# Risk Seeking or Risk aversion? Phenomenology and Perception

Caterina Lucarelli* Mario Maggi† Pierpaolo Uberti‡

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**Abstract**

We relax assumptions on individual risk preference, and set two theoretical rules for portfolio choices: either minimize or maximize risk, for any return. Risk is modeled by four alternative formulas. We empirically test these rules by observing $N = 690$ individuals (Caucasians, bank customers and financial professionals, aged 18-88), while making risky decisions, with measurement of Skin Conductance Response. Two perspectives are assumed to evaluate portfolio efficiency: individuals uniquely consider 'money'; or they experience a 'subjective' perception of money. We find a large dominance of risk-seeking behaviors, if observed through the phenomenology of money, independently from the risk measure used. Conversely, the same individuals appear risk averter, when values include the subjective experiences, and risk is assumed to be mentally projected with standard deviation formula. These results are consistent for sub-groups of individuals, by gender, age, education and profession. Implications are severe, as a sign of unawareness of behavior under risk.

**JEL: C91, D81, D87, G20, G11**

**Keywords:** Risk aversion; Heterogeneity; Risk Measures; Subjective Values; Model Evaluation and Selection; Skin Conductance Response.

## 1 Introduction

Perception of risk largely affects human decision-making. Most economic theories need to simplify human behavior and generally assume that people are risk-averse, since seminal papers of, among others, Arrow (1951) and Pratt (1964). Individual heterogeneity is seldom considered, even if both evidence from financial markets, and research from psychology and neuroscience indicate that risk-seeking behavior cannot be excluded, in several dimensions (among others Bechara et al., 2000; Damasio, 1994; Loewenstein et al., 2001; Lopes, 1987; Zaleskiewick, 2011).

In this paper we relax assumptions on individual risk preference, and set two theoretical selection rules for portfolio choices, for any given average return: a minimization-of-risk selection rule (MIN-R model), and a maximization-of-risk selection rule (MAX-R model). It is straightforward that the MIN-R selection rule unfolds a risk-aversion behavior; conversely, the MAX-R rule manifests a risk-seeking behavior.

*Faculty of Economics, Università Politecnica delle Marche – ITALY; c.lucarelli@univpm.it
†Department of Economics and Management, Università di Pavia – ITALY; maggma@eco.unipv.it
‡Department of Economics (DIEC), Università degli Studi di Genova – ITALY; uberti@economia.unige.it

We empirically test the descriptive efficacy of these models, by observing the decision-making of a large and variegated sample of individuals (N=690, Caucasians, bank customers and financial professionals, aged from 18 to 88 years), within a neurophysiological experiment. While individuals where making risky decisions, we measured their emotional arousal via changes in Skin Conductance Response (SCR).

Adherence of observed choices to theoretical selection rules is revealed by portfolio efficiency measures, in the sense of reward-risk Pareto dominance, as in Markowitz (1952). Degree of efficiency is computed considering two evaluations of outcomes: firstly, we imagine that, when making decisions, individuals uniquely consider the 'value of money', and risk/return outcomes simply result from monetary pay-offs. Alternatively, we consider that individuals are guided by their 'subjective' perception of values, in line with neuroeconomics underpinnings (Loewenstein, 2000; Rustichini, 2005; Bechara and Damasio, 2005): gains/losses are weighted by the emotional arousal – here the SCR change – which individuals experienced after each pay-off is received. In line with the neuroeconomic approach of this paper, this emotional experience generates a personal evaluation of the asset performance, transforming the traditional monetary outcome of an investment (i.e. a monetary gain or loss) into an 'emotional value' (Stevens, 1957; Lucarelli et al., 2015).

In order to exclude that results depend on a risk measure, we use an array of alternative risk measures: 1. standard deviation of outcomes (stdev); 2. value at risk at 95% confidence level ($VaR_{5\%}$); 3. conditional value at risk at 95% confidence level ($C\text{-}VaR_{5\%}$); 4. maximum drawdown (Max DD).

We find that the MAX-R rule is the best descriptive model when considering the monetary payoffs, and this model's descriptive performance seems in no way to be affected by risk measures. Monetary outcomes indicate that individuals appear risk seekers.

When introducing emotion, risk measures lead to different performances. Precisely, the MIN-R rule becomes the best descriptive model, under standard deviation computation. These findings supports that individuals result to be risk-avert, when observing behaviors through the perspective of emotional values, and assuming a mental processing coherent with a standard deviation function.

Considering separate sub-groups of individuals, by gender (men/women), by age (under/over 40 years old), education (graduated/non graduated), profession (financial professionals/non financial professionals; asset managers/non asset managers), we remark no statistical difference in such descriptive performance of models.

# 2 Portfolio Selection Rules

We set the selection rule, based on $n$ alternative risky assets and within a sequence $D$ of choices. We consider two dimension preferences, that is, preferences are defined in terms of reward/risk comparison of portfolios.

The reward dimension is measured by the expected return of portfolios, and we assume that all individuals prefer larger expected return with respect to lower ones, for the entire family of models we consider.

For the risk component of preferences, we assume two opposite preference rules:

- MIN-R: for any given average return, individuals prefer the portfolio with the lowest risk;
- MAX-R: for any given average return, individuals prefer the portfolio with the highest risk.

In order to reproduce the actual possibilities available to individuals within an experimental task, no short sales are allowed.

# 3 Methods

## 3.1 Recruitment, sample and reward scheme

We carried on a psycho-physiological experiment on a large and variegated sample of individuals (N=690, Caucasians, non students, aged from 18 to 88 years). Banks and investment firms cooperated with the research team, both in recruiting and hosting the psycho-physiological task inside their offices, across the nation (Italy). The recruitment consisted in asking CEOs of financial intermediaries to invite people randomly selected from the population of their clients, on the one hand, and employees, on the other[1]. Therefore, the sample of interviewees is made of bank customers and financial professionals: 539 males, and 151 females; 259 under 40 years old, and 431 over-40; 351 graduated, and 339 not-graduated; 292 financial professionals (84 professional asset managers, 51 on-line traders and 157 professional financial advisors), and 398 not financial professionals.[2]

A team of psychologists and economists were involved in conducting the task. Due to the prevailing national (public) funding of the research, we were not allowed to provide participants with a monetary reward, and opted for a hypothetical reward scheme. Precisely, an individual feedback was offered as a personal risk profiling delivered at the end of the task in the form of a preliminary verbal discussion offered by psychologists, and followed by a written text reporting the risk attitude revealed during the experiment, plus other psychological traits, delivered via web or in sealed envelopes.[3]

Engagement of individuals to our task has been monitored at the most. Participants considered the feed-back of their personal risk profiling as an improvement of their risk tolerance knowledge/self-consciousness, valuable in their real-life investment decisions, either as clients, or as professionals engaged in risky choices as a daily occupation.[4] Note that the period in which we run experiments was 2008-2011, when an European regulatory reform was just enforced (November 2007), addressing a tremendous

[1]We collected socio-demographic information of bank customers both accepting and refusing to take part to the experiment. By comparing the two groups of individuals, that are not statistically different, we can exclude a selection bias.

