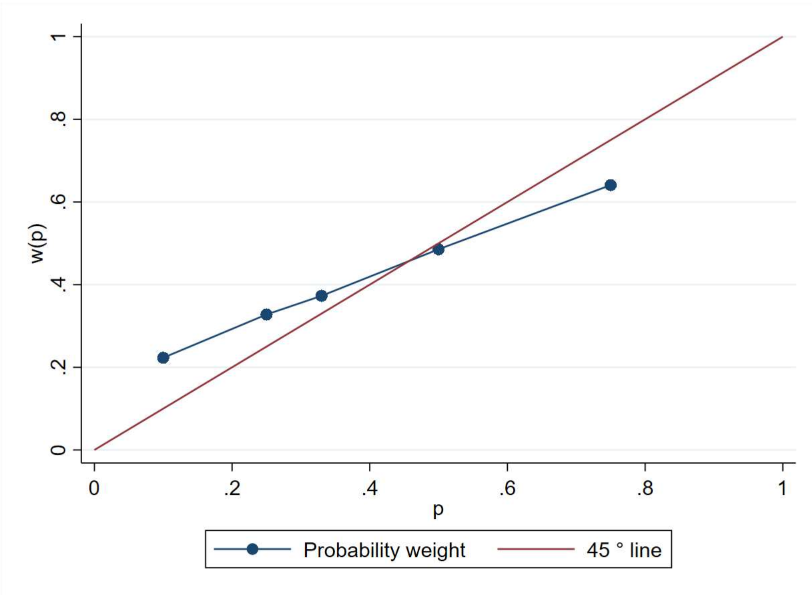


Figure 4: Estimated probability weights under RDU

4.1.2 Classification of agent types

Based on the previous estimates of risk attitude parameters, we use Akaike Information Criterion (AIC) to classify participants as either EUT, RDU or MVS (see Appendix F for details of the classification procedure). Doing so, we find that the decisions of 66 (27.85 %), 160 (67.51%) and 11 (4.64%) participants are best explained by EUT, RDU and MVS, respectively. In sum, the choices of a vast majority of our participants are in line with RDU. Next, we test the RIT predictions of the various theories, which are formally stated in Propositions 1 to 3 and summarized in Table 1.

4.2 RIT and risk attitudes

We start by estimating model-free risk attitudes for all participants. To do that, we compare the fixed pay in the absence of shock $\alpha_m^0 = 1000 - \dfrac{\beta^2\theta^2}{4\psi}$ with the fixed pay α_m^3 (α_m^4) elicited for shock $\epsilon = 3$ ($\epsilon = 4$). This procedure is used because the minimum value of the fixed pay an agent is ready to accept in the absence of shock is equal to the minimum fixed pay a risk-neutral agent would require when $\epsilon \neq 0$. The difference in the elicited minimum fixed pay in the presence of a small shock (α_m^3) and α_m^0 enables us to measure the risk premium of the agent associated with the contract (α_m^3, β). This risk premium equals the difference between the expected value of the accepted contract (which is calculated as the average of the expected values of the last accepted and the first rejected contracts), and the outside option ($y_0 = 1,000$)

which equals the certainty equivalent of the contract. Thus, an agent is considered to be risk-averse (risk-seeking) [risk-neutral] if $\alpha_m^0 < \alpha_m^3$ ($\alpha_m^0 > \alpha_m^3$) [$\alpha_m^0 = \alpha_m^3$] given the contract (α_m^3, β). Similarly, the difference in the elicited minimum fixed pay in the presence of a large shock (α_m^4) and α_m^0 measures the risk premium of the agent associated with the contract (α_m^4, β). Thus, an agent is considered to be risk-averse (risk-seeking) [risk-neutral] if $\alpha_m^0 < \alpha_m^4$ ($\alpha_m^0 > \alpha_m^4$) [$\alpha_m^0 = \alpha_m^4$] given the contract (α_m^4, β).

Table 5 provides aggregate estimates of the underlying risk attitudes associated with individual choices for the two values of the shock considered in our experiment. Given (α_m^3, β), the percentage of choices in which people are risk-averse, risk-neutral and risk-seeking are 49.96%, 20.34% and 29.70%, respectively. Increasing the shock size when considering the contract (α_m^4, β) shifts these preferences towards more risk-aversion.

Table 5: Risk attitudes and contracts[†]

Number (%)	$\epsilon = 3$		$\epsilon = 4$	
Risk-averse ($\alpha_m^0 < \alpha_m^\epsilon$)	1,776	(49.96 %)	2,052	(57.72 %)
Risk-neutral ($\alpha_m^0 = \alpha_m^\epsilon$)	723	(20.34 %)	598	(16.82 %)
Risk-seeking ($\alpha_m^0 > \alpha_m^\epsilon$)	1,056	(29.70 %)	905	(25.46 %)
Total	3,555	(100 %)	3,555	(100 %)

[†] Note that α_m^ϵ is measured as a midpoint of a range of values that is equal to 50, which is 5% of the outside option value. To account for this imprecision in our measure, we classify a participant as risk-neutral if $|\alpha_m^\epsilon - \alpha_m^0| < 25$, risk-averse if $\alpha_m^\epsilon - \alpha_m^0 \geq 25$ and risk-seeking if $\alpha_m^\epsilon - \alpha_m^0 \leq -25$.

We now consider individual-level analyses. An agent exhibits RIT (reversed RIT) [no RIT] if $\alpha_m^3 < \alpha_m^4$ ($\alpha_m^3 > \alpha_m^4$) [$\alpha_m^3 = \alpha_m^4$][14], that is the agent asks for a higher (lower) [identical] minimum fixed pay for a larger shock. Table 6 provides an overview of our empirical findings on the occurrence of RIT depending on individual risk attitudes.

Result 1 (RIT and risk attitudes at the individual level): Most risk-averse (50.96%) and risk-seeking (60.04%) agents make choices that are consistent with RIT. Most risk-neutral agents (52.42%) make choices that are consistent with the absence of RIT.

According to the theoretical predictions in Table 1, the data should be concentrated on the diagonal of Table 6 under EUT. However, we observe that only 41.29% of the choices are on the diagonal, thus rejecting EUT predictions. The main deviation from EUT resides in the fact that risk-seeking agents also make choices that are consistent with RIT ('Risk-seeking and RIT' cell) – a pattern predicted by RDU, but not by MVS.

We then split the cells in Table 6 according to the estimated risk preferences under EUT, MVS and RDU (see Tables 11- 13 in Appendix G). In particular, we focus on the decomposition of the most populated cell in Table 6 ('Risk-seeking and RIT'). Not surprisingly, most choices (63.88%) in this cell are characterized by a convex utility function under EUT (see Table 11). Since agents characterized by a convex utility function should exhibit reversed RIT, our findings are incompatible with EUT (see Proposition 1).

Under MVS, most choices in the 'Risk-seeking and RIT' cell show an aversion to variance and a preference for positive skewness (61.67%, see Table 13). However, agents should not exhibit RIT in this case under MVS (see Proposition 3).

Under RDU, most choices in the 'Risk-seeking and RIT' cell are characterized by a concave utility coupled with overweighting of probabilities (61.20%, see Table 12). This pattern is

[14]RIT could also be defined using the differences $\alpha_m^3 - \alpha_m^0$ and $\alpha_m^4 - \alpha_m^0$. Instead, we use the term "risk attitudes" to refer to these differences as they coincide with the existence of a risk premium for contracts (α_m^3, β) and (α_m^4, β).

consistent with RDU, which predicts that RIT is observed for risk-seeking agents when they exhibit utility risk-aversion and probability risk-seeking (see Propositions 2iii and 4iv, and Example 1). The alternative pattern of risk-seeking attitudes in which agents exhibit utility risk-seeking and probability risk-aversion (probability risk-seeking) characterizes only 11.36% (8.04%) of the choices in the 'Risk-seeking and RIT' cell.

A direct implication of Propositions 2v and 3v is that RDU and MVS have opposite predictions regarding the relationship between the shock magnitude, the variable pay, RIT and risk-attitudes. To test these predictions, we estimate an ordered logit model (see Table 7) to assess the effect of the shock magnitude (ϵ) and the variable pay (β) on risk attitudes (first three columns) and the occurrence of RIT (last three columns).

Result 2 (Shock size, variable pay, individual risk attitudes and RIT) An increase in the variable pay (β) or the shock size (ϵ) increases the likelihood of risk-aversion while decreasing the likelihood of risk-neutrality and risk-seeking attitudes. In addition, an increase in the variable pay increases the probability of RIT while decreasing the probabilities of No-RIT and Reversed-RIT.

Result 2 corroborates the RDU predictions (Proposition 2v) and contradicts MVS (Proposition 3v). This result also contradicts EUT which posits that both RIT and risk attitudes should not be impacted by changes in the variable pay or the shock.

We now turn to the aggregate analysis of risk attitudes and RIT. Figure 5 plots the average risk premium associated with a given combination of parameters (p, β, ϵ). Across the 30 combinations, participants are risk-averse (i.e., exhibit positive risk premium) in 80% of the cases (24 out of 30 combinations). Yet, participants are risk-seeking (i.e., exhibit a negative risk premium) for $(p, \beta, \epsilon) = (0.1, 0.3, 3), (0.25, 0.3, 3)$ and $(0.33, 0.3, 3)$, and risk-neutral for $(p, \beta, \epsilon) = (0.1, 0.5, 3), (0.1, 0.3, 4)$ and $(0.25, 0.3, 4)$. In Figure 6 we show that the difference in minimum fixed pay across shocks $(\alpha_m^4 - \alpha_m^3)$ is systematically positive pointing to RIT at the aggregate level for all 30 combinations of parameters regardless of risk attitudes. These aggregate results once again provide support for RDU while contradicting MVS and EUT. We summarize these aggregate findings below.

Result 3 (RIT at the aggregate level) RIT holds at the aggregate level for all combinations of parameters.

Figure 5: Risk premium: $\alpha_m^3 - \alpha_m^0$ and $\alpha_m^4 - \alpha_m^0$

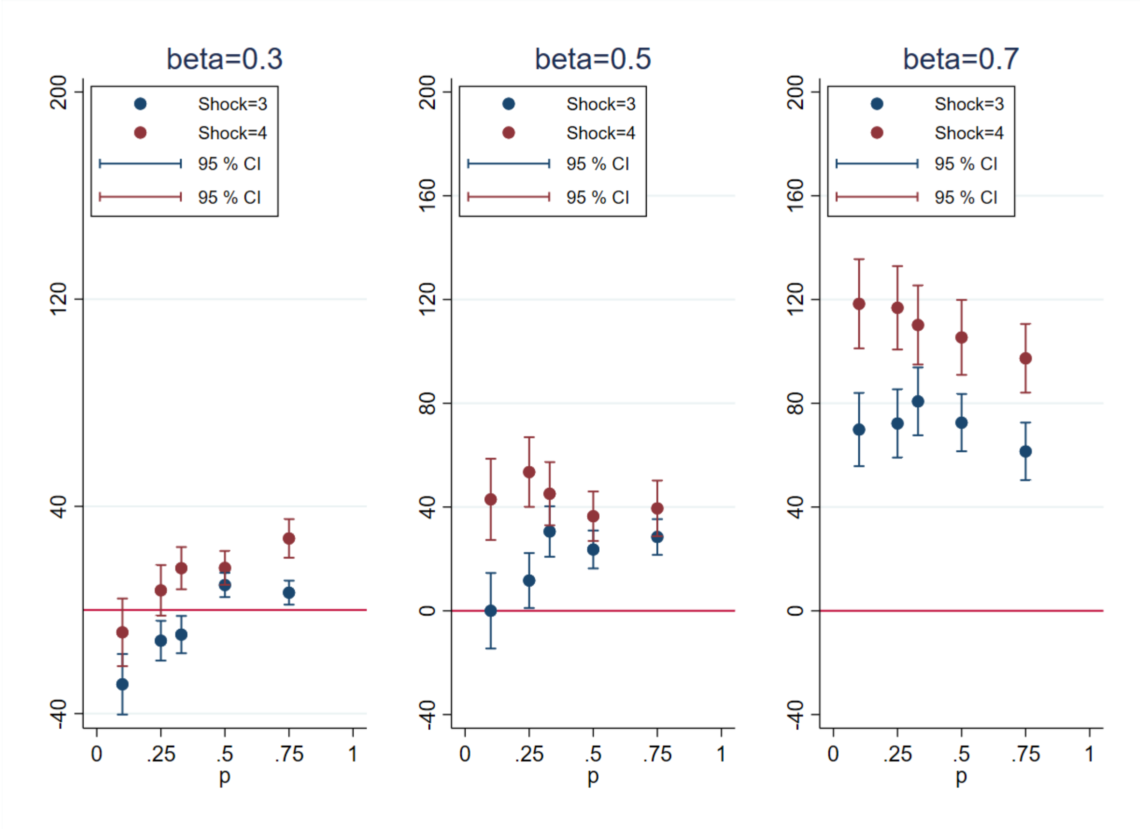


Figure 6: RIT and the variation in fixed pay $\alpha_m^4 - \alpha_m^3$

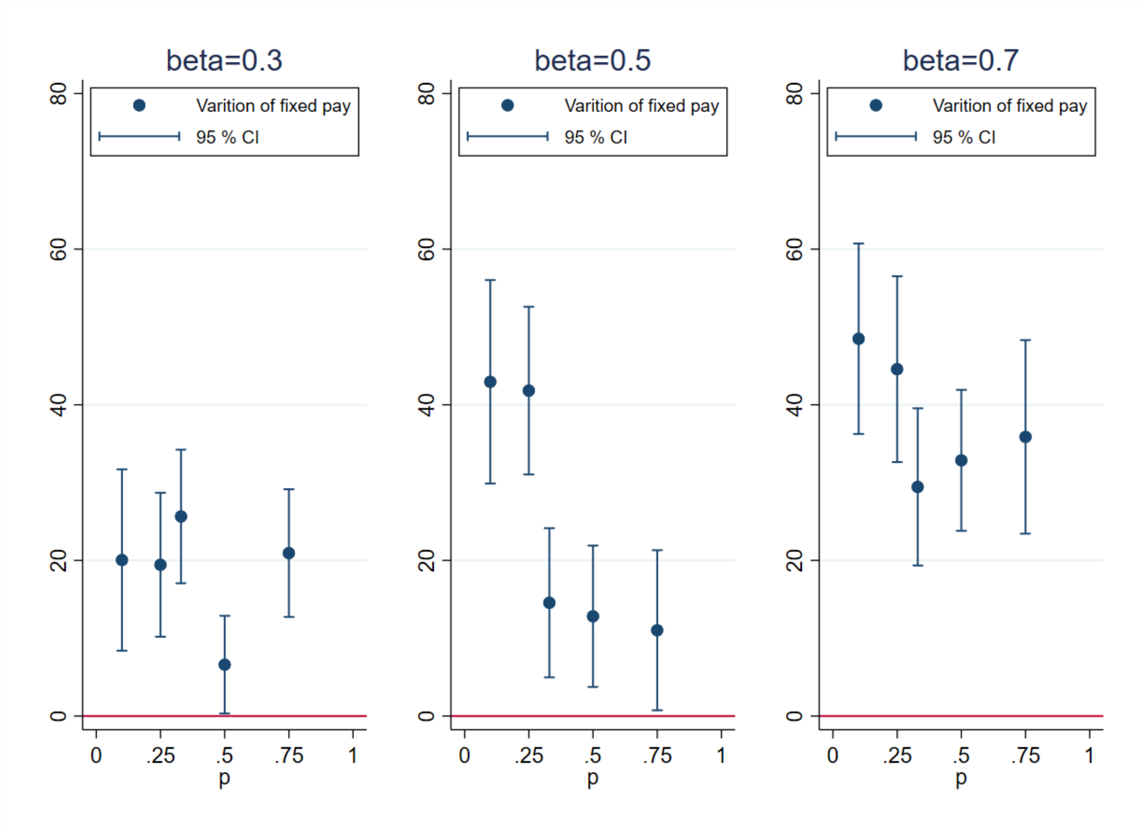


Table 6: RIT and risk attitudes

Risk attitudes \ RIT	RIT : $\alpha_m^3 < \alpha_m^4$	No RIT : $\alpha_m^3 = \alpha_m^4$	Reversed RIT : $\alpha_m^3 > \alpha_m^4$	Total
Risk-averse† : $\alpha_m^0 < \alpha_m^3$	905 50.96 %	474 26.69 %	397 22.35 %	1776 100 %
Risk-neutral† : $\alpha_m^0 = \alpha_m^3$	231 31.95 %	379 52.42 %	113 15.63 %	723 100 %
Risk-seeking† : $\alpha_m^0 > \alpha_m^3$	634 60.04 %	238 22.54 %	184 17.42 %	1056 100 %
Total	1770 49.79 %	1091 30.69 %	694 19.52 %	3555 100 %

† To account for the estimation inaccuracy due to the use of midpoint of the range of possible values of α_m^3 (see Figure 3), we classify subject as risk-neutral if $|\alpha_m^3 - \alpha_m^0| < 25$, risk-averse if $\alpha_m^3 - \alpha_m^0 \geq 25$ and risk-seeking if $\alpha_m^3 - \alpha_m^0 \leq -25$.

Table 7: Ordered logit (average marginal effects)$^{(a)}$

	Risk attitudes			RIT		
	Aversion	Neutral	Seeking	RIT	No-RIT	Reversed RIT
β	0.882***	-0.163***	-0.719***	0.376***	-0.137***	-0.239***
ϵ	0.0675***	-0.0126***	-0.0549***	$^{(b)}$	$^{(b)}$	$^{(b)}$
p	-0.020	0.004	0.016	-0.185***	0.068***	0.118***

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ for the significance of coefficient tests.

$^{(a)}$ Control variables include: numeracy test score, cognitive reflection test score, gender, and age.
$^{(b)}$ We cannot estimate the margina effect ϵ on RIT because we already exploit the data on both small and large shocks to estimate RIT.

5 Conclusion

This paper studies the tradeoff between risk and incentives (RIT) under alternatives to the standard EUT model: the mean-variance-skewness (MVS) model and the the rank-dependent utility (RDU) model. At a theoretical level, we show that RIT is a robust phenomenon under RDU (and notwithstanding EUT and MVS) because it can be observed even when agents are risk-seeking. By contrast, we show that RIT is less robust under MVS than under EUT since it may not hold even for risk-averse agents, thus offering a possible explanation for the limited empirical support for the tradeoff.

To test the predictions of the three theories, we develop a novel experimental design that eliminates the potential confounds appearing in the existing literature. To our surprise, we found extensive evidence for RIT. Most strikingly, RIT emerges even in situations in which agents are risk-seeking, which is a distinct prediction of RDU.

Our findings are not only reassuring for the principal-agent theory, but also suggest RIT predictions can be applied to a broader range of situations than originally anticipated. These situations include contractual settings in which agents are likely to exhibit risk-seeking attitudes such as executive compensation (Garen, 1994; Edmans and Gabaix, 2011; Edmans et al., 2012, 2017; Ma et al., 2019). It follows that risk-seeking agents might demand a fixed monetary compensation for any additional risk. This novel finding can also have interesting implications in fields like finance and entrepreneurship. For example, financial advisors might need to craft portfolios with a substantial share of safe assets for clients that are otherwise categorized as risk-tolerant. Furthermore, our findings suggest that, unlike "Knightian" theory of entrepreneurship

(Knight, 1921; Kihlstrom and Laffont, 1979; Newman, 2007), risk-seeking entrepreneurs might want to share part of the risk associated with new ventures.

Appendix

A- Proofs for Section 2.1.3

EUT

The main implications of Assumptions A0, A1, A2, A3', A3", A4, A5 are captured in Proposition A1.

Proposition A1 (Risk-incentives tradeoff with EUT): Under A0, A1, A2, A3', A4 and A5 EUT, optimal variable pay $\beta^*(\epsilon, r, \psi, \theta)$ decreases with ϵ whereas optimal fixed pay $\alpha^*(\epsilon, r, \psi, \theta)$ increases with ϵ.

Proof of Proposition A1

Given the linear contract (α, β), the objective function of an expected utility agent with a cost function $C(e) = \psi e^2$ is given by

$$EU(L) = pu(y_+) + (1-p)u(y_-)$$

with $u(y) = \dfrac{1 - exp(-ry)}{r}$, $y_+ = \alpha + \beta\theta\Big(e + \frac{1-p}{p}\epsilon\Big) - \psi e^2$ and $y_- = \alpha + \beta\theta\Big(e - \epsilon\Big) - \psi e^2$

The first-order condition of the agent's maximization problem is given by

$$(\beta\theta - 2\psi e)[pu'(y_+) + (1-p)u'(y_-)] = 0$$

Since $pu'(y_+) + (1-p)u'(y_-) \neq 0$, it turns out that the best response effort function of the agent is given by

$$e = \frac{\beta\theta}{2\psi}$$

Hence, the best response effort function is an increasing function of the variable pay and does not vary with respect to the shock ϵ, the relative risk-aversion coefficient r and the fixed pay α. The proof with $p = 1/2$ is provided in Appendix A2 of Corgnet and Hernan-Gonzalez (2019). The optimization problem of the principal is to maximize the expected value of $\theta z - y$ by accounting for agent's incentive compatibility constraint (IC) and participation constraint (PC)

$$\begin{cases} \max\limits_{\alpha,\beta} \quad \theta e - (\alpha + \beta\theta e) \\ s.t.: \\ e = \frac{\beta\theta}{2\psi} \\ \alpha + \beta\theta e - \psi e^2 - \dfrac{1-p}{2p} r\beta^2\theta^2\epsilon^2 \simeq y_0 \end{cases}$$

The participation constraint is an application of the Pratt (1964) approximation of the risk premium to the agent's maximization problem as in Milgrom and Roberts (1992). The optimal linear contact (α^*, β^*) of the principal is given by

$$\beta^*(\epsilon, r, \psi, \theta) \simeq \frac{1}{1 + 2\psi r\epsilon^2\frac{1-p}{p}} \tag{5}$$

$$\alpha^*(\epsilon, r, \psi, \theta) \simeq y_0 + \frac{1}{2}\Big(\frac{1-p}{p}r\epsilon^2 - \frac{1}{2\psi}\Big)\Big(\theta\beta^*(\epsilon, r, \psi, \theta)\Big)^2 \tag{6}$$

Furthermore, the expression of $\beta^*(\epsilon, r, \psi, \theta)$, yields

$$\frac{\partial \beta^*(\epsilon, r, \psi, \theta)}{\partial \epsilon} < 0$$

$$\frac{\partial \beta^*(\epsilon, r, \psi, \theta)}{\partial r} < 0$$

For $k = \frac{1-p}{p}\epsilon$, Assumption 3" yields $r[\alpha + \beta\theta k] < 1$. Using $e > \epsilon$ and $e = \frac{\beta\theta}{2\psi}$, we have

$$\frac{1-p}{p} r\epsilon^2 - \frac{1}{2\psi} < 0 \tag{7}$$

Inequalities (7) and (6) jointly imply

$$sign\Big(\frac{\partial \alpha^*(\epsilon, r, \psi, \theta)}{\partial t}\Big) = -sign\Big(\frac{\partial \beta^*(\epsilon, r, \psi, \theta)}{\partial t}\Big) \qquad \text{for} \quad t = \epsilon, r, \psi, \theta$$

In particular

$$\frac{\partial \alpha^*(\epsilon, r, \psi, \theta)}{\partial \epsilon} > 0$$

$$\frac{\partial \alpha^*(\epsilon, r, \psi, \theta)}{\partial r} > 0$$

Remark: expressions (5) and (6) also hold for risk-neutral agent ($r = 0$) and risk-seeking agent ($r < 0$) as long as the second-order condition obtained from the derivative of the first-order condition A1.2 is negative. Hence, for a risk-neutral agent the fixed pay and performance do not vary with ϵ. For a risk-seeking agent, we have reversed RIT. Also, note that the agent's optimal level of effort e^* is given by

$$e = \frac{\theta}{2\psi}\beta^*(\epsilon, r, \psi, \theta)$$

It turns out that the partial derivatives $\frac{\partial e^*(\epsilon, r, \psi, \theta)}{\partial \epsilon}$ and $\frac{\partial e^*(\epsilon, r, \psi, \theta)}{\partial r}$ are negatives as $\frac{\partial \alpha^*(\epsilon, r, \psi, \theta)}{\partial \epsilon}$ and $\frac{\partial \alpha^*(\epsilon, r, \psi, \theta)}{\partial r}$ are negative.

QED.

RDU

Before showing the proofs, let us first state and provide some explanations of Lemma 1 and Propositions A2 and A3. Under RDU, we derive our first lemma below:

Lemma 1 Under RDU, maximizing the objective function of the agent amounts to maximizing his certainty equivalent CE:

$$CE = \alpha + \beta\theta e - \psi e^2 + \Big(\frac{w(p)}{p} - 1\Big) - \frac{\beta^2\theta^2\epsilon^2}{2}\Big(1 + \frac{w(p)}{p}\frac{1-2p}{p}\Big)A_a\Big(\alpha + \beta\theta e - \psi e^2\Big) + o(\epsilon^2) \tag{8}$$

with $A_a(z) = -\frac{u''(z)}{u''(z)}$ being the absolute risk-aversion index evaluated at the outcome z and $o(\epsilon^2)$ denoting the approximation error.

Lemma 1 provides an approximation of the certainty equivalent. This approximation allows us to generate a closed-form solution for the optimal contract (α^*, β^*) by assuming CARA utility function (Milgrom and Roberts, 1992), that is $A_a(z) = r$ for all z. Similar to EUT, we capture

RIT in RDU in Proposition A2ii below.

Proposition A2 (RIT with RDU).[15] Under A0, A1, A2, A3', A3", A4, A5 and assuming RDU agent, for any probability $p \in (0, 1)$:
i) Optimal variable pay $\beta^*(\epsilon, r, w(p), \psi, \theta)$ decreases with r and probability risk-aversion whereas the fixed pay $\alpha^*(\epsilon, r, w(p), \psi, \theta)$ increases with r and probability risk-aversion.
ii) If the agent exhibits probability risk-aversion, the optimal variable pay $\beta^*(\epsilon, r, w(p), \psi, \theta)$ decreases with ϵ whereas the optimal fixed pay $\alpha^*(\epsilon, r, w(p), \psi, \theta)$ increases with ϵ.
iii) If the agent exhibits probability risk-seeking, there is $r_{to}(\beta^*, \epsilon)$ such that for $r < r_{to}(\beta^*, \epsilon)$ the optimal variable pay$\beta^*(\epsilon, r, w(p), \psi, \theta)$ increases with ϵ and the optimal fixed pay $\alpha^*(\epsilon, r, w(p), \psi, \theta)$ decreases with ϵ.

Proposition A2iii points to the absence of RIT under probability risk-seeking. Furthermore, Proposition A3 provides results on RIT under general risk attitudes which are a combination of utility curvature and probability risk attitudes.

Proposition A3 (Risk attitudes and absence of tradeoff with RDU): Assume that the agent exhibits probability risk-seeking for a given probability p. Let $r_N(\beta^*, \epsilon)$ be the absolute risk-aversion index that allows probability risk-seeking agent to exhibit risk-neutrality for the lottery

$$L = \left(\alpha^* + \beta^*\theta\left(e^* + \frac{1-p}{p}\epsilon\right) - \psi e^{*2}, \alpha^* + \beta^*\theta\left(e^* - \epsilon\right) - \psi e^{*2}; p, 1-p\right)$$

associated with the optimal linear contract (α^*, β^*). Then, $r_N(\beta^*, \epsilon) > r_{to}(\beta^*, \epsilon)$.

Figure 7 illustrates Proposition A3. It shows that, in line with RIT a principal facing a risk-averse agent who exhibits probability risk-seeking proposes an optimal variable pay $\beta^*(\epsilon, r, w(p), \psi, \theta)$ that decreases in ϵ. In addition, a principal facing an agent who exhibits probability risk-seeking with absolute risk-aversion index $r \in \big(r_{to}(\beta^*, \epsilon), r_N(\beta^*, \epsilon)\big)$ also proposes an optimal variable pay $\beta^*(\epsilon, r, w(p), \psi, \theta)$ that decreases in ϵ. Note that such agent exhibits risk-seeking behavior since $r < r_N(\beta^*, \epsilon)$. Finally, the principal only proposes an optimal variable pay $\beta^*(\epsilon, r, w(p), \psi, \theta)$ that increases in ϵ when facing an agent that exhibits probability risk-seeking with absolute risk-aversion index $r \in \big(0, r_{to}(\beta^*, \epsilon)\big)$. Unlike EUT, RIT under RDU depends on the probability of the binary shock and becomes more pervasive because it now applies to risk-seeking agent (on top of risk-averse agent, as in EUT).

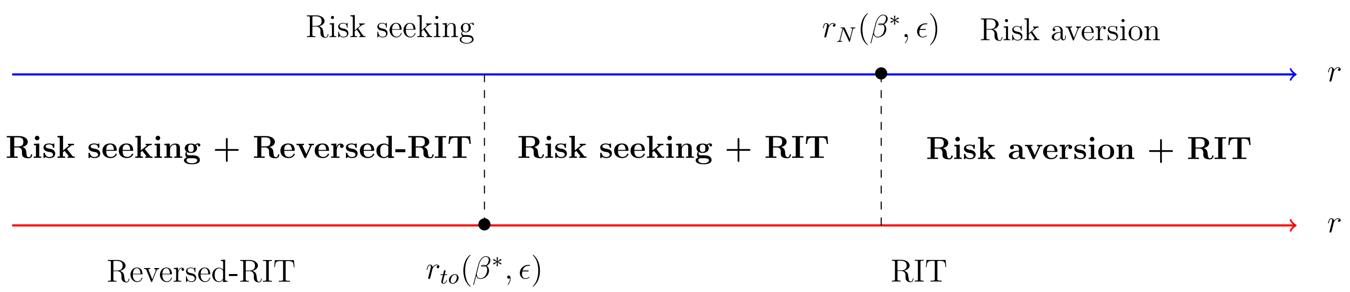


Figure 7: Risk attitudes and RIT with RDU (agent exhibits $w(p) > p$)

Proof of Lemma 1

[15]In Appendix E, we extend proposition A2 to the case of the prospect theory agent exhibiting loss aversion and reference-dependence.

In the Lemma, we derive an equivalent of the Pratt (1964) approximation of risk premium for RDU and use it to provide incentive compatibility and participation constraints as in Milgrom and Roberts (1992). To do so, let us first consider a binary random variable $\tilde{x} = \big(x + \frac{1-p}{p}\sigma, x - \sigma; p, 1-p\big)$ with $\sigma > 0$, $p \in (0,1)$ so that $E(\tilde{x}) = x$ and $V(\tilde{x}) = \frac{1-p}{p}\sigma^2$. Under RDU theory, the certainty equivalent (ce) of $\tilde{x}$ satisfies

$$u(ce) = w(p)\Big[u\Big(x + \frac{1-p}{p}\sigma\Big) - u\big(x-\sigma\big)\Big] + u\big(x-\sigma\big) \tag{9}$$

Applying second-order Taylor approximation to the right-hand side (RHS) of expression (9) around the expected value x leads to

$$RHS = u(x) + \sigma\Big(\frac{w(p)}{p} - 1\Big)u'(x) + \frac{\sigma^2}{2}\Big(1 + \frac{w(p)}{p}\frac{1-2p}{p}\Big)u''(x) + o(\sigma^2) \tag{10}$$

with $o(\sigma^2)$ denoting the approximation error such that $\lim\limits_{\sigma \longrightarrow 0} \dfrac{o(\sigma^2)}{\sigma^2} = 0$.

