Eliciting risk and time preferences under induced mood states

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ELICITING RISK AND TIME PREFERENCES UNDER INDUCED MOOD STATES[1]

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Abstract

We test whether induced mood states have an effect on elicited risk and time preferences in a conventional laboratory experiment. We jointly estimate risk and time preferences and use a mixture specification that allows choices to be consistent with Expected Utility theory or with probability weighting. For choices consistent with Expected Utility Theory, we find that subjects induced into a negative mood exhibit higher risk aversion than those in either the control treatment or the positive mood treatment. For choices that are consistent with probability weighting, we find no effect of mood on risk aversion. Subjects induced into negative mood exhibit lower discount rates. Results also suggest that risk preferences are affected by whether a cognitively demanding task precedes a risk preference elicitation task or whether subjects were placed in a gender-specific session rather than a mixed-gender session.

Keywords: discount rates, risk aversion, lab experiment, mood, affect

JEL codes: D81, C91, D00

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1. Introduction

In the beginning of the 20^{th} century, economics was generally devoid of psychological concepts by basing economic theory on the principles of rational choice (see Bruni and Sugden 2007 for a historical perspective). However, with the advent of "behavioral economics", there has been considerable effort lately in bringing out psychological concepts in economics. Hence, economics and psychology no longer stand in complete isolation. Reviews of the fruitfulness of this interaction have appeared in core economic journals. For example, Elster (1998) brought out the interesting features of "emotions" in the development of economic theory and in explaining human behavior. The seminal work of Kahneman and Tversky (1979) and the collective volume edited by Camerer, Loewenstein, and Rabin (2004) have been extremely influential in this respect as well.

The literature in economics usually confounds emotions and mood in an almost indistinguishable way. However, there are stark differences between emotions and moods, as described in the psychology literature. Emotions tend to be extremely brief, lasting for a few seconds (Izard 1991; Larsen 2000) while moods typically last longer (Watson and Vaidya 2003). To quote the example provided in Watson and Vaidya (2003), the full emotion of anger might last for only a few seconds while an annoyed or irritable mood may persist for several hours or even for a few days. In essence, the concept of mood subsumes all subjective feeling states, not simply those experiences that accompany classical, prototypical emotions such as fear and anger (Watson and Vaidya 2003). Therefore, it appears that in order to explore all aspects of affective states on human behavior, it would be necessary to go beyond examining the narrow boundaries of emotions and delve into studying the much broader concept of mood.

In this study, we examine the role of mood in joint elicitation of risk and time preferences. Studies in the literature that examine the role of mood on risk and time preferences have focused only on either risk or time preferences but not both at the same time. The examination of both risk and time preferences is important since they are fundamental economic preferences that have been found to influence many facets of economic decision-making and human behavior. For example, risk and time preferences have been shown to influence self-control problems that could lead to negative health outcomes (e.g., Benhabib and Bisin 2005; Bernheim and Rangel 2004; Fudenberg and Levine 2009).

The hypothesis that people tend to make judgments that are mood congruent, dates back to Johnson and Tversky (1983). Johnson and Tversky (1983) found that bad mood increased subjective probabilities of risk assessments while positive mood produced a comparable decrease in subjective probabilities. This hypothesis of mood congruent judgments implies that moods may affect preference formation by influencing judgments.

In psychology, two models of decision making which relate mood states with risk-taking, predict the exact opposite things. One of these models is the Affect Infusion Model (AIM) which suggests that positive mood increases risk-taking behavior while negative mood reduces the tendency to take risks (Forgas 1995). This is because individuals in an elated mood rely on positive cues in making judgments and thus are more likely to think about the positive aspects of risky situations than those in a negative mood. The other model is the Mood Maintenance Hypothesis (MMH) which asserts that people in elated moods may not want to risk losing the elated state and thus render themselves more risk averse (Isen and Patrick 1983). Hence, according to this model, people in negative moods will be willing to take more risk (be less risk averse) in order to obtain greater potential gains and consequently a better mood. Many studies in the literature have since then taken one side or the other. For example, Isen and Patrick (1983) found that subjects under positive affect were betting less on gambles. Those in positive mood have also been found to require a higher probability of winning when taking bets (Isen and Geva 1987).