[2]In the early stage, the study received financial support from the Italian Government (PRIN2007-MIUR -years 2008-2010), national project entitled: 'Risk attitude in investment and debt decision-making'. We run 445 experiments. Additional funding was provided by ASSORETI, the Italian Association of Financial Advisors (years 2010-2011), who requested a focus on behaviors of professional financial advisors, adding 200 interviews. A final follow-up (2012-2013) has been financially supported by the Italian Association of Wealth Managers- AIPB (Associazione Italiana Private Banking), that allowed 45 additional experiments, involving both high-net-worth individuals and private bankers.

[3]Our reward was dispatched directly to participants in order to ensure the confidentiality of the statements: the final feedback on personal risk profiling, and behavioral traits shown during the psycho-physiological task, were partly delivered to participants through the research web-site (http://www.risktolerance.univpm.it/). Alternatively, it has been delivered by the hosting institution to her/his customer, in sealed envelopes. Individual IDs and passwords were created during the experiment and personally given to each participant to allow anonymity of feedback.

[4]Comments collected from participants during experiments indicate that our reward scheme has been strongly appreciated by both bank customers and financial professionals. A proof is that all the feed-backs were downloaded from the research web-site, or were picked-up if dispatched in a paper version.

attention of both financial intermediaries and customers on individual risk tolerance evaluation.[5]

### 3.2 The Empirical Portfolio Selection

In our experiment, well-known in literature (Bechara et al., 1997, 2000) and described in Lucarelli et al. (2015), each individual is asked to select $D = 100$ times one out of 4 risky assets (four decks), while the SCR was recorded (a brief reminder of decks' pay-offs, and of SCR measurements is offered in Appendix 1). As it is conventional for such experiment (Bechara et al., 1997), the 100 choices are divided into a training period (first $t$ choices) and an evaluation period (last $100 - t$ choices). We set $t = 80$; other (reasonable) cut-off periods have been tested without leading to qualitatively different conclusions. In order to measure the efficiency of the portfolio selection, we consider the portfolio obtained from the last 20 choices, where the 4 assets' weights equal the distribution of the choices in the evaluation period. To avoid the introduction of additional assumptions about the return distribution and to consider only the outcomes effectively observed by individuals, we apply a bootstrap re-sampling of size 2000 to compute the risk indicators of the portfolios. The bootstrap is applied on the training observed outcomes. Moreover, in this way we overcome the need to solve constrained maximization problems.[6]

Let $X = \left\{x \in \mathcal{R}^4 : x'\mathbf{1} = 1, x \geqq [0]\right\}$ be the portfolio set, where $x'\mathbf{1}$ is the scalar product between the portfolio weight vector $x$ and the vector $\mathbf{1} = [1\ 1\ 1\ 1]'$.

We remark that the problem has a finite set $X$ of admissible portfolios; it is an integer programming problem. In fact, the portfolio weights can assume only the values $x_j = \dfrac{k}{100 - t}$, where $k = 0, \ldots, (100 - t)$ is the number of choices of the $j^{\text{th}}$ "asset" out of the last $t$ choices. Therefore, the number $N$ of admissible portfolios in our case is quite small ($N = 1771$), making it possible to directly evaluate the risk and return of each one.

The expected return for the portfolio $x$ is $\mu^x = (x)'\mu$, where $\mu$ is the vector of average returns of the 4 assets. Moreover, a risk measure $R$ associate a scalar risk indicator to each admissible portfolio: $R : \{X \subset \mathcal{R}^4\} \to \mathcal{R}^+$, so that, the risk of the portfolio $x$ is $R(x)$. To avoid that the results depend on a given risk function, we measure the risk of the portfolios by various common risk indicators. We compute the following risk measures:

1. the standard deviation of outcomes (stdev);
2. the value at risk at 95% confidence interval ($\text{VaR}_{5\%}$);
3. the conditional value at risk at 95% confidence interval ($\text{C-VaR}_{5\%}$);
4. the maximum drawdown (Max DD).

Under the MIN-R selection rule, the portfolio $x$ is efficient ($x^*$) if

$$\mu^* \geq \mu^x, \quad \forall x \in X : R(x) \leq R(x^*),$$

[5]The Markets in Financial Instruments Directive 2004/39/EC (MiFID) imposes intermediaries to profile customers in order to assess the appropriateness and suitability of their financial services. A specif item of this profile was dedicated to individual risk tolerance.

[6]For uniformity sake, this numerical technique is applied even for the standard deviation measure where a closed form is available. The bootstrap error is kept small thanks to the bootstrap size (2000) and the application of the same random sequences to compute both actual and emotionally distorted quantities. (The bootstrap standard errors are between 0.48% and 3.54%).

or

$$R(x^*) \leq R(x), \quad \forall x \in X : \mu^x \geq \mu^*.$$

Under the MAX-R selection rule, the portfolio $x$ is efficient ($x^*$) if

$$\mu^* \geq \mu^x, \quad \forall x \in X : R(x) \geq R(x^*),$$

or

$$R(x^*) \geq R(x), \quad \forall x \in X : \mu^x \geq \mu^*.$$

## 3.3 Two perceptions of outcomes: money and 'emotional values'

Efficiency of portfolio choices is observed from two perspective of perception: on the one hand, we suppose that individuals appreciate exclusively the 'value of money' (monetary values, $MV$,); on the other hand, we propose that they follow their subjective experience of 'emotional values', $EV$. We approximate the subjective experience by weighting pay-offs with the emotional arousal experienced while making decisions. Precisely, applying the power law of perception, as in Stevens (1957) and in line with Lucarelli et al. (2015), the neurophysiological substrate of risky decisions here is the somatic past reinforcement experience, i.e., the SCR ($E$) recorded after each choice (Wong et al., 2011, see Appendix 1, Figure 8). Emotional values, $EV$, are intended as emotionally balanced payoffs that are obtained from a weighting function of the monetary payoff $MV$ that is rescaled by a non-negative power $\omega$ of the emotion $E$:

$$EV = \frac{|MV|}{E^{\omega}}, \quad \omega \geq 0. \tag{1}$$

Note that when $\omega = 0$ the 'value' is uniquely driven by MV, i.e., money.

We refer to Lucarelli et al. (2015) for the empirical calibration of the parameter $\omega$, on the same sample.[7] Here, we rescale monetary payoff by $\omega = 3$, which is basically the mid-point of its permissible bounce, that is $0 \leq \omega < 6.48635$ as in (Lucarelli et al., 2015, Tab. 4).