We furthermore impose the following linear form for the certainty equivalent with an unknown slope a

$$ce = x + a\sigma^2 + o(\sigma^2) \tag{11}$$

Plugging (11) into (9) and applying first-order Taylor approximation on the left-hand side (LHS) of the expression (9) around the expected value x yields

$$LHS = u(x) + a\sigma^2 u'(x) + o(\sigma^2) \tag{12}$$

Since LHS=RHS, according to (9), we can identify the unknown slope a

$$a = \frac{1}{\sigma}\Big(\frac{w(p)}{p} - 1\Big) + \frac{1}{2}\Big(1 + \frac{w(p)}{p}\frac{1-2p}{p}\Big)\frac{u''(x)}{u'(x)} \tag{13}$$

Let $A_a(z) = -\dfrac{u''(z)}{u''(z)}$ be the absolute risk-aversion index evaluated at x. Plugging (13) in (11) gives the Pratt (1964) risk premium π under RDU for the binary random variable $\tilde{x} = \big(x + \frac{1-p}{p}\sigma, x - \sigma; p, 1-p\big)$.

$$\pi := x - ce = -\Big(\frac{w(p)}{p} - 1\Big)\sigma + \frac{\sigma^2}{2}\Big(1 + \frac{w(p)}{p}\frac{1-2p}{p}\Big)A_a(x) + o(\sigma^2) \tag{14}$$

So that the certainty equivalent is

$$ce = x + \Big(\frac{w(p)}{p} - 1\Big)\sigma - \frac{\sigma^2}{2}\Big(1 + \frac{w(p)}{p}\frac{1-2p}{p}\Big)A_a(x) + o(\sigma^2) \tag{15}$$

Note that RDU becomes EUT if $w(p) = p$. Since $V(\tilde{x}) = \frac{1-p}{p}\sigma^2$, (14) collapses to the usual Pratt (1964) formula $\pi = -\frac{1}{2}\frac{u''(x)}{u'(x)}V(\tilde{x}) + o(\sigma^2)$ whenever $w(p) = p$. Relation (15) allows us to define the incentive compatibility and participation constraints. In the context of RDU (see Section 2), we set $x = \alpha + \beta\theta e - \psi e^2$ and $\sigma = \beta\theta\epsilon$ so that the certainty equivalent equation (15) becomes:

$$ce = \alpha + \beta\theta e - \psi e^2 + \Big(\frac{w(p)}{p} - 1\Big)\beta\theta\epsilon - \frac{\beta^2\theta^2\epsilon^2}{2}\Big(1 + \frac{w(p)}{p}\frac{1-2p}{p}\Big)A_a\Big(\alpha + \beta\theta e - \psi e^2\Big) + o(\epsilon^2) \tag{16}$$

QED.

Proof of Proposition A2

Given the linear contract (α, β), the objective function of a RDU agent with cost function $C(e) = \psi e^2$ is given by

$$RDU(L) = w(p)u(y_+) + (1 - w(p))u(y_-)$$

with $u(x) = \dfrac{1 - exp(-rx)}{r}$, $y_+ = \alpha + \beta\theta\Big(e + \frac{1-p}{p}\epsilon\Big) - \psi e^2$ and $y_- = \alpha + \beta\theta\Big(e - \epsilon\Big) - \psi e^2$

The first-order condition of the agent's maximization problem is given by

$$(\beta\theta - 2\psi e)[w(p)u'(y_+) + (1 - w(p))u'(y_-)] = 0$$

Since $w(p)u'(y_+) + (1 - w(p))u'(y_-) \neq 0$, it turns out that the optimal effort function of the agent is given by

$$e = \frac{\beta\theta}{2\psi}$$

Hence, the optimal effort function is increasing in the variable pay and does not vary with respect to chock ϵ, the relative risk-aversion coefficient r, the fixed pay α and probability risk attitude $w(p)$.

Point i)

The optimization problem of the principal is to maximize the expected value of $\theta z - y$ by accounting for the agent's incentive compatibility constraint (IC) and participation constraint (PC):

$$\begin{cases} \max\limits_{\alpha,\beta} \quad \pi = \theta e - (\alpha + \beta\theta e) \\ s.t.: \\ e = \frac{\beta\theta}{2\psi} \\ \alpha + \beta\theta e - \psi e^2 + \Big(\frac{w(p)}{p} - 1\Big)\beta\theta\epsilon - \frac{\beta^2\theta^2\epsilon^2}{2}\Big(1 + \frac{w(p)}{p}\frac{1-2p}{p}\Big)r \simeq y_0 \end{cases}$$

Like in Proposition A1 above, the participation constraint is an application of the Pratt (1964) approximation of the risk premium. The optimal linear contact (α^*, β^*) of the principal is given by

$$\beta^*(\epsilon, r, w(p), \psi, \theta) \simeq \frac{1 + \frac{2\psi\epsilon}{\theta}\Big(\frac{w(p)}{p} - 1\Big)}{1 + 2\psi r\epsilon^2\Big(1 + \frac{w(p)}{p}\frac{1-2p}{p}\Big)} \tag{17}$$

$$\alpha^*(\epsilon, r, w(p), \psi, \theta) \simeq y_0 + \frac{1}{2}\Big[r\epsilon^2\Big(1 + \frac{w(p)}{p}\frac{1-2p}{p}\Big) - \frac{1}{2\psi}\Big]\Big(\theta\beta^*(\epsilon, r, w(p), \psi, \theta)\Big)^2 - \epsilon\theta\beta^*(\epsilon, r, w(p), \psi, \theta) \tag{18}$$

Expression (17) implies that

$$Sign\Big(\frac{\partial\beta^*(\epsilon, r, w(p), \psi, \theta)}{\partial r}\Big) = -Sign\Bigg(1 + \frac{w(p)}{p}\frac{1-2p}{p}\Bigg) \times Sign\Bigg(1 + \frac{2\psi\epsilon}{\theta}\Big(\frac{w(p)}{p} - 1\Big)\Bigg) \tag{19}$$

Note that $1 + \frac{w(p)}{p}\frac{1-2p}{p} = w(p)\Big(\frac{1-p}{p}\Big)^2 + 1 - w(p)$. Since $w(p) < 1$, it turns out that

$$1 + \frac{w(p)}{p}\frac{1-2p}{p} > 0 \tag{20}$$

This means that the certainty equivalent ce (16) decreases in r (or equivalently, the risk premium increases in r).[16]

Since $\beta^*(\epsilon, r, w(p), \psi, \theta)$ is positive, the relation 20 and the expression of $\beta^*(\epsilon, r, w(p), \psi, \theta)$ jointly imply that

$$1 + \frac{2\psi\epsilon}{\theta}\Big(\frac{w(p)}{p} - 1\Big) > 0 \tag{21}$$

Plugging (20) and (21) into the relation (19) yields

$$\frac{\partial \beta^*(\epsilon, r, w(p), \psi, \theta)}{\partial r} < 0$$

For $k = \Big(1 + \frac{w(p)}{p}\frac{1-2p}{p}\Big)\epsilon > 0$, we have under Assumption 3" that $r[\alpha + \beta\theta k] < 1$. Then, for $e > \epsilon$ and $e = \frac{\beta\theta}{2\psi}$, we have that

$$r\epsilon^2\Big(1 + \frac{w(p)}{p}\frac{1-2p}{p}\Big) - \frac{1}{2\psi} < 0 \tag{22}$$

Relations (22) and (18) imply for $t = \epsilon, r, w(p), \psi, \theta$ that

$$sign\Big(\frac{\partial \alpha^*(\epsilon, r, w(p), \psi, \theta)}{\partial t}\Big) = -sign\Big(\frac{\partial \beta^*(\epsilon, r, w(p), \psi, \theta)}{\partial t}\Big) \tag{23}$$

In particular, we have that

$$\frac{\partial \alpha^*(\epsilon, r, \psi, \theta)}{\partial r} > 0$$

From (17), we have that

$$Sign\Big(\frac{\partial \beta^*(\epsilon, r, \delta, \psi, \theta)}{\partial \delta}\Big) = Sign\left(1 - r\theta\epsilon\frac{1-2p}{p} + 2\psi r\epsilon^2\frac{1-p}{p}\right) \tag{24}$$

with $\delta = w(p)$. Let us now consider (24) under two cases: $p \geq \frac{1}{2}$ and $p < \frac{1}{2}$.

For $p \geq \frac{1}{2}$, we have $\frac{1-2p}{p} \leq 0$ so that $\dfrac{\partial \beta^*(\epsilon, r, \delta, \psi, \theta)}{\partial \delta}$ is positive.

For $p < \frac{1}{2}$, we have $\frac{1-2p}{p} > 0$. Take $k = \frac{\epsilon}{\beta^*(\epsilon, r, \delta, \psi, \theta)}\frac{1-2p}{p} > 0$. It follows from Assumption 3" that $1 - r\theta\beta^*(\epsilon, r, w(p), \psi, \theta)k = 1 - r\theta\epsilon\frac{1-2p}{p} > 0$. Thus, for $p < \frac{1}{2}$ we have $\dfrac{\partial \beta^*(\epsilon, r, \delta, \psi, \theta)}{\partial \delta}$ also positive. This means that for all p

$$\frac{\partial \beta^*(\epsilon, r, \delta, \psi, \theta)}{\partial \delta} > 0 \tag{25}$$

From (23) and (25), it also follows that

$$\frac{\partial \alpha^*(\epsilon, r, \delta, \psi, \theta)}{\partial \delta} < 0 \tag{26}$$

Note that probability risk-aversion corresponds to a lower level of δ. Hence, equations (25) and (26) mean that the optimal variable pay $\beta^*(\epsilon, r, \delta, \psi, \theta)$ decreases as the probability risk-aversion increases while the fixed pay $\alpha^*(\epsilon, r, \delta, \psi, \theta)$ increases as the probability risk-aversion increases.

Point ii)

[16] See also Theorem 6.1 in Eeckhoudt and Laeven (2015).

It follows from the expression (17) that

$$Sign\Big(\frac{\partial\beta^*(\epsilon,r,\delta,\psi,\theta)}{\partial\epsilon}\Big) = Sign\Big(A(\epsilon,r,\delta,\psi,\theta)\Big) \tag{27}$$

with

$$A(\epsilon,r,\delta,\psi,\theta) = \theta^{-1}\Big(\frac{w(p)}{p}-1\Big)\Big[1-2\psi r\epsilon^2\Big(1+\frac{w(p)}{p}\frac{1-2p}{p}\Big)\Big] - 2r\epsilon\Big(1+\frac{w(p)}{p}\frac{1-2p}{p}\Big) \tag{28}$$

From 20 and 22 we have respectively that $1+\frac{w(p)}{p}\frac{1-2p}{p} > 0$ and $1-2\psi r\epsilon^2\Big(1+\frac{w(p)}{p}\frac{1-2p}{p}\Big) > 0$. If the agent exhibits probability risk-aversion or probability risk-neutral for probability p (i.e., $w(p) \leq p$), (27) and (28) jointly imply

$$\frac{\partial\beta^*(\epsilon,r,\delta,\psi,\theta)}{\partial\epsilon} < 0$$

while (23) implies

$$\frac{\partial\alpha^*(\epsilon,r,\delta,\psi,\theta)}{\partial\epsilon} > 0$$

Recall that $e^*(\epsilon,r,\delta,\psi,\theta) = \frac{\theta}{2\psi}\beta^*(\epsilon,r,\delta,\psi,\theta)$. Hence,

$$\frac{\partial e^*(\epsilon,r,\delta,\psi,\theta)}{\partial\epsilon} < 0 \quad \text{as} \quad \frac{\partial\beta^*(\epsilon,r,\delta,\psi,\theta)}{\partial\epsilon} < 0$$

Point iii) Assume that the agent exhibits probability risk-seeking for probability p (*i.e.*, $w(p) > p$). Hence, (27) and (28) jointly imply the following equivalence

$$r < r_{to}(\beta^*,\epsilon) \qquad \Longleftrightarrow \qquad \frac{\partial\beta^*(\epsilon,r,\psi,\theta)}{\partial\epsilon} > 0$$

with

$$r_{to}(\beta^*,\epsilon) \cong \frac{1}{2\epsilon}\frac{\frac{w(p)}{p}-1}{\Big(\theta+\epsilon\psi\Big(\frac{w(p)}{p}-1\Big)\Big)\Big(1+\frac{w(p)}{p}\frac{1-2p}{p}\Big)} \tag{29}$$

From (23), it also follows that

$$r < r_{to}(\beta^*,\epsilon) \qquad \Longleftrightarrow \qquad \frac{\partial\alpha^*(\epsilon,r,\delta,\psi,\theta)}{\partial\epsilon} < 0$$

Since $e^*(\epsilon,r,\delta,\psi,\theta) = \frac{\theta}{2\psi}\beta^*(\epsilon,r,\delta,\psi,\theta)$, we have

$$r < r_{to}(\beta^*,\epsilon) \qquad \Longleftrightarrow \qquad \frac{\partial e^*(\epsilon,r,\psi,\theta)}{\partial\epsilon} > 0$$

Also, we have

$$\frac{\partial e^*(\epsilon,r,\delta,\psi,\theta)}{\partial r} < 0 \quad \text{as} \quad \frac{\partial\beta^*(\epsilon,r,\delta,\psi,\theta)}{\partial r} < 0$$

$$\frac{\partial e^*(\epsilon,r,\delta,\psi,\theta)}{\partial\delta} > 0 \quad \text{as} \quad \frac{\partial\beta^*(\epsilon,r,\delta,\psi,\theta)}{\partial\delta} > 0$$

QED.

Proof of Proposition A3

From Lemma 1, the absolute risk-aversion index $r_N(\beta^*, \epsilon)$ that makes an agent with probability risk-seeking behavior to exhibit risk-neutrality (i.e., null risk premium) for the lottery

$$L^* = \left(\alpha^* + \theta\beta^*\left(e^* + \frac{1-p}{p}\epsilon\right) - \psi e^{*2}, \alpha^* + \theta\beta^*\left(e^* - \epsilon\right) - \psi e^{*2}; p, 1-p\right)$$

associated with the optimal linear contract (α^*, β^*) and optimal effort e^* is given by

$$r_N(\beta^*, \epsilon) \cong \frac{2}{\epsilon\theta\beta^*}\frac{\frac{\delta}{p} - 1}{1 + \frac{\delta}{p}\frac{1-2p}{p}}$$

with $\delta = w(p)$.

From Proposition A2, the threshold $r_{to}(\beta^*, \epsilon)$ of the absolute risk-aversion index of an agent with probability risk-seeking behavior that leads the principal to propose an optimal variable pay $\beta^*(\epsilon, r, \delta, \psi, \theta)$ that decreases in ϵ is

$$r_{to}(\beta^*, \epsilon) \cong \frac{1}{2\epsilon}\frac{\frac{w(p)}{p} - 1}{\left(\theta + \epsilon\psi\left(\frac{w(p)}{p} - 1\right)\right)\left(1 + \frac{w(p)}{p}\frac{1-2p}{p}\right)}$$

Computing the difference between the two thresholds leads to

$$Sign\left(r_N(\beta^*, \epsilon) - r_{to}(\beta^*, \epsilon)\right) = Sign\left[N\left(\beta^*(\epsilon, r, \delta, \psi, \theta)\right)\right]$$

with

$$N\left(\beta^*(\epsilon, r, \delta, \psi, \theta)\right) = 4 - \beta^*(\epsilon, r, \delta, \psi, \theta) + \frac{4\epsilon\psi}{\theta}\left(\frac{w(p)}{p} - 1\right)$$

Recall that $\dfrac{\partial\beta^*(\epsilon, r, \delta, \psi, \theta)}{\partial r} < 0$ so that we have $\dfrac{\partial N\left(\beta^*(\epsilon, r, \delta, \psi, \theta)\right)}{\partial r} < 0$. Furthermore, we have $\lim\limits_{r\longrightarrow 0} N(\beta^*(\epsilon, r, \delta, \psi, \theta)) = 3 + \dfrac{2\epsilon\psi}{\theta}\left(\dfrac{w(p)}{p} - 1\right)$. Hence, for all $r > 0$ we have $N\left(\beta^*(\epsilon, r, \delta, \psi, \theta)\right) > 0$ so that $r_N(\beta^*, \epsilon) > r_{to}(\beta^*, \epsilon)$.

QED.

MVS

Before providing the proofs, we first state and provide some explanations for Propositions A4 and A5.

Proposition A4 (Risk-incentives tradeoff with MVS). Under A0, A1, A2 and A4 and assuming the agent is MVS as specified in (4):

i) Optimal variable pay $\beta^*(\epsilon, a_v, a_s, \psi, \theta)$ decreases with a_v

ii) Optimal variable pay $\beta^*(\epsilon, a_v, a_s, \psi, \theta)$ increases (resp. decreases) with a_s for $p < \frac{1}{2}$ (resp. $p > \frac{1}{2}$).

iii) If $p \geq \frac{1}{2}$, the optimal variable pay $\beta^*(\epsilon, a_v, a_s, \psi, \theta)$ decreases with ϵ.
iv) If $p < \frac{1}{2}$, there is $g(\epsilon, p, a_v, a_s, \psi, \theta)$ such that if $g(\epsilon, p, a_v, a_s, \psi, \theta) < \frac{9}{4}$, then $\beta^*(\epsilon, a_v, a_s, \psi, \theta)$ increases with ϵ.

Proposition A4iv shows that the absence of the tradeoff can be expected for p<1/2, i.e., when the lottery

$$L^* = \left(\alpha^* + \theta\beta^*\left(e^* + \frac{1-p}{p}\epsilon\right) - \psi e^{*2}, \alpha^* + \theta\beta^*\left(e^* - \epsilon\right) - \psi e^{*2}; p, 1-p\right)$$

associated with the optimal contract (α^*, β^*) is positively skewed. Since risk attitudes are driven by both aversions to variance and preference for positive skewness, it remains unclear if the absence of the tradeoff arises for a risk-seeking or a risk-averse agent. Proposition B5 provides such information.

Proposition A5 (Risk attitudes and absence of tradeoff with MVS):
Consider p<1/2. Hence, we have the following results:
i) At the optimal contract, agent's risk-aversion (risk-seeking) corresponds to $g(\epsilon, p, a_v, a_s, \psi, \theta) > 1$ ($g(\epsilon, p, a_v, a_s, \psi, \theta) < 1$)
ii) If the agent is a risk-seeker, then the optimal variable pay $\beta^*(\epsilon, p, a_v, a_s, \psi, \theta)$ increases with ϵ
iii) For $g(\epsilon, p, a_v, a_s, \psi, \theta) \in \left(1, \frac{9}{4}\right)$, the agent exhibits risk-aversion and the optimal variable pay β^* increases with ϵ.

According to Proposition A5, if the agent exhibits risk-seeking behavior at the optimal contract proposed by the principal, then the optimal variable pay $\beta^*(\epsilon, p, a_v, a_s, \psi, \theta)$ increases with ϵ. However, if the agent is risk-averse at the optimal contract proposed by the principal [i.e., $g(\epsilon, p, a_v, a_s, \psi, \theta) > 1$], the optimal variable pay $\beta^*(\epsilon, p, a_v, a_s, \psi, \theta)$ can either increase or decrease with ϵ depending on whether $g(\epsilon, p, a_v, a_s, \psi, \theta)$ is greater or smaller than $\frac{9}{4}$.

Remark [RDU vs. MVS]: Proposition A5 echoes Proposition A3 for RDU once we consider, in line with literature (e.g., Gonzalez and Wu, 1999; Tversky and Wakker, 1995; Gonzalez-Jimenez, 2019; Kpegli et al., 2022), that overweighting occurs for $p < \frac{1}{2}$. Then, both MVS and RDU predict the possibility of the absence of tradeoff only for $p < \frac{1}{2}$. However, the MVS and RDU provide different rationale for the absence of tredeoff. The RDU rules out the possibility of the absence of the tradeoff for a risk-averse agent. In contrast, MVS points to the absence of tradeoff for certain risk-averse agent and all risk-seeking agents.

Proof of Proposition A4:

Given the linear contract (α, β), the objective function of an MVS agent with a cost function $C(e) = \psi e^2$ is given by

$$MVS(L) = \alpha + \beta\theta e - \psi e^2 + a_v \frac{1-p}{p}\beta^2\theta^2\epsilon^2 + a_s \frac{1-p}{p}\frac{1-2p}{p}\beta^3\theta^3\epsilon^3$$

The first-order condition of the agent's maximization problem leads to the optimal effort function $e(\beta)$ that increases in the variable pay:

$$e = \frac{\beta\theta}{2\psi}$$

The principal's optimization problem is to maximizes the expected value of $\theta z - y$ by accounting for the agent's incentive compatibility constraint (IC) and participation constraint (PC).

$$\begin{cases} \max_{\alpha,\beta} \quad \theta e - (\alpha + \beta\theta e) \\ s.t.: \\ e = \frac{\beta\theta}{2\psi} \\ \alpha + \beta\theta e - \psi e^2 + a_v \frac{1-p}{p}\beta^2\theta^2\epsilon^2 + a_s \frac{1-p}{p}\frac{1-2p}{p}\beta^3\theta^3\epsilon^3 \simeq y_0 \end{cases}$$

which is equivalent to

$$\max_{\beta} \quad \theta^2 \left[\frac{\beta}{2\psi} + a_v \frac{1-p}{p}\beta^2\epsilon^2 + a_s \frac{1-2p}{p}\frac{1-p}{p}\beta^3\theta\epsilon^3 - \frac{\beta^2}{4\psi} \right] - y_0$$

The first-order condition is given by

$$\frac{1}{2\psi} + 2a_v\beta\frac{1-p}{p}\epsilon^2 + 3a_s\frac{1-2p}{p}\frac{1-p}{p}\beta^2\theta\epsilon^3 - \frac{\beta}{2\psi} = 0 \tag{30}$$

The second-order condition is given by

$$2a_v\frac{1-p}{p}\epsilon^2 + 6a_s\frac{1-2p}{p}\frac{1-p}{p}\beta\theta\epsilon^3 - \frac{1}{2\psi} < 0 \tag{31}$$

Equation (30) implicitly defines the optimal variable pay $\beta^*(\epsilon, a_v, a_s, \psi, \theta)$. In particular, it follows that the optimal variable pay in the absence of shock ($\epsilon = 0$) is given by $\beta^*(0, a_v, a_s, \psi, \theta) = 1$. Moreover, for $a_s \longrightarrow 0$ we have

$$\lim_{a_s \longrightarrow 0} \beta^*(\epsilon, a_v, a_s, \psi, \theta) = \frac{1}{1 - 4a_v\frac{1-p}{p}\psi\epsilon^2} < 1 = \beta^*(0, a_v, a_s, \psi, \theta)$$

Also, for $p = \frac{1}{2}$, we have $\beta^*(\epsilon, a_v, 0, \psi, \theta) = \dfrac{1}{1 - 4a_v\frac{1-p}{p}}$.

For $\epsilon > 0$ and $p \neq \frac{1}{2}$, the two possible solutions of (30) are given by

$$\beta_1^*(\epsilon, a_v, a_s, \psi, \theta) = \frac{\frac{1}{2\psi} - 2a_v\frac{1-p}{p}\epsilon^2 - \sqrt{\left(2a_v\frac{1-p}{p}\epsilon^2 - \frac{1}{2\psi}\right)^2 - 6a_s\frac{1-2p}{p}\frac{1-p}{p}\frac{\theta\epsilon^3}{\psi}}}{6a_s\frac{1-2p}{p}\frac{1-p}{p}\theta\epsilon^3}$$

$$\beta_2^*(\epsilon, a_v, a_s, \psi, \theta) = \frac{\frac{1}{2\psi} - 2a_v\frac{1-p}{p}\epsilon^2 + \sqrt{\left(2a_v\frac{1-p}{p}\epsilon^2 - \frac{1}{2\psi}\right)^2 - 6a_s\frac{1-2p}{p}\frac{1-p}{p}\frac{\theta\epsilon^3}{\psi}}}{6a_s\frac{1-2p}{p}\frac{1-p}{p}\theta\epsilon^3}$$

When $\epsilon > 0$, the right solution needs to satisfy the continuity condition $\lim_{\epsilon \longrightarrow 0} \beta_i^*(\epsilon, a_v, a_s, \psi, \theta) = 1$, $i = 1, 2$. Using this continuity condition, and applying l'Hôpital's rule, it follows that the solution is given by $\beta_1^*(\epsilon, a_v, a_s, \psi, \theta)$: [17]

$$\beta^*(\epsilon, a_v, a_s, \psi, \theta) = \frac{\frac{1}{2\psi} - 2a_v\frac{1-p}{p}\epsilon^2 - \sqrt{\left(2a_v\frac{1-p}{p}\epsilon^2 - \frac{1}{2\psi}\right)^2 - 6a_s\frac{1-2p}{p}\frac{1-p}{p}\frac{\theta\epsilon^3}{\psi}}}{6a_s\frac{1-2p}{p}\frac{1-p}{p}\theta\epsilon^3} \tag{32}$$

Point i and ii)

Implicit function theorem on (30) leads to

[17] Another way to find the right solution is to plug the two possible solutions into the second-order condition (31) to see that it is solely satisfied by (32).

$$\frac{\partial \beta^*(\epsilon, a_v, a_s, \psi, \theta)}{\partial a_v} > 0$$

Since $e^*(\epsilon, a_v, a_s, \psi, \theta) = \frac{\theta}{2\psi}\beta^*(\epsilon, a_v, a_s, \psi, \theta)$, it also follows $\dfrac{\partial e^*}{\partial a_v} > 0$. Note that the aversion to variance corresponds to $a_v < 0$. Hence, $\dfrac{\partial \beta^*}{\partial a_v} > 0$ and $\dfrac{\partial e^*}{\partial a_v} > 0$ mean that the optimal variable pay and optimal effort both decrease as the aversion to variance increases.
Also, from (30) we have that

$$\frac{\partial \beta^*}{\partial a_s} > 0 \qquad \text{if} \qquad p < \frac{1}{2} \;\; \text{(positive skewness)}$$

$$\frac{\partial \beta^*}{\partial a_s} < 0 \qquad \text{if} \qquad p > \frac{1}{2} \;\; \text{(negative skewness)}$$

The optimal variable pay increases as the preference for positive skewness increases if $p < \frac{1}{2}$ (i.e., positive skewness) and decreases as the preference for positive skewness increases if $p > \frac{1}{2}$ (i.e., negative skewness). Also, because $e^*(\epsilon, a_v, a_s, \psi, \theta) = \dfrac{\theta}{2\psi}\beta^*(\epsilon, a_v, a_s, \psi, \theta)$, it also follows

$$\frac{\partial e^*}{\partial a_s} > 0 \qquad \text{if} \qquad p < \frac{1}{2} \;\; \text{(positive skewness)}$$

$$\frac{\partial e^*}{\partial a_s} < 0 \qquad \text{if} \qquad p > \frac{1}{2} \;\; \text{(negative skewness)}$$

Point iii)

From (30), the implicit function theorem implies that

$$Sign\left[\frac{\partial \beta^*}{\partial \epsilon}\right] = Sign\left[4a_v + 9a_s\frac{1-2p}{p}\theta\epsilon\beta^*(\epsilon, a_v, a_s, \psi, \theta)\right] \tag{33}$$

with $\beta^*(\epsilon, a_v, a_s, \psi, \theta)$ given in (32) Since $a_v < 0$, $a_s > 0$ and $\beta^*(\epsilon, a_v, a_s, \psi, \theta) > 0$ it turns out that for $p \geq \frac{1}{2}$ we have $\dfrac{\partial \beta^*}{\partial \epsilon} < 0$.

Since $e^*(\epsilon, a_v, a_s, \psi, \theta) = \dfrac{\theta}{2\psi}\beta^*(\epsilon, a_v, a_s, \psi, \theta)$, it also follows that $\dfrac{\partial e^*}{\partial \epsilon} < 0$ for $p \geq \frac{1}{2}$.

Point iv)

For $p < \frac{1}{2}$, either $\frac{\partial \beta^*}{\partial \epsilon} < 0$ and $\frac{\partial \beta^*}{\partial \epsilon} > 0$ are possible according to (33) and (32). Replacing (32) in (33), it turns out that

$$\frac{\partial \beta^*}{\partial \epsilon} > 0 \quad \iff \quad g(\epsilon, a_v, a_s, \psi, \theta) < \frac{9}{4} \tag{34}$$

with

$$g(\epsilon, a_v, a_s, \psi, \theta) := -\frac{6a_v\frac{1-p}{p}\epsilon^2}{\frac{1}{2\psi} - 2a_v\frac{1-p}{p}\epsilon^2 - \sqrt{\left(2a_v\frac{1-p}{p}\epsilon^2 - \frac{1}{2\psi}\right)^2 - 6a_s\frac{1-2p}{p}\frac{1-p}{p}\frac{\theta\epsilon^3}{\psi}}} \tag{35}$$

Since $e^*(\epsilon, a_v, a_s, \psi, \theta) = \dfrac{\theta}{2\psi}\beta^*(\epsilon, a_v, a_s, \psi, \theta)$, it also follows that when $p < \frac{1}{2}$ we have $\frac{\partial e^*}{\partial \epsilon} > 0$ if and only if $g(\epsilon, a_v, a_s, \psi, \theta) < \frac{9}{4}$.

For example, Spiliopoulos and Hertwig (2019) estimate $a_v = -0.0229$ and $a_s = 0.0037$. Using these estimated values and setting $(\epsilon, p, \psi, \theta) = (0.7, 0.1, 0.5, 1)$, the condition (34) holds. This yields $\beta^*(\epsilon, a_v, a_s, \psi, \theta) = 1.12$ which is greater than the variable pay of 1 corresponding to the absence of noise.
QED.

Proof of Proposition A5:

Point i)

At the optimal contract, the agent is risk-averse if $a_v + a_s \dfrac{1-2p}{p}\theta\epsilon\beta^*(\epsilon, a_v, a_s, \psi, \phi) < 0$ and risk-seeking if $a_v + a_s\frac{1-2p}{p}\theta\epsilon\beta^*(\epsilon, a_v, a_s, \psi, \theta) > 0$. Using the expression (32) of $\beta^*(\epsilon, a_v, a_s, \psi, \theta)$ it follows that the agent is risk-averse at the optimal contract if $g(\epsilon, a_v, a_s, \psi, \theta) > 1$ and risk-seeking if $g(\epsilon, a_v, a_s, \psi, \theta) < 1$.

Point ii)

First, note that for any $p < \frac{1}{2}$ and variable pay $\beta > 0$ we have

$$a_v + \frac{9}{4}a_s\frac{1-2p}{p}\beta\theta\epsilon > a_v + a_s\frac{1-2p}{p}\beta\theta\epsilon \tag{36}$$

Second, for any $p < \frac{1}{2}$ and a given triplet (α, β, e), the MVS decision maker exhibits risk-seeking for the positively skewed lottery $L = \Big(\alpha + \theta\beta\Big(e + \frac{1-p}{p}\epsilon\Big) - \psi e^2, \alpha + \theta\beta\Big(e - \epsilon\Big) - \psi e^2; p, 1-p\Big)$ if

$$a_v + a_s\frac{1-2p}{p}\beta\theta\epsilon > 0 \tag{37}$$

Hence, if the agent exhibits risk-seeking for the optimal triplet (α^*, β^*, e^*), then we should have

$$a_v + a_s\frac{1-2p}{p}\beta^*\theta\epsilon > 0 \tag{38}$$

Given the expression (32) of the optimal variable pay $\beta^*(\epsilon, a_v, a_s, \psi, \theta)$, the condition (38) holds iff

$$g(\epsilon, a_v, a_s, \psi, \theta) < 1 \tag{39}$$

with $g(\epsilon, a_v, a_s, \psi, \theta)$ given in (35).