Much of the literature on mood and risk aversion appeared only over the last decade. Most of these studies can be found not in the economics but in the psychology literature[2]. For example, Hockey et al. (2000) examined the effect of naturally occurring and induced negative moods (in particular anxiety, depression and fatigue) on risk in every day (hypothetical) decision making and found that fatigue was more strongly linked to increased riskiness. In another study, Hills et al. (2001) examined the effect of mood states on the amount of time devoted to playing gambling games and found that negative moods had an inhibitory effect (which can be interpreted as less risk taking) but only for non-regular gamblers. Regular gamblers were completely unaffected. Similarly, Yuen and Lee (2003) found that people in induced depressed mood had lower willingness to take risk (where risk was defined based on hypothetical choices from everyday life dilemmas) than people in neutral and in positive mood while Williams et al. (2003) found that decision makers (managers) with high negative affect were more likely to avoid risk (as measured by hypothetical choices of actions to varied business scenarios). In a related study, Chou et al. (2007) reconfirmed that individuals in a negative mood are less willing to take up more risk (where risk was defined similar to Yuen and Lee 2003). However, they found an asymmetric age effect, where positive mood affects risk taking only for older individuals. More recently, Kugler, Connolly, and Ordóñez (2010) found that the impact of prototypical emotions such as fear and anger is contingent upon the type of risk. They found that fearful participants were *more* risk-averse than angry participants in lottery-risk tasks. The fearful participants, however, were less risk-averse than the angry participants in tasks where risk was generated by another person's uncertain behavior.

[2] We only focus on the literature on mood and risk/time preferences for brevity and due to journal page restrictions.

Grable and Roszkowski (2008) found that incidental positive mood was positively associated with having a higher level of financial risk tolerance (as measured on a financial risk tolerance scale). In a laboratory experiment, Fehr-Duda et al. (2011) showed that incidental (not induced) good mood has a significant effect on the shape of the probability weighting function for women (but not men); that is, women weighed probabilities of gains and losses relatively more optimistically than men. In contrast, Walser and Eckel (2010) found no effect of mood on risk preferences.

Although there have been a few studies in the economics literature, as discussed above, that examined the relation between mood and risk preferences, there have only been two studies that explored the link between mood and time preferences. Specifically, McLeish and Oxoby (2007) found evidence that inducing subjects with negative mood results in greater impatience (i.e., increased discount rates) but only among women. Ifcher and Zarghamee (2010) found that mild positive affect significantly reduces time preference. In the marketing literature, Pyone and Isen (2011) found that subjects in a positive mood were more forward looking.

In this study, we revisit the issue of determining the effect of mood states on preferences but in contrast to previous studies, we elicit measures of risk and time preferences using a non-hypothetical conventional lab experiment (according to the terminology of Harrison and List 2004) and jointly estimate the parameters of interest in a structural econometric model. This is an important topic that has not been examined in the literature since joint estimation of risk and time preferences could potentially provide a different set of results on mood effects than what has been found in previous studies that did not jointly elicit or estimate these preferences. For example, Andersen et al. (2008) have shown that credible estimation of discount rates rely on the joint estimation of risk and time preferences.

In addition, we also utilize the statistical specification and theoretical framework of Andersen et al. (2008). Unlike much of the previously cited literature (with the exception of Fehr-Duda et al. 2011; Hills et al. 2001; Ifcher and Zarghamee 2010; McLeish and Oxoby 2007; Walser and Eckel 2010), we use non-hypothetical elicitation procedures and use real monetary incentives for recruitment and elicitation of risk and time preferences. We also explore if a cognitively demanding task right after mood inducement could affect risk preferences and whether there are gender differences in elicited risk and time preferences.

To further assess the contribution of our study in the literature and be able to compare our findings with other studies, we developed a table (see Table A1 in the Appendix) that summarizes the relevant literature that relates mood states with risk or time preferences. From the 15 studies we identified, only five of them used real financial commitments to elicit risk or time preferences and none conducted joint elicitation/estimation of risk and time preferences. Of these five studies that used real financial commitments, one study examined incidental moods instead of induced mood (Fehr-Duda et al. 2011) while only a single study (Walser and Eckel 2010) used validated scales from psychology to measure the success of the induction procedure (i.e., mood measurement). Our study uses similar procedures used in four out of these five studies (Fehr-Duda et al. 2011; Ifcher and Zarghamee 2010; McLeish and Oxoby 2007; Walser and Eckel 2010). Our sample size is also comparable to most of the above cited studies.