Based on our empirical experiment, for each individual $i = 1, 2, \ldots, 690$, we proceed as follows:

1. compute the distributions of the 4 assets emerging from the first $N - t = 80$ choices;
2. compute the risk and the return indicators for each of the $X$ admissible portfolios;
3. compute the risk and the return indicators for the portfolio that has been selected by the individual;
4. compute an efficiency measure for each individual (see Section 3.4).

## 3.4 The degree of portfolio efficiency

Efficiency of portfolios selected by individuals is essential for assessing the adherence of observed choices to our two theoretical selection rules.

[7] This paper enlarges the sample of 645 individuals used in Lucarelli et al. (2015) with further 45 subjects obtained with the research follow-up financially supported by the Italian Association of wealth managers. Results of calibration have not been changed by this increment of the sample.

Let $x^i \in X$ be the portfolio selected by the individual $i$, with $i = 1, \dots, 690$. To evaluate the efficiency of the choice of the $i$-th individual, we compute the number $d^i$ of dominating portfolios, that is the number of portfolios such that

$$\begin{array}{ll} \text{under MIN-R}: & \mu^x \geq \mu^i, \quad \forall x \in X : R(x) \leq R(x^i) \\ \text{under MAX-R}: & \mu^x \geq \mu^i, \quad \forall x \in X : R(x) \geq R(x^i) \end{array}$$

The fraction $s^i = \frac{N-d^i}{N}$ of portfolios non-dominating the selected one is used as efficiency indicator, and it measures the degree of efficiency of the portfolio selected by each individual, during the experimental task.

By definition, $s \in [0, 1]$, where $s = 1$ means that the selected portfolio belongs to the efficient frontier of the portfolio set. The cumulative distribution function (cdf) of $s$ on the sample can be used as a synthetic indicator of the efficiency of the entire population. Note that:

- the case where all individuals achieve the efficient frontier corresponds to the cdf of a degenerate distribution with $P[s = 1] = 1$;
- comparison of two non intersecting cdfs is straightforward: the rightmost one (the closest to case of the previous point) is relative to the case which better explains the individual behavior in terms of Paretian risk-reward efficiency;
- the goodness of a model in explaining efficiency can be measured by the normalized area over the cdf $\int_0^1 (1 - F(s))\mathrm{d}s$, as commonly carried out in data analysis for the ROC curves and the Gini coefficient. Remark, however, that in our case, given the non-negativity of $s$, this area corresponds to its expected value $E[s] = \int_0^1 (1 - F(s))\mathrm{d}s$.

The descriptive efficacy of the two selection rules, theoretically set in MIN-R and MAX-R models, is shown running the procedure described in Sections 3.3 and 3.4, using the 4 risk measures as risk indicators.

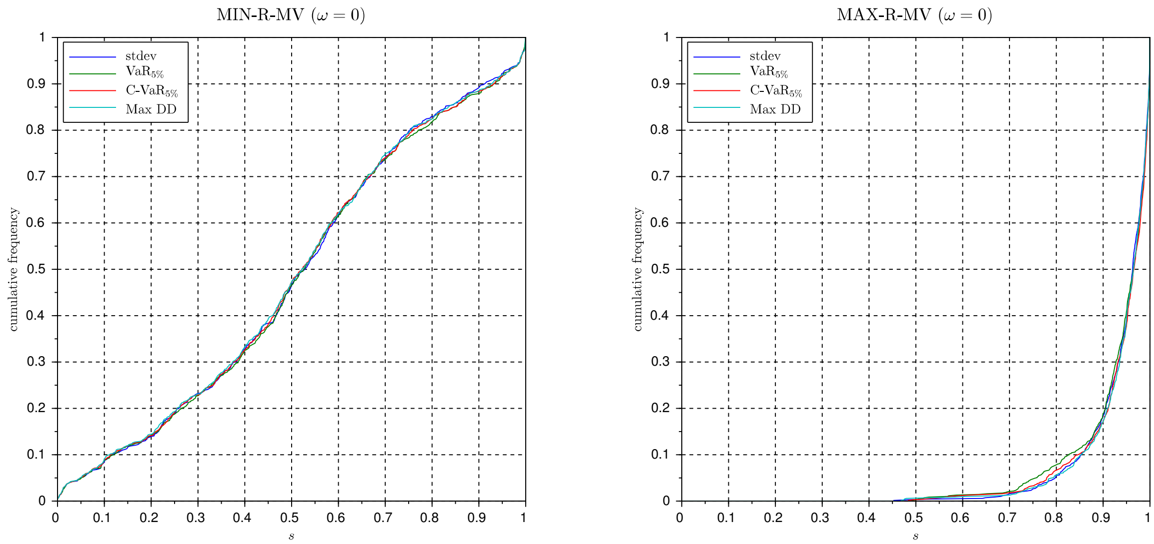
# 4 Results and Discussion

Goodness of models in explaining experimental decision-making reveals whether individuals followed a MIN-R selection rule, and implicitly a risk-aversion behavior; or, conversely, if they followed a MAX-R rule, as a risk-seeking behavior. Results of the descriptive efficacy of these two opposite rules are reported in Figures 1 and 2, drawing the cumulative distribution function of $s$, for the various risk indicators here considered, based on either the MV or the EV perspective, respectively.

From Figure 1 we can remark that in MIN-R-MV plot, all the lines are very close, almost overlapping, and consequently the expected values, reported in the table at the bottom of Figure 1, are statistically indistinguishable. Values are close to 0.5, showing that this model has no descriptive power in terms of efficiency. In MAX-R-MV plot, all the lines are also very close, and coherently the reported expected values are statistically indistinguishable. Values are quite close to 1, showing that this model highly describes behaviors.

From Figure 2, that offers the same cumulative distribution functions of $s$ based on emotional values, we note that in MAX-R-EV plot, the standard deviation line is dominated by the other three risk functions; the $\mathrm{VaR}_{5\%}$, C-$\mathrm{VaR}_{5\%}$ and Max DD lines are close to each other and the corresponding expected values are not statistically distinguishable.