It follows that when the condition (38) holds, the agent exhibits risk-seeking for the positively skewed lottery $L^* = \Big(\alpha^* + \theta\beta^*\Big(e^* + \frac{1-p}{p}\epsilon\Big) - \psi e^{*2}, \alpha^* + \theta\beta^*\Big(e^* - \epsilon\Big) - \psi e^{*2}; p, 1-p\Big)$. Being risk-seeking means that (39) holds, and hence from (36) we have that the optimal variable pay satisfies $a_v + a_s\dfrac{1-2p}{p}\beta^*\theta\epsilon > 0$. Hence, we have $\dfrac{\partial\beta^*}{\partial\epsilon} > 0$ and in particular $\beta^*(\epsilon, a_v, a_s, \psi, \theta) > 1$ for $\epsilon > 0$.

Point iii)

For any $p < \frac{1}{2}$ and an agent who exhibits risk-aversion at the optimal triplet (α^*, β^*, e^*) with an optimal variable pay β^* that increases with ϵ, we have

$$a_v + a_s \frac{1-2p}{p} \beta^* \theta \epsilon < 0 < a_v + \frac{9}{4} a_s \frac{1-2p}{p} \beta^* \theta \epsilon \tag{40}$$

Given the expression (32) for the optimal variable pay $\beta^*(\epsilon, a_v, a_s, \psi, \theta)$, the condition that ensures (40) is given by

$$g(\epsilon, a_v, a_s, \psi, \theta) \in \left(1, \frac{9}{4}\right) \tag{41}$$

with $g(\epsilon, a_v, a_s, \psi, \theta)$ given in (35).

It follows that when the condition (41) holds, the agent exhibits risk-aversion at the optimal triplet (α^*, β^*, e^*) such that variable payβ^* increases with ϵ.

QED.

B- Extension to general utility function

In section 2, we employ the LEN model with CARA utility function. This approach provides a closed-form solution to the principal-agent problem through the Arrow-Pratt approximation of the risk premium. We investigate the robustness of the results under general utility specification for EUT and RDU. Denote by $A_a(z) = -\frac{u''(x)}{u'(x)}$ the absolute risk-aversion index evaluated at x.

We provide the followings results and their proofs.

Proposition B1 (Consistency of results under EUT): the optimal variable pay is a decreasing function of ϵ.

Proposition B1 shows that the tradeoff between risk and incentives in EUT framework does not depend on the utility function specifications and is not driven by approximation errors in the Arrow-Pratt risk premium.

Example 3 (An illustration of Proposition B1 using expo-power utility function):

To illustrate this point, we consider the expo-power utility function (Saha, 1993) $u(z) = \frac{1-exp(-rz^{\gamma})}{r}$ of which CARA (CRRA) is a special case when $r = 1$ ($r \longrightarrow 0$). The alternative level of utility is given by $y_0 = \frac{1-exp(-ry_0^{\gamma})}{r}$ with y_0 being the alternative (outside) outcome. We set $(r, \gamma) = (0.029, 0.731)$ as found by Holt and Laury (2002) and $(\psi, \theta, y_0) = (0.5, 1, 4)$. In the absence of shock ($\epsilon = 0$), the optimal variable pay is $\beta^* = 1$ and the optimal fixed pay is $\alpha^* = 3.5$. In the presence of shock $(\epsilon, p) = (1, 0.5)$, the optimal variable pay is $\beta^* = 0.89$ and the optimal fixed pay is $\alpha^* = 3.65$. Hence, the optimal variable pay in absence of shock is indeed greater than the variable pay in the presence of the shock.[18]

Proposition B2 (Consistency of results under RDU):

i) If the agent's absolute risk-aversion index does not sufficiently decrease with the outcome, then the optimal variable pay decreases with the probability risk-aversion.

ii) If the agent exhibits probability risk-aversion or probability risk-neutrality, then the optimal variable pay decreases with ϵ.

iii) Assume the agent exhibits probability risk-seeking and that for any couple (α, β) the ratio between the average slope of the probability weighting function on the interval $(0, p)$ and the

[18]Note that the problem does not have an explicit analytic solution. Our solution is numerical.

average slope of the probability weighting on the interval $(p, 1)$ are greater than the ratio between the slope of the utility function at the lowest possible value of the reward (net of cost) and the slope of the utility function at the highest possible value (net of cost). Then, the optimal variable pay is greater in the presence of shock than in its absence.
iv) There exist $A_a^{to}(\beta)$ such that if the agent exhibits probability risk-seeking and $A_a\Big(\alpha+\frac{\beta^2\theta^2}{4\psi}\Big) < A_a^{to}(\beta,\epsilon)$ for any couple (α,β), then the optimal variable pay is greater in the presence of the shock than in its absence.

Proposition B3 (Risk attitudes and absence of tradeoff with RDU):
Assume that the agent exhibits probability risk-seeking for a given probability p. Denote by $A_a^N\Big(\alpha^* + \frac{\beta^{*2}\theta^2}{4\psi}\Big)$ the absolute risk-aversion index that allows a probability risk-seeking agent to exhibit risk-neutrality for the lottery $L^* = \Bigg(\alpha^* + \theta\beta^*\Big(e^* + \frac{1-p}{p}\epsilon\Big) - \psi e^{*2}, \alpha^* + \theta\beta^*\Big(e^* - \epsilon\Big) - \psi e^{*2}; p, 1-p\Bigg)$ associated with the optimal linear contract (α^*, β^*). Then, $A_a^N\Big(\alpha^* + \frac{\beta^{*2}\theta^2}{4\psi}\Big) > A_a^{to}(\beta^*,\epsilon)$.

Propositions B2 and B3 are generalizations of Propositions A2 and A3. They show that the results on the comparisons of the variable pay in the absence of shock and in its presence shown under CARA utility function specification also hold under a general setting where the utility function is just required to be increasing and concave.

Example 4 (An illustration of Proposition B3: presence of tradeoff with risk-seeking agent using expo-power utility function): Consider again the expo-power utility function $u(z) = \frac{1-exp(-rz^\gamma)}{r}$ with $(r,\gamma) = (0.029, 0.731)$ as found by Holt and Laury (2002). We set $(\psi,\theta,y_0) = (0.5, 1, 4)$, with y_0 being the alternative (outside) outcome. In the absence of shock $(\epsilon = 0)$, the optimal variable pay is $\beta^* = 1$ and the optimal fixed pay is $\alpha^* = 3.5$. In the presence of shock, we set $(\epsilon, p, w(p)) = (1, 0.1, 0.15)$. The optimal variable pay is $\beta^* = 0.95$ and the optimal fixed pay is $\alpha^* = 3.37$. The optimal variable pay in the absence of shock is greater than the variable pay in the presence of shock. We have the expected value $E[L^*] = 3.83$ and the certainty equivalent of L^* is 4. Hence, the agent exhibits risk-seeking at the optimal contract $(\alpha^*, \beta^*) = (3.37, 0.95)$ where the tradeoff between risk and incentives is observed.

Example 5 (An illustration of Proposition 12: absence of tradeoff with risk-seeking agent using expo-power utility function): Consider the parameter calibration from example 4 with the only change being $w(0.1) = 0.2$. In the absence of a shock $(\epsilon = 0)$, the optimal variable pay is $\beta^* = 1$ and the optimal fixed pay is $\alpha^* = 3.5$. In the presence of a shock, the optimal variable pay is $\beta^* = 1.17$ and the optimal fixed pay is $\alpha^* = 2.73$. The optimal variable pay in the absence of a shock is less than the variable pay in presence of a shock. We have that the expected value is $E[L^*] = 3.41$ and the certainty equivalent of L^* is 4. Hence, the agent exhibits risk-seeking behavior at the optimal contract $(\alpha^*, \beta^*) = (2.73, 1.17)$ where the tradeoff between risk and incentives is not observed.

Proof of Proposition B1:

Given the linear contract (α, β), the objective function of a EUT agent with cost function $C(e) = \psi e^2$ is given by

$$EU(L) = pu(y_+) + (1-p)u(y_-)$$

with $u(x) = \dfrac{1 - exp(-rx)}{r}$, $y_+ = \alpha + \beta\theta\Big(e + \frac{1-p}{p}\epsilon\Big) - \psi e^2$ and $y_- = \alpha + \beta\theta\Big(e - \epsilon\Big) - \psi e^2$

The first-order condition of the agent's maximization problem is given by

$$(\beta\theta - 2\psi e)[pu'(y_+) + (1-p)u'(y_-)] = 0$$

Since $pu'(y_+) + (1-p)u'(y_-) \neq 0$, it turns out that the agent's optimal effort function is given by

$$e = \frac{\beta\theta}{2\psi}$$

Hence, the optimal effort function is an increasing function of the variable pay and does not vary with respect to ϵ, the utility function or the fixed pay α.

The optimization problem of the principal is to maximize the expected value of $\theta z - y$ by accounting for the agent's incentive compatibility constraint (IC) and participation constraint (PC):

$$\begin{cases} \max\limits_{\alpha,\beta} \ \ \theta e - (\alpha + \beta\theta e) \\ s.t. : \\ e = \frac{\beta\theta}{2\psi} \\ pu\Bigg(\alpha + \beta\theta\Big(e + \frac{1-p}{p}\epsilon\Big) - \psi e^2\Bigg) + (1-p)u\Big(\alpha + \beta\theta(e - \epsilon) - \psi e^2\Big) = u(y_0) \end{cases}$$

which is equivalent to

$$\begin{cases} \max\limits_{\alpha,\beta} \ \ \dfrac{\theta^2}{2\psi}\Big(\beta - \beta^2\Big) - \alpha \\ s.t. : \\ pu\Bigg(\alpha + \frac{\beta^2\theta^2}{4\psi} + \frac{1-p}{p}\beta\theta\epsilon\Bigg) + (1-p)u\Big(\alpha + \frac{\beta^2\theta^2}{4\psi} - \epsilon\Big) = y_0 \end{cases}$$

The corresponding Lagrangian function is given by

$$\mathcal{L}(\alpha,\beta,\mu) = \frac{\theta^2}{2\psi}\Big(\beta - \beta^2\Big) - \alpha + \mu\Bigg[pu\Bigg(\alpha + \frac{\beta^2\theta^2}{4\psi} + \frac{1-p}{p}\beta\theta\epsilon\Bigg) + (1-p)u\Big(\alpha + \frac{\beta^2\theta^2}{4\psi} - \epsilon\Big) - y_0\Bigg]$$

Denote by

$$y'_+ = \theta\Big(\frac{1-p}{p}\epsilon + \frac{\beta\theta}{2\psi}\Big) > 0$$

$$y'_- = \theta\Big(-\epsilon + \frac{\beta\theta}{2\psi}\Big) > 0$$

Then, the first-order conditions are given by

$$\frac{\partial\mathcal{L}}{\partial\beta} = \frac{\theta^2}{2\psi}\Big(1 - 2\beta\Big) + \mu\Bigg[pu'(y_+)y'_+ + (1-p)u'(y_-)y'_- - y_0\Bigg] = 0 \tag{42}$$

$$\frac{\partial\mathcal{L}}{\partial\alpha} = -1 + \mu\Bigg[pu'(y_+) + (1-p)u'(y_-)\Bigg] = 0 \tag{43}$$

$$\frac{\partial \mathcal{L}}{\partial \mu} = pu(y_+) + (1-p)u(y_-) - y_0 = 0 \tag{44}$$

with $y_- = \alpha + \frac{\beta^2\theta^2}{4\psi} - \beta\theta\epsilon$ and $y_+ = \alpha + \frac{\beta^2\theta^2}{4\psi} + \frac{1-p}{p}\beta\theta\epsilon$.

Note that from (42) and (43), it turns out that the optimal variable pay β satisfies

$$\beta = 1 + (1-p)\frac{2\psi\epsilon}{\theta}\frac{u'(y_+) - u'(y_-)}{pu'(y_+) + (1-p)u'(y_-)} \leq 1 \tag{45}$$

This shows that the optimal variable pay in the absence of shock ($\epsilon = 0$) is 1. Since $u'(y_+) < u'(y_-)$, it also follows that the optimal variable pay in the absence of shock is greater than the optimal variable pay in the presence of shock ($\epsilon > 0$). Let us now derive an even stronger result according to which the optimal variable pay is a decreasing function of ϵ.

Totally differentiating the first-order conditions (42)-(44) with respect to β, α, μ and ϵ leads to

$$Hess(\alpha,\beta,\mu) \times \begin{pmatrix} \frac{d\beta}{d\epsilon} \\ \frac{d\alpha}{d\epsilon} \\ \frac{d\mu}{d\epsilon} \end{pmatrix} = - \begin{pmatrix} \frac{\partial^2\beta}{\partial\beta\partial\epsilon} \\ \frac{\partial^2\beta}{\partial\alpha\partial\epsilon} \\ \frac{\partial^2\beta}{\partial\mu\partial\epsilon} \end{pmatrix} \tag{46}$$

with $Hess(\alpha,\beta,\mu)$ being the Hessian matrix defined as follows

$$Hess(\alpha,\beta,\mu) = \begin{pmatrix} \frac{\partial^2\mathcal{L}}{\partial\beta^2} & \frac{\partial^2\mathcal{L}}{\partial\alpha\partial\beta} & \frac{\partial^2\mathcal{L}}{\partial\mu\partial\beta} \\ \frac{\partial^2\mathcal{L}}{\partial\alpha\partial\beta} & \frac{\partial^2\mathcal{L}}{\partial\alpha^2} & \frac{\partial^2\mathcal{L}}{\partial\alpha\partial\mu} \\ \frac{\partial^2\mathcal{L}}{\partial\mu\partial\beta} & \frac{\partial^2\mathcal{L}}{\partial\alpha\partial\mu} & \frac{\partial^2\mathcal{L}}{\partial\mu^2} \end{pmatrix}$$

Assuming that there exists at least a local maximum so that the determinant of the Hessian matrix is positive, it follows from (46) that

$$Sing\left(\frac{d\beta}{d\epsilon}\right) = Sign(E) \tag{47}$$

with

$$E = \frac{\partial^2\mathcal{L}}{\partial\alpha\partial\mu}\left(\frac{\partial^2\mathcal{L}}{\partial\beta\partial\epsilon}\frac{\partial^2\mathcal{L}}{\partial\alpha\partial\mu} - \frac{\partial^2\mathcal{L}}{\partial\alpha\partial\epsilon}\frac{\partial^2\mathcal{L}}{\partial\beta\partial\mu}\right) - \frac{\partial^2\mathcal{L}}{\partial\mu\partial\epsilon}\left(\frac{\partial^2\mathcal{L}}{\partial\alpha\partial\beta}\frac{\partial^2\mathcal{L}}{\partial\alpha\partial\mu} - \frac{\partial^2\mathcal{L}}{\partial\alpha^2}\frac{\partial^2\mathcal{L}}{\partial\beta\partial\mu}\right)$$

$$\mu = \frac{1}{pu'(y_+) + (1-p)u'(y_-)} \tag{48}$$

$$\frac{\partial^2\mathcal{L}}{\partial\beta\partial\epsilon} = \mu\theta(1-p)\Big[u'(y_+) - u'(y_-) + \beta\Big(u''(y_+)y'_+ - u''(y_-)y'_-\Big)\Big]$$

$$\frac{\partial^2\mathcal{L}}{\partial\mu\partial\alpha} = pu'(y_+) + (1-p)u'(y_-) > 0$$

$$\frac{\partial^2\mathcal{L}}{\partial\alpha\partial\epsilon} = \mu\beta\theta(1-p)\Big(u''(y_+) - u''(y_-)\Big) > 0$$

$$\frac{\partial^2 \mathcal{L}}{\partial\mu\partial\beta} = py'_+u'(y_+) + (1-p)y'_-u'(y_-) > 0$$

$$\frac{\partial^2 \mathcal{L}}{\partial\mu\partial\epsilon} = \beta\theta(1-p)\Big(u'(y_+) - u'(y_-)\Big) < 0$$

$$\frac{\partial^2 \mathcal{L}}{\partial\alpha\partial\beta} = \mu\Big[py'_+u''(y_+) + (1-p)y'_-u''(y_-)\Big] \leq 0$$

$$\frac{\partial^2 \mathcal{L}}{\partial\alpha^2} = \mu\Big[pu''(y_+) + (1-p)u''(y_-)\Big] \leq 0$$

Using all the previous derivatives, we have

$$\frac{\partial^2 \mathcal{L}}{\partial\beta\partial\epsilon}\frac{\partial^2 \mathcal{L}}{\partial\alpha\partial\mu} - \frac{\partial^2 \mathcal{L}}{\partial\alpha\partial\epsilon}\frac{\partial^2 \mathcal{L}}{\partial\beta\partial\mu} = \theta(1-p)\Big(u'(y_+) - u'(y_-)\Big) - \mu\frac{\theta^2\beta\epsilon}{p}(1-p)u'(y_+)u'(y_-)\Big((1-p)A_a(y_+) + pA_a(y_-)\Big) \leq 0$$

$$\frac{\partial^2 \mathcal{L}}{\partial\alpha\partial\beta}\frac{\partial^2 \mathcal{L}}{\partial\alpha\partial\mu} - \frac{\partial^2 \mathcal{L}}{\partial\alpha^2}\frac{\partial^2 \mathcal{L}}{\partial\beta\partial\mu} = \mu\theta\epsilon(1-p)u'(y_+)u'(y_-)\Big(A_a(y_-) - A_a(y_+)\Big) \geq 0$$

$$E = \theta(1-p)\bigg[\Big(u'(y_+) - u'(y_-)\Big)\frac{1}{\mu} - \mu\beta\theta\epsilon u'(y_+)u'(y_-)\Big(u'(y_+)A_a(y_-) + \frac{1-p}{p}u'(y_-)A_a(y_+)\Big)\bigg]$$

Since the utility function is concave, we have $u'(y_+) < u'(y_-)$, $A_a(y_-) > 0$ and $A_a(y_+) > 0$ so that $E < 0$. It turns out that

$$\frac{d\beta}{d\epsilon} < 0$$

To illustrate this, consider again the expo-power utility function (Saha, 1993). The alternative level of utility is given by $y_0 = \dfrac{1 - exp(-ry_0^\gamma)}{r}$ with y_0 the alternative (outside) outcome. Hence, the first-order conditions are given by

$$\frac{\partial L}{\partial\beta} = \frac{\theta^2}{2\psi}(1-2\beta) + \mu\gamma\theta\Bigg[p\bigg(\frac{1-p}{p}\epsilon + \frac{\beta\theta}{2\psi}\bigg)exp\bigg(-r\Big(\alpha + \beta\theta\frac{1-p}{p}\epsilon + \frac{\beta^2\theta^2}{4\psi}\Big)^\gamma\bigg)\Big(\alpha + \beta\theta\frac{1-p}{p}\epsilon + \frac{\beta^2\theta^2}{4\psi}\Big)^{\gamma-1} +$$

$$(1-p)\bigg(-\epsilon + \frac{\beta\theta}{2\psi}\bigg)exp\bigg(-r\Big(\alpha - \beta\theta\epsilon + \frac{\beta^2\theta^2}{4\psi}\Big)^\gamma\bigg)\Big(\alpha - \beta\theta\epsilon + \frac{\beta^2\theta^2}{4\psi}\Big)^{\gamma-1}\Bigg] = 0$$

$$\frac{\partial L}{\partial\alpha} = -1 + \mu\gamma\Bigg[pexp\bigg(-r\Big(\alpha + \beta\theta\frac{1-p}{p}\epsilon + \frac{\beta^2\theta^2}{4\psi}\Big)^\gamma\bigg)\Big(\alpha + \beta\theta\frac{1-p}{p}\epsilon + \frac{\beta^2\theta^2}{4\psi}\Big)^{\gamma-1} +$$

$$(1-p)exp\bigg(-r\Big(\alpha - \beta\theta\epsilon + \frac{\beta^2\theta^2}{4\psi}\Big)^\gamma\bigg)\Big(\alpha - \beta\theta\epsilon + \frac{\beta^2\theta^2}{4\psi}\Big)^{\gamma-1}\Bigg] = 0$$

$$\frac{\partial L}{\partial\mu} = p\frac{1 - exp\bigg(-r\Big(\alpha + \beta\theta\frac{1-p}{p}\epsilon + \frac{\beta^2\theta^2}{4\psi}\Big)^\gamma\bigg)}{r} + (1-p)\frac{1 - exp\bigg(-r\Big(\alpha - \beta\theta\epsilon + \frac{\beta^2\theta^2}{4\psi}\Big)^\gamma\bigg)}{r}$$

$$-\frac{1 - exp(-ry_0^\gamma)}{r} = 0$$

We set $(r, \gamma) = (0.029, 0.731)$ as in by Holt and Laury (2002) and $(\psi, \theta, y_0) = (0.5, 1, 4)$. In the absence of a shock ($\epsilon = 0$), the optimal variable pay is $\beta^* = 1$ and the optimal fixed pay is $\alpha^* = 3.5$. In the presence of a shock, we set $(\epsilon, p) = (1, 0.5)$. The optimal variable pay is $\beta^* = 0.92$ and the optimal fixed pay is $\alpha^* = 3.61$. The optimal variable pay in the absence of shock is thus greater than the variable pay in the presence of a shock.

QED.

Proof of Proposition B2

Given the linear contract (α, β), the objective function of an expected utility agent with cost function $C(e) = \psi e^2$ is given by

$$RDU(L) = w(p)u(y_+) + (1 - w(p))u(y_-)$$

with $u(x) = \dfrac{1 - exp(-rx)}{r}$, $y_+ = \alpha + \beta\theta\Big(e + \frac{1-p}{p}\epsilon\Big) - \psi e^2$ and $y_- = \alpha + \beta\theta\Big(e - \epsilon\Big) - \psi e^2$

The first-order condition of the agent's maximization problem is given by

$$(\beta\theta - 2\psi e)[w(p)u'(y_+) + (1 - w(p))u'(y_-)] = 0$$

Since $w(p)u'(y_+) + (1 - w(p))u'(y_-) \neq 0$, it turns out that the optimal effort function is given by

$$e = \frac{\beta\theta}{2\psi}$$

Hence, the optimal effort function is an increasing function of the variable pay and does not vary with respect to ϵ, the utility curvature, the fixed pay α or the probability risk attitude captured by $w(p)$.

Point i)

The optimization problem of the principal is to maximize the expected value of $\theta z - y$ by accounting for the agent's incentive compatibility constraint (IC) and participation constraint (PC):

$$\begin{cases} \max\limits_{\alpha,\beta} \quad \theta e - (\alpha + \beta\theta e) \\ s.t. : \\ e = \frac{\beta\theta}{2\psi} \\ w(p)u\left(\alpha + \beta\theta\left(e + \frac{1-p}{p}\epsilon\right) - \psi e^2\right) + (1 - w(p))u\Big(\alpha + \beta\theta(e - \epsilon) - \psi e^2\Big) = y_0 \end{cases}$$

which is equivalent to

$$\begin{cases} \max\limits_{\alpha,\beta} \quad \frac{\theta^2}{2\psi}\Big(\beta - \beta^2\Big) - \alpha \\ s.t. : \\ w(p)u\left(\alpha + \frac{\beta^2\theta^2}{4\psi} + \frac{1-p}{p}\beta\theta\epsilon\right) + (1 - w(p))u\Big(\alpha + \frac{\beta^2\theta^2}{4\psi} - \epsilon\Big) = y_0 \end{cases}$$

The corresponding Lagrangian function is given by

$$\mathcal{L}(\alpha,\beta,\mu)=\frac{\theta^2}{2\psi}\Big(\beta-\beta^2\Big)-\alpha+\mu\left[w(p)u\left(\alpha+\frac{\beta^2\theta^2}{4\psi}+\frac{1-p}{p}\beta\theta\epsilon\right)+(1-w(p))u\Big(\alpha+\frac{\beta^2\theta^2}{4\psi}-\epsilon\Big)-y_0\right]$$

Denote by

$$y'_+=\theta\Big(\frac{1-p}{p}\epsilon+\frac{\beta\theta}{2\psi}\Big)>0$$

$$y'_-=\theta\Big(-\epsilon+\frac{\beta\theta}{2\psi}\Big)>0$$

Then, the first-order conditions are given by

$$\frac{\partial\mathcal{L}}{\partial\beta}=\frac{\theta^2}{2\psi}\Big(1-2\beta\Big)+\mu\left[w(p)u'(y_+)y'_++(1-w(p))u'(y_-)y'_-\right]=0 \tag{49}$$

$$\frac{\partial\mathcal{L}}{\partial\alpha}=-1+\mu\left[w(p)u'(y_+)+(1-w(p))u'(y_-)\right]=0 \tag{50}$$

$$\frac{\partial\mathcal{L}}{\partial\mu}=w(p)u(y_+)+(1-w(p))u(y_-)-y_0=0 \tag{51}$$

with $y_-=\alpha+\frac{\beta^2\theta^2}{4\psi}-\beta\theta\epsilon$ and $y_+=\alpha+\frac{\beta^2\theta^2}{4\psi}+\frac{1-p}{p}\beta\theta\epsilon$.

Denote by $\delta:=w(p)$. Then, totally differentiating the first-order conditions (49)-(51) with respect to β,α,μ and δ leads to

$$Hess(\alpha,\beta,\mu)\times\begin{pmatrix}\frac{d\beta}{d\delta}\\ \frac{d\alpha}{d\delta}\\ \frac{d\mu}{d\delta}\end{pmatrix}=-\begin{pmatrix}\frac{\partial^2\beta}{\partial\beta\partial\delta}\\ \frac{\partial^2\beta}{\partial\alpha\partial\delta}\\ \frac{\partial^2\beta}{\partial\mu\partial\delta}\end{pmatrix} \tag{52}$$

with $Hess(\alpha,\beta,\mu)$ being the Hessian matrix defined as follows

$$Hess(\alpha,\beta,\mu)=\begin{pmatrix}\frac{\partial^2\mathcal{L}}{\partial\beta^2} & \frac{\partial^2\mathcal{L}}{\partial\alpha\partial\beta} & \frac{\partial^2\mathcal{L}}{\partial\mu\partial\beta}\\ \frac{\partial^2\mathcal{L}}{\partial\alpha\partial\beta} & \frac{\partial^2\mathcal{L}}{\partial\alpha^2} & \frac{\partial^2\mathcal{L}}{\partial\alpha\partial\mu}\\ \frac{\partial^2\mathcal{L}}{\partial\mu\partial\beta} & \frac{\partial^2\mathcal{L}}{\partial\alpha\partial\mu} & \frac{\partial^2\mathcal{L}}{\partial\mu^2}\end{pmatrix}$$

Assuming that there exists at least a local maximum so that the determinant of the Hessian matrix is positive, it follows from (52) that

$$Sing\left(\frac{d\beta}{d\delta}\right)=Sign(\Delta) \tag{53}$$

with

$$\Delta=\frac{\partial^2\mathcal{L}}{\partial\alpha\partial\mu}\left(\frac{\partial^2\mathcal{L}}{\partial\beta\partial\delta}\frac{\partial^2\mathcal{L}}{\partial\alpha\partial\mu}-\frac{\partial^2\mathcal{L}}{\partial\alpha\partial\delta}\frac{\partial^2\mathcal{L}}{\partial\beta\partial\mu}\right)-\frac{\partial^2\mathcal{L}}{\partial\mu\partial\delta}\left(\frac{\partial^2\mathcal{L}}{\partial\alpha\partial\beta}\frac{\partial^2\mathcal{L}}{\partial\alpha\partial\mu}-\frac{\partial^2\mathcal{L}}{\partial\alpha^2}\frac{\partial^2\mathcal{L}}{\partial\beta\partial\mu}\right)$$

$$\mu = \frac{1}{pu'(y_+) + (1-p)u'(y_-)} \tag{54}$$

$$\frac{\partial^2 \mathcal{L}}{\partial\beta\partial\delta} = \mu\Big[u'(y_+)y'_+ - u'(y_-)y'_-)\Big]$$

$$\frac{\partial^2 \mathcal{L}}{\partial\mu\partial\alpha} = w(p)u'(y_+) + (1-w(p))u'(y_-) > 0$$

$$\frac{\partial^2 \mathcal{L}}{\partial\alpha\partial\delta} = \mu\Big(u'(y_+) - u'(y_-)\Big) > 0$$

$$\frac{\partial^2 \mathcal{L}}{\partial\mu\partial\beta} = w(p)y'_+u'(y_+) + (1-w(p))y'_-u'(y_-) > 0$$

$$\frac{\partial^2 \mathcal{L}}{\partial\mu\partial\delta} = u(y_+) - u(y_-) > 0$$

$$\frac{\partial^2 \mathcal{L}}{\partial\alpha\partial\beta} = \mu\Bigg[w(p)y'_+u''(y_+) + (1-w(p))y'_-u''(y_-)\Bigg] \leq 0$$

$$\frac{\partial^2 \mathcal{L}}{\partial\alpha^2} = \mu\Bigg[w(p)u''(y_+) + (1-w(p))u''(y_-)\Bigg] \leq 0$$

Using all the previous derivatives, we have

$$\frac{\partial^2 \mathcal{L}}{\partial\beta\partial\delta}\frac{\partial^2 \mathcal{L}}{\partial\alpha\partial\mu} - \frac{\partial^2 \mathcal{L}}{\partial\alpha\partial\delta}\frac{\partial^2 \mathcal{L}}{\partial\beta\partial\mu} = \mu\frac{\theta\epsilon}{p}u'(y_+)u'(y_-) > 0$$

$$\frac{\partial^2 \mathcal{L}}{\partial\alpha\partial\beta}\frac{\partial^2 \mathcal{L}}{\partial\alpha\partial\mu} - \frac{\partial^2 \mathcal{L}}{\partial\alpha^2}\frac{\partial^2 \mathcal{L}}{\partial\beta\partial\mu} = \mu\frac{\theta\epsilon}{p}u'(y_+)u'(y_-)w(p)(1-w(p))\Big(A_a(y_-) - A_a(y_+)\Big) \geq 0$$

Hence

$$\Delta = \mu\frac{\theta\epsilon}{p}u'(y_+)u'(y_-)\Bigg[w(p)u'(y_+) + (1-w(p))u'(y_-) - w(p)(1-w(p))\Big(u(y_+) - u(y_-)\Big)\Big(A_a(y_-) - A_a(y_+)\Big)\Bigg]$$

Clearly $\Delta > 0$ (*i.e.*, $\frac{d\beta}{d\delta} > 0$) under CARA utility assumption, indicating that the approximation errors in Arrow-Pratt risk premium does not alter the results established in previous propositions. For utility function such that $A_a(y_-) - A_a(y_+) \longrightarrow 0$, we have $\Delta > 0$ (*i.e.*, $\frac{d\beta}{d\delta} > 0$).