In terms of the results, one of the studies found no effect of mood (Walser and Eckel 2010) on risk, two of the studies found mood effects on time preferences (McLeish and Oxoby 2007) and risk preferences (Fehr-Duda et al. 2011) but only for women, one study found a significant mood effect on risk preferences but only for a sub-sample (i.e, non-gamblers) (Hills et al. 2001), and one study found significant effects on time preferences that hold across all subject groups (Ifcher and

Zarghamee 2010). In contrast to Walser and Eckel (2010) that did not find an effect of mood on risk, we find that both positive and negative moods increase risk aversion but this depends on whether choices are explained by either Expected Utility theory (EUT) or probability weighting. In contrast to Ifcher and Zarghamee (2010), we find no effect of mood on elicited discount rates.

In addition to the joint elicitation and estimation of risk and time preferences, we also extend our design in two directions. First, we inserted a cognitively demanding task (preference reversals phase) in half of the sessions. Kim and Kanfer (2009) addressed the inconsistencies between AIM and MMH by evaluating what they called “an integrative explanation”. Specifically, they showed that if a cognitively demanding task intervenes between mood induction and risk-taking judgments (defined as choices over dilemmas), the observed trend reverts; i.e., subjects exhibited lower levels of risk-taking judgments (offering support for AIM) as opposed to higher levels of risk-taking when there is no intervening cognitive task (offering support for MMH). In contrast to their study, however, our results suggest that subjects become more risk averse under negative mood when no intervention stage is used. We find support for the AIM when no intervention stage is used for choices consistent with EUT and find support for the MMH when an intervention stage is used for choices consistent with probability weighting. Hence, the important factors that seem to influence results are the cognitively demanding task and the assumption related to probability weighting. We note that Kim and Kanfer’s (2009)study did not use real monetary incentives.

Secondly, due to the widespread evidence of gender differences on choice under risk (e.g., Booth and Nolen 2009a, 2009b; Gneezy, Leonard, and List 2009; Niederle and Vesterlund 2007), we revisit this important issue by employing gender-specific sessions and contrasting these with mixed gender sessions. Interestingly, we find evidence that a same-gender environment can alter elicited risk preferences (but not discount rates) even though subjects are aware that the outcome of their decisions does not depend on decisions made by others.

In the next sections we describe in detail our experimental procedures, present the framework for the analysis and then the results and discussion.

2. Experimental procedures

The experiment we designed was part of a larger project on choice under risk that also involved a lottery choice task and a lottery auction task aimed at identifying preference reversals. In this paper, we used a preference reversal task as a cognitive intervening stage before risk elicitation to check if this intervening stage would make a difference in the measurement of risk preferences under different mood states, as has been proposed in the literature (Kim and Kanfer 2009). Following Andersen et al. (2008), the time preference task was placed at the very end of each session since it involved winning a considerable amount of money and we did not want to risk contaminating the previous tasks with income effects. Andersen et al. (2010) found in one of their treatments that there are no statistically or economically significant order effects in the risk and time preference tasks. Order effects are more likely to appear in situations where a similar task is repeated twice (or more) as in Harrison et al. (2005). Since our risk and preference reversal tasks both involve lotteries and might be considered similar, we presented them to subjects in alternating order between sessions.

As discussed earlier, due to the widespread evidence of gender differences on choice under risk (e.g., Booth and Nolen 2009a, 2009b; Gneezy, Leonard, and List 2009; Niederle and Vesterlund 2007), we also tested whether risk and time preferences might be affected when we alter the environment of the session in terms of gender. Therefore, we conducted additional sessions with males only and females only.

To minimize the number of sessions that we would need to run the full design, we decided to induce different mood states to subjects in the same session. Given that our computer lab is equipped with private booths and no communication between subjects was aloud, we were certain that no mood contagion took place. Our mood inducement technique is described in detail below.

Our full design involved six treatments in six sessions[3]. In the first two treatments we induced half of the subjects with positive mood and half of the subjects with negative mood. The only difference between the first two treatments was that the order of the preference reversals and risk preferences task were alternated. In treatments 3 and 4 (our control treatments), mood was only measured and not induced. The order of the preference reversals and the risk preferences task was also alternated in these treatments. Treatments 5 and 6 were similar to treatment 1 except that subjects in these treatments were all females and males, respectively. Table I shows the experimental design. We only used one proctor or monitor (i.e., one of the authors) for all sessions. To isolate the role of mood and order of the tasks on risk and time preferences we first analyzed treatments 1 to 4 together and then analyzed treatments 1, 5, and 6 together to explore gender differences in our data.