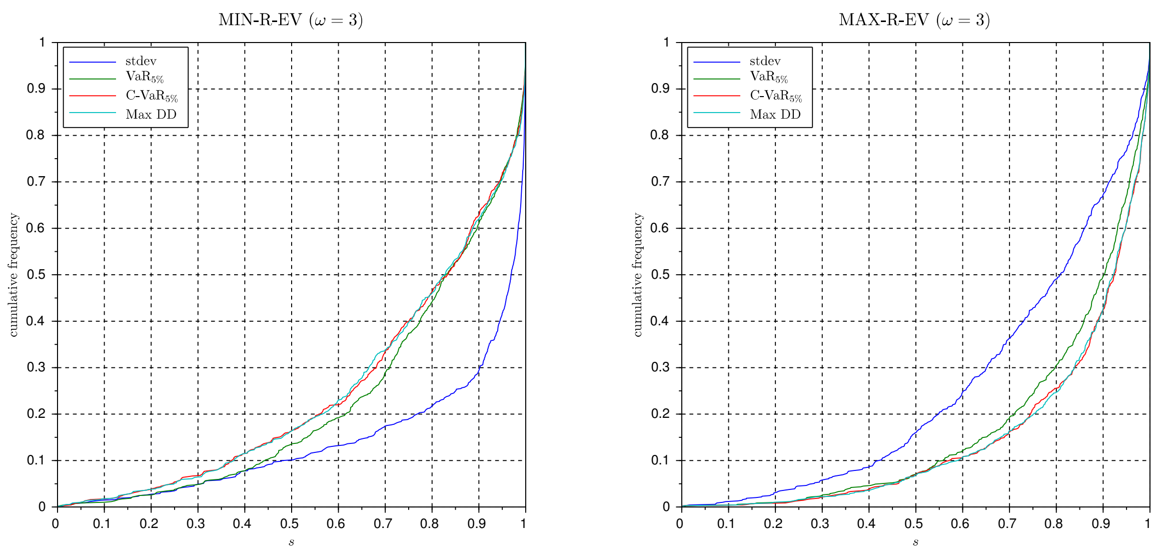
Figure 1: Efficiency for monetary values (MV)




The cumulative distribution function of $s$ for monetary values.

| Averages of $s$ (95% confidence intervals) | | | | |
|---|---|---|---|---|
| plot | stdev. | VaR$_{5\%}$ | C-VaR$_{5\%}$ | Max DD |
| MIN-R-MV | 0.5202 (0.5000, 0.5403) | 0.5229 (0.5025, 0.5433) | 0.5201 (0.4998, 0.5405) | 0.5178 (0.4974, 0.5382) |
| MAX-R-MV | 0.9409 (0.9356, 0.9462) | 0.9364 (0.9302, 0.9425) | 0.9409 (0.9351, 0.9466) | 0.9420 (0.9365, 0.9475) |

Figure 2: Efficiency for emotional values (EV)




The cumulative distribution function of $s$ for emotional values.

| Averages of $s$ (95% confidence intervals) | | | | |
|---|---|---|---|---|
| plot | stdev. | VaR$_{5\%}$ | C-VaR$_{5\%}$ | Max DD |
| MIN-R-EV | **0.8626** (0.8458, 0.8793) | 0.7758 (0.7591, 0.7925) | 0.7556 (0.7374, 0.7739) | 0.7556 (0.7374, 0.7739) |
| MAX-R-EV | 0.7452 (0.7282, 0.7622) | 0.8320 (0.8181, 0.8459) | 0.8521 (0.8386, 0.8656) | 0.8521 (0.8386, 0.8656) |

Conversely, in MIN-R-EV plot, the standard deviation line largely dominates the other three risk functions, which are not statistically distinguishable. It is remarkable that the efficiency measures resulting for this model, using the standard deviation function, are those describing behaviors at the most. Average values of s (bottom of Figure 2) indicate that, within the EV perspective, the descriptive power of the MIN-R-EV rule, with standard deviation (**0.8626** in bold), is statistically superior compared to the MAX-R-EV one, for all the risk measures considered.

Therefore, Figures 1 and 2 definitively shows that if we believe that individuals uniquely appreciate money (MV perspective) they appear to follow a MAX-R rule, that is significantly dominant over the MIN-R rule. This evidence is consistent across risk indicators. These findings implicate that, when consequences of choices are limited to the exterior phenomenology of money, risk-seeking behaviors appear prevailing, compared to risk aversion, independently from the function used to represent risk.

When we suppose that individuals experienced a wider perception of what is 'valuable', and assume that the monetary pay-off is mediated by a subjective emotional experience, the MIN-R rule is dominant over the MAX-R rule. This becomes evident if individuals design in their mind a representation of risk based on a standard deviation formula. A definitive deduction is that individuals result to be adherent to a risk-aversion behavior. Finally, this is consistent with the standard risk-averse assumption which is common in the foundations of the economics of risk (Arrow, 1951; Pratt, 1964).

Figures 3 to 7, with their respective Tables, indicate that this opposite evidence of dominance for selection preferences is confirmed by sub-groups of very different individuals: men against women (Figure 3), under-40 against over-40 (Figure 4), graduated against not graduated (Figure 5), financial professionals and not financial professionals (Figure 6), asset managers against all the other interviewees (Figure 7). We deduce a sort of 'universal' risk-aversion, manifest through the lens of emotions and the standard deviation functioning, while the objective/monetary pay-offs indicates risk-propensity on the outside, for any risk measure considered.

# 5 Concluding remark

In this paper, we relax any assumption on individual attitude towards risk, allowing that a person can theoretically behave either as risk-seeker or risk-advert. When we check empirical behaviors in relation to two opposite selection rules of risk-taking, we find evidence of behaviors classifiable as risk-seeking, if observed through the exterior phenomenology of the monetary pay-off of their investments. Conversely, the same individuals are discovered to adhere to a risk-aversion paradigm, when values of their choices are balanced with the individual emotional experiences, and risk is thought to be mentally projected within a standard deviation formula.

We acknowledge that this conclusion is exclusively driven by our experimental data. Nevertheless, we believe that any counter factual proof appears quite unlikely to be obtained. Firstly, most of the emotional arousal (here, the change in SCR) experienced by individuals during their decision-making was unconscious, and they practically reacted without an explicit awareness. Moreover, it appears quite impracticable to obtain a response, reliable for any level of education, about which is the formula individuals mentally apply to represent risk, when observing a sequence of payoffs, such as those offered during the task.

Reverting the view of our findings, we cannot paradoxically exclude, and it is reasonable also, that individuals were ‘subjectively’ convinced to be making prudent choices, while in the truth of monetary results, their choices were strongly risky. Implications of this deduction are severe, and worthy of attention both for regulators and financial industry, as a sign of unawareness of risky behaviors.

Conversely, implications are reassuring economic theory for assuming risk aversion in decision-making, because this behavior is largely coherent with a ’subjective’ perception of values.