Point ii)

From (49) and (50), it turns out that the optimal variable pay β^* satisfies the following equation

$$\beta = 1 + \frac{2\psi\epsilon}{\theta}\frac{w(p)\frac{1-p}{p}u'(y_+) - (1-w(p))u'(y_-)}{w(p)u'(y_+) + (1-w(p))u'(y_-)} \leq 1 \tag{55}$$

Thus, the optimal variable pay in the absence of shock ($\epsilon = 0$) is 1. Since $u'(y_+) < u'(y_-)$, it also follows under the assumption of probability risk-aversion/neutrality (i.e., $w(p) \leq p$) that the optimal variable pay in the absence of shock is greater than the optimal variable pay in the presence of shock ($\epsilon > 0$).

Now, we show a stronger result according to which the optimal variable pay is indeed a decreasing function of ϵ under the assumption of probability risk-aversion/neutrality.

Totally differentiating the first-order conditions (49)-(51) with respect to β, α, μ and ϵ leads to

$$Hess(\alpha, \beta, \mu) \times \begin{pmatrix} \frac{d\beta}{d\epsilon} \\ \frac{d\alpha}{d\epsilon} \\ \frac{d\mu}{d\epsilon} \end{pmatrix} = - \begin{pmatrix} \frac{\partial^2 \beta}{\partial \beta \partial \epsilon} \\ \frac{\partial^2 \beta}{\partial \alpha \partial \epsilon} \\ \frac{\partial^2 \beta}{\partial \mu \partial \epsilon} \end{pmatrix} \tag{56}$$

with $Hess(\alpha, \beta, \mu)$ being the Hessian matrix defined as follows

$$Hess(\alpha, \beta, \mu) = \begin{pmatrix} \frac{\partial^2 \mathcal{L}}{\partial \beta^2} & \frac{\partial^2 \mathcal{L}}{\partial \alpha \partial \beta} & \frac{\partial^2 \mathcal{L}}{\partial \mu \partial \beta} \\ \frac{\partial^2 \mathcal{L}}{\partial \alpha \partial \beta} & \frac{\partial^2 \mathcal{L}}{\partial \alpha^2} & \frac{\partial^2 \mathcal{L}}{\partial \alpha \partial \mu} \\ \frac{\partial^2 \mathcal{L}}{\partial \mu \partial \beta} & \frac{\partial^2 \mathcal{L}}{\partial \alpha \partial \mu} & \frac{\partial^2 \mathcal{L}}{\partial \mu^2} \end{pmatrix}$$

Assuming there exists at least a local maximum so that the determinant of the Hessian matrix is positive, it follows from (56) that

$$Sing\left(\frac{d\beta}{d\epsilon}\right) = Sign(R) \tag{57}$$

with

$$E = \frac{\partial^2 \mathcal{L}}{\partial \alpha \partial \mu}\left(\frac{\partial^2 \mathcal{L}}{\partial \beta \partial \epsilon}\frac{\partial^2 \mathcal{L}}{\partial \alpha \partial \mu} - \frac{\partial^2 \mathcal{L}}{\partial \alpha \partial \epsilon}\frac{\partial^2 \mathcal{L}}{\partial \beta \partial \mu}\right) - \frac{\partial^2 \mathcal{L}}{\partial \mu \partial \epsilon}\left(\frac{\partial^2 \mathcal{L}}{\partial \alpha \partial \beta}\frac{\partial^2 \mathcal{L}}{\partial \alpha \partial \mu} - \frac{\partial^2 \mathcal{L}}{\partial \alpha^2}\frac{\partial^2 \mathcal{L}}{\partial \beta \partial \mu}\right)$$

$$\mu = \frac{1}{pu'(y_+) + (1-p)u'(y_-)} \tag{58}$$

$$\frac{\partial^2 \mathcal{L}}{\partial \beta \partial \epsilon} = \mu\theta\Big[w(p)\frac{1-p}{p}u'(y_+) - (1-w(p))u'(y_-) + \beta\Big(w(p)\frac{1-p}{p}u''(y_+)y'_+ - (1-w(p))u''(y_-)y'_-\Big)\Big]$$

$$\frac{\partial^2 \mathcal{L}}{\partial \mu \partial \alpha} = w(p)u'(y_+) + (1-w(p))u'(y_-) > 0$$

$$\frac{\partial^2 \mathcal{L}}{\partial \alpha \partial \epsilon} = \mu\beta\theta\Big(w(p)\frac{1-p}{p}u''(y_+) - (1-w(p))u''(y_-)\Big)$$

$$\frac{\partial^2 \mathcal{L}}{\partial \mu \partial \beta} = w(p)y'_+u'(y_+) + (1-w(p))y'_-u'(y_-) > 0$$

$$\frac{\partial^2 \mathcal{L}}{\partial \mu \partial \epsilon} = \beta\theta\Big(w(p)\frac{1-p}{p}u'(y_+) - (1-w(p))u'(y_-)\Big) < 0$$

$$\frac{\partial^2 \mathcal{L}}{\partial \alpha \partial \beta} = \mu \Big[w(p) y'_+ u''(y_+) + (1 - w(p)) y'_- u''(y_-) \Big] \leq 0$$

$$\frac{\partial^2 \mathcal{L}}{\partial \alpha^2} = \mu \Big[w(p) u''(y_+) + (1 - w(p)) u''(y_-) \Big] \leq 0$$

Using all the previous derivatives, we have

$$\frac{\partial^2 \mathcal{L}}{\partial \beta \partial \epsilon} \frac{\partial^2 \mathcal{L}}{\partial \alpha \partial \mu} - \frac{\partial^2 \mathcal{L}}{\partial \alpha \partial \epsilon} \frac{\partial^2 \mathcal{L}}{\partial \beta \partial \mu} = \theta \Big(w(p) \frac{1-p}{p} u'(y_+) - (1 - w(p)) u'(y_-) \Big) - \mu \frac{\theta^2 \beta \epsilon}{p} w(p)(1 - w(p)) u'(y_+) u'(y_-) \Big(\frac{1-p}{p} A_a(y_+) + A_a(y_-) \Big) \leq 0$$

$$\frac{\partial^2 \mathcal{L}}{\partial \alpha \partial \beta} \frac{\partial^2 \mathcal{L}}{\partial \alpha \partial \mu} - \frac{\partial^2 \mathcal{L}}{\partial \alpha^2} \frac{\partial^2 \mathcal{L}}{\partial \beta \partial \mu} = \mu \frac{\theta \epsilon}{p} w(p)(1 - w(p)) u'(y_+) u'(y_-) \Big(A_a(y_-) - A_a(y_+) \Big) \geq 0$$

Hence

$$R = R_1 - R_2$$

with

$$R_1 = \theta \Big(w(p) u'(y_+) + (1 - w(p)) u'(y_-) \Big) \Big(w(p) \frac{1-p}{p} u'(y_+) - (1 - w(p)) u'(y_-) \Big)$$

$$R_2 = \frac{\beta \theta^2 \epsilon u'(y_+) u'(y_-) \frac{w(p)}{p} (1 - w(p)) \left(\frac{w(p)}{p} u'(y_+) A_a(y_-) + \frac{1 - w(p)}{p} u'(y_-) A_a(y_+) \right)}{w(p) u'(y_+) + (1 - w(p)) u'(y_-)}$$

$$E = \theta(1-p) \Big[\Big(u'(y_+) - u'(y_-) \Big) \frac{1}{\mu} - \mu \beta \theta \epsilon u'(y_+) u'(y_-) \Big(u'(y_+) A_a(y_-) + \frac{1-p}{p} u'(y_-) A_a(y_+) \Big) \Big]$$

Since the utility function is increasing and concave, we have $0 < u'(y_+) < u'(y_-)$, $A_a(y_-) > 0$ and $A_a(y_+) > 0$ so that $R_2 > 0$.

Also note that the agent's probability risk-aversion/risk-neutrality (i.e., $w(p) \leq p$) implies $R_1 < 0$. It follows that in the presence of probability risk-aversion/risk-neutrality we have $R < 0$ and hence

$$\frac{d\beta}{d\epsilon} < 0$$

Point iii)

Recall that the equation (55) satisfies by the optimal variable pay

$$\beta = 1 + \frac{2\psi \epsilon}{\theta} \frac{w(p) \frac{1-p}{p} u'(y_+) - (1 - w(p)) u'(y_-)}{w(p) u'(y_+) + (1 - w(p)) u'(y_-)} \leq 1 \tag{59}$$

It follows directly that

$$\beta > 1 \qquad \Longleftrightarrow \qquad \frac{\frac{w(p)}{p}}{\frac{1-w(p)}{1-p}} > \frac{u'(y_-)}{u'(y_+)} > 1$$

Point iv)

From (59), it follows directly

$$\beta > 1 \qquad \Longleftrightarrow \qquad w(p)\frac{1-p}{p}u'\Big(\alpha+\beta\theta\frac{1-p}{p}\epsilon+\frac{\beta^2\theta^2}{4\psi}\Big)-(1-w(p))u'\Big(\alpha+\frac{\beta^2\theta^2}{4\psi}-\beta\theta\epsilon\Big)$$

Denote by

$$H(\epsilon)=w(p)\frac{1-p}{p}u'\Big(\alpha+\beta\theta\frac{1-p}{p}\epsilon+\frac{\beta^2\theta^2}{4\psi}\Big)-(1-w(p))u'\Big(\alpha+\frac{\beta^2\theta^2}{4\psi}-\beta\theta\epsilon\Big)+o(\epsilon)$$

Then, the first-order Taylor approximation of $H(\epsilon)$ around $\epsilon=0$ gives

$$\frac{H(\epsilon)}{u'\Big(\alpha+\frac{\beta^2\theta^2}{4\psi}\Big)}=\frac{w(p)}{p}-1-\left(1+\frac{w(p)}{p}\frac{1-2p}{p}\right)\beta\theta\epsilon A_a\Big(\alpha+\frac{\beta^2\theta^2}{4\psi}\Big) \tag{60}$$

with $o(\epsilon)$ the approximation error which is such that $\lim_{\epsilon\longrightarrow 0}=\frac{o(\epsilon)}{\epsilon}=0$. It turns out that $H(\epsilon)>0$ if the following condition holds

$$A_a\Big(\alpha+\frac{\beta^2\theta^2}{4\psi}\Big)<\frac{1}{\beta\theta\epsilon}\frac{\frac{w(p)}{p}-1}{1+\frac{w(p)}{p}\frac{1-2p}{p}}:=A_a^{to}(\beta,\epsilon) \tag{61}$$

QED.

Proof of Proposition B3:

From Lemma 1, the absolute risk-aversion index $A_a^N\Big(\alpha^*+\frac{{\beta^*}^2\theta^2}{4\psi}\Big)$ that makes an agent with probability risk-seeking behavior to exhibit risk-neutrality (i.e., risk premium equals 0) for the lottery $L=\left(\alpha^*+\beta^*\theta\Big(e^*+\frac{1-p}{p}\epsilon\Big)-\psi {e^*}^2,\alpha^*+\beta^*\theta\Big(e^*-\epsilon\Big)-\psi {e^*}^2;p,1-p\right)$ associated with the optimal linear contract (α^*,β^*) and optimal effort e^* is given by

$$A_a^N\Big(\alpha^*+\frac{{\beta^*}^2\theta^2}{4\psi}\Big):=\frac{2}{\theta\epsilon\beta^*}\frac{\frac{\delta}{p}-1}{1+\frac{\delta}{p}\frac{1-2p}{p}} \tag{62}$$

with $\delta=w(p)$

From Proposition B2, the threshold $A_a^{to}(\beta^*,\epsilon)$ of the absolute risk-aversion index of an agent with probability risk-seeking behavior that leads the principal to propose an optimal variable pay that is greater in presence of the shock than in its absence is given by

$$A_a^{to}(\beta^*,\epsilon)\cong\frac{1}{\beta\theta\epsilon}\frac{\frac{w(p)}{p}-1}{1+\frac{w(p)}{p}\frac{1-2p}{p}} \tag{63}$$

Since $A_a^N\Big(\alpha^* + \frac{\beta^{*2}\theta^2}{4\psi}\Big) \simeq 2A_a^{to}\Big(\beta^*, \epsilon\Big)$, then $A_a^N\Big(\alpha^* + \frac{\beta^{*2}\theta^2}{4\psi}\Big) > 2A_a^{to}\Big(\beta^*, \epsilon\Big)$

As an example, consider the expo-power utility function (Saha, 1993). The alternative level of utility is given by $y_0 = \frac{1 - exp(-ry_0^\gamma)}{r}$ with y_0 being the alternative (outside) outcome. Hence, the first-order conditions are given by

$$\frac{\partial L}{\partial \beta} = \frac{\theta^2}{2\psi}(1-2\beta)+\mu\gamma\theta\Bigg[w(p)\Big(\frac{1-p}{p}\epsilon+\frac{\beta\theta}{2\psi}\Big)exp\Big(-r\Big(\alpha+\beta\theta\frac{1-p}{p}\epsilon+\frac{\beta^2\theta^2}{4\psi}\Big)^\gamma\Big)\Big(\alpha+\beta\theta\frac{1-p}{p}\epsilon+\frac{\beta^2\theta^2}{4\psi}\Big)^{\gamma-1}+$$

$$(1-w(p))\Big(-\epsilon+\frac{\beta\theta}{2\psi}\Big)exp\Big(-r\Big(\alpha-\beta\theta\epsilon+\frac{\beta^2\theta^2}{4\psi}\Big)^\gamma\Big)\Big(\alpha-\beta\theta\epsilon+\frac{\beta^2\theta^2}{4\psi}\Big)^{\gamma-1}\Bigg] = 0$$

$$\frac{\partial L}{\partial \alpha} = -1+\mu\gamma\Bigg[w(p)exp\Big(-r\Big(\alpha+\beta\theta\frac{1-p}{p}\epsilon+\frac{\beta^2\theta^2}{4\psi}\Big)^\gamma\Big)\Big(\alpha+\beta\theta\frac{1-p}{p}\epsilon+\frac{\beta^2\theta^2}{4\psi}\Big)^{\gamma-1}+$$

$$(1-w(p))exp\Big(-r\Big(\alpha-\beta\theta\epsilon+\frac{\beta^2\theta^2}{4\psi}\Big)^\gamma\Big)\Big(\alpha-\beta\theta\epsilon+\frac{\beta^2\theta^2}{4\psi}\Big)^{\gamma-1}\Bigg] = 0$$

$$\frac{\partial L}{\partial \mu} = w(p)\frac{1-exp\Big(-r\Big(\alpha+\beta\theta\frac{1-p}{p}\epsilon+\frac{\beta^2\theta^2}{4\psi}\Big)^\gamma\Big)}{r} + (1-w(p))\frac{1-exp\Big(-r\Big(\alpha-\beta\theta\epsilon+\frac{\beta^2\theta^2}{4\psi}\Big)^\gamma\Big)}{r}$$

$$-\frac{1-exp(-ry_0^\gamma)}{r} = 0$$

- We set $(r, \gamma) = (0.029, 0.731)$ as found by Holt and Laury (2002) and $(\psi, \theta, y_0) = (0.5, 1, 4)$. In the absence of shock ($\epsilon = 0$), the optimal variable pay is $\beta^* = 1$ and the optimal fixed pay is $\alpha^* = 3.5$. In the presence of a shock $(\epsilon, p, w(p)) = (1, 0.1, 0.15)$, the optimal variable pay is $\beta^* = 0.95$ and the optimal fixed pay is $\alpha^* = 3.37$. The optimal variable pay in the absence of a shock is greater than the variable pay in presence of a shock. The expected value is $E[L] = 3.83$ and the certainty equivalent of L is 4. Hence, the agent exhibits risk-seeking at the optimal contract $(\alpha^*, \beta^*) = (3.37, 0.95)$ where the tradeoff between risk and incentive is observed.

- Consider the calibration from the previous example with one change: $w(0.1) = 0.2$. In the absence of a shock (i.e., $\epsilon = 0$), the optimal variable pay is $\beta^* = 1$ and the optimal fixed pay is $\alpha^* = 3.5$. In the presence of a shock $(\epsilon, p) = (1, 0.1)$, the optimal variable pay is $\beta^* = 1.17$ and the optimal fixed pay is $\alpha^* = 2.73$. The optimal variable pay in the absence of shock is less than the variable pay in the presence of shock. The expected value is $E[L] = 3.41$ and the certainty equivalent of L is 4. Hence, the agent exhibits risk-seeking at the optimal contract $(\alpha^*, \beta^*) = (2.73, 1.17)$ where the tradeoff between risk and incentive is not observed.

QED.

C- Extension to continuous random shocks

In Section 2, we focus on binary shocks. Herein, we extend this framework to the case of continuous random shocks. We denote by $f(.)(F(.))$ the probability density (cumulative distribution) function of a continuous random shock $\tilde{\epsilon}$ such that $E(\tilde{\epsilon}) = 0$ and $V(\tilde{\epsilon})$. We further assume that the distribution is symmetric around 0, that is $f(\epsilon) = f(-\epsilon)$ for all $\epsilon > 0$.

Proposition C1 (Consistency of results under RDU):[19]

i) Assume that the agent exhibits probability risk-aversion or probability risk-neutrality (i.e., $w'(.) \geq 0$). Hence, the optimal variable pay is greater in the absence of shock than in its presence.

ii) Assume that the agent exhibits probability risk-seeking (i.e., $w'(.) < 0$) or inverse-s-shaped probability weighting (i.e.,$\exists\ a \in (0,1)$ such that $w''(p) < 0$ for $p \in (0, a)$ and $w''(p) > 0$ for $p \in (a, 1)$). Hence the optimal performance can be greater in the presence of shock than in its absence.

Proof of Proposition C1:

Given the linear contract (α, β), the objective function of an expected utility agent with cost function $C(e) = \psi e^2$ is given by

$$RDU(L) = \int_{-\infty}^{+\infty} u\Big(\alpha + \beta\theta(e+\epsilon) - \psi e^2\Big) d\big[1 - w\big(1 - F(\epsilon)\big)\big] \qquad (64)$$

Noting that $d\big[1 - w\big(1 - F(\epsilon)\big)\big] = w'\big(1 - F(\epsilon)\big) f(\epsilon) d\epsilon$, the derivative of (64) with respect to e is given by

$$(\beta\theta - 2\psi e) \int_{-\infty}^{+\infty} u'\Big(\alpha + \beta\theta(e+\epsilon) - \psi e^2\Big) w'\big(1 - F(\epsilon)\big) f(\epsilon) d\epsilon = 0$$

Since both $u(.)$ and $w(.)$ are strictly increasing functions, it turns out that the optimal effort function of the agent is given by

$$e = \frac{\beta\theta}{2\psi}$$

Hence, the optimal effort function is an increasing function of the variable pay and does not vary with respect to ϵ, the utility curvature r, the fixed pay α or the probability risk attitude captured by $w(p)$.

Point i)

The principal's optimization problem is to maximize the expected value of $\theta z - y$ by accounting for the agent's incentive compatibility constraint (IC) and participation constraint (PC):

$$\begin{cases} \max\limits_{\alpha,\beta} \ \ \theta e - (\alpha + \beta\theta e) \\ s.t. : \\ e = \frac{\beta\theta}{2\psi} \\ \int_{-\infty}^{+\infty} u\Big(\alpha + \beta\theta(e+\epsilon) - \psi e^2\Big) w'\big(1 - F(\epsilon)\big) f(\epsilon) d\epsilon = y_0 \end{cases}$$

[19] We focus here on symmetric distributions for which MVS boils down to mean-variance preference. The mean-variance preference corresponds to the RDU with quadratic utility function and probabilistic risk-neutrality (i.e., linear weighting function). In this context, the tradeoff between risk and incentive holds.

which is equivalent to

$$\begin{cases} \max_{\alpha,\beta} \quad \frac{\theta^2}{2\psi}\Big(\beta - \beta^2\Big) - \alpha \\ s.t. : \\ \int_{-\infty}^{+\infty} u\Big(\alpha + \frac{\beta^2\theta^2}{4\psi} + \beta\theta\epsilon\Big) w'\big(1 - F(\epsilon)\big) f(\epsilon) d\epsilon = y_0 \end{cases}$$

The corresponding Lagrangian function is given by

$$\mathcal{L}(\alpha, \beta, \mu) = \frac{\theta^2}{2\psi}\Big(\beta - \beta^2\Big) - \alpha + \mu\Bigg[\int_{-\infty}^{+\infty} u\Big(\alpha + \frac{\beta^2\theta^2}{4\psi} + \beta\theta\epsilon\Big) w'\big(1 - F(\epsilon)\big) f(\epsilon) d\epsilon - y_0\Bigg]$$

The first-order conditions are given by

$$\frac{\partial \mathcal{L}}{\partial \beta} = \frac{\theta^2}{2\psi}\Big(1 - 2\beta\Big) + \mu\theta \int_{-\infty}^{+\infty} \Big(\frac{\beta\theta}{2\psi} + \epsilon\Big) u'\Big(\alpha + \frac{\beta^2\theta^2}{4\psi} + \beta\theta\epsilon\Big) w'\big(1 - F(\epsilon)\big) f(\epsilon) d\epsilon = 0 \quad (65)$$

$$\frac{\partial \mathcal{L}}{\partial \alpha} = -1 + \mu \int_{-\infty}^{+\infty} u'\Big(\alpha + \frac{\beta^2\theta^2}{4\psi} + \beta\theta\epsilon\Big) w'\big(1 - F(\epsilon)\big) f(\epsilon) d\epsilon = 0 \quad (66)$$

$$\frac{\partial \mathcal{L}}{\partial \mu} = \int_{-\infty}^{+\infty} u\Big(\alpha + \frac{\beta^2\theta^2}{4\psi} + \beta\theta\epsilon\Big) w'\big(1 - F(\epsilon)\big) f(\epsilon) d\epsilon - y_0 = 0 \quad (67)$$

From (65) and (66), it follows that the optimal variable pay β^* satisfies the following equation

$$\beta = 1 + \frac{2\psi}{\theta} \frac{\int_{-\infty}^{+\infty} \epsilon u\Big(\alpha + \frac{\beta^2\theta^2}{4\psi} + \beta\theta\epsilon\Big) w'\big(1 - F(\epsilon)\big) f(\epsilon) d\epsilon}{\int_{-\infty}^{+\infty} u\Big(\alpha + \frac{\beta^2\theta^2}{4\psi} + \beta\theta\epsilon\Big) w'\big(1 - F(\epsilon)\big) f(\epsilon) d\epsilon} \quad (68)$$

It follows directly from (68) that if $w'(.) \geq 0$, then $\int_{-\infty}^{+\infty} \epsilon u\Big(\alpha + \frac{\beta^2\theta^2}{4\psi} + \beta\theta\epsilon\Big) w'\big(1 - F(\epsilon)\big) f(\epsilon) d\epsilon < 0$ so that $\beta < 1$.

Point ii) From (68), it follows directly

$$\beta > 1 \quad \Longleftrightarrow \quad G(\alpha, \beta) := \int_{-\infty}^{+\infty} \epsilon u\Big(\alpha + \frac{\beta^2\theta^2}{4\psi} + \beta\theta\epsilon\Big) w'\big(1 - F(\epsilon)\big) f(\epsilon) d\epsilon > 0 \quad (69)$$

Example:

Consider that the relationship between output and effort is affected by a shock that follows a logistic distribution with mean 0 and variance $\frac{\pi^2}{3}$. The probability density function and cumulative distribution functions are given by

$$f(\epsilon) = \frac{exp(-\epsilon)}{(1 + exp(-\epsilon))^2} \qquad \textbf{and} \qquad F(\epsilon)\frac{1}{1 + exp(-\epsilon)}$$

Assume that the weighting function is the following linear combination of logarithmic and quadratic functions

$$w(p) = a\frac{ln(\delta p + 1)}{ln(1+\delta)} + (1-a-b)p^2 + bp$$

with δ, a and b being parameters of the weighting function. The derivative of $w(p)$ is given by

$$w'(p) = a\frac{\delta a}{(\delta p + 1)ln(1+\delta)} + 2(1-a-b)p + b$$

We set $(\delta, a, b) = (19, 1.25, -2)$. Figure 8 plots the density and probability weighting functions. Note that (i) the weighting function is differentiable on $[0, 1]$, (ii) the derivative function $w'(p)$ is U-shaped and (iii) the derivatives of small probabilities are greater than the derivatives of high probabilities (see Figure 9).

Furthermore, assume a quadratic utility function $u(x) = x - rx^2$ that is concave (i.e., $r > 0$).

- **Case 1 (presence of tradeoff with risk-seeking agent):** we set $(r, \psi, \theta, y_0) = (0.02, 0.5, 0.5, 4)$, with y_0 being the alternative (outside) outcome. Let $E = \alpha + \frac{\beta\theta}{4\psi}$, $S_1 = \int_{-\infty}^{+\infty} \epsilon w'(1 - F(\epsilon))f(\epsilon)d\epsilon$ and $S_2 = \int_{-\infty}^{+\infty} \epsilon^2 w'(1 - F(\epsilon))f(\epsilon)d\epsilon$, then the optimal contract is given by the following system of two equations

$$\frac{\partial \mathcal{L}}{\partial \mu} = E(1 - rE) + \beta\theta(1 - 2rE)S_1 - r\beta^2\theta^2 S_2 - y_0 + ry_0^2 = 0$$

$$\beta = 1 + \frac{2\psi}{\theta}\frac{(1 - 2rE)S_1 - 2r\beta\theta S_2}{1 - 2rE - 2r\beta\theta S_1}$$

  The optimal variable pay is $\beta^* = 0.93$ and the optimal fixed pay is $\alpha^* = 3.87$. Recall that in the absence of a shock, the optimal variable pay is $\beta^* = 1$ and the optimal fixed pay is $\alpha^* = 3.5$. Hence, the optimal variable pay in the absence of a shock is greater than the variable pay in presence of the shock. The expected value is $E[L] = 3.97$ and the certainty equivalent of L is 4. Hence, the agent exhibits risk-seeking at the optimal contract $(\alpha^*, \beta^*) = (3.87, 0.93)$ where the tradeoff between risk and incentive is observed.

- **Case 2 (absence of tradeoff with risk-seeking agent):** Consider the calibration of parameters as before with the only change that $r = 0.01$. The optimal variable pay is $\beta^* = 1.08$ and the optimal fixed pay is $\alpha^* = 3.81$. The optimal variable pay in the absence of shock is less than the variable pay in the presence of shock. We have the expected value $E[L] = 3.95$ and the certainty equivalent of L is 4. Hence, the agent exhibits risk-seeking at the optimal contract $(\alpha^*, \beta^*) = (3.95, 1.08)$ where the tradeoff between risk and incentive is not observed.

QED.

Figure 8: Density function and probability weighting function

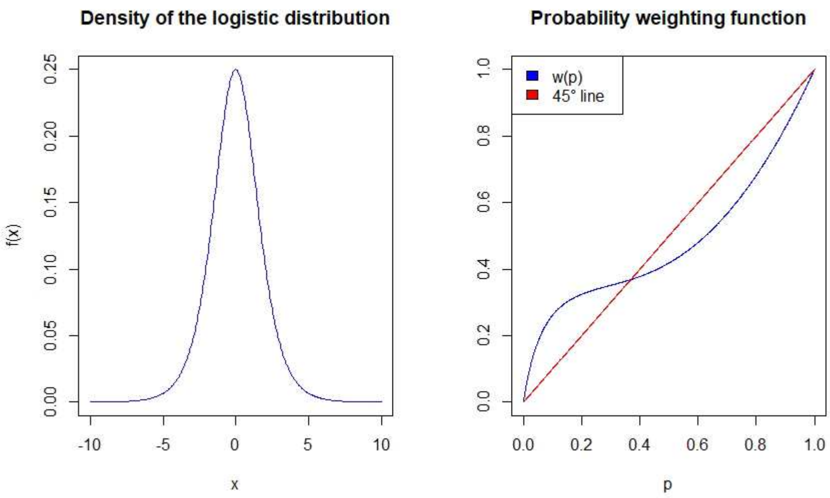
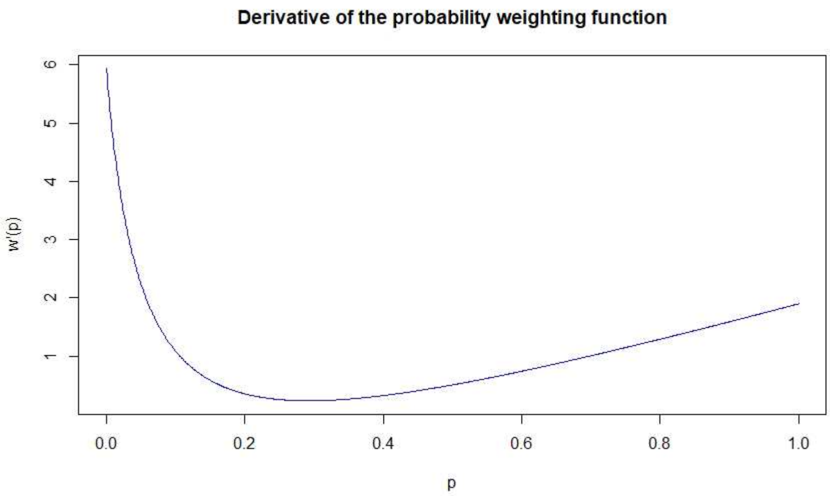


Figure 9: Derivative of probability weighting function



D- Proofs of propositions in the BB model

Proof of Proposition 1

The minimum fixed pay accepted by an agent to work increases with the shock ϵ. The expected utility associated with the contract is given by

$$EU(L) = pu\left(\alpha + \beta\theta\left(e + \frac{1-p}{p}\epsilon\right) - \psi e^2\right) + (1-p)u\left(\alpha + \beta\theta\left(e - \epsilon\right) - \psi e^2\right)$$

For any given contract (α, β), the agent's optimal level of effort is given by

$$e = \frac{\beta\theta}{2\psi}$$

Note that this level of effort does not depend on α. The agent accepts to provide the level of effort if

$$pu\left(\alpha+\frac{\beta^2\theta^2}{4\psi}+\frac{1-p}{p}\beta\theta\epsilon\right)+(1-p)u\left(\alpha+\frac{\beta^2\theta^2}{4\psi}-\beta\theta\epsilon\right)\geq u(y_0)$$

Note that the left-hand side of the above inequality is strictly increasing in α. Hence, there exists a minimum level of fixed pay α_m such that the participation constraint is binding, that is

$$F(\alpha_m,\epsilon):=pu\left(e\right)+(1-p)u\left(\alpha_m+\frac{\beta^2\theta^2}{4\psi}-\beta\theta\epsilon\right)-u(y_0)=0 \quad (70)$$

Denote by $y_-^*=\alpha+\frac{\beta^2\theta^2}{4\psi}-\beta\theta\epsilon$ and $y_+^*=\alpha+\frac{\beta^2\theta^2}{4\psi}+\frac{1-p}{p}\beta\theta\epsilon$, then $y_-^*<y_+^*$.