2.1. Description of the experiment

[3] In our very first session a couple of things went wrong which prompted us to rerun this session with a completely different set of subjects. First, one of the subjects could not keep himself quiet during the experiment although we pointed out the necessity of no communication. Improper behavior resulted in early termination of his participation in the session. In addition, a server failure resulted in having subjects wait for more than 10 minutes doing nothing. Since the necessary control was lost and given the sensitivity of our design to contaminating mood behavior, we decided to dismiss all data from this session. Therefore, in total we ran seven sessions, the seventh being a re-run of treatment one. We dismissed data from session 1 from all further analysis.

The conventional lab experiment was conducted using the z-Tree software (Fischbacher 2007).[4] Subjects consisted of undergraduate students at Agricultural University of Athens. During the recruitment, the nature of the experiment and the expected earnings were not mentioned. However, subjects were told that they will be given the chance to make more money during the experiment. Stochastic fees have been shown to be able to generate samples that are less risk averse than would otherwise have been observed (Harrison, Lau, and Rutström 2009).

Each subject participated in only one of the treatments exhibited in Table I. The size of the groups varied from 15 to 18 subjects per treatment. Each treatment lasted a little more than an hour. In total, 101 subjects participated in our experiments, which were conducted in March 2010. This number does not include 15 subjects from session 1 that were dismissed from any further data analysis. We considered these data contaminated as noted in footnote 2.

Each session consisted of different phases: the mood induction phase, the lottery choice phase, the lottery auction phase, the mood measurement phase, the risk preferences phase, the time preferences phase and the post-auction phase[5]. The lottery auction and choice phases are not part of the research agenda of this paper and will not be given further consideration. Subjects were given prior instructions on the overall layout of the session and were also reminded about the procedures at the beginning of each phase. Experimental instructions are available at the anonymous website https://sites.google.com/site/risktimemood/.

2.2. The mood induction phase

[4] z-Tree is a software package designed to facilitate computer-based economic experiments. It has been used in numerous experiments as evident by the more than 2300 citations that the paper documenting the software has collected in Google scholar.

[5] We also measured the rate of preference reversals using lottery choice tasks and lottery auction tasks but since these phases are not part of this paper's research focus, we are not giving a detailed discussion. Prior to the auction phase and mood induction there was also significant training with the auction mechanism which included hypothetical as well as real auctions. These phases of the experiment are discussed in Drichoutis et al., (2011).

Mood induction procedures have been widely used by psychologists and have also been adopted by economists (e.g., Capra 2004; Kirchsteiger, Rigotti, and Rustichini 2006). Capra et al. (2010) give a brief summary of the different methods used in the psychology literature. In this study we used experience of success/failure as our mood induction procedure, similar to what was used in many other studies (Barone, Miniard, and Romeo 2000; Capra 2004; Capra, Lanier, and Meer 2010; Curtis 2006; Hill and Ward 1989; Swinyard 1993, 2003). Specifically, subjects in the mood induction treatments were given a MENSA test that had to be completed within 6 minutes. Half of the subjects received a 16-question *hard* MENSA test and half of the subjects received an *easy* MENSA test (the tests are available at https://sites.google.com/site/risktimemood/).

The questions were first *pretested* in an online survey with a convenience sample using snowballing methods. Subjects were randomly exposed to one of the two versions. After taking the MENSA test online, we then measured subjects' moods (see next subsection). In the *online* hard version, the pretest subjects answered on average 4.5 questions correctly while in the *online* easy version, the pretest subjects answered 12.9 questions. Their scores were displayed right after the expiration of the time required to complete the test, along with a phrase based on previous research stating that a person between 18-55 years old normally answers about 10 questions correctly, that 95% of the people answer at least 6 questions correctly and that only 5% answer more than 12 questions correctly. For the online sample this phrase corresponds to the performance of subjects in our online survey which also received an average of 10 correct questions and have the same age distribution when averaging across both versions of the test. The same phrase was used in the online test and since it was effective in inducing mood (see next paragraph) and generally corresponded with the actual distribution of correct answers, we decided to use the same phrase for the lab auction experiment.

Given subjects' scores in the two versions, this feedback immediately placed the average subject in the *hard* version to the low 5% of the population while the average subject in the easy version was placed at the top 5%. This way subjects in the hard version experienced failure and subjects in the easy version experienced success