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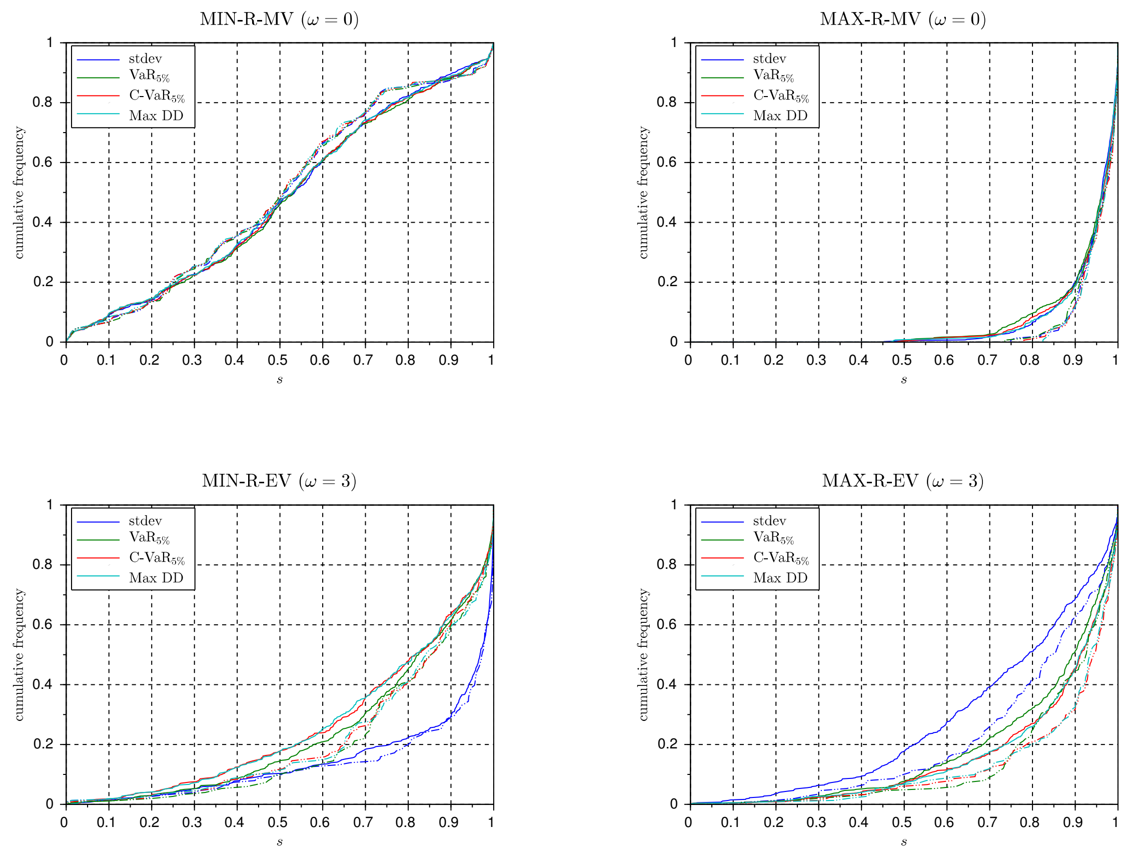
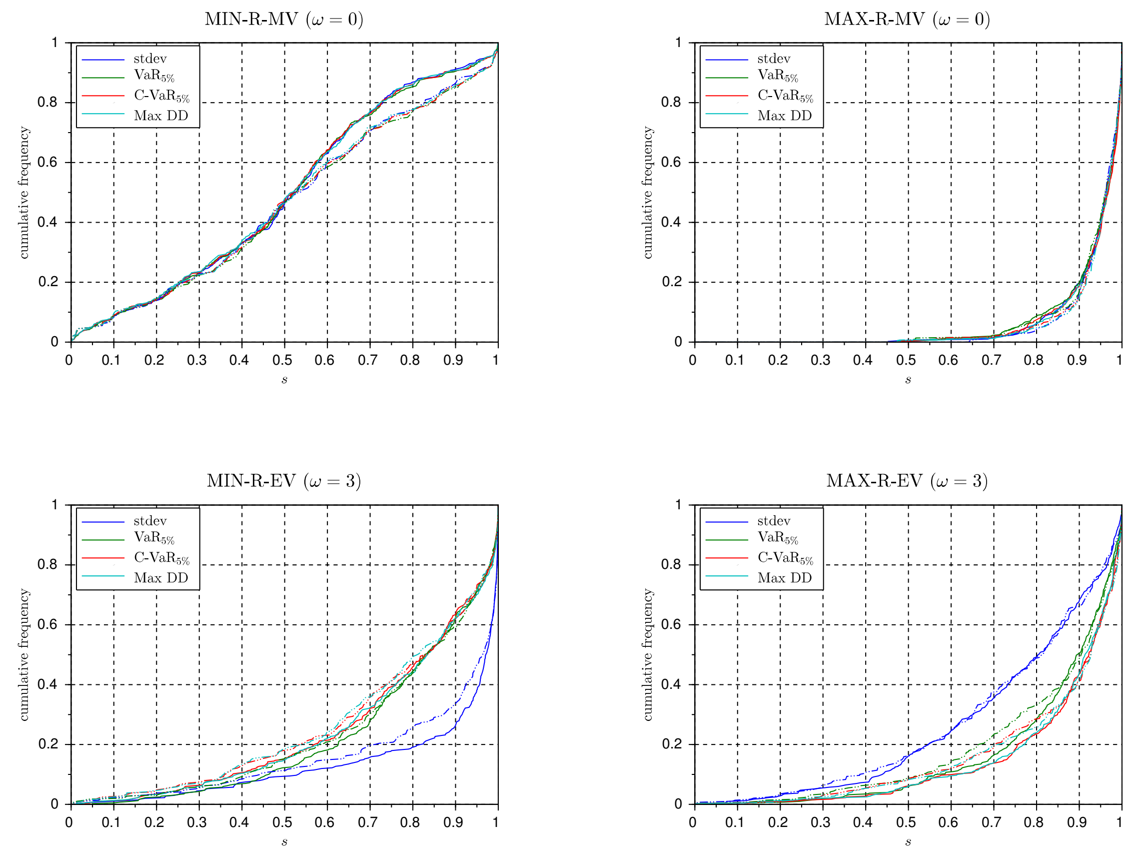
Figure 3: Efficiency for MV and EV: gender




The cumulative distribution function of $s$ for various cases: solid male, dashed female.

| Averages of $s$ (95% confidence intervals) | | | | |
|---|---|---|---|---|
| plot | stdev. | VaR$_{5\%}$ | C-VaR$_{5\%}$ | Max DD |
| MIN-R-MV male | 0.5231 (0.5002, 0.5460) | 0.5266 (0.5034, 0.5498) | 0.5237 (0.5005, 0.5469) | 0.5211 (0.4979, 0.5443) |
| female | 0.5096 (0.4667, 0.5524) | 0.5096 (0.4669, 0.5524) | 0.5074 (0.4645, 0.5503) | 0.5061 (0.4631, 0.5491) |
| MAX-R-MV male | 0.9373 (0.9309, 0.9437) | 0.9319 (0.9244, 0.9394) | 0.9366 (0.9296, 0.9437) | 0.9380 (0.9313, 0.9447) |
| female | 0.9538 (0.9461, 0.9615) | 0.9523 (0.9442, 0.9603) | 0.9560 (0.9487, 0.9633) | 0.9562 (0.9492, 0.9632) |
| MIN-R-EV male | 0.8597 (0.8406, 0.8789) | 0.7685 (0.7491, 0.7878) | 0.7465 (0.7254, 0.7676) | 0.7459 (0.7248, 0.7669) |
| female | 0.8727 (0.8380, 0.9073) | 0.8019 (0.7695, 0.8343) | 0.7884 (0.7532, 0.8235) | 0.7905 (0.7550, 0.8259) |
| MAX-R-EV male | 0.7312 (0.7114, 0.7509) | 0.8224 (0.8061, 0.8387) | 0.8444 (0.8288, 0.8600) | 0.8450 (0.8294, 0.8606) |
| female | 0.7953 (0.7636, 0.8269) | 0.8660 (0.8411, 0.8909) | 0.8796 (0.8533, 0.9058) | 0.8775 (0.8512, 0.9037) |