Point i) The minimum fixed pay increases with the utility (outcome)-risk aversion

Assuming CARA utility function, equation (70) becomes

$$F(\alpha_m,\epsilon):=pexp\left(-r\left(\alpha_m+\frac{\beta^2\theta^2}{4\psi}+\frac{1-p}{p}\beta\theta\epsilon\right)\right)+(1-p)exp\left(-r\left(\alpha_m+\frac{\beta^2\theta^2}{4\psi}-\beta\theta\epsilon\right)\right)-exp(-ry_0)=0$$

$$sign\left(\frac{d\alpha_m}{dr}\right)=sign\left(-py_+^*exp(-ry_+^*)-(1-p)y_-^*exp(-ry_-^*)+y_0exp(-ry_0)\right)$$

Denote by $v(x)=xexp(-rx)$ a utility function over $[0,\infty)$ with $rx<1$ (Assumption A3"). The certainty equivalent y_0^* of the lottery $(y_+^*,y_-^*;p,1-p)$ according to the utility function $v(.)$ is implicitly defined by

$$y_0^*exp(-ry_0^*)=py_+^*exp(-ry_+^*)+(1-p)y_-^*exp(-ry_-^*)$$

Take the absolute risk aversion index of $v(.)$,

$$-\frac{v''(x)}{v'(x)}=r\frac{2-rx}{1-rx}>r$$

Hence the utility function $v(.)$ is associated to higher risk-aversion index than $u(.)$. By the Pratt (1964) approximation, we have $y_0^*<y_0$. Hence,

$$y_0^*exp(-ry_0^*)=py_+^*exp(-ry_+^*)+(1-p)y_-^*exp(-ry_-^*)<y_0exp(-ry_0)$$

This yields

$$sign\left(\frac{d\alpha_m}{dr}\right)=sign\left(-py_+^*exp(-ry_+^*)-(1-p)y_-^*exp(-ry_-^*)+y_0exp(-ry_0)\right)>0$$

Point ii) The implicit function theorem yields

$$\frac{d\alpha_m}{d\epsilon}=\beta\theta(1-p)\frac{u'(y_-^*)-u'(y_+^*)}{pu'(y_+^*)+(1-p)u'(y_-^*)}>0$$

Under Assumption A3', the minimum α increases with the shock size. Note that if the utility function is instead convex and the second-order condition resulting from the second derivative of $EU(L)$ with respect to the effort is negative, then $\frac{d\alpha_m}{d\epsilon}<0$.
QED.

Proof of Proposition 2

The rank dependent utility associated with the contract is given by

$$RDU(L) = w(p)u\left(\alpha + \beta\theta\left(e + \frac{1-p}{p}\epsilon\right) - \psi e^2\right) + (1-w(p))u\left(\alpha + \beta\theta\left(e - \epsilon\right) - \psi e^2\right)$$

For any given contract (α, β), agent's optimal level of effort under the accepted contract is

$$e = \frac{\beta\theta}{2\psi}$$

Note that this level of effort does not depend on α. The agent accepts to provide a given level of effort if

$$w(p)u\left(\alpha + \frac{\beta^2\theta^2}{4\psi} + \frac{1-p}{p}\beta\theta\epsilon\right) + (1-w(p))u\left(\alpha + \frac{\beta^2\theta^2}{4\psi} - \beta\theta\epsilon\right) \geq u(y_0)$$

Note that the left-hand side of the above inequality is strictly increasing in α. Hence, there exists a minimum level of fixed pay α_m such that the previous participation constraint is binding, that is

$$F(\alpha_m, \epsilon) := w(p)u\left(\alpha + \frac{\beta^2\theta^2}{4\psi} + \frac{1-p}{p}\beta\theta\epsilon\right) + (1-w(p))u\left(\alpha + \frac{\beta^2\theta^2}{4\psi} - \beta\theta\epsilon\right) - u(y_0) = 0 \quad (71)$$

Point i) The minimum fixed pay increases with the utility risk-aversion and probability risk-aversion

Assuming CARA utility function, the equation (71) becomes

$$\begin{aligned} F(\alpha_m, \epsilon) :=& - exp(-ry_0) + w(p)exp\left(-r\left(\alpha_m + \frac{\beta^2\theta^2}{4\psi} + \frac{1-p}{p}\beta\theta\epsilon\right)\right) \\ &+ (1-w(p))exp\left(-r\left(\alpha_m + \frac{\beta^2\theta^2}{4\psi} - \beta\theta\epsilon\right)\right) = 0 \end{aligned} \quad (72)$$

$$sign\left(\frac{d\alpha_m}{dr}\right) = sign\left(-w(p)y_+^*exp(-ry_+^*) - (1-w(p))y_-^*exp(-ry_-^*) + y_0exp(-ry_0)\right)$$

Denote by $v(x) = xexp(-rx)$ a utility function over $[0, \infty)$ with $rx < 1$. The certainty equivalent y_0^* of the lottery $(y_+^*, y_-^*; p, 1-p)$ according to the utility function $v(.)$ is implicitly defined by

$$y_0^*exp(-ry_0^*) = w(p)y_+^*exp(-ry_+^*) + (1-w(p))y_-^*exp(-ry_-^*)$$

Take the absolute risk-aversion index of $v(.)$,

$$-\frac{v''(x)}{v'(x)} = r\frac{2-rx}{1-rx} > r$$

Hence the utility function $v(.)$ is associated with a higher risk-aversion index than $u(.)$. By Lemma 1 (Appendix A) that provides the equivalent of Pratt (1964) approximation in our setting, we have $y_0^* < y_0$. Hence,

$$y_0^* exp(-ry_0^*) = w(p)y_+^* exp(-ry_+^*) + (1-w(p))y_-^* exp(-ry_-^*) < y_0 exp(-ry_0)$$

This yields

$$sign\Big(\frac{d\alpha_m}{dr}\Big) = sign\Big(-w(p)y_+^* exp(-ry_+^*) - (1-w(p))y_-^* exp(-ry_-^*) + y_0 exp(-ry_0)\Big) > 0$$

Also, for a given probability $p = \overline{p}$ with $\delta := w(\overline{p})$, the minimum fixed pay decreases with degree of probability overweighting.

The implicit function theorem applied to (71) directly leads to

$$\frac{d\alpha_m}{d\delta} = -\frac{u(y_+^*) - u(y_-^*)}{w(p)u'(y_+^*) + (1-w(p))u'(y_-^*)} < 0$$

Hence, fixed pay increases with probability risk-aversion.

Point ii) Implicit function theorem leads to

$$\frac{d\alpha_m}{d\epsilon} = \beta\theta \frac{(1-w(p))u'(y_-^*) - \frac{w(p)}{p}u'(y_+^*)}{w(p)u'(y_+^*) + (1-w(p))u'(y_-^*)}$$

It follows that for $w(p) \leq p$ (underweighting), we have directly $\frac{d\alpha_m}{d\epsilon} > 0$.
Similarly, we find that $\frac{d\alpha_m}{d\beta} > 0$ under the assumption that $e = \dfrac{\beta\theta}{2\psi} > \epsilon$.
Point iii) In contrast, assuming $w(p) > p$ (overweighting), we have

$$\frac{d\alpha_m}{d\epsilon} < 0 \iff \frac{\frac{w(p)}{p}}{\frac{1-w(p)}{1-p}} > \frac{u'\Big(\alpha_m + \frac{\beta^2\theta^2}{4\psi} - \beta\theta\epsilon\Big)}{u'\Big(\alpha_m + \frac{\beta^2\theta^2}{4\psi} + \frac{1-p}{p}\beta\theta\epsilon\Big)}$$

For CARA utility function this implies that

$$\frac{d\alpha_m}{d\epsilon} < 0 \iff r < r_{to}(\beta, \epsilon)$$

with the threshold defined as

$$r_{to}(\beta, \epsilon) := \frac{p}{\beta\theta\epsilon}\Bigg[ln\Big(\frac{w(p)}{p}\Big) - ln\Big(\frac{1-w(p)}{1-p}\Big)\Bigg] > 0$$

Hence, under rank dependent utility theory, the minimum accepted α decreases with the shock size if we have substantial overweighting and moderate utility curvature.

Point iv)

The certainty equivalent $ce = y_0$ of a lottery $L = \Big(\alpha_m + \beta\theta\big(e + \frac{1-p}{p}\epsilon\big), \alpha_m + \beta\theta(e-\epsilon); p, 1-p\Big)$ with $e = \frac{\beta\theta}{2\psi}$ is given by

$$u(ce) = \delta \frac{1 - exp\Bigg(-r\Big(\alpha_m + \frac{\beta^2\theta^2}{4\psi} + \frac{1-p}{p}\beta\theta\epsilon\Big)\Bigg)}{r} + (1-\delta)\frac{1 - exp\Bigg(-r\Big(\alpha_m + \frac{\beta^2\theta^2}{4\psi} - \beta\theta\epsilon\Big)\Bigg)}{r}$$

The utility of the expected value $E[L] = \alpha_m + \beta\theta e - \psi e^2 = \alpha_m + \frac{\beta^2\theta^2}{4\psi}$ is given by

$$u\big(E[L]\big) = \frac{1 - exp\Bigg(- r\Big(\alpha_m + \frac{\beta^2\theta^2}{4\psi}\Big)\Bigg)}{r}$$

Define by $g(.)$ the following differential function over $[0, \infty)$

$$g(r) = \delta exp\Big[- r\beta\theta\frac{1-p}{p}\epsilon\Big] + (1-\delta)exp[r\beta\theta\epsilon]$$

The absolute risk-aversion $r_N(\beta)$ for which the equality $u\big(ce\big) = u\big(E[L]\big)$ holds for a risk-neutral agent is implicitly defined by

$$g(r_N(\beta, \epsilon)) = 1$$

Note that $g(.)$ has the following three characteristics: (i) $g(.)$ is convex on $[0, \infty)$; (ii) $g(0) = 1$ and $\lim\limits_{r \longrightarrow +\infty} g(r) = +\infty$; (iii) $g(.)$ attains its minimum exactly at the thresholds of the tradeoff $r_{to}(\beta, \epsilon)$

$$r_{to}(\beta, \epsilon) = \frac{p}{\beta\theta\epsilon}\Bigg[ln\Big(\frac{w(p)}{p}\Big) - ln\Big(\frac{1-w(p)}{1-p}\Big)\Bigg]$$

These three characteristics yield two solutions for $r_N(\beta, \epsilon)$: $r_1 = 0 < r_{to}(\beta, \epsilon)$ and $r_2 > r_{to}(\beta, \epsilon)$.

It is clear that we should rule out the case $r_1 = 0 < r_{to}(\beta, \epsilon)$. Indeed, for $r_1 = 0$ we have a linear utility function. Then, to have risk-neutral agent under linear utility function, we should have also $\delta = w(p) = p$. This contradicts our initial assumption $\delta > p$.

Ruling out the case $r_1 = 0$, it follows that the value of $r_N(\beta, \epsilon)$ that allows the equality $u(ce) = u(E[L])$ for a risk-neutral agent (that compensates probability risk-seeking with utility risk aversion) is such that $r_N(\beta, \epsilon) > r_{to}(\beta, \epsilon)$.

Finally, note that this result holds for general utility function (see our Proposition B3).

Point v) A simple derivative of the expression of $r_{to}(\beta, \epsilon)$ shows that this threshold decreases with β and ϵ.

The CARA coefficient for risk-neutrality is implicitly determined by

$$F(r_N, \beta) := \delta exp\Big[- r\beta\theta\frac{1-p}{p}\epsilon\Big] + (1-\delta)exp[r\beta\theta\epsilon] - 1 = 0$$

The implicit function theorem yields

$$\frac{r_N}{\beta}\frac{dr_N(\beta, \epsilon)}{d\beta} = -1 < 0$$

Hence, the agent becomes risk-seeking for a sufficiently small value of variable pay β. In particular, if the agent is risk-neutral or risk-seeking for a contract involving β_1; then the agent is risk-seeking for contract involving $\beta_0 < \beta_1$.

Similarly,

$$\frac{r_N}{\epsilon}\frac{dr_N(\beta, \epsilon)}{d\epsilon} = -1 < 0$$

QED.

Proof of Proposition 3:

The mean-variance-skewness preference associated with the contract is given by

$$MVS(L) = \alpha + \beta\theta e - \psi e^2 + a_v \frac{1-p}{p}\beta^2\theta^2\epsilon^2 + a_s \frac{1-p}{p}\frac{1-2p}{p}\beta^3\theta^3\epsilon^3$$

For any accepted contract (α, β), the agant's optimal level of effort is given by

$$e = \frac{\beta\theta}{2\psi}$$

Note that this level of effort does not depend on α. The agent agrees to provide the level of effort if

$$\alpha + \beta\theta e - \psi e^2 + a_v \frac{1-p}{p}\beta^2\theta^2\epsilon^2 + a_s \frac{1-p}{p}\frac{1-2p}{p}\beta^3\theta^3\epsilon^3 \geq y_0$$

Note that the left hand side of the above inequality is strictly increasing in α. Hence, there is a minimum level of fixed pay α_m such that the previous participation constraint is binding, that is

$$F(\alpha_m, \epsilon) := \alpha_m + \beta\theta e - \psi e^2 + a_v \frac{1-p}{p}\beta^2\theta^2\epsilon^2 + a_s \frac{1-p}{p}\frac{1-2p}{p}\beta^3\theta^3\epsilon^3 - y_0 = 0 \qquad (73)$$

Point i) The minimum fixed pay increases with the aversion to variance

From (73), we have

$$\frac{d\alpha_m}{da_v} = -\frac{1-p}{p}\beta^2\theta^2\epsilon^2 < 0$$

Hence, when a_v decreases (i.e., high aversion to variance), then the minimum fixed pay increases.

Moreover

$$\frac{d\alpha_m}{da_s} = -\frac{1-p}{p}\frac{1-2p}{p}\beta^3\theta^3\epsilon^3$$

Hence, $\frac{d\alpha_m}{da_s} < 0$ if $p < \frac{1}{2}$ and $\frac{d\alpha_m}{da_s} < 0$ if $p > \frac{1}{2}$.

This means that for $p < \frac{1}{2}$ (resp. $p > \frac{1}{2}$) , the minimum fixed pay decreases (resp. increases) with the preference for positively skewed lotteries.

Point ii)

The implicit function theorem applied to (73) leads to

$$\frac{d\alpha_m}{d\epsilon} = -\frac{1-p}{p}\beta^2\theta^2\epsilon\Big(2a_v + 3a_s\frac{1-2p}{p}\beta\theta\epsilon\Big)$$

It follows that for $p > \frac{1}{2}$ (negative skewness), we have $\frac{d\alpha_m}{d\epsilon} > 0$.

Point iii)

In contrast, for $p < \frac{1}{2}$ (positive skewness), we have

$$\frac{d\alpha_m}{d\epsilon} > 0 \Longleftrightarrow -\frac{a_v}{a_s} > \tau_{to}(\beta, \epsilon)$$

with $\tau_{to}(\beta, \epsilon) = \frac{3}{2}\frac{1-2p}{p}\beta\theta\epsilon$.

Point iv) Denote by $\tau_N(\beta,\epsilon) = \dfrac{S(L)}{V(L)} = \dfrac{1-2p}{p}\beta\theta\epsilon$. Hence, the agent exhibits risk-aversion if $-\dfrac{a_v}{a_s} > \tau_N(\beta,\epsilon)$, is risk-neutral if $-\dfrac{a_v}{a_s} = \tau_N(\beta,\epsilon)$ and risk-seeking if $-\dfrac{a_v}{a_s} < \tau_N(\beta,\epsilon)$.

Clearly, $\tau_N(\beta,\epsilon) = \dfrac{S(L)}{V(L)} = \dfrac{1-2p}{p}\beta\theta\epsilon < \dfrac{3}{2}\dfrac{1-2p}{p}\beta\theta\epsilon = \tau_{to}(\beta,\epsilon)$.

Hence, for any couple (a_v, a_S) such that $-\dfrac{a_v}{a_s} \in (\tau_N(\beta,\epsilon), \tau_{to}(\beta,\epsilon))$ the agent is risk-averse and the minimum fixed pay accepted α decreases with shock.

Point v)

Clearly, $\tau_{to}(\beta,\epsilon)$ and $\tau_N(\beta,\epsilon)$ increase with the shock ϵ and β.

QED.

E- Prospect theory (PT) analysis

In this section, we assume the agent is endowed with a reference-dependence utility function of the following form:

$$u^R(x,R) = x + v(x-R) \tag{74}$$

where x is the absolute outcome, R the reference point and $v(.)$ is a value function à la Tversky and Kahneman (1992), that is assumed to be continuous and strictly increasing with v(0)=0. Following Tversky and Kahneman (1992) and Abdellaoui et al. (2008), we specify the value function as follows:

$$v(x-R) = \begin{cases} u(x-R) & \text{if} \quad x \geq R \\ \lambda u(x-R) & \text{if} \quad x < R \end{cases} \tag{75}$$

where $\lambda > 0$ is the loss-aversion index and $u(.)$ is the basic utility function. Following the LEN model, we assume the following exponential utility function:

$$v(x-R) = \begin{cases} \dfrac{1-exp\big(-r^+(x-R)\big)}{r^+} & \text{if} \quad x \geq R \\ -\lambda\dfrac{exp\big(r^-(x-R)\big)-1}{r^-} & \text{if} \quad x < R \end{cases} \tag{76}$$

with r^+ and r^- representing the index of absolute risk-aversion in the gain and loss domains respectively.

We denote the probability weighting function in the gain ($x \geq R$) and loss ($x < R$) domains by $w^+(.)$ and $w^-(.)$. We refer to probability risk-aversion [risk-seeking] as the case in which $w^+(p) \leq p$ and $w^-(1-p) \geq 1-p$ [$w^+(p) > p$ and $w^-(1-p) < 1-p$]

We consider the mixed lottery $L = (x_1, x_2; p, 1-p)$ with $x_1 \geq R \geq x_2$, which is valued as follows:

$$V(L) = w^+(p)u^R(x_1,R) + w^-(1-p)u^R(x_2,R) \tag{77}$$

In our principal-agent setup (see Section 2.1), the agent is facing a lottery with $x_1 = \alpha + \beta\theta\Big(e + \frac{1-p}{p}\epsilon\Big) - \psi e^2$ and $x_2 = \alpha + \beta\theta\Big(e - \epsilon\Big) - \psi e^2$. We further assume that the agent's reference point is given by the expected value of the lottery:

$$R = \alpha + \beta\theta e - \psi e^2 \tag{78}$$

The risk-free reference point ensures that the agent is systematically in the gain domain when the random shock yields a positive outcome (i.e., $\frac{1-p}{p}\epsilon$) and in the loss domain otherwise (i.e., $-\epsilon$).

Based on the previous assumptions, the following proposition summarizes the results regarding the optimal behavior of the agent and the principal.

Proposition E1 (Risk-incentives tradeoff with PT). Under A0, A1, A2, A3', A3", A4, A5 and assuming a PT agent as specified in (77):
i) For a given contract (α, β), the optimal level of effort increases with θ, decreases with ψ and does not depend on the fixed pay α, the utility curvature in loss domain r^-, the utility curvature in gain domain r^+, the loss aversion index λ and the shock.
ii) $\beta^*(\epsilon, r, \psi, \theta)$ and $e^*(\epsilon, r, \psi, \theta)$ decrease with λ, r^+ (the utility risk-aversion in the gain domain), probability risk-aversion (i.e., overweighting in loss domain and underweighting in gain domain), while increases with r^- (the utility risk-aversion in the loss domain).
iii) $\beta^*(\epsilon, r, \psi, \theta)$ and $e^*(\epsilon, r, \psi, \theta)$ are higher in the presence of shock than in its absence if the agent exhibits sufficient probability risk-seeking, moderate utility curvature and loss-aversion.

Proof of Proposition E1:

Given the linear contract (α, β), the objective function of agent with a cost function$C(e) = \psi e^2$ is given by

$$PT(L) = w^+(p)\left[x_1 + \frac{1 - exp\Big(-r^+\beta\theta\frac{1p}{p}\epsilon\Big)}{r^+}\right] + w^-(1-p)\left[x_2 + \lambda\frac{exp\Big(-r^-\beta\theta\epsilon\Big) - 1}{r^-}\right] \quad (79)$$

with

$x_1 = \alpha + \beta\theta\Big(e + \frac{1-p}{p}\epsilon\Big) - \psi e^2$ and $x_2 = \alpha + \beta\theta\Big(e - \epsilon\Big) - \psi e^2$.

The first-order condition of the agent's maximization problem is given by

$$(\beta\theta - 2\psi e)[w^+(p) + w^-(1-p)] = 0$$

Since $w^+(p) + w^-(1-p) \neq 0$, it follows that the optimal effort function is given by

$$e = \frac{\beta\theta}{2\psi}$$

Point i)

The optimization problem of the principal is to maximize the expected value of $\theta z - y$ by accounting for the agent's incentive compatibility constraint (IC) and participation constraint (PC):

$$\begin{cases} \max_{\alpha,\beta} \quad \pi = \theta e - (\alpha + \beta\theta e) \\ s.t.: \\ e = \frac{\beta\theta}{2\psi} \\ w^+(p)\left[x_1 + \frac{1 - exp\Big(-r^+\beta\theta\frac{1p}{p}\epsilon\Big)}{r^+}\right] + w^-(1-p)\left[x_2 + \lambda\frac{exp\Big(-r^-\beta\theta\epsilon\Big) - 1}{r^-}\right] = y_0 \end{cases}$$

which is equivalent to

$$\max_{\beta}\ \frac{\theta^2}{2\psi}\Big(\beta-0.5\beta^2\Big)+\frac{1}{w^+(p)+w^-(1-p)}\Bigg[w^+(p)\frac{1-exp\Big(-r^+\beta\theta\frac{1-p}{p}\epsilon\Big)}{r^+}+\lambda w^-(1-p)\frac{exp\Big(-r^-\beta\theta\epsilon\Big)-1}{r^-}+\beta\theta\epsilon\Big(w^+(p)\frac{1-p}{p}-w^-(1-p)\Big)-y_0\Bigg]$$

The first-order conditions are given by

$$\frac{\theta^2}{2\psi}\Big(1-\beta\Big)+\frac{\theta\epsilon}{w^+(p)+w^-(1-p)}\Bigg[w^+(p)\frac{1-p}{p}exp\Big(-r^+\beta\theta\frac{1-p}{p}\epsilon\Big)-\lambda w^-(1-p)exp\Big(-r^-\beta\theta\epsilon\Big)+w^+(p)\frac{1-p}{p}-w^-(1-p)\Bigg]=0 \quad (80)$$

Equation (80) defines the optimal variable pay $\beta^*\ (\alpha,\beta,\epsilon,r^+,r^-,\lambda,w^+,w^-,\psi,\theta)$. The optimal variable pay in the absence of shock ($\epsilon=0$) is given by $\lim_{\epsilon\longrightarrow 0}\beta^*(\alpha,\beta,\epsilon,r^+,r^-,\lambda,w^+,w^-,\psi,\theta)=1$.

The implicit function theorem applied to (80) leads to

$$\frac{\partial\beta^*}{\partial\lambda}<0 \quad (81)$$

$$\frac{\partial\beta^*}{\partial r^+}<0 \quad (82)$$

$$\frac{\partial\beta^*}{\partial r^-}>0 \quad (83)$$

Since $e^*(\alpha,\beta,\epsilon,r^+,r^-,\lambda,w^+,w^-,\psi,\theta)=\frac{\theta}{2\psi}\beta^*(\alpha,\beta,\epsilon,r^+,r^-,\lambda,w^+,w^-,\psi,\theta)$, it also follows that $\dfrac{\partial e^*}{\partial\lambda}<0$, $\dfrac{\partial e^*}{\partial r^+}<0$, $\dfrac{\partial e^*}{\partial r^-}>0$.

For given probability $p=\overline{p}$, denote by $\delta^+=w^+(\overline{p})$ and $\delta^-=w^+(1-\overline{p})$; then implicit function theorem applied to (80) leads to

$$\frac{\partial\beta^*}{\partial\delta^+}>0$$

$$\frac{\partial\beta^*}{\partial\delta^-}<0$$

Since $e^*(\alpha,\epsilon,r^+,r^-,\lambda,w^+,w^-,\psi,\theta)=\frac{\theta}{2\psi}\beta^*(\alpha,\beta,\epsilon,r^+,r^-,\lambda,w^+,w^-,\psi,\theta)$, it also follows that $\dfrac{\partial e^*}{\partial\delta^+}>0$, $\dfrac{\partial e^*}{\partial\delta^-}<0$.

Point iii)

From (80) we have

$$\frac{\frac{w^+(p)}{p}}{\frac{w^-(1-p)}{1-p}}>\frac{1+\lambda exp(-r^-\beta^*\theta\epsilon)}{1+exp\Big(-r^+\beta^*\theta\frac{1-p}{p}\epsilon\Big)}\quad\Longleftrightarrow\quad\beta^*>1=\lim_{\epsilon\longrightarrow 0}\beta^*(\alpha,\beta,\epsilon,r^+,r^-,\lambda,w^+,w^-,\psi,\theta)$$

Since $e^*(\alpha,\epsilon,r^+,r^-,\lambda,w^+,w^-,\psi,\theta)=\frac{\theta}{2\psi}\beta^*(\alpha,\beta,\epsilon,r^+,r^-,\lambda,w^+,w^-,\psi,\theta)$, it also follows that

$$\frac{\frac{w^+(p)}{p}}{\frac{w^-(1-p)}{1-p}}>\frac{1+\lambda exp(-r^-\beta^*\theta\epsilon)}{1+exp\Big(-r^+\beta^*\theta\frac{1-p}{p}\epsilon\Big)}\quad\Longleftrightarrow\quad e^*>\frac{\theta}{2\psi}=\lim_{\epsilon\longrightarrow 0}e^*(\alpha,\beta,\epsilon,r^+,r^-,\lambda,w^+,w^-,\psi,\theta)$$

Hence, $\beta^*(\alpha,\beta,\epsilon,r^+,r^-,\lambda,w^+,w^-,\psi,\theta)$ and $e^*(\alpha,\beta,\epsilon,r^+,r^-,\lambda,w^+,w^-,\psi,\theta)$ are higher in the presence of shock than in its absence if the agent exhibits sufficient probability risk-seeking, moderate utility curvature and loss-aversion.
QED.

F- Elicitation of risk preferences

We consider binary lotteries denoted by $L = (x, y; p, 1-p)$, with x being the outcome that occurs with probability p, and y being the outcome that occurs with probability $1-p$. We use 15 lotteries presented in the Table 8. They are a combination of 5 probabilities $(p_1, p_2, p_3, p_4, p_5) = (0.1, 0.25, 0.33, 0.50, 0.75)$ and three couples of outcomes $\{(100, 0), (100, 50), (50, 0)\}$. The elicit certainty equivalents for each lotteries using the switching outcomes technique (e.g., Tversky and Kahneman, 1992; Gonzalez and Wu, 1999; Abdellaoui et al., 2008).

Table 8: Lotteries in the experiment

$N°$ Lottery	x	y	p
1	100	0	0.1
2	100	50	0.1
3	50	0	0.1
4	100	0	0.25
5	100	50	0.25
6	50	0	0.25
7	100	0	0.33
8	100	50	0.33
9	50	0	0.33
10	100	0	0.50
11	100	50	0.50
12	50	0	0.50
13	100	0	0.75
14	100	50	0.75
15	50	0	0.75

In addition, we utilize the 30 values of the minimum fixed pay elicited in the main experiment to obtain further certainty equivalent data. The insight is that the outside option of 1000 is the certainty equivalent of the lottery $L = (x, y; p, 1-p)$ in which

$$x = \alpha_m + \frac{\beta^2\theta^2}{4\psi} + \frac{1-p}{p}\beta\theta\epsilon \qquad \textbf{and} \qquad y = \alpha_m + \frac{\beta^2\theta^2}{4\psi} - \beta\theta\epsilon$$

We then have in total 45 certainty equivalent data points per individual such that each of the 5 probabilities is presented in 9 binary lotteries. We use this dataset to estimate the parameters of EUT, RDU and MVS at the individual level.

RDU and EUT

For RDU, we follow the procedure developed in Kpegli et al. (2022) to estimate probability weights. Denote by $\boldsymbol{ce}, \boldsymbol{x}$ and $\boldsymbol{y}$ respectively the values of certainty equivalent, the high outcome x and the small outcome y. Also, denote by $\boldsymbol{I}^k$ the dummy variable for the probability p_k, that is a variable that takes value 1 if probability is equal to p_k and 0 otherwise. We assume CARA utility function so that we have the following empirical equation for certainty equivalent:

$$\boldsymbol{ce}_l = -\frac{1}{r} ln\left[\Big(exp\big(-r\boldsymbol{x}_l\big) - exp\big(-r\boldsymbol{y}_l\big)\Big)\sum_{k=1}^{K}\delta_k \boldsymbol{I}_l^k + exp\big(-r\boldsymbol{y}_l\big)\right] + \boldsymbol{e}_l \qquad (84)$$

where $\boldsymbol{e}$ is the error term, l is the lth line in $\boldsymbol{ce}, \boldsymbol{x}, \boldsymbol{y}$ and $\boldsymbol{e}$; $\boldsymbol{r}$ the CARA coefficient and $w(p_k) = \delta_k$ for $k = 1, 2, ..., 5$. We assume that the error term is normally distributed with mean

0 and heteroscedastic variance $\sigma_l = \sigma|\boldsymbol{x}_l - \boldsymbol{y}_l|$. We then estimate r, δ_k and σ by maximum likelihood method.

For the special case of EUT, we assume $\delta_k = p_k$ and estimate only r and σ.

MVS

Under MVS, certainty equivalents satisfy the following empirical equation

$$\boldsymbol{ce}_l = \boldsymbol{E}_l + a_v \boldsymbol{V}_l + a_v \boldsymbol{S}_l + e_l$$

with $\boldsymbol{ce}, \boldsymbol{E}, \boldsymbol{V}$ and $\boldsymbol{S}$ denoting respectively values of certainty equivalent, mean, variance and skewness associated with each of the 45 lotteries.

We assume that the error term is normally distributed with mean 0 and heteroscedastic variance $\sigma_l = \sigma|\boldsymbol{x}_l - \boldsymbol{y}_l|$. We then estimate a_v, a_s and σ by maximum likelihood method.

Table 9: Mean of individual estimates†,‡

	EU		MVS		RDU	
	Coef.	95% CI	Coef.	95% CI	Coef.	95% CI$^{(b)}$
r	0.0038	[0.0022,0.0055]	-	-	0.0023	[0.0015,0.0031]
a_v	-	-	-0.00097	[-0.0011, -0.0008]	-	-
a_s	-	-	4.8×10^{-7}	$[4.0 \times 10^{-7}, 5.6 \times 10^{-7}]$	-	-
$w(0.10)$	-	-	-	-	0.2231	[0.2034,0.2429]
$w(0.25)$	-	-	-	-	0.3278	[0.3105,0.3450]
$w(0.33)$	-	-	-	-	0.3729	[0.3553,0.3904]
$w(0.50)$	-	-	-	-	0.4856	[0.4685,0.5026]
$w(0.75)$	-	-	-	-	0.6409	[0.6208,0.6610]

† The parameters are computed from regression models controlling for individual heteroscedasticity due to observable individual characteristics (i.e., numeracy test score, cognitive reflection test score, gender and age).

‡ Standard errors clustered at the individual level when computing 95% CI due to multiple probability weights per subject.

Table 10: Mean of minimum fixed pay across treatments[†]

p	β	$e^{\ddagger}$	α_3^m	α_m^4	$\alpha_4^m - \alpha_3^m$	α_m^0	$\alpha_m^3 - \alpha_m^0$	$\alpha_m^4 - \alpha_m^0$
0.1	0.30	3.00	881.3***	901.4***	20.05***	910.00	-28.69***	-8.64
0.1	0.50	5.00	750.0***	792.9***	42.95***	750.00	-0.01	42.95***
0.1	0.70	7.00	579.9***	628.3***	48.49***	510.00	69.86***	118.3***
0.25	0.30	3.00	898.1***	917.6***	19.44***	910.00	-11.87***	7.57
0.25	0.50	5.00	761.7***	803.5***	41.82***	750.00	11.67**	53.49***
0.25	0.70	7.00	582.2***	626.8***	44.57***	510.00	72.22***	116.8***
0.33	0.30	3.00	900.5***	926.1***	25.65***	910.00	-9.505***	16.14***
0.33	0.50	5.00	780.6***	795.1***	14.56***	750.00	30.55***	45.11***
0.33	0.70	7.00	590.7***	620.2***	29.44***	510.00	80.72***	110.2***
0.5	0.30	3.00	919.6***	926.2***	6.597**	910.00	9.642***	16.24***
0.5	0.50	5.00	773.6***	786.4***	12.82***	750.00	23.63***	36.45***
0.5	0.70	7.00	582.5***	615.4***	32.86***	510.00	72.53***	105.4***
0.75	0.30	3.00	916.7***	937.6***	20.94***	910.00	6.685***	27.63***
0.75	0.50	5.00	778.4***	789.5***	11.02**	750.00	28.45***	39.47***
0.75	0.70	7.00	571.5***	607.3***	35.87***	510.00	61.45***	97.32***

Standard errors in parentheses.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ for the significance of coefficient tests.

[†] Mean of fixed pay are computed from regression analyses by allowing heteroscedasticity due to observable individual characteristics (i.e., numeracy skills, cognitive skills, gender and age).
[‡] According to the calibration $(\psi, \theta) = (2.5, 100)$, the effort is computed as $e = \frac{\beta\theta}{2\psi}$.

G - Decomposition of the cells in Table 6 according to the estimated risk attitudes

Table 11: RIT, risk-attitudes, and curvature of utility under EUT

RIT and Risk-averse		
	Number	Percentage
Concave	14	1.55 %
Convex	891	98.45%
Total	905	100%
RIT and Risk-neutral		
	Number	Percentage
Concave	23	9.96%
Convex	208	90.04%
Total	231	100%
RIT and Risk-seeking		
	Number	Percentage
Concave	229	36.12%
Convex	405	63.88%
Total	634	100%
No-RIT and Risk-averse		
	Number	Percentage
Concave	24	5.06%
Convex	450	94.94%
Total	474	100%
No-RIT and Risk-neutral		
	Number	Percentage
Concave	40	10.55%
Convex	339	89.45%
Total	379	100%
No-RIT and Risk-seeking		
	Number	Percentage
Concave	112	47.06%
Convex	126	52.94%
Total	238	100%
Reversed RIT and Risk-averse		
	Number	Percentage
Concave	77	19.40%
Convex	320	80.60%
Total	397	100%
Reversed RIT and Risk-neutral		
	Number	Percentage
Concave	32	28.32%
Convex	81	71.68%
Total	113	100%
Reversed RIT and Risk-seeking		
	Number	Percentage
Concave	124	67.39%
Convex	60	32.61%
Total	184	100%

Table 12: RIT, risk attitudes, and utility curvature and probability weighting under RDU

Number (%)	Underweighting	Overweighting	Total
	RIT and Risk-averse		
Convex	18 (1.99 %)	0 (0.00 %)	18 (1.99%)
Concave	404 (44.64%)	484 (53.37%)	887 (98.01%)
Total	422 (46.63%)	483 (53.37%)	905 (100%)
	RIT and Risk-neutral		
Convex	8 (19.41%)	2 (68.78%)	10 (4.33%)
Concave	105 (45.45%)	116 (50.22%)	221 (95.67%)
Total	113 (48.92%)	118 (51.08%)	231 (100%)
	RIT and Risk-seeking		
Convex	72 (11.36%)	51 (8.04%)	123 (19.40%)
Concave	123 (19.40%)	388 (61.20%)	511 (80.60%)
Total	195 (40.08%)	439 (69.24%)	634 (100%)
	No RIT and Risk-averse		
Convex	48 (10.13%)	2 (0.42%)	50 (10.55%)
Concave	206 (43.46%)	218 (45.99%)	424 (89.45%)
Total	254 (53.59%)	220 (46.41%)	474 (100%)
	No RIT and Risk-neutral		
Convex	46 (12.14%)	8 (2.11%)	54 (14.25%)
Concave	180 (47.49%)	145 (38.26%)	325 (85.75%)
Total	226 (59.63%)	153 (40.37%)	379 (100%)
	No RIT and Risk-seeking		
Convex	28 (11.76%)	31 (13.03%)	59 (24.79%)
Concave	31 (13.03%)	148 (62.18%)	179 (75.21%)
Total	59 (24.79%)	179 (75.21%)	238 (100%)
	Reversed RIT and Risk-aversion		
Convex	30 (7.56%)	9 (2.27%)	39 (9.82%)
Concave	168 (42.32%)	190 (47.86%)	358 (90.18%)
Total	198 (49.87%)	199 (50.13%)	397 (100%)
	Reversed RIT and Risk-neutral		
Convex	10 (8.85%)	6 (5.31 %)	16 (14.16%)
Concave	29 (25.66%)	68 (60.18%)	97 (85.84%)
Total	39 (34.51%)	74 (65.49%)	113 (100%)
	Reversed RIT and Risk-seeking		
Convex	16 (8.7%)	35 (19.02%)	51 (27.72%)
Concave	14 (7.61%)	119 (64.67%)	133 (72.28%)
Total	30 (16.3%)	154 (83.7%)	184 (100%)

Table 13: RIT, risk-attitudes, and preference/aversion for skewness and variance under MVS

Number (%)	Aversion for skewness	Preference for skewness	Total
	RIT and Risk-averse		
Preference for variance	13 (1.44%)	1 (0.11%)	14 (1.55%)
Aversion to variance	20 (2.21%)	871 (96.24 %)	891 (98.45%)
Total	33 (3.65%)	872 (96.35 %)	905 (100.00 %)
	RIT and Risk-neutral		
Preference for variance	19 (8.23%)	1 (0.43%)	20 (8.66%)
Aversion to variance	3 (1.30%)	208 (90.04%)	211 (91.34%)
Total	22 (9.52%)	209 (90.48%)	231 (100.00%)
	RIT and Risk-seeking		
Preference for variance	213 (33.60%)	13 (2.05%)	226 (35.65%)
Aversion for variance	17 (2.68%)	391 (61.67%)	408 (64.35%)
Total	230 (36.28%)	404 (63.72%)	634 (100.00%)
	No RIT and Risk-averse		
Preference for variance	21 (4.43%)	4 (0.84%)	25 (5.27%)
Aversion for variance	10 (2.11%)	439 (92.62%)	449 (94.73%)
Total	31 (6.54%)	443 (93.46%)	474 (100.00%)
	No RIT and Risk-neutral		
Preference for variance	27 (7.12%)	11 (2.90%)	38 (10.03%)
Aversion for variance	9 (2.37%)	332 (87.60%)	341 (89.97%)
Total	36 (9.50%)	343 (90.50%)	379 (100.00%)
	No RIT and Risk-seeking		
Preference for variance	100 (42.02%)	11 (4.62%)	111 (46.64%)
Aversion for variance	10 (4.20%)	117 (49.16%)	127 (53.36%)
Total	110 (46.22%)	128 (53.78%)	238 (100.00%)
	Reversed RIT and Risk-aversion		
Preference for variance	66 (16.62%)	6 (1.51%)	72 (18.14%)
Aversion for variance	12 (3.02%)	313 (78.84%)	325 (81.86%)
Total	78 (19.65%)	319 (80.35%)	397 (100.00%)
	Reversed RIT and Risk-neutral		
Preference for variance	29 (25.66%)	2 (1.77%)	31 (27.43%)
Aversion for variance	4 (3.54%)	78 (69.03%)	82 (72.57%)
Total	33 (29.20%)	80 (70.80%)	113 (100.00%)
	Reversed RIT and Risk-seeking		
Preference for variance	112 (60.87%)	11 (5.98%)	123 (66.85%)
Aversion for variance	5 (2.72%)	56 (30.43%)	61 (33.15%)
Total	117 (63.59%)	67 (36.41%)	184 (100.00%)

H-Experimental instructions

H1- Instruction for Day 1

H1-1: Numeracy Test

Thank you for participating in this experiment. This experiment is composed of two parts. In the first part that you will perform today, you will answer a series of questions. The duration of this first part of the experiment will be approximately 30 minutes. After completing the first part, you will be invited to participate in a second part in the next few days. By participating in this first part, you agree to complete the second part.

Payments for both parts will be made early next week once you have completed the second part of the experience. A participation bonus of 4 euros will be added to your payments for your participation in both parts.

The experience will be done entirely online. All the information you need to make your decisions will be visible on the screen. You will not need to consult any other documents, so we ask you to stay focused on the instructions and on your decisions during the experiment.

Please answer the following questions carefully.

Each question has one and only one correct solution.

If you are ready, please proceed to the next page.

Imagine that we toss an undamaged coin 1,000 times. What is your best estimate of the number of times the coin will land on the face side over 1,000 tosses?

Indicate your answer (integer between 0 and 1,000) below:

[ ]

A lottery ticket has a 1% chance of winning a $10 prize. Suppose 1,000 people buy a ticket, what is your best estimate of the number of people who would win the $10 prize?

Indicate your answer (integer between 0 and 1,000) below:

[ ]

In a television show, the probability of winning a car is 1 in 1,000. What percentage of the contestants on the television show win a car?

State your answer (in percentages, use the comma "," if necessary) below:

Out of 1,000 students at a university, 500 are enrolled in the economics-management field. Of these 500 economics and management students, 100 are male students. Out of the 500 students who are not in economics and management, 300 are male students. What is the probability that a randomly drawn male student will be enrolled in the economics-management major? Please state the probability as a percentage.

Indicate your answer (whole number between 0 and 100) below:

Imagine that we roll a five-sided die 50 times. On average, out of these 50 throws, how many times will this five-sided die show an odd number (1, 3 or 5)?

Indicate your answer (integer between 0 and 50) below:

H1-2: Probability training

In the next screen, we will show you a table with a certain number of cells. The cells with the same number will be represented with the same color. The computer will choose a cell at random and repeat this operation a large number of times. Each time the computer chooses a square, it will appear dark. The percentage of times a number was chosen by the computer during the simulation will appear at the bottom of the table.

So a number that appears in more boxes will be selected by the computer more often. For example, if the number 400 appears in 7 out of 9 cells, it will be chosen 7 times out of 9 if the simulation is long enough, that is, 78% of the time (7/9=78%).

Here is an example of a table. You can finish the simulation performed by the computer by clicking on the 'Finish Simulation' button.

100	100	400	400	400	400	400	400	400
23%		77%						

Terminer Simulation

Below each table, you will be asked to enter an estimate of the percentage of times the computer will choose a number represented in the table in the case of a simulation of 100,000 numbers.

You will earn 10 cents for each correct answer, i.e., an answer that does not differ from the simulation result by more than 5%.

TABLEAU #1

300	300	300	300	300	300	400	400	400
0%						0%		

Given the numbers in the table, what do you think will be the percentage of cases where the result obtained by the computer will be 400 on a simulation of 100 000 numbers?

[ ] %

(Enter an integer between 0 and 100)

TABLEAU #2

500	500	500	500	500	500	600	600
0%						0%	

Given the numbers in the table, what do you think will be the percentage of cases where the result obtained by the computer will be 600 on a simulation of 100 000 numbers?

[ ] %

(Enter an integer between 0 and 100)

TABLEAU #3

200	200	200	200	200	300	300	300	300	300
0%					0%				

Given the numbers in the table, what do you think will be the percentage of cases where the result obtained by the computer will be 300 on a simulation of 100 000 numbers?

[ ] %

(Enter an integer between 0 and 100)

TABLEAU #4

400	400	400	900	900	900	900	900	900
0%			0%					

Given the numbers in the table, what do you think will be the percentage of cases where the result obtained by the computer will be 900 on a simulation of 100 000 numbers?

[ ] %

(Enter an integer between 0 and 100)

TABLEAU #5

600	600	700	700	700	700	700	700
0%		0%					

Given the numbers in the table, what do you think will be the percentage of cases where the result obtained by the computer will be 700 on a simulation of 100 000 numbers?

%

(Enter an integer between 0 and 100)

TABLEAU #6

100	100	100	100	100	100	100	100	100	800
0%									0%

Given the numbers in the table, what do you think will be the percentage of cases where the result obtained by the computer will be 800 on a simulation of 100 000 numbers?

%

(Enter an integer between 0 and 100)

TABLEAU #7

700	900	900	900	900	900	900	900	900	900
0%	0%								

Given the numbers in the table, what do you think will be the percentage of cases where the result obtained by the computer will be 900 on a simulation of 100 000 numbers?

%

(Enter an integer between 0 and 100)

H1-3: Probability weighting

In this task you will be asked to make a series of choices. You will see 15 tables, each consisting of 11 rows. Each row has two options; of which you must choose one: 'Option A' or 'Option B'.

Option A gives you a sure win.

Option B is a lottery that gives you a certain win with a 33% chance and another win with a 67% chance. Option B changes from table to table, but it is the same for all 11 rows in a given table.

All amounts in the tables are in euro cents.

When the experiment is over, only one row from all the rows in all the tables will be randomly selected for payment. Thus, each line has the same probability of being chosen for the payouts, so you should pay equal attention to all your choices.

<u>Example of a table:</u>

Option A		Option B	
100	A1	B1	
90	A2	B2	
80	A3	B3	
70	A4	B4	
60	A5	B5	
50	A6	B6	33% de chances pour gagner 100 67% de chances pour gagner 50
40	A7	B7	
30	A8	B8	
20	A9	B9	
10	A10	B10	
0	A11	B11	

In each line, you will be asked to indicate whether you prefer option A or option B.

Both options are initially displayed in gray. Click on either option to select it. Your selection will be highlighted in orange. You can change your selection at any time by clicking on the box that corresponds to the desired option.

The computer will help you make your choices by avoiding mistakes. For example, if you select 'Option A' for a given line, the computer will mark 'Option A' for all previous lines (up to the first). Similarly, if you select 'Option B' for a line, the computer will mark 'Option B' for all subsequent lines (up to the last one).

Let's assume that the following line has been chosen for the payment calculation:

70	A4	B4	33% de chances pour gagner 100 67% de chances pour gagner 50

- If you selected 'Option A' for this line, you will win 70 cents.
- If you selected 'Option B' for this line, the computer will randomly choose a number between 1 and 3 to determine your winnings.
  - If the randomly selected number is 1 (33% chance), you will win 100 cents.
  - If the randomly chosen number is 2 or 3 (67% chance), you will win 50 cents.

If you are ready, click on '>>' to start.

TABLEAU #1

Option A		Option B	
100	A1	B1	10% de chances pour gagner 100 90% de chances pour gagner 0
90	A2	B2	
80	A3	B3	
70	A4	B4	
60	A5	B5	
50	A6	B6	
40	A7	B7	
30	A8	B8	
20	A9	B9	
10	A10	B10	
0	A11	B11	

Select an option for TABLEAU#1

TABLEAU #2

Option A		Option B	
100	A1	B1	10% de chances pour gagner 50 90% de chances pour gagner 0
90	A2	B2	
80	A3	B3	
70	A4	B4	
60	A5	B5	
50	A6	B6	
40	A7	B7	
30	A8	B8	
20	A9	B9	
10	A10	B10	
0	A11	B11	

Select an option for TABLEAU#2

TABLEAU #3

Option A		Option B	
100	A1	B1	10% de chances pour gagner 100 90% de chances pour gagner 50
90	A2	B2	
80	A3	B3	
70	A4	B4	
60	A5	B5	
50	A6	B6	
40	A7	B7	
30	A8	B8	
20	A9	B9	
10	A10	B10	
0	A11	B11	

Select an option for TABLEAU#3

TABLEAU #4

Option A		Option B	
100	A1	B1	25% de chances pour gagner 100 75% de chances pour gagner 0
90	A2	B2	
80	A3	B3	
70	A4	B4	
60	A5	B5	
50	A6	B6	
40	A7	B7	
30	A8	B8	
20	A9	B9	
10	A10	B10	
0	A11	B11	

Select an option for TABLEAU#4

TABLEAU #5

Option A		Option B	
100	A1	B1	25% de chances pour gagner 50 75% de chances pour gagner 0
90	A2	B2	
80	A3	B3	
70	A4	B4	
60	A5	B5	
50	A6	B6	
40	A7	B7	
30	A8	B8	
20	A9	B9	
10	A10	B10	
0	A11	B11	

Select an option for TABLEAU#5

TABLEAU #6

Option A			Option B
100	A1	B1	25% de chances pour gagner 100 75% de chances pour gagner 50
90	A2	B2	
80	A3	B3	
70	A4	B4	
60	A5	B5	
50	A6	B6	
40	A7	B7	
30	A8	B8	
20	A9	B9	
10	A10	B10	
0	A11	B11	

Select an option for TABLEAU#6

TABLEAU #7

Option A		Option B	
100	A1	B1	33% de chances pour gagner 100 67% de chances pour gagner 0
90	A2	B2	
80	A3	B3	
70	A4	B4	
60	A5	B5	
50	A6	B6	
40	A7	B7	
30	A8	B8	
20	A9	B9	
10	A10	B10	
0	A11	B11	

Select an option for TABLEAU#7

TABLEAU #8

Option A		Option B	
100	A1	B1	33% de chances pour gagner 50 67% de chances pour gagner 0
90	A2	B2	
80	A3	B3	
70	A4	B4	
60	A5	B5	
50	A6	B6	
40	A7	B7	
30	A8	B8	
20	A9	B9	
10	A10	B10	
0	A11	B11	

Select an option for TABLEAU#8

TABLEAU #9

Option A		Option B	
100	A1	B1	33% de chances pour gagner 100 67% de chances pour gagner 50
90	A2	B2	
80	A3	B3	
70	A4	B4	
60	A5	B5	
50	A6	B6	
40	A7	B7	
30	A8	B8	
20	A9	B9	
10	A10	B10	
0	A11	B11	

Select an option for TABLEAU#9

TABLEAU #10

Option A		Option B	
100	A1	B1	50% de chances pour gagner 100 50% de chances pour gagner 0
90	A2	B2	
80	A3	B3	
70	A4	B4	
60	A5	B5	
50	A6	B6	
40	A7	B7	
30	A8	B8	
20	A9	B9	
10	A10	B10	
0	A11	B11	

Select an option for TABLEAU#10

TABLEAU #11

Option A		Option B	
100	A1	B1	50% de chances pour gagner 50 50% de chances pour gagner 0
90	A2	B2	
80	A3	B3	
70	A4	B4	
60	A5	B5	
50	A6	B6	
40	A7	B7	
30	A8	B8	
20	A9	B9	
10	A10	B10	
0	A11	B11	

Select an option for TABLEAU#11

TABLEAU #12

Option A		Option B	
100	A1	B1	50% de chances pour gagner 100 50% de chances pour gagner 50
90	A2	B2	
80	A3	B3	
70	A4	B4	
60	A5	B5	
50	A6	B6	
40	A7	B7	
30	A8	B8	
20	A9	B9	
10	A10	B10	
0	A11	B11	

Select an option for TABLEAU#12

TABLEAU #13

Option A		Option B	
100	A1	B1	75% de chances pour gagner 100 25% de chances pour gagner 0
90	A2	B2	
80	A3	B3	
70	A4	B4	
60	A5	B5	
50	A6	B6	
40	A7	B7	
30	A8	B8	
20	A9	B9	
10	A10	B10	
0	A11	B11	

Select an option for TABLEAU#13

TABLEAU #14

Option A		Option B	
100	A1	B1	75% de chances pour gagner 50 25% de chances pour gagner 0
90	A2	B2	
80	A3	B3	
70	A4	B4	
60	A5	B5	
50	A6	B6	
40	A7	B7	
30	A8	B8	
20	A9	B9	
10	A10	B10	
0	A11	B11	

Select an option for TABLEAU#14

TABLEAU #15

Option A		Option B	
100	A1	B1	75% de chances pour gagner 100 25% de chances pour gagner 50
90	A2	B2	
80	A3	B3	
70	A4	B4	
60	A5	B5	
50	A6	B6	
40	A7	B7	
30	A8	B8	
20	A9	B9	
10	A10	B10	
0	A11	B11	

Select an option for TABLEAU#15

H1-4: : Holt&Laury_1Switch

In the next screen, you will be asked to make ten choices (one choice for each row of the table). Each time, you will be asked to indicate whether you prefer 'Option A' or 'Option B'. When the experiment is complete, one row of the table will be randomly selected for payment. This means that each row has the same probability of being selected for the payout, so you should pay equal attention to all your choices.

Your winnings will depend on whether you choose 'Option A' or 'Option B'. To determine your winnings, a number between 1 and 10 will be randomly selected by the computer.

All amounts in the tables are in cents.

For each of the 10 rows in the table, you will be asked to indicate whether you prefer 'Option A' or 'Option B'.

Both options are initially displayed in gray. Click on one of the two options to select it. Your selection will be highlighted in orange. You can change your selection at any time by clicking on the box that corresponds to the desired option.

The computer will help you make your selection without errors. For example, if you select 'Option A' for a given line, the computer will mark 'Option A' for all previous lines (up to the first). Similarly, if you select 'Option B' for a line, the computer will mark 'Option B' for all subsequent lines (up to the last one).

Suppose the following line was randomly selected for payment:

Option A		Nombre au hasard										Option B	
100	80											190	5
A4		1	2	3	4	5	6	7	8	9	10	B4	

- If you selected 'Option A' (by clicking on the box 'A4') and the computer randomly selected the number :

- 1, 2, 3 or 4 you win 100 euro cents
  - 5, 6, 7, 8, 9 or 10 you win 80 cents
- If you have selected 'Option B' (by clicking on the box 'B4') and the second number is :
  - 1, 2, 3 or 4 you win 190 cents
  - 5, 6, 7, 8, 9 or 10 you win 5 euro cents

You can click on the 'A4' or 'B4' boxes now to practice selecting an option (it will be highlighted in orange).

Therefore, the color of the numbers in the 'Random Number' column represents your chances of getting each possible payout.

The more purple numbers in a row, the more likely you are to get 100 or 190 cents, depending on whether you select 'Option A' or 'Option B', and the less likely you are to get the green amounts if that row is selected at random for payment.

The more numbers colored green on a line, the more likely you are to get 80 or 5 cents, depending on whether you select 'Option A' or 'Option B', and the less likely you are to get the purple amounts if that line is randomly selected for payment.

In summary, you will have ten choices: in each row of the table, you will have to choose between Option A and Option B. You can choose option A in some rows and option B in others, and you can change your choices and take them in any order.

If you are ready, click on '>>' to begin.

In each of the following 10 lines, indicate whether you prefer 'Option A' or 'Option B'.

Option A		Nombre au hasard										Option B	
100	80											190	5
A1		1	2	3	4	5	6	7	8	9	10	B1	
A2		1	2	3	4	5	6	7	8	9	10	B2	
A3		1	2	3	4	5	6	7	8	9	10	B3	
A4		1	2	3	4	5	6	7	8	9	10	B4	
A5		1	2	3	4	5	6	7	8	9	10	B5	
A6		1	2	3	4	5	6	7	8	9	10	B6	
A7		1	2	3	4	5	6	7	8	9	10	B7	
A8		1	2	3	4	5	6	7	8	9	10	B8	
A9		1	2	3	4	5	6	7	8	9	10	B9	
A10		1	2	3	4	5	6	7	8	9	10	B10	

Select 'Option A' or 'Option B' for line #1 by clicking on box 'A1' or box 'B1'.

H1-5: Loss aversion

In the next screen, you will be asked to make ten choices (one choice for each row of the table). Each time, you will be asked to indicate whether you prefer 'Option A' or 'Option B'. When the experiment is complete, one row of the table will be randomly selected for payment. This means that each row has the same probability of being selected for the payout, so you should pay equal attention to all your choices. Your winnings will depend on whether you choose 'Option A' or 'Option B'. To determine your winnings, a number between 1 and 10 will be randomly selected by the computer.

In each case, 'Option A' and 'Option B' are such that they generate losses with a 50% probability and wins with a 50% probability.

In the table, option A is different in each row, while option B remains the same in all rows: 'lose 100 cents with 50% chance, win 100 cents with 50% chance'.

All the amounts that appear in the tables are in euro cents.

In this part of the experiment, any winnings you make will be added to your total winnings and any losses you suffer will be subtracted from your total winnings.

For each of the 10 rows in the table, you will be asked to indicate whether you prefer 'Option A' or 'Option B'.

Both options are initially displayed in gray. Click on one of the two options to select it. Your selection will be highlighted in orange. You can change your selection at any time by clicking on the box that corresponds to the desired option.

The computer will help you make your choices by avoiding mistakes. For example, if you select 'Option A' for a given line, the computer will mark 'Option A' for all previous lines (up to the first). Similarly, if you select 'Option B' for a line, the computer will mark 'Option B' for all subsequent lines (up to the last one).

Example:

Suppose the following line was randomly selected for payment:

#	Option A	Option B
4	perdre 175 avec 50% de chances gagner 500 avec 50% de chances	perdre 100 avec 50% de chances gagner 100 avec 50% de chances

- If you selected 'Option A', you have a 50% chance of losing 175 cents and a 50% chance of winning 500 cents
- If you selected 'Option B', you will have a 50% chance of losing 100 cents and a 50% chance of winning 100 cents

Now you can click on the boxes corresponding to 'Option A' or 'Option B' to practice selecting an option (it will be highlighted in orange).

In summary, 1 of the 10 rows in the table will be selected at random, and your choice ('Option A' or 'Option B') will determine how much money you can receive in that part of the experiment.

- If you chose 'Option A' for the randomly selected row, you will either win the corresponding amount of money (with a 50% chance) or lose the corresponding amount of money (with a 50% chance).
- If you chose 'Option B' for the randomly selected line, you will either win 100 cents (with a 50% chance) or lose 100 cents (with a 50% chance).

If you are ready, click on '>>' to start.

In each of the following 10 lines, indicate whether you prefer 'Option A' or 'Option B'.

#	Option A	Option B
1	perdre 140 avec 50% de chances gagner 500 avec 50% de chances	perdre 100 avec 50% de chances gagner 100 avec 50% de chances
2	perdre 150 avec 50% de chances gagner 500 avec 50% de chances	perdre 100 avec 50% de chances gagner 100 avec 50% de chances
3	perdre 160 avec 50% de chances gagner 500 avec 50% de chances	perdre 100 avec 50% de chances gagner 100 avec 50% de chances
4	perdre 175 avec 50% de chances gagner 500 avec 50% de chances	perdre 100 avec 50% de chances gagner 100 avec 50% de chances
5	perdre 190 avec 50% de chances gagner 500 avec 50% de chances	perdre 100 avec 50% de chances gagner 100 avec 50% de chances
6	perdre 210 avec 50% de chances gagner 500 avec 50% de chances	perdre 100 avec 50% de chances gagner 100 avec 50% de chances
7	perdre 240 avec 50% de chances gagner 500 avec 50% de chances	perdre 100 avec 50% de chances gagner 100 avec 50% de chances
8	perdre 290 avec 50% de chances gagner 500 avec 50% de chances	perdre 100 avec 50% de chances gagner 100 avec 50% de chances
9	perdre 395 avec 50% de chances gagner 500 avec 50% de chances	perdre 100 avec 50% de chances gagner 100 avec 50% de chances
10	perdre 700 avec 50% de chances gagner 500 avec 50% de chances	perdre 100 avec 50% de chances gagner 100 avec 50% de chances

Select 'Option A' or 'Option B' for line #1 by clicking on box 'A1' or box 'B1'.

H1-6: Cognitive reflection test - Problems

Please answer the following questions carefully.

Each question has only one solution.

You will have exactly 5 minutes to answer all the questions.

If you are ready, click on '>>' to begin.

A table and a chair cost 150 euros in total. The table costs 100 euros more than the chair. How much does the chair cost?

(answer below in euros)

If it takes 10 hours for 10 mechanics to repair 10 cars, how long would it take 80 mechanics to repair 80 cars?

(answer below in hours)

A new library buys books for its collection. Each week the number of books purchased doubles. If it takes 36 weeks to buy all the books they need, how long would it take the library to buy half the books they need?

(answer below in weeks)

In the zoo, the lions eat a ton of meat every 6 weeks, and the tigers eat a ton of meat every 12 weeks, how long would it take the lions and tigers together to eat a ton of meat?

(answer below in weeks)

John had the 25th fastest time and the 25th slowest time in a race. How many people participated in the race?

(answer below)

An art collector buys a famous painting for 50 million and sells it for 60 million. A few years later, the collector buys it back for 70 million and sells it for 80 million. How much money did the collector make in the end?

(answer below in millions)

Marie invested 12,000 euros in the stock market in November 2013. Six months later, in May 2014, the shares she had bought had fallen by 50%. Fortunately for Marie, from May 2014 to August 2014, the shares she had purchased had increased by 75%. At this point, Mary:

- earned money
- lost money
- did not make or lose any money

H1-7: Demographics
Please answer the following sociodemographic questions:

Gender:

- Male
- Female
- Other

Age (in years):

Nationality:

What was the size of the community where you lived the most time in your life?

- Less than 2000 inhabitants
- Between 2000 and 10000 inhabitants
- Between 10000 and 100000 inhabitants
- More than 10000 inhabitants

How many brothers and sisters do you have?

What is your position among your siblings?

(Please answer with a number. 1 = oldest)

To what extent have you been involved in other studies like this?

1 - Jamais	2	3	4	5 - Souvent

How do you see yourself: are you generally a person who is fully willing to take risks or do you try to avoid taking risks?

Please select a number on the scale, where 0 means 'not at all willing to take risks' and 10 means 'very willing to take risks'.

0 - pas du tout disposé à prendre des risques	1	2	3	4	5	6	7	8	9	10 - très disposé à prendre des risques

H2- Instruction for Day 2

Welcome to the second part of the experiment!

We remind you that this experiment will take place entirely online. All the information you need to make your decisions will be visible on the screen. You will not need to consult any other documents, so we ask you to stay focused on the instructions and your decisions during the experiment.

A participation bonus of €4 will be added to your winnings from the experiment and will be paid to you at the end of this part of the experiment.

Pour commencer, veuillez saisir votre IDENTIFIANT ci-dessous.

Cet IDENTIFIANT vous a été donné lors de votre participation à la première partie de l'expérience. Vous ne pourrez pas participer et être rémunéré pour cette deuxième partie si vous n'avez pas effectué la première partie.

En général, votre IDENTIFIANT est composé des trois premières lettres de votre nom de famille et des six derniers chiffres de votre IBAN.

Si vous ne vous souvenez pas de votre IDENTIFIANT et avez des difficultés à vous connecter, veuillez contacter kpegli@gate.cnrs.fr

H2-1 : Probability training

In the next screen we will show you a table with a number of cells. Identical numbers will be shown in the same colour. The computer will choose a square at random and repeat this operation a large number of times. Each time the computer chooses a square, it will appear dark. The percentage of times that a number has been chosen by the computer during the simulation will appear at the bottom of the table.

Therefore, a number that appears in more boxes will be selected by the computer more often. For example, if the number 400 appears in 7 out of 9 cells, it will be chosen 7 times out of 9 if the simulation is long enough, i.e., 78% of the time (7/9=78%).

Example:

Here is an example of a table. You can end the computer simulation by clicking on the 'End Simulation' button.

100	100	400	400	400	400	400	400	400
21%		79%						

Terminer Simulation

Please click on '>>' to continue.