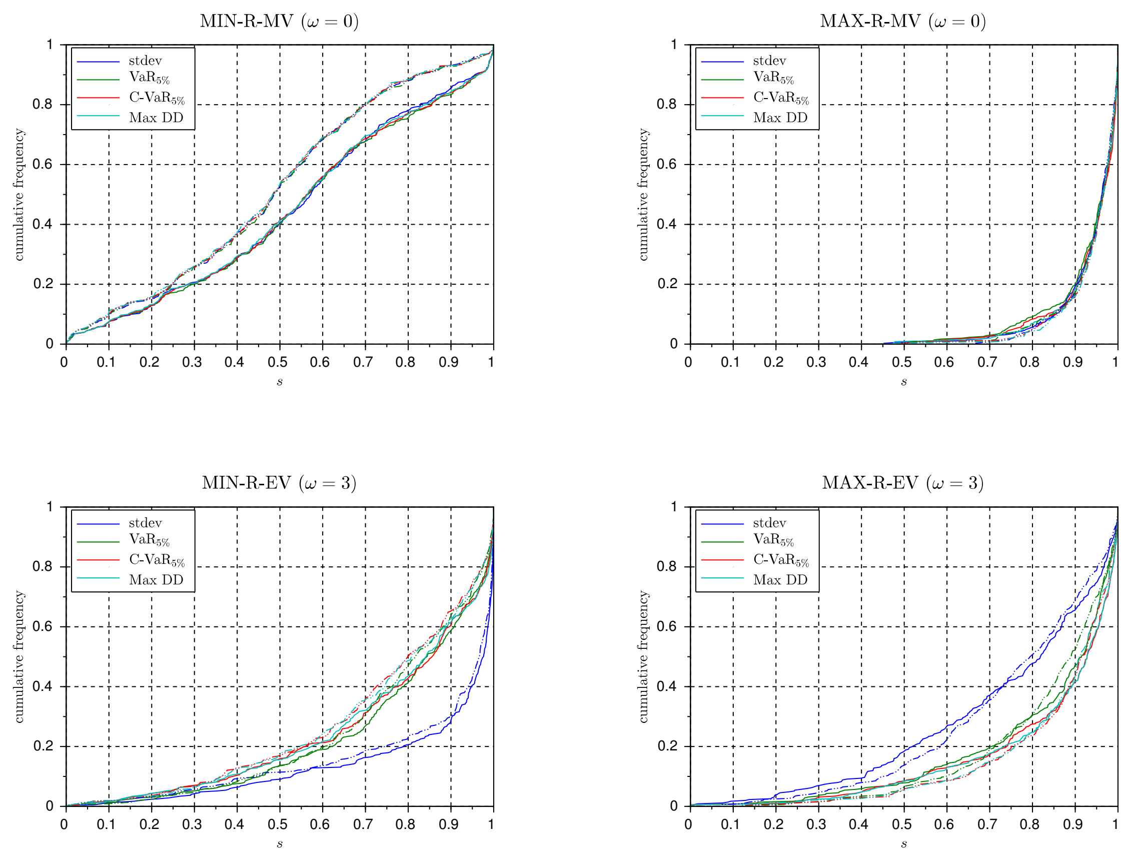
Figure 4: Efficiency for MV and EV: age




The cumulative distribution function of $s$ for various cases: solid over 40, dashed under 40.

| Averages of $s$ (95% confidence intervals) | | | | |
|---|---|---|---|---|
| plot | stdev. | VaR$_{5\%}$ | C-VaR$_{5\%}$ | Max DD |
| MIN-R-MV over 40 | 0.5086 (0.4831, 0.5342) | 0.5097 (0.4840, 0.5354) | 0.5073 (0.4816, 0.5331) | 0.5058 (0.4800, 0.5316) |
| $\leq 40$ | 0.5362 (0.5035, 0.5688) | 0.5412 (0.5083, 0.5742) | 0.5379 (0.5049, 0.5709) | 0.5345 (0.5015, 0.5674) |
| MAX-R-MV over 40 | 0.9388 (0.9314, 0.9463) | 0.9361 (0.9280, 0.9442) | 0.9401 (0.9325, 0.9477) | 0.9404 (0.9331, 0.9476) |
| $\leq 40$ | 0.9438 (0.9365, 0.9511) | 0.9367 (0.9273, 0.9462) | 0.9419 (0.9331, 0.9507) | 0.9442 (0.9358, 0.9526) |
| MIN-R-EV over 40 | 0.8740 (0.8530, 0.8951) | 0.7807 (0.7596, 0.8017) | 0.7616 (0.7384, 0.7848) | 0.7641 (0.7409, 0.7874) |
| $\leq 40$ | 0.8466 (0.8194, 0.8739) | 0.7690 (0.7417, 0.7963) | 0.7474 (0.7181, 0.7766) | 0.7439 (0.7147, 0.7731) |
| MAX-R-EV over 40 | 0.7472 (0.7252, 0.7692) | 0.8406 (0.8236, 0.8575) | 0.8596 (0.8430, 0.8763) | 0.8571 (0.8403, 0.8740) |
| $\leq 40$ | 0.7424 (0.7155, 0.7693) | 0.8200 (0.7966, 0.8434) | 0.8417 (0.8191, 0.8642) | 0.8452 (0.8230, 0.8673) |