Below each table, you will be asked to enter an estimate of the percentage of times the computer will choose a number represented in the table in the case of a simulation of 100,000 numbers.

You will earn 10 cents for each correct answer, i.e., an answer that does not differ from the simulation result by more than 5%.

TABLEAU #1

100	100	100	100	100	100	100	100	100	800
0%									0%

Given the numbers in the table, what do you think will be the percentage of cases where the result obtained by the computer will be 800 on a simulation of 100 000 numbers?

[ ] %

(Enter an integer between 0 and 100)

TABLEAU #2

500	500	500	500	500	500	600	600
0%						0%	

Given the numbers in the table, what do you think will be the percentage of cases where the result obtained by the computer will be 600 on a simulation of 100 000 numbers?

%

(Enter an integer between 0 and 100)

TABLEAU #3

300	300	300	300	300	300	400	400	400
0%						0%		

Given the numbers in the table, what do you think will be the percentage of cases where the result obtained by the computer will be 400 on a simulation of 100 000 numbers?

%

(Enter an integer between 0 and 100)

TABLEAU #4

200	200	200	200	200	300	300	300	300	300
0%					0%				

Given the numbers in the table, what do you think will be the percentage of cases where the result obtained by the computer will be 300 on a simulation of 100 000 numbers?

%

(Enter an integer between 0 and 100)

TABLEAU #5

600	600	700	700	700	700	700	700
0%		0%					

Given the numbers in the table, what do you think will be the percentage of cases where the result obtained by the computer will be 500 on a simulation of 100 000 numbers?

%

(Enter an integer between 0 and 100)

TABLEAU #6

700	900	900	900	900	900	900	900	900	900
0%	0%								

Given the numbers in the table, what do you think will be the percentage of cases where the result obtained by the computer will be 900 on a simulation of 100 000 numbers?

%

(Enter an integer between 0 and 100)

TABLEAU #7

400	400	400	900	900	900	900	900	900
0%			0%					

Given the numbers in the table, what do you think will be the percentage of cases where the result obtained by the computer will be 900 on a simulation of 100 000 numbers?

%

(Enter an integer between 0 and 100)

H2-2: Main task

In this task, you will be asked to make a series of choices. You will see several tables displayed one by one, each consisting of several rows. Each row has two options, of which you must choose one: either Option A or Option B.

Option A gives you a sure win. This option will remain the same throughout this part of the experience. This option will not change within a table or between tables.

Option B is a lottery where only one amount is drawn from two possible amounts. One of the two amounts is coloured green and the other blue, and each has its own probability of being drawn at random. These probabilities are represented by the number of boxes of a certain colour (either green or blue) among all the coloured boxes (green or blue) in a row. This means that a number that appears on more squares has a higher chance of being chosen. The amounts and the distribution of the colours of the boxes change between the rows within each table, but also from one table to another.

For each table, the computer will help you to make your choices without making mistakes. For example, if you select 'Option A' for a given row, the computer will mark 'Option A' for all the preceding rows (up to the first). Similarly, if you select 'Option B' for a line, the computer will mark 'Option B' for all subsequent lines (up to the last one).

Once the experiment is complete, 1 table will be drawn from the 30 tables. For each of these boards, a line will be randomly selected for payment. Depending on your decisions, your payout for the board will be either the amount (in euro cents) of option A or the result (in euro cents) of the lottery for option B.

Since each table has the same probability of being chosen for the payments, you should therefore pay the same attention to all your choices. All amounts that appear in the tables are in euro cents. For example, the amount 1000 corresponds to 10 euros.

Example:

Let's imagine that we have a table with a total of 7 possible payments associated with option B, and the following row of this table has been chosen for the calculation of the payments:

If you selected 'Option A' for this line, you will win 1,000 cents.

- If you selected 'Option B' for this line, the computer will randomly choose a number between 1 and 7 to determine your winnings.
  - If the randomly chosen number is 1 or 2 (2/7=29% chance), you will win 250 cents.
  - If the randomly chosen number is 3, 4, 5, 6 or 7 (5/7=71% chance), you will win 1,150 euro cents.

If you are ready, click on '>>' to start.

TABLEAU #1

Option A		Option B										
1000	A1	B1	50	50	50	50	50	450	450	450	450	450
1000	A2	B2	100	100	100	100	100	500	500	500	500	500
1000	A3	B3	150	150	150	150	150	550	550	550	550	550
1000	A4	B4	200	200	200	200	200	600	600	600	600	600
1000	A5	B5	250	250	250	250	250	650	650	650	650	650
1000	A6	B6	300	300	300	300	300	700	700	700	700	700
1000	A7	B7	350	350	350	350	350	750	750	750	750	750
1000	A8	B8	400	400	400	400	400	800	800	800	800	800
1000	A9	B9	450	450	450	450	450	850	850	850	850	850
1000	A10	B10	500	500	500	500	500	900	900	900	900	900
1000	A11	B11	550	550	550	550	550	950	950	950	950	950
1000	A12	B12	600	600	600	600	600	1000	1000	1000	1000	1000
1000	A13	B13	650	650	650	650	650	1050	1050	1050	1050	1050
1000	A14	B14	700	700	700	700	700	1100	1100	1100	1100	1100
1000	A15	B15	750	750	750	750	750	1150	1150	1150	1150	1150
1000	A16	B16	800	800	800	800	800	1200	1200	1200	1200	1200
1000	A17	B17	850	850	850	850	850	1250	1250	1250	1250	1250
1000	A18	B18	900	900	900	900	900	1300	1300	1300	1300	1300
1000	A19	B19	950	950	950	950	950	1350	1350	1350	1350	1350
1000	A20	B20	1000	1000	1000	1000	1000	1400	1400	1400	1400	1400
1000	A21	B21	1050	1050	1050	1050	1050	1450	1450	1450	1450	1450

Select an option for TABLEAU #1

TABLEAU #2

Option A		Option B										
1000	A1	B1	50	50	50	50	50	50	50	50	50	2050
1000	A2	B2	100	100	100	100	100	100	100	100	100	2100
1000	A3	B3	150	150	150	150	150	150	150	150	150	2150
1000	A4	B4	200	200	200	200	200	200	200	200	200	2200
1000	A5	B5	250	250	250	250	250	250	250	250	250	2250
1000	A6	B6	300	300	300	300	300	300	300	300	300	2300
1000	A7	B7	350	350	350	350	350	350	350	350	350	2350
1000	A8	B8	400	400	400	400	400	400	400	400	400	2400
1000	A9	B9	450	450	450	450	450	450	450	450	450	2450
1000	A10	B10	500	500	500	500	500	500	500	500	500	2500
1000	A11	B11	550	550	550	550	550	550	550	550	550	2550
1000	A12	B12	600	600	600	600	600	600	600	600	600	2600
1000	A13	B13	650	650	650	650	650	650	650	650	650	2650
1000	A14	B14	700	700	700	700	700	700	700	700	700	2700
1000	A15	B15	750	750	750	750	750	750	750	750	750	2750
1000	A16	B16	800	800	800	800	800	800	800	800	800	2800
1000	A17	B17	850	850	850	850	850	850	850	850	850	2850
1000	A18	B18	900	900	900	900	900	900	900	900	900	2900
1000	A19	B19	950	950	950	950	950	950	950	950	950	2950
1000	A20	B20	1000	1000	1000	1000	1000	1000	1000	1000	1000	3000
1000	A21	B21	1050	1050	1050	1050	1050	1050	1050	1050	1050	3050

Select an option for TABLEAU #2

TABLEAU #3

Option A		Option B										
1000	A1	B1	0	0	0	0	0	180	180	180	180	180
1000	A2	B2	50	50	50	50	50	230	230	230	230	230
1000	A3	B3	100	100	100	100	100	280	280	280	280	280
1000	A4	B4	150	150	150	150	150	330	330	330	330	330
1000	A5	B5	200	200	200	200	200	380	380	380	380	380
1000	A6	B6	250	250	250	250	250	430	430	430	430	430
1000	A7	B7	300	300	300	300	300	480	480	480	480	480
1000	A8	B8	350	350	350	350	350	530	530	530	530	530
1000	A9	B9	400	400	400	400	400	580	580	580	580	580
1000	A10	B10	450	450	450	450	450	630	630	630	630	630
1000	A11	B11	500	500	500	500	500	680	680	680	680	680
1000	A12	B12	550	550	550	550	550	730	730	730	730	730
1000	A13	B13	600	600	600	600	600	780	780	780	780	780
1000	A14	B14	650	650	650	650	650	830	830	830	830	830
1000	A15	B15	700	700	700	700	700	880	880	880	880	880
1000	A16	B16	750	750	750	750	750	930	930	930	930	930
1000	A17	B17	800	800	800	800	800	980	980	980	980	980
1000	A18	B18	850	850	850	850	850	1030	1030	1030	1030	1030
1000	A19	B19	900	900	900	900	900	1080	1080	1080	1080	1080
1000	A20	B20	950	950	950	950	950	1130	1130	1130	1130	1130
1000	A21	B21	1000	1000	1000	1000	1000	1180	1180	1180	1180	1180

Select an option for TABLEAU #3

TABLEAU #4

Option A		Option B									
1000	A1	B1	0	0	0	0	0	0	0	0	0	900
1000	A2	B2	50	50	50	50	50	50	50	50	50	950
1000	A3	B3	100	100	100	100	100	100	100	100	100	1000
1000	A4	B4	150	150	150	150	150	150	150	150	150	1050
1000	A5	B5	200	200	200	200	200	200	200	200	200	1100
1000	A6	B6	250	250	250	250	250	250	250	250	250	1150
1000	A7	B7	300	300	300	300	300	300	300	300	300	1200
1000	A8	B8	350	350	350	350	350	350	350	350	350	1250
1000	A9	B9	400	400	400	400	400	400	400	400	400	1300
1000	A10	B10	450	450	450	450	450	450	450	450	450	1350
1000	A11	B11	500	500	500	500	500	500	500	500	500	1400
1000	A12	B12	550	550	550	550	550	550	550	550	550	1450
1000	A13	B13	600	600	600	600	600	600	600	600	600	1500
1000	A14	B14	650	650	650	650	650	650	650	650	650	1550
1000	A15	B15	700	700	700	700	700	700	700	700	700	1600
1000	A16	B16	750	750	750	750	750	750	750	750	750	1650
1000	A17	B17	800	800	800	800	800	800	800	800	800	1700
1000	A18	B18	850	850	850	850	850	850	850	850	850	1750
1000	A19	B19	900	900	900	900	900	900	900	900	900	1800
1000	A20	B20	950	950	950	950	950	950	950	950	950	1850
1000	A21	B21	1000	1000	1000	1000	1000	1000	1000	1000	1000	1900

Select an option for TABLEAU #4

TABLEAU #5

Option A		Option B										
1000	A1	B1	210	210	210	210	210	210	1050	1050	1050	[redacted]
1000	A2	B2	260	260	260	260	260	260	1100	1100	1100	[redacted]
1000	A3	B3	310	310	310	310	310	310	1150	1150	1150	[redacted]
1000	A4	B4	360	360	360	360	360	360	1200	1200	1200	[redacted]
1000	A5	B5	410	410	410	410	410	410	1250	1250	1250	[redacted]
1000	A6	B6	460	460	460	460	460	460	1300	1300	1300	[redacted]
1000	A7	B7	510	510	510	510	510	510	1350	1350	1350	[redacted]
1000	A8	B8	560	560	560	560	560	560	1400	1400	1400	[redacted]
1000	A9	B9	610	610	610	610	610	610	1450	1450	1450	[redacted]
1000	A10	B10	660	660	660	660	660	660	1500	1500	1500	[redacted]
1000	A11	B11	710	710	710	710	710	710	1550	1550	1550	[redacted]
1000	A12	B12	760	760	760	760	760	760	1600	1600	1600	[redacted]
1000	A13	B13	810	810	810	810	810	810	1650	1650	1650	[redacted]
1000	A14	B14	860	860	860	860	860	860	1700	1700	1700	[redacted]
1000	A15	B15	910	910	910	910	910	910	1750	1750	1750	[redacted]
1000	A16	B16	960	960	960	960	960	960	1800	1800	1800	[redacted]
1000	A17	B17	1010	1010	1010	1010	1010	1010	1850	1850	1850	[redacted]
1000	A18	B18	1060	1060	1060	1060	1060	1060	1900	1900	1900	[redacted]
1000	A19	B19	1110	1110	1110	1110	1110	1110	1950	1950	1950	[redacted]
1000	A20	B20	1160	1160	1160	1160	1160	1160	2000	2000	2000	[redacted]
1000	A21	B21	1210	1210	1210	1210	1210	1210	2050	2050	2050	[redacted]

Select an option for TABLEAU #5

TABLEAU #6

Option A		Option B										
1000	A1	B1	100	100	100	100	100	100	700	700		
1000	A2	B2	150	150	150	150	150	150	750	750		
1000	A3	B3	200	200	200	200	200	200	800	800		
1000	A4	B4	250	250	250	250	250	250	850	850		
1000	A5	B5	300	300	300	300	300	300	900	900		
1000	A6	B6	350	350	350	350	350	350	950	950		
1000	A7	B7	400	400	400	400	400	400	1000	1000		
1000	A8	B8	450	450	450	450	450	450	1050	1050		
1000	A9	B9	500	500	500	500	500	500	1100	1100		
1000	A10	B10	550	550	550	550	550	550	1150	1150		
1000	A11	B11	600	600	600	600	600	600	1200	1200		
1000	A12	B12	650	650	650	650	650	650	1250	1250		
1000	A13	B13	700	700	700	700	700	700	1300	1300		
1000	A14	B14	750	750	750	750	750	750	1350	1350		
1000	A15	B15	800	800	800	800	800	800	1400	1400		
1000	A16	B16	850	850	850	850	850	850	1450	1450		
1000	A17	B17	900	900	900	900	900	900	1500	1500		
1000	A18	B18	950	950	950	950	950	950	1550	1550		
1000	A19	B19	1000	1000	1000	1000	1000	1000	1600	1600		
1000	A20	B20	1050	1050	1050	1050	1050	1050	1650	1650		
1000	A21	B21	1100	1100	1100	1100	1100	1100	1700	1700		

Select an option for TABLEAU #6

TABLEAU #7

Option A		Option B										
1000	A1	B1	100	100	100	100	100	100	100	100	100	1600
1000	A2	B2	150	150	150	150	150	150	150	150	150	1650
1000	A3	B3	200	200	200	200	200	200	200	200	200	1700
1000	A4	B4	250	250	250	250	250	250	250	250	250	1750
1000	A5	B5	300	300	300	300	300	300	300	300	300	1800
1000	A6	B6	350	350	350	350	350	350	350	350	350	1850
1000	A7	B7	400	400	400	400	400	400	400	400	400	1900
1000	A8	B8	450	450	450	450	450	450	450	450	450	1950
1000	A9	B9	500	500	500	500	500	500	500	500	500	2000
1000	A10	B10	550	550	550	550	550	550	550	550	550	2050
1000	A11	B11	600	600	600	600	600	600	600	600	600	2100
1000	A12	B12	650	650	650	650	650	650	650	650	650	2150
1000	A13	B13	700	700	700	700	700	700	700	700	700	2200
1000	A14	B14	750	750	750	750	750	750	750	750	750	2250
1000	A15	B15	800	800	800	800	800	800	800	800	800	2300
1000	A16	B16	850	850	850	850	850	850	850	850	850	2350
1000	A17	B17	900	900	900	900	900	900	900	900	900	2400
1000	A18	B18	950	950	950	950	950	950	950	950	950	2450
1000	A19	B19	1000	1000	1000	1000	1000	1000	1000	1000	1000	2500
1000	A20	B20	1050	1050	1050	1050	1050	1050	1050	1050	1050	2550
1000	A21	B21	1100	1100	1100	1100	1100	1100	1100	1100	1100	2600

Select an option for TABLEAU #7

TABLEAU #8

Option A		Option B										
1000	A1	B1	210	210	583	583	583	583	583	583		
1000	A2	B2	260	260	633	633	633	633	633	633		
1000	A3	B3	310	310	683	683	683	683	683	683		
1000	A4	B4	360	360	733	733	733	733	733	733		
1000	A5	B5	410	410	783	783	783	783	783	783		
1000	A6	B6	460	460	833	833	833	833	833	833		
1000	A7	B7	510	510	883	883	883	883	883	883		
1000	A8	B8	560	560	933	933	933	933	933	933		
1000	A9	B9	610	610	983	983	983	983	983	983		
1000	A10	B10	660	660	1033	1033	1033	1033	1033	1033		
1000	A11	B11	710	710	1083	1083	1083	1083	1083	1083		
1000	A12	B12	760	760	1133	1133	1133	1133	1133	1133		
1000	A13	B13	810	810	1183	1183	1183	1183	1183	1183		
1000	A14	B14	860	860	1233	1233	1233	1233	1233	1233		
1000	A15	B15	910	910	1283	1283	1283	1283	1283	1283		
1000	A16	B16	960	960	1333	1333	1333	1333	1333	1333		
1000	A17	B17	1010	1010	1383	1383	1383	1383	1383	1383		
1000	A18	B18	1060	1060	1433	1433	1433	1433	1433	1433		
1000	A19	B19	1110	1110	1483	1483	1483	1483	1483	1483		
1000	A20	B20	1160	1160	1533	1533	1533	1533	1533	1533		
1000	A21	B21	1210	1210	1583	1583	1583	1583	1583	1583		

Select an option for TABLEAU #8

TABLEAU #9

Option A		Option B										
1000	A1	B1	280	280	560	560	560	560	560	560		
1000	A2	B2	330	330	610	610	610	610	610	610		
1000	A3	B3	380	380	660	660	660	660	660	660		
1000	A4	B4	430	430	710	710	710	710	710	710		
1000	A5	B5	480	480	760	760	760	760	760	760		
1000	A6	B6	530	530	810	810	810	810	810	810		
1000	A7	B7	580	580	860	860	860	860	860	860		
1000	A8	B8	630	630	910	910	910	910	910	910		
1000	A9	B9	680	680	960	960	960	960	960	960		
1000	A10	B10	730	730	1010	1010	1010	1010	1010	1010		
1000	A11	B11	780	780	1060	1060	1060	1060	1060	1060		
1000	A12	B12	830	830	1110	1110	1110	1110	1110	1110		
1000	A13	B13	880	880	1160	1160	1160	1160	1160	1160		
1000	A14	B14	930	930	1210	1210	1210	1210	1210	1210		
1000	A15	B15	980	980	1260	1260	1260	1260	1260	1260		
1000	A16	B16	1030	1030	1310	1310	1310	1310	1310	1310		
1000	A17	B17	1080	1080	1360	1360	1360	1360	1360	1360		
1000	A18	B18	1130	1130	1410	1410	1410	1410	1410	1410		
1000	A19	B19	1180	1180	1460	1460	1460	1460	1460	1460		
1000	A20	B20	1230	1230	1510	1510	1510	1510	1510	1510		
1000	A21	B21	1280	1280	1560	1560	1560	1560	1560	1560		

Select an option for TABLEAU #9

TABLEAU #10

Option A		Option B										
1000	A1	B1	210	210	210	210	210	210	210	210	210	3010
1000	A2	B2	260	260	260	260	260	260	260	260	260	3060
1000	A3	B3	310	310	310	310	310	310	310	310	310	3110
1000	A4	B4	360	360	360	360	360	360	360	360	360	3160
1000	A5	B5	410	410	410	410	410	410	410	410	410	3210
1000	A6	B6	460	460	460	460	460	460	460	460	460	3260
1000	A7	B7	510	510	510	510	510	510	510	510	510	3310
1000	A8	B8	560	560	560	560	560	560	560	560	560	3360
1000	A9	B9	610	610	610	610	610	610	610	610	610	3410
1000	A10	B10	660	660	660	660	660	660	660	660	660	3460
1000	A11	B11	710	710	710	710	710	710	710	710	710	3510
1000	A12	B12	760	760	760	760	760	760	760	760	760	3560
1000	A13	B13	810	810	810	810	810	810	810	810	810	3610
1000	A14	B14	860	860	860	860	860	860	860	860	860	3660
1000	A15	B15	910	910	910	910	910	910	910	910	910	3710
1000	A16	B16	960	960	960	960	960	960	960	960	960	3760
1000	A17	B17	1010	1010	1010	1010	1010	1010	1010	1010	1010	3810
1000	A18	B18	1060	1060	1060	1060	1060	1060	1060	1060	1060	3860
1000	A19	B19	1110	1110	1110	1110	1110	1110	1110	1110	1110	3910
1000	A20	B20	1160	1160	1160	1160	1160	1160	1160	1160	1160	3960
1000	A21	B21	1210	1210	1210	1210	1210	1210	1210	1210	1210	4010

Select an option for TABLEAU #10

TABLEAU #11

Option A		Option B										
1000	A1	B1	280	280	280	280	280	280	910	910	910	
1000	A2	B2	330	330	330	330	330	330	960	960	960	
1000	A3	B3	380	380	380	380	380	380	1010	1010	1010	
1000	A4	B4	430	430	430	430	430	430	1060	1060	1060	
1000	A5	B5	480	480	480	480	480	480	1110	1110	1110	
1000	A6	B6	530	530	530	530	530	530	1160	1160	1160	
1000	A7	B7	580	580	580	580	580	580	1210	1210	1210	
1000	A8	B8	630	630	630	630	630	630	1260	1260	1260	
1000	A9	B9	680	680	680	680	680	680	1310	1310	1310	
1000	A10	B10	730	730	730	730	730	730	1360	1360	1360	
1000	A11	B11	780	780	780	780	780	780	1410	1410	1410	
1000	A12	B12	830	830	830	830	830	830	1460	1460	1460	
1000	A13	B13	880	880	880	880	880	880	1510	1510	1510	
1000	A14	B14	930	930	930	930	930	930	1560	1560	1560	
1000	A15	B15	980	980	980	980	980	980	1610	1610	1610	
1000	A16	B16	1030	1030	1030	1030	1030	1030	1660	1660	1660	
1000	A17	B17	1080	1080	1080	1080	1080	1080	1710	1710	1710	
1000	A18	B18	1130	1130	1130	1130	1130	1130	1760	1760	1760	
1000	A19	B19	1180	1180	1180	1180	1180	1180	1810	1810	1810	
1000	A20	B20	1230	1230	1230	1230	1230	1230	1860	1860	1860	
1000	A21	B21	1280	1280	1280	1280	1280	1280	1910	1910	1910	

Select an option for TABLEAU #11

TABLEAU #12

Option A		Option B										
1000	A1	B1	-30	-30	130	130	130	130	130	130		
1000	A2	B2	20	20	180	180	180	180	180	180		
1000	A3	B3	70	70	230	230	230	230	230	230		
1000	A4	B4	120	120	280	280	280	280	280	280		
1000	A5	B5	170	170	330	330	330	330	330	330		
1000	A6	B6	220	220	380	380	380	380	380	380		
1000	A7	B7	270	270	430	430	430	430	430	430		
1000	A8	B8	320	320	480	480	480	480	480	480		
1000	A9	B9	370	370	530	530	530	530	530	530		
1000	A10	B10	420	420	580	580	580	580	580	580		
1000	A11	B11	470	470	630	630	630	630	630	630		
1000	A12	B12	520	520	680	680	680	680	680	680		
1000	A13	B13	570	570	730	730	730	730	730	730		
1000	A14	B14	620	620	780	780	780	780	780	780		
1000	A15	B15	670	670	830	830	830	830	830	830		
1000	A16	B16	720	720	880	880	880	880	880	880		
1000	A17	B17	770	770	930	930	930	930	930	930		
1000	A18	B18	820	820	980	980	980	980	980	980		
1000	A19	B19	870	870	1030	1030	1030	1030	1030	1030		
1000	A20	B20	920	920	1080	1080	1080	1080	1080	1080		
1000	A21	B21	970	970	1130	1130	1130	1130	1130	1130		

Select an option for TABLEAU #12

TABLEAU #13

Option A		Option B										
1000	A1	B1	280	280	280	280	280	280	1120	1120		
1000	A2	B2	330	330	330	330	330	330	1170	1170		
1000	A3	B3	380	380	380	380	380	380	1220	1220		
1000	A4	B4	430	430	430	430	430	430	1270	1270		
1000	A5	B5	480	480	480	480	480	480	1320	1320		
1000	A6	B6	530	530	530	530	530	530	1370	1370		
1000	A7	B7	580	580	580	580	580	580	1420	1420		
1000	A8	B8	630	630	630	630	630	630	1470	1470		
1000	A9	B9	680	680	680	680	680	680	1520	1520		
1000	A10	B10	730	730	730	730	730	730	1570	1570		
1000	A11	B11	780	780	780	780	780	780	1620	1620		
1000	A12	B12	830	830	830	830	830	830	1670	1670		
1000	A13	B13	880	880	880	880	880	880	1720	1720		
1000	A14	B14	930	930	930	930	930	930	1770	1770		
1000	A15	B15	980	980	980	980	980	980	1820	1820		
1000	A16	B16	1030	1030	1030	1030	1030	1030	1870	1870		
1000	A17	B17	1080	1080	1080	1080	1080	1080	1920	1920		
1000	A18	B18	1130	1130	1130	1130	1130	1130	1970	1970		
1000	A19	B19	1180	1180	1180	1180	1180	1180	2020	2020		
1000	A20	B20	1230	1230	1230	1230	1230	1230	2070	2070		
1000	A21	B21	1280	1280	1280	1280	1280	1280	2120	2120		

Select an option for TABLEAU #13

TABLEAU #14

Option A		Option B										
1000	A1	B1	-30	-30	-30	-30	-30	-30	450	450		
1000	A2	B2	20	20	20	20	20	20	500	500		
1000	A3	B3	70	70	70	70	70	70	550	550		
1000	A4	B4	120	120	120	120	120	120	600	600		
1000	A5	B5	170	170	170	170	170	170	650	650		
1000	A6	B6	220	220	220	220	220	220	700	700		
1000	A7	B7	270	270	270	270	270	270	750	750		
1000	A8	B8	320	320	320	320	320	320	800	800		
1000	A9	B9	370	370	370	370	370	370	850	850		
1000	A10	B10	420	420	420	420	420	420	900	900		
1000	A11	B11	470	470	470	470	470	470	950	950		
1000	A12	B12	520	520	520	520	520	520	1000	1000		
1000	A13	B13	570	570	570	570	570	570	1050	1050		
1000	A14	B14	620	620	620	620	620	620	1100	1100		
1000	A15	B15	670	670	670	670	670	670	1150	1150		
1000	A16	B16	720	720	720	720	720	720	1200	1200		
1000	A17	B17	770	770	770	770	770	770	1250	1250		
1000	A18	B18	820	820	820	820	820	820	1300	1300		
1000	A19	B19	870	870	870	870	870	870	1350	1350		
1000	A20	B20	920	920	920	920	920	920	1400	1400		
1000	A21	B21	970	970	970	970	970	970	1450	1450		

Select an option for TABLEAU #14

TABLEAU #15

Option A		Option B										
1000	A1	B1	280	280	280	280	280	700	700	700	700	700
1000	A2	B2	330	330	330	330	330	750	750	750	750	750
1000	A3	B3	380	380	380	380	380	800	800	800	800	800
1000	A4	B4	430	430	430	430	430	850	850	850	850	850
1000	A5	B5	480	480	480	480	480	900	900	900	900	900
1000	A6	B6	530	530	530	530	530	950	950	950	950	950
1000	A7	B7	580	580	580	580	580	1000	1000	1000	1000	1000
1000	A8	B8	630	630	630	630	630	1050	1050	1050	1050	1050
1000	A9	B9	680	680	680	680	680	1100	1100	1100	1100	1100
1000	A10	B10	730	730	730	730	730	1150	1150	1150	1150	1150
1000	A11	B11	780	780	780	780	780	1200	1200	1200	1200	1200
1000	A12	B12	830	830	830	830	830	1250	1250	1250	1250	1250
1000	A13	B13	880	880	880	880	880	1300	1300	1300	1300	1300
1000	A14	B14	930	930	930	930	930	1350	1350	1350	1350	1350
1000	A15	B15	980	980	980	980	980	1400	1400	1400	1400	1400
1000	A16	B16	1030	1030	1030	1030	1030	1450	1450	1450	1450	1450
1000	A17	B17	1080	1080	1080	1080	1080	1500	1500	1500	1500	1500
1000	A18	B18	1130	1130	1130	1130	1130	1550	1550	1550	1550	1550
1000	A19	B19	1180	1180	1180	1180	1180	1600	1600	1600	1600	1600
1000	A20	B20	1230	1230	1230	1230	1230	1650	1650	1650	1650	1650
1000	A21	B21	1280	1280	1280	1280	1280	1700	1700	1700	1700	1700

Select an option for TABLEAU #15

TABLEAU #16

Option A		Option B										
1000	A1	B1	280	280	280	280	280	280	280	280	280	2380
1000	A2	B2	330	330	330	330	330	330	330	330	330	2430
1000	A3	B3	380	380	380	380	380	380	380	380	380	2480
1000	A4	B4	430	430	430	430	430	430	430	430	430	2530
1000	A5	B5	480	480	480	480	480	480	480	480	480	2580
1000	A6	B6	530	530	530	530	530	530	530	530	530	2630
1000	A7	B7	580	580	580	580	580	580	580	580	580	2680
1000	A8	B8	630	630	630	630	630	630	630	630	630	2730
1000	A9	B9	680	680	680	680	680	680	680	680	680	2780
1000	A10	B10	730	730	730	730	730	730	730	730	730	2830
1000	A11	B11	780	780	780	780	780	780	780	780	780	2880
1000	A12	B12	830	830	830	830	830	830	830	830	830	2930
1000	A13	B13	880	880	880	880	880	880	880	880	880	2980
1000	A14	B14	930	930	930	930	930	930	930	930	930	3030
1000	A15	B15	980	980	980	980	980	980	980	980	980	3080
1000	A16	B16	1030	1030	1030	1030	1030	1030	1030	1030	1030	3130
1000	A17	B17	1080	1080	1080	1080	1080	1080	1080	1080	1080	3180
1000	A18	B18	1130	1130	1130	1130	1130	1130	1130	1130	1130	3230
1000	A19	B19	1180	1180	1180	1180	1180	1180	1180	1180	1180	3280
1000	A20	B20	1230	1230	1230	1230	1230	1230	1230	1230	1230	3330
1000	A21	B21	1280	1280	1280	1280	1280	1280	1280	1280	1280	3380

Select an option for TABLEAU #16

TABLEAU #17

Option A		Option B										
1000	A1	B1	210	210	210	210	210	210	1330	1330		
1000	A2	B2	260	260	260	260	260	260	1380	1380		
1000	A3	B3	310	310	310	310	310	310	1430	1430		
1000	A4	B4	360	360	360	360	360	360	1480	1480		
1000	A5	B5	410	410	410	410	410	410	1530	1530		
1000	A6	B6	460	460	460	460	460	460	1580	1580		
1000	A7	B7	510	510	510	510	510	510	1630	1630		
1000	A8	B8	560	560	560	560	560	560	1680	1680		
1000	A9	B9	610	610	610	610	610	610	1730	1730		
1000	A10	B10	660	660	660	660	660	660	1780	1780		
1000	A11	B11	710	710	710	710	710	710	1830	1830		
1000	A12	B12	760	760	760	760	760	760	1880	1880		
1000	A13	B13	810	810	810	810	810	810	1930	1930		
1000	A14	B14	860	860	860	860	860	860	1980	1980		
1000	A15	B15	910	910	910	910	910	910	2030	2030		
1000	A16	B16	960	960	960	960	960	960	2080	2080		
1000	A17	B17	1010	1010	1010	1010	1010	1010	2130	2130		
1000	A18	B18	1060	1060	1060	1060	1060	1060	2180	2180		
1000	A19	B19	1110	1110	1110	1110	1110	1110	2230	2230		
1000	A20	B20	1160	1160	1160	1160	1160	1160	2280	2280		
1000	A21	B21	1210	1210	1210	1210	1210	1210	2330	2330		