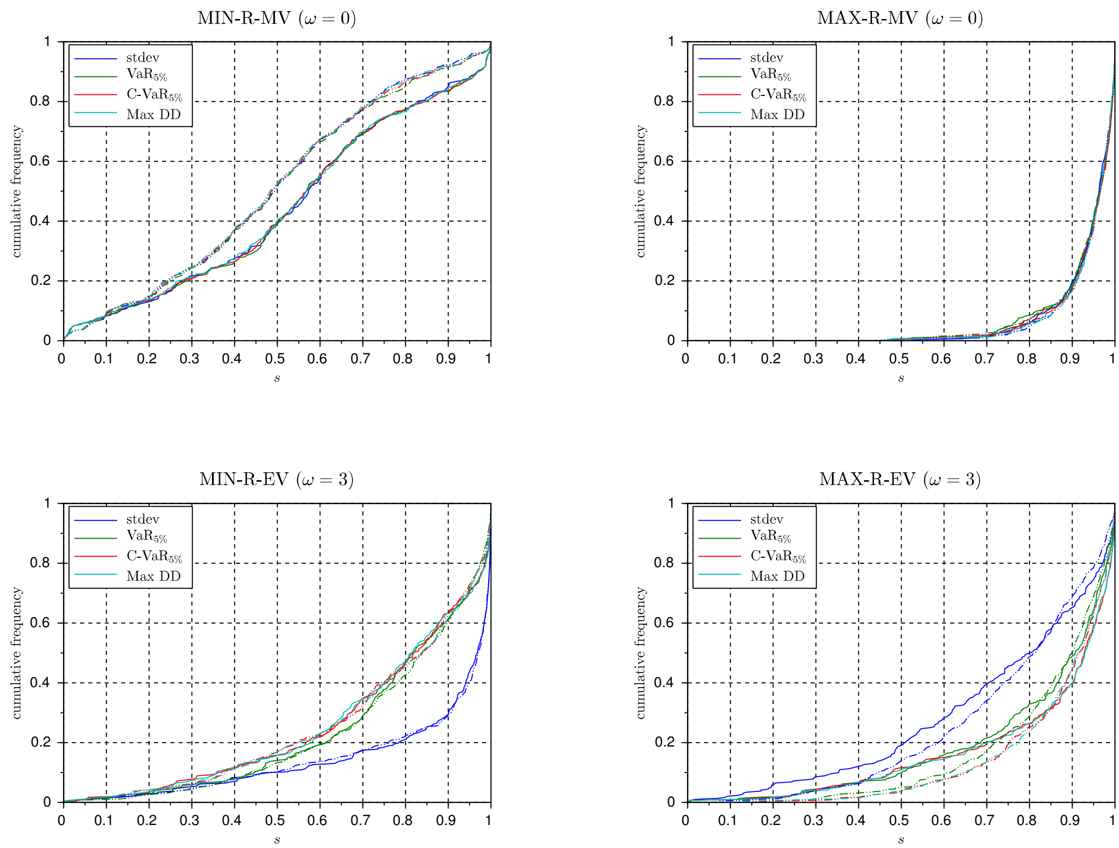
Figure 5: Efficiency for MV and EV: education




The cumulative distribution function of $s$ for various cases: solid graduated, dashed non graduated.

| Averages of $s$ (95% confidence intervals) | | | | | |
|---|---|---|---|---|---|
| plot | | stdev. | $\mathrm{VaR}_{5\%}$ | C-$\mathrm{VaR}_{5\%}$ | Max DD |
| MIN-R-MV | graduated | 0.5571 (0.5280, 0.5863) | 0.5614 (0.5320, 0.5909) | 0.5585 (0.5290, 0.5880) | 0.5561 (0.5266, 0.5856) |
| | non graduated | 0.4819 (0.4545, 0.5092) | 0.4830 (0.4555, 0.5105) | 0.4804 (0.4529, 0.5079) | 0.4782 (0.4507, 0.5058) |
| MAX-R-MV | graduated | 0.9395 (0.9313, 0.9476) | 0.9333 (0.9240, 0.9425) | 0.9380 (0.9293, 0.9467) | 0.9392 (0.9308, 0.9477) |
| | non graduated | 0.9424 (0.9357, 0.9492) | 0.9396 (0.9314, 0.9477) | 0.9438 (0.9364, 0.9513) | 0.9448 (0.9379, 0.9518) |
| MIN-R-EV | graduated | 0.8717 (0.8493, 0.8941) | 0.7824 (0.7586, 0.8061) | 0.7669 (0.7413, 0.7924) | 0.7641 (0.7385, 0.7897) |
| | non graduated | 0.8531 (0.8281, 0.8781) | 0.7690 (0.7454, 0.7925) | 0.7440 (0.7180, 0.7699) | 0.7469 (0.7209, 0.7728) |
| MAX-R-EV | graduated | 0.7407 (0.7155, 0.7659) | 0.8300 (0.8090, 0.8510) | 0.8455 (0.8250, 0.8660) | 0.8483 (0.8282, 0.8684) |
| | non graduated | 0.7498 (0.7270, 0.7727) | 0.8340 (0.8158, 0.8521) | 0.8590 (0.8414, 0.8765) | 0.8561 (0.8382, 0.8740) |

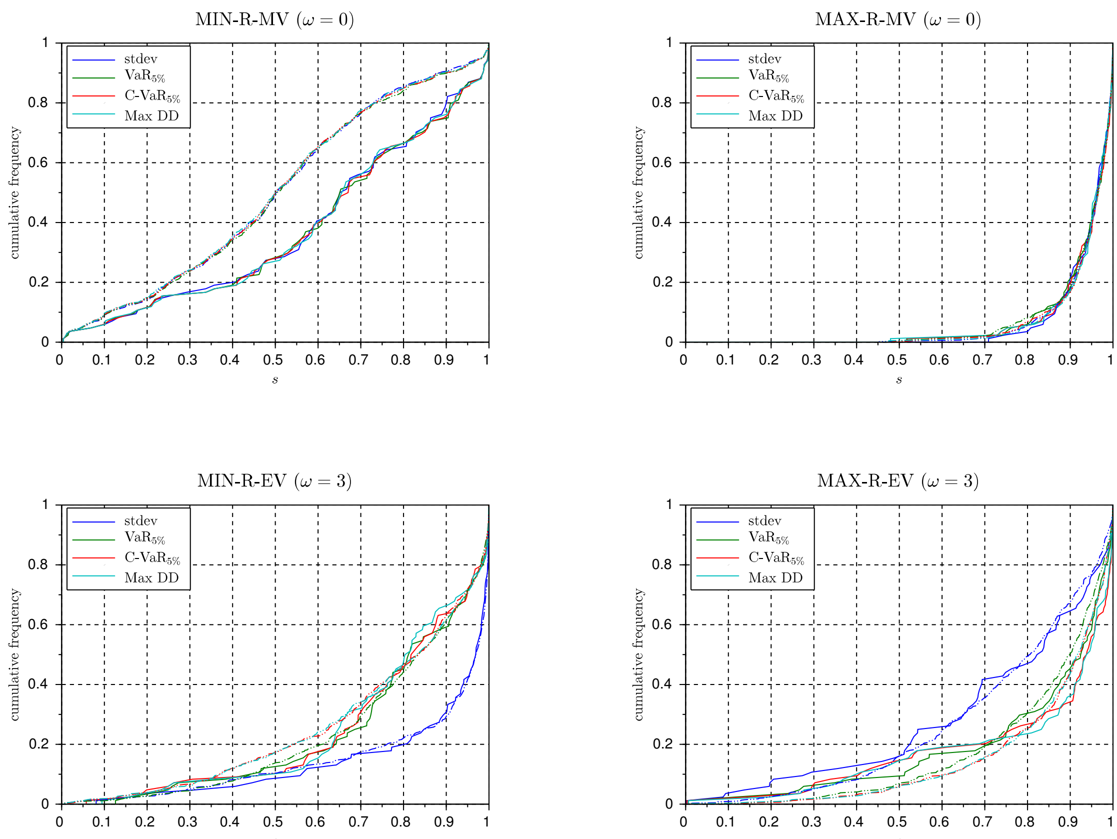
Figure 6: Efficiency for MV and EV: profession (financial)




The cumulative distribution function of $s$ for various cases: solid financial professional, dashed non financial professional.

| Averages of $s$ (95% confidence intervals) | | | | |
|---|---|---|---|---|
| plot | stdev. | VaR$_{5\%}$ | C-VaR$_{5\%}$ | Max DD |
| MIN-R-MV fin.prof | 0.5584 (0.5261, 0.5907) | 0.5599 (0.5274, 0.5923) | 0.5583 (0.5257, 0.5909) | 0.5563 (0.5236, 0.5890) |
| non fin.prof | 0.4921 (0.4667, 0.5175) | 0.4958 (0.4700, 0.5216) | 0.4922 (0.4665, 0.5179) | 0.4896 (0.4640, 0.5153) |
| MAX-R-MV fin.prof | 0.9399 (0.9316, 0.9482) | 0.9363 (0.9270, 0.9457) | 0.9399 (0.9309, 0.9489) | 0.9407 (0.9319, 0.9495) |
| non fin.prof | 0.9417 (0.9348, 0.9486) | 0.9364 (0.9282, 0.9446) | 0.9416 (0.9341, 0.9490) | 0.9429 (0.9359, 0.9499) |
| MIN-R-EV fin.prof | 0.8636 (0.8381, 0.8892) | 0.7722 (0.7459, 0.7985) | 0.7559 (0.7278, 0.7840) | 0.7543 (0.7263, 0.7823) |
| non fin.prof | 0.8618 (0.8396, 0.8840) | 0.7784 (0.7568, 0.8001) | 0.7555 (0.7315, 0.7794) | 0.7566 (0.7326, 0.7806) |
| MAX-R-EV fin.prof | 0.7286 (0.6996, 0.7577) | 0.8201 (0.7958, 0.8444) | 0.8364 (0.8117, 0.8610) | 0.8380 (0.8136, 0.8623) |
| non fin.prof | 0.7573 (0.7370, 0.7777) | 0.8407 (0.8245, 0.8569) | 0.8636 (0.8488, 0.8785) | 0.8625 (0.8475, 0.8775) |

Figure 7: Efficiency for MV and EV: profession (asset manager)




The cumulative distribution function of $s$ for various cases: solid asset manager, dashed non asset manager.

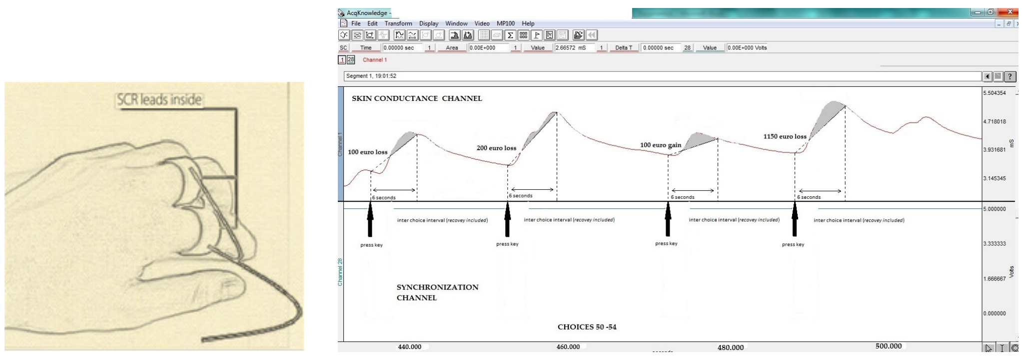
| Averages of $s$ (95% confidence intervals) | | | | | |
|---|---|---|---|---|---|
| plot | | stdev. | $\mathrm{VaR}_{5\%}$ | C-$\mathrm{VaR}_{5\%}$ | Max DD |
| MIN-R-MV | ass.man | 0.6343 (0.5739, 0.6947) | 0.6376 (0.5769, 0.6983) | 0.6378 (0.5770, 0.6985) | 0.6366 (0.5761, 0.6971) |
| | non ass.man | 0.5043 (0.4832, 0.5255) | 0.5070 (0.4857, 0.5283) | 0.5038 (0.4825, 0.5252) | 0.5014 (0.4800, 0.5227) |
| MAX-R-MV | ass.man | 0.9445 (0.9317, 0.9573) | 0.9388 (0.9222, 0.9555) | 0.9410 (0.9246, 0.9573) | 0.9409 (0.9241, 0.9577) |
| | non ass.man | 0.9404 (0.9346, 0.9462) | 0.9360 (0.9294, 0.9427) | 0.9409 (0.9347, 0.9470) | 0.9421 (0.9363, 0.9480) |
| MIN-R-EV | ass.man | 0.8717 (0.8269, 0.9165) | 0.7801 (0.7325, 0.8277) | 0.7752 (0.7267, 0.8236) | 0.7705 (0.7233, 0.8178) |
| | non ass.man | 0.8613 (0.8433, 0.8793) | 0.7752 (0.7573, 0.7931) | 0.7529 (0.7333, 0.7726) | 0.7536 (0.7339, 0.7733) |
| MAX-R-EV | ass.man | 0.7337 (0.6777, 0.7896) | 0.8252 (0.7771, 0.8734) | 0.8302 (0.7787, 0.8817) | 0.8348 (0.7845, 0.8851) |
| | non ass.man | 0.7468 (0.7290, 0.7646) | 0.8329 (0.8185, 0.8473) | 0.8551 (0.8415, 0.8688) | 0.8545 (0.8408, 0.8682) |

# 6 Appendix 1

Table 1: Moments of the payoff distribution of the four decks

| | A | B | C | D |
|---|---|---|---|---|
| Expected payoffs | -28.233 | -31.933 | 26.447 | 28.449 |
| Standard deviation of payoffs | 136.613 | 384.083 | 26.864 | 70.168 |

Figure 8: The Skin Conductance Response measurement




*Note: The left figure shows the two electrodes placed on the skin surface of the agent running the experiment. Electrodes are attached to the palm surface of the second phalanx of the index and middle fingers of the non-dominant hand, after the agent is seated in front of the computer screen. The right chart shows the typical trend of SCR during the experiment, with upward and downward trends, due to activation and recovery towards the individual's baseline. SCR measures used in the paper correspond to the grey areas under the curve, within 6 seconds after each selection.*

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