Select an option for TABLEAU #17

TABLEAU #18

Option A		Option B										
1000	A1	B1	100	100	100	100	100	100	550	550	550	
1000	A2	B2	150	150	150	150	150	150	600	600	600	
1000	A3	B3	200	200	200	200	200	200	650	650	650	
1000	A4	B4	250	250	250	250	250	250	700	700	700	
1000	A5	B5	300	300	300	300	300	300	750	750	750	
1000	A6	B6	350	350	350	350	350	350	800	800	800	
1000	A7	B7	400	400	400	400	400	400	850	850	850	
1000	A8	B8	450	450	450	450	450	450	900	900	900	
1000	A9	B9	500	500	500	500	500	500	950	950	950	
1000	A10	B10	550	550	550	550	550	550	1000	1000	1000	
1000	A11	B11	600	600	600	600	600	600	1050	1050	1050	
1000	A12	B12	650	650	650	650	650	650	1100	1100	1100	
1000	A13	B13	700	700	700	700	700	700	1150	1150	1150	
1000	A14	B14	750	750	750	750	750	750	1200	1200	1200	
1000	A15	B15	800	800	800	800	800	800	1250	1250	1250	
1000	A16	B16	850	850	850	850	850	850	1300	1300	1300	
1000	A17	B17	900	900	900	900	900	900	1350	1350	1350	
1000	A18	B18	950	950	950	950	950	950	1400	1400	1400	
1000	A19	B19	1000	1000	1000	1000	1000	1000	1450	1450	1450	
1000	A20	B20	1050	1050	1050	1050	1050	1050	1500	1500	1500	
1000	A21	B21	1100	1100	1100	1100	1100	1100	1550	1550	1550	

Select an option for TABLEAU #18

TABLEAU #19

Option A		Option B										
1000	A1	B1	100	100	100	100	100	400	400	400	400	400
1000	A2	B2	150	150	150	150	150	450	450	450	450	450
1000	A3	B3	200	200	200	200	200	500	500	500	500	500
1000	A4	B4	250	250	250	250	250	550	550	550	550	550
1000	A5	B5	300	300	300	300	300	600	600	600	600	600
1000	A6	B6	350	350	350	350	350	650	650	650	650	650
1000	A7	B7	400	400	400	400	400	700	700	700	700	700
1000	A8	B8	450	450	450	450	450	750	750	750	750	750
1000	A9	B9	500	500	500	500	500	800	800	800	800	800
1000	A10	B10	550	550	550	550	550	850	850	850	850	850
1000	A11	B11	600	600	600	600	600	900	900	900	900	900
1000	A12	B12	650	650	650	650	650	950	950	950	950	950
1000	A13	B13	700	700	700	700	700	1000	1000	1000	1000	1000
1000	A14	B14	750	750	750	750	750	1050	1050	1050	1050	1050
1000	A15	B15	800	800	800	800	800	1100	1100	1100	1100	1100
1000	A16	B16	850	850	850	850	850	1150	1150	1150	1150	1150
1000	A17	B17	900	900	900	900	900	1200	1200	1200	1200	1200
1000	A18	B18	950	950	950	950	950	1250	1250	1250	1250	1250
1000	A19	B19	1000	1000	1000	1000	1000	1300	1300	1300	1300	1300
1000	A20	B20	1050	1050	1050	1050	1050	1350	1350	1350	1350	1350
1000	A21	B21	1100	1100	1100	1100	1100	1400	1400	1400	1400	1400

Select an option for TABLEAU #19

TABLEAU #20

Option A		Option B										
1000	A1	B1	50	50	50	50	50	50	850	850		
1000	A2	B2	100	100	100	100	100	100	900	900		
1000	A3	B3	150	150	150	150	150	150	950	950		
1000	A4	B4	200	200	200	200	200	200	1000	1000		
1000	A5	B5	250	250	250	250	250	250	1050	1050		
1000	A6	B6	300	300	300	300	300	300	1100	1100		
1000	A7	B7	350	350	350	350	350	350	1150	1150		
1000	A8	B8	400	400	400	400	400	400	1200	1200		
1000	A9	B9	450	450	450	450	450	450	1250	1250		
1000	A10	B10	500	500	500	500	500	500	1300	1300		
1000	A11	B11	550	550	550	550	550	550	1350	1350		
1000	A12	B12	600	600	600	600	600	600	1400	1400		
1000	A13	B13	650	650	650	650	650	650	1450	1450		
1000	A14	B14	700	700	700	700	700	700	1500	1500		
1000	A15	B15	750	750	750	750	750	750	1550	1550		
1000	A16	B16	800	800	800	800	800	800	1600	1600		
1000	A17	B17	850	850	850	850	850	850	1650	1650		
1000	A18	B18	900	900	900	900	900	900	1700	1700		
1000	A19	B19	950	950	950	950	950	950	1750	1750		
1000	A20	B20	1000	1000	1000	1000	1000	1000	1800	1800		
1000	A21	B21	1050	1050	1050	1050	1050	1050	1850	1850		

Select an option for TABLEAU #20

TABLEAU #21

Option A		Option B										
1000	A1	B1	0	0	0	0	0	0	270	270	270	
1000	A2	B2	50	50	50	50	50	50	320	320	320	
1000	A3	B3	100	100	100	100	100	100	370	370	370	
1000	A4	B4	150	150	150	150	150	150	420	420	420	
1000	A5	B5	200	200	200	200	200	200	470	470	470	
1000	A6	B6	250	250	250	250	250	250	520	520	520	
1000	A7	B7	300	300	300	300	300	300	570	570	570	
1000	A8	B8	350	350	350	350	350	350	620	620	620	
1000	A9	B9	400	400	400	400	400	400	670	670	670	
1000	A10	B10	450	450	450	450	450	450	720	720	720	
1000	A11	B11	500	500	500	500	500	500	770	770	770	
1000	A12	B12	550	550	550	550	550	550	820	820	820	
1000	A13	B13	600	600	600	600	600	600	870	870	870	
1000	A14	B14	650	650	650	650	650	650	920	920	920	
1000	A15	B15	700	700	700	700	700	700	970	970	970	
1000	A16	B16	750	750	750	750	750	750	1020	1020	1020	
1000	A17	B17	800	800	800	800	800	800	1070	1070	1070	
1000	A18	B18	850	850	850	850	850	850	1120	1120	1120	
1000	A19	B19	900	900	900	900	900	900	1170	1170	1170	
1000	A20	B20	950	950	950	950	950	950	1220	1220	1220	
1000	A21	B21	1000	1000	1000	1000	1000	1000	1270	1270	1270	

Select an option for TABLEAU #21

TABLEAU #22

Option A		Option B										
1000	A1	B1	0	0	0	0	0	0	360	360		
1000	A2	B2	50	50	50	50	50	50	410	410		
1000	A3	B3	100	100	100	100	100	100	460	460		
1000	A4	B4	150	150	150	150	150	150	510	510		
1000	A5	B5	200	200	200	200	200	200	560	560		
1000	A6	B6	250	250	250	250	250	250	610	610		
1000	A7	B7	300	300	300	300	300	300	660	660		
1000	A8	B8	350	350	350	350	350	350	710	710		
1000	A9	B9	400	400	400	400	400	400	760	760		
1000	A10	B10	450	450	450	450	450	450	810	810		
1000	A11	B11	500	500	500	500	500	500	860	860		
1000	A12	B12	550	550	550	550	550	550	910	910		
1000	A13	B13	600	600	600	600	600	600	960	960		
1000	A14	B14	650	650	650	650	650	650	1010	1010		
1000	A15	B15	700	700	700	700	700	700	1060	1060		
1000	A16	B16	750	750	750	750	750	750	1110	1110		
1000	A17	B17	800	800	800	800	800	800	1160	1160		
1000	A18	B18	850	850	850	850	850	850	1210	1210		
1000	A19	B19	900	900	900	900	900	900	1260	1260		
1000	A20	B20	950	950	950	950	950	950	1310	1310		
1000	A21	B21	1000	1000	1000	1000	1000	1000	1360	1360		

Select an option for TABLEAU #22

TABLEAU #23

Option A		Option B										
1000	A1	B1	100	100	300	300	300	300	300	300		
1000	A2	B2	150	150	350	350	350	350	350	350		
1000	A3	B3	200	200	400	400	400	400	400	400		
1000	A4	B4	250	250	450	450	450	450	450	450		
1000	A5	B5	300	300	500	500	500	500	500	500		
1000	A6	B6	350	350	550	550	550	550	550	550		
1000	A7	B7	400	400	600	600	600	600	600	600		
1000	A8	B8	450	450	650	650	650	650	650	650		
1000	A9	B9	500	500	700	700	700	700	700	700		
1000	A10	B10	550	550	750	750	750	750	750	750		
1000	A11	B11	600	600	800	800	800	800	800	800		
1000	A12	B12	650	650	850	850	850	850	850	850		
1000	A13	B13	700	700	900	900	900	900	900	900		
1000	A14	B14	750	750	950	950	950	950	950	950		
1000	A15	B15	800	800	1000	1000	1000	1000	1000	1000		
1000	A16	B16	850	850	1050	1050	1050	1050	1050	1050		
1000	A17	B17	900	900	1100	1100	1100	1100	1100	1100		
1000	A18	B18	950	950	1150	1150	1150	1150	1150	1150		
1000	A19	B19	1000	1000	1200	1200	1200	1200	1200	1200		
1000	A20	B20	1050	1050	1250	1250	1250	1250	1250	1250		
1000	A21	B21	1100	1100	1300	1300	1300	1300	1300	1300		

Select an option for TABLEAU #23

TABLEAU #24

Option A		Option B										
1000	A1	B1	0	0	120	120	120	120	120	120		
1000	A2	B2	50	50	170	170	170	170	170	170		
1000	A3	B3	100	100	220	220	220	220	220	220		
1000	A4	B4	150	150	270	270	270	270	270	270		
1000	A5	B5	200	200	320	320	320	320	320	320		
1000	A6	B6	250	250	370	370	370	370	370	370		
1000	A7	B7	300	300	420	420	420	420	420	420		
1000	A8	B8	350	350	470	470	470	470	470	470		
1000	A9	B9	400	400	520	520	520	520	520	520		
1000	A10	B10	450	450	570	570	570	570	570	570		
1000	A11	B11	500	500	620	620	620	620	620	620		
1000	A12	B12	550	550	670	670	670	670	670	670		
1000	A13	B13	600	600	720	720	720	720	720	720		
1000	A14	B14	650	650	770	770	770	770	770	770		
1000	A15	B15	700	700	820	820	820	820	820	820		
1000	A16	B16	750	750	870	870	870	870	870	870		
1000	A17	B17	800	800	920	920	920	920	920	920		
1000	A18	B18	850	850	970	970	970	970	970	970		
1000	A19	B19	900	900	1020	1020	1020	1020	1020	1020		
1000	A20	B20	950	950	1070	1070	1070	1070	1070	1070		
1000	A21	B21	1000	1000	1120	1120	1120	1120	1120	1120		

Select an option for TABLEAU #24

TABLEAU #25

Option A		Option B										
1000	A1	B1	-30	-30	-30	-30	-30	210	210	210	210	210
1000	A2	B2	20	20	20	20	20	260	260	260	260	260
1000	A3	B3	70	70	70	70	70	310	310	310	310	310
1000	A4	B4	120	120	120	120	120	360	360	360	360	360
1000	A5	B5	170	170	170	170	170	410	410	410	410	410
1000	A6	B6	220	220	220	220	220	460	460	460	460	460
1000	A7	B7	270	270	270	270	270	510	510	510	510	510
1000	A8	B8	320	320	320	320	320	560	560	560	560	560
1000	A9	B9	370	370	370	370	370	610	610	610	610	610
1000	A10	B10	420	420	420	420	420	660	660	660	660	660
1000	A11	B11	470	470	470	470	470	710	710	710	710	710
1000	A12	B12	520	520	520	520	520	760	760	760	760	760
1000	A13	B13	570	570	570	570	570	810	810	810	810	810
1000	A14	B14	620	620	620	620	620	860	860	860	860	860
1000	A15	B15	670	670	670	670	670	910	910	910	910	910
1000	A16	B16	720	720	720	720	720	960	960	960	960	960
1000	A17	B17	770	770	770	770	770	1010	1010	1010	1010	1010
1000	A18	B18	820	820	820	820	820	1060	1060	1060	1060	1060
1000	A19	B19	870	870	870	870	870	1110	1110	1110	1110	1110
1000	A20	B20	920	920	920	920	920	1160	1160	1160	1160	1160
1000	A21	B21	970	970	970	970	970	1210	1210	1210	1210	1210

Select an option for TABLEAU #25

TABLEAU #26

Option A		Option B										
1000	A1	B1	50	50	50	50	50	50	650	650	650	
1000	A2	B2	100	100	100	100	100	100	700	700	700	
1000	A3	B3	150	150	150	150	150	150	750	750	750	
1000	A4	B4	200	200	200	200	200	200	800	800	800	
1000	A5	B5	250	250	250	250	250	250	850	850	850	
1000	A6	B6	300	300	300	300	300	300	900	900	900	
1000	A7	B7	350	350	350	350	350	350	950	950	950	
1000	A8	B8	400	400	400	400	400	400	1000	1000	1000	
1000	A9	B9	450	450	450	450	450	450	1050	1050	1050	
1000	A10	B10	500	500	500	500	500	500	1100	1100	1100	
1000	A11	B11	550	550	550	550	550	550	1150	1150	1150	
1000	A12	B12	600	600	600	600	600	600	1200	1200	1200	
1000	A13	B13	650	650	650	650	650	650	1250	1250	1250	
1000	A14	B14	700	700	700	700	700	700	1300	1300	1300	
1000	A15	B15	750	750	750	750	750	750	1350	1350	1350	
1000	A16	B16	800	800	800	800	800	800	1400	1400	1400	
1000	A17	B17	850	850	850	850	850	850	1450	1450	1450	
1000	A18	B18	900	900	900	900	900	900	1500	1500	1500	
1000	A19	B19	950	950	950	950	950	950	1550	1550	1550	
1000	A20	B20	1000	1000	1000	1000	1000	1000	1600	1600	1600	
1000	A21	B21	1050	1050	1050	1050	1050	1050	1650	1650	1650	

Select an option for TABLEAU #26

TABLEAU #27

Option A		Option B									
1000	A1	B1	-30	-30	-30	-30	-30	-30	330	330	330	
1000	A2	B2	20	20	20	20	20	20	380	380	380	
1000	A3	B3	70	70	70	70	70	70	430	430	430	
1000	A4	B4	120	120	120	120	120	120	480	480	480	
1000	A5	B5	170	170	170	170	170	170	530	530	530	
1000	A6	B6	220	220	220	220	220	220	580	580	580	
1000	A7	B7	270	270	270	270	270	270	630	630	630	
1000	A8	B8	320	320	320	320	320	320	680	680	680	
1000	A9	B9	370	370	370	370	370	370	730	730	730	
1000	A10	B10	420	420	420	420	420	420	780	780	780	
1000	A11	B11	470	470	470	470	470	470	830	830	830	
1000	A12	B12	520	520	520	520	520	520	880	880	880	
1000	A13	B13	570	570	570	570	570	570	930	930	930	
1000	A14	B14	620	620	620	620	620	620	980	980	980	
1000	A15	B15	670	670	670	670	670	670	1030	1030	1030	
1000	A16	B16	720	720	720	720	720	720	1080	1080	1080	
1000	A17	B17	770	770	770	770	770	770	1130	1130	1130	
1000	A18	B18	820	820	820	820	820	820	1180	1180	1180	
1000	A19	B19	870	870	870	870	870	870	1230	1230	1230	
1000	A20	B20	920	920	920	920	920	920	1280	1280	1280	
1000	A21	B21	970	970	970	970	970	970	1330	1330	1330	

Select an option for TABLEAU #27

TABLEAU #28

Option A		Option B										
1000	A1	B1	-30	-30	-30	-30	-30	-30	-30	-30	-30	1170
1000	A2	B2	20	20	20	20	20	20	20	20	20	1220
1000	A3	B3	70	70	70	70	70	70	70	70	70	1270
1000	A4	B4	120	120	120	120	120	120	120	120	120	1320
1000	A5	B5	170	170	170	170	170	170	170	170	170	1370
1000	A6	B6	220	220	220	220	220	220	220	220	220	1420
1000	A7	B7	270	270	270	270	270	270	270	270	270	1470
1000	A8	B8	320	320	320	320	320	320	320	320	320	1520
1000	A9	B9	370	370	370	370	370	370	370	370	370	1570
1000	A10	B10	420	420	420	420	420	420	420	420	420	1620
1000	A11	B11	470	470	470	470	470	470	470	470	470	1670
1000	A12	B12	520	520	520	520	520	520	520	520	520	1720
1000	A13	B13	570	570	570	570	570	570	570	570	570	1770
1000	A14	B14	620	620	620	620	620	620	620	620	620	1820
1000	A15	B15	670	670	670	670	670	670	670	670	670	1870
1000	A16	B16	720	720	720	720	720	720	720	720	720	1920
1000	A17	B17	770	770	770	770	770	770	770	770	770	1970
1000	A18	B18	820	820	820	820	820	820	820	820	820	2020
1000	A19	B19	870	870	870	870	870	870	870	870	870	2070
1000	A20	B20	920	920	920	920	920	920	920	920	920	2120
1000	A21	B21	970	970	970	970	970	970	970	970	970	2170

Select an option for TABLEAU #28

TABLEAU #29

Option A		Option B										
1000	A1	B1	210	210	210	210	210	770	770	770	770	770
1000	A2	B2	260	260	260	260	260	820	820	820	820	820
1000	A3	B3	310	310	310	310	310	870	870	870	870	870
1000	A4	B4	360	360	360	360	360	920	920	920	920	920
1000	A5	B5	410	410	410	410	410	970	970	970	970	970
1000	A6	B6	460	460	460	460	460	1020	1020	1020	1020	1020
1000	A7	B7	510	510	510	510	510	1070	1070	1070	1070	1070
1000	A8	B8	560	560	560	560	560	1120	1120	1120	1120	1120
1000	A9	B9	610	610	610	610	610	1170	1170	1170	1170	1170
1000	A10	B10	660	660	660	660	660	1220	1220	1220	1220	1220
1000	A11	B11	710	710	710	710	710	1270	1270	1270	1270	1270
1000	A12	B12	760	760	760	760	760	1320	1320	1320	1320	1320
1000	A13	B13	810	810	810	810	810	1370	1370	1370	1370	1370
1000	A14	B14	860	860	860	860	860	1420	1420	1420	1420	1420
1000	A15	B15	910	910	910	910	910	1470	1470	1470	1470	1470
1000	A16	B16	960	960	960	960	960	1520	1520	1520	1520	1520
1000	A17	B17	1010	1010	1010	1010	1010	1570	1570	1570	1570	1570
1000	A18	B18	1060	1060	1060	1060	1060	1620	1620	1620	1620	1620
1000	A19	B19	1110	1110	1110	1110	1110	1670	1670	1670	1670	1670
1000	A20	B20	1160	1160	1160	1160	1160	1720	1720	1720	1720	1720
1000	A21	B21	1210	1210	1210	1210	1210	1770	1770	1770	1770	1770

Select an option for TABLEAU #29

TABLEAU #30

Option A		Option B										
1000	A1	B1	50	50	317	317	317	317	317	317		
1000	A2	B2	100	100	367	367	367	367	367	367		
1000	A3	B3	150	150	417	417	417	417	417	417		
1000	A4	B4	200	200	467	467	467	467	467	467		
1000	A5	B5	250	250	517	517	517	517	517	517		
1000	A6	B6	300	300	567	567	567	567	567	567		
1000	A7	B7	350	350	617	617	617	617	617	617		
1000	A8	B8	400	400	667	667	667	667	667	667		
1000	A9	B9	450	450	717	717	717	717	717	717		
1000	A10	B10	500	500	767	767	767	767	767	767		
1000	A11	B11	550	550	817	817	817	817	817	817		
1000	A12	B12	600	600	867	867	867	867	867	867		
1000	A13	B13	650	650	917	917	917	917	917	917		
1000	A14	B14	700	700	967	967	967	967	967	967		
1000	A15	B15	750	750	1017	1017	1017	1017	1017	1017		
1000	A16	B16	800	800	1067	1067	1067	1067	1067	1067		
1000	A17	B17	850	850	1117	1117	1117	1117	1117	1117		
1000	A18	B18	900	900	1167	1167	1167	1167	1167	1167		
1000	A19	B19	950	950	1217	1217	1217	1217	1217	1217		
1000	A20	B20	1000	1000	1267	1267	1267	1267	1267	1267		
1000	A21	B21	1050	1050	1317	1317	1317	1317	1317	1317		

Select an option for TABLEAU #30

Thank you for your participation. Your response has been recorded.

Payments will be made early next week to allow all participants to complete the session and calculate your winnings.

References

Abdellaoui, M., Bleichrodt, H., and l'Haridon, O. (2008). A tractable method to measure utility and loss aversion under prospect theory. *Journal of Risk and Uncertainty*, 36(3):245.

Adams, C. (2005). Agent discretion, adverse selection, and the risk-incentive trade-off.

Anderhub, V., Gächter, S., and Königstein, M. (2002). Efficient contracting and fair play in a simple principal-agent experiment. *Experimental Economics*, 5(1):5–27.

Besanko, D., Dranove, D., Shanley, M., and Schaefer, S. (2017). *Economics of Strategy.* John Wiley & Sons.

Bleichrodt, H. and Pinto, J. L. (2000). A parameter-free elicitation of the probability weighting function in medical decision analysis. *Management Science*, 46(11):1485–1496.

Bolton, P. and Dewatripont, M. (2005). Contract theory–cambridge. *MA, T.*

Borch, K. (1962). Equilibrium in a reinsurance market. *Econometrica: Journal of the Econometric Society*, pages 424–444.

Brenner, S. (2015). The risk preferences of us executives. *Management Science*, 61(6):1344–1361.

Brink, A. G. and Rankin, F. W. (2013). The effects of risk preference and loss aversion on individual behavior under bonus, penalty, and combined contract frames. *Behavioral Research in Accounting*, 25(2):145–170.

Brocas, I. and Carrillo, J. D. (2008). The brain as a hierarchical organization. *American Economic Review*, 98(4):1312–46.

Bruhin, A., Fehr-Duda, H., and Epper, T. (2010). Risk and rationality: Uncovering heterogeneity in probability distortion. *Econometrica*, 78(4):1375–1412.

Carroll, G. (2015). Robustness and linear contracts. *American Economic Review*, 105(2):536–63.

Charness, G., Gneezy, U., and Halladay, B. (2016). Experimental methods: Pay one or pay all. *Journal of Economic Behavior & Organization*, 131:141–150.

Chowdhury, S. M. and Karakostas, A. (2020). An experimental investigation of the 'tenuous trade-off'between risk and incentives in organizations. *Theory and Decision*, 88(1):153–190.

Cokely, E. T., Galesic, M., Schulz, E., Ghazal, S., and Garcia-Retamero, R. (2012). Measuring risk literacy: The berlin numeracy test. *Judgment and Decision making.*

Corgnet, B. and Hernan-Gonzalez, R. (2019). Revisiting the trade-off between risk and incentives: The shocking effect of random shocks? *Management Science*, 65(3):1096–1114.

DeVaro, J. and Kurtulus, F. A. (2010). An empirical analysis of risk, incentives and the delegation of worker authority. *ILR Review*, 63(4):641–661.

Diamond, P. (1998). Managerial incentives: On the near linearity of optimal compensation. *Journal of Political Economy*, 106(5):931–957.

Dohmen, T., Non, A., and Stolp, T. (2021). Reference points and the tradeoff between risk and incentives. *Journal of Economic Behavior & Organization*, 192:813–831.

Dranove, D., Besanko, D., Shanley, M., and Schaefer, S. (2017). *Economics of strategy*. John Wiley & Sons.

Edmans, A. and Gabaix, X. (2011). The effect of risk on the ceo market. *The Review of Financial Studies*, 24(8):2822–2863.

Edmans, A., Gabaix, X., and Jenter, D. (2017). Executive compensation: A survey of theory and evidence. *The handbook of the economics of corporate governance*, 1:383–539.

Edmans, A., Gabaix, X., Sadzik, T., and Sannikov, Y. (2012). Dynamic ceo compensation. *The Journal of Finance*, 67(5):1603–1647.

Eeckhoudt, L. R. and Laeven, R. J. (2015). Risk aversion in the small and in the large under rank-dependent utility. *arXiv preprint arXiv:1512.08037*.

Frederick, S. (2005). Cognitive reflection and decision making. *Journal of Economic perspectives*, 19(4):25–42.

Gächter, S. and Königstein, M. (2009). Design a contract: A simple principal-agent problem as a classroom experiment. *The Journal of Economic Education*, 40(2):173–187.

Garen, J. E. (1994). Executive compensation and principal-agent theory. *Journal of political economy*, 102(6):1175–1199.

Gibbons, R. and Roberts, J. (2013). Economic theories of incentives in organizations. *Handbook of organizational economics*, pages 56–99.

Gonzalez, R. and Wu, G. (1999). On the shape of the probability weighting function. *Cognitive Psychology*, 38(1):129–166.

Gonzalez-Jimenez, V. H. (2019). Contracting probability distortions. Technical report, University of Vienna, Department of Economics.

Grossman, S. J. and Hart, O. D. (1983). Implicit contracts under asymmetric information. *The Quarterly Journal of Economics*, pages 123–156.

He, Z., Li, S., Wei, B., and Yu, J. (2014). Uncertainty, risk, and incentives: theory and evidence. *Management Science*, 60(1):206–226.

Holmström, B. (1979). Moral hazard and observability. *The Bell journal of economics*, pages 74–91.

Holmström, B. (2017). Pay for performance and beyond. *American Economic Review*, 107(7):1753–77.

Holmstrom, B. and Milgrom, P. (1987). Aggregation and linearity in the provision of intertemporal incentives. *Econometrica: Journal of the Econometric Society*, pages 303–328.

Holt, C. A. and Laury, S. K. (2002). Risk aversion and incentive effects. *American Economic Review*, 92(5):1644–1655.

Jensen, M. C. and Meckling, W. H. (1976). Theory of the firm: Managerial behavior, agency costs and ownership structure. *Journal of Financial Economics*, 3(4):305–360.

Jensen, M. C. and Meckling, W. H. (1995). Specific and general knowledge, and organizational structure. In *Knowledge management and organizational design*, pages 17–38. Routledge.

Keser, C. and Willinger, M. (2007). Theories of behavior in principal–agent relationships with hidden action. *European Economic Review*, 51(6):1514–1533.

Kihlstrom, R. E. and Laffont, J.-J. (1979). A general equilibrium entrepreneurial theory of firm formation based on risk aversion. *Journal of political economy*, 87(4):719–748.

Knight, F. H. (1921). *Risk, uncertainty and profit*, volume 31. Houghton Mifflin.

Kpegli, Y. T., Corgnet, B., and Zylbersztejn, A. (2022). All at once! a comprehensive and tractable semi-parametric method to elicit prospect theory components. *Journal of Mathematical Economics*, page 102790.

Kraus, A. and Litzenberger, R. H. (1976). Skewness preference and the valuation of risk assets. *The Journal of Finance*, 31(4):1085–1100.

Laffont, J.-J. and Martimort, D. (2002). The theoy of incentives: The principal agent problem.

Laffont, J.-J. and Martimort, D. (2009). The theory of incentives. In *The Theory of Incentives*. Princeton university press.

Lambert, R. A. (2001). Contracting theory and accounting. *Journal of accounting and economics*, 32(1-3):3–87.

Lazear, E. P. and Oyer, P. (2013). Personnel economics.

Ma, L., Tang, Y., and Gomez, J.-P. (2019). Portfolio manager compensation in the us mutual fund industry. *The Journal of Finance*, 74(2):587–638.

MacCrimmon, K. R. and Wehrung, D. A. (1990). Characteristics of risk taking executives. *Management science*, 36(4):422–435.

Milgrom, P. R. and Roberts, J. D. (1992). Economics, organization and management.

Miller, G. J. (2005). The political evolution of principal-agent models. *ANNUAL REVIEW OF POLITICAL SCIENCE-PALO ALTO-*, 8:203.

Mirrlees, J. (1974). Notes on welfare economics, information and uncertainty. *Essays on economic behavior under uncertainty*, pages 243–261.

Mitton, T. and Vorkink, K. (2007). Equilibrium underdiversification and the preference for skewness. *The Review of Financial Studies*, 20(4):1255–1288.

Newman, A. F. (2007). Risk-bearing and entrepreneurship. *Journal of Economic Theory*, 137(1):11–26.

Pratt, J. W. (1964). Risk aversion in the small and in the large. *Econometrica*, 32(1/2):122–136.

Prendergast, C. (2002). The tenuous trade-off between risk and incentives. *Journal of political Economy*, 110(5):1071–1102.

Quiggin, J. (1982). A theory of anticipated utility. *Journal of Economic Behavior & Organization*, 3(4):323–343.

Raith, M. (2008). Specific knowledge and performance measurement. *The Rand journal of economics*, 39(4):1059–1079.

Rogerson, W. P. (1985). The first-order approach to principal-agent problems. *Econometrica: Journal of the Econometric Society*, pages 1357–1367.

Saha, A. (1993). Expo-power utility: a 'flexible' form for absolute and relative risk aversion. *American Journal of Agricultural Economics*, 75(4):905–913.

Schwartz, L. M., Woloshin, S., Black, W. C., and Welch, H. G. (1997). The role of numeracy in understanding the benefit of screening mammography. *Annals of internal medicine*, 127(11):966–972.

Shavell, S. (1979). On moral hazard and insurance. In *Foundations of insurance economics*, pages 280–301. Springer.

Sloof, R. and Van Praag, C. M. (2010). The effect of noise in a performance measure on work motivation: A real effort laboratory experiment. *Labour Economics*, 17(5):751–765.

Spiliopoulos, L. and Hertwig, R. (2019). Nonlinear decision weights or moment-based preferences? a model competition involving described and experienced skewness. *Cognition*, 183:99–123.

Stiglitz, J. E. (1974). Incentives and risk sharing in sharecropping. *The Review of Economic Studies*, 41(2):219–255.

Toplak, M. E., West, R. F., and Stanovich, K. E. (2014). Assessing miserly information processing: An expansion of the cognitive reflection test. *Thinking & Reasoning*, 20(2):147–168.

Tversky, A. and Kahneman, D. (1992). Advances in prospect theory: Cumulative representation of uncertainty. *Journal of Risk and Uncertainty*, 5(4):297–323.

Tversky, A. and Wakker, P. (1995). Risk attitudes and decision weights. *Econometrica*, pages 1255–1280.

Varian, H. R. (1992). *Microeconomic analysis*, volume 3. Norton New York.

Zeckhauser, R. (1970). Medical insurance: A case study of the tradeoff between risk spreading and appropriate incentives. *Journal of Economic theory*, 2(1):10–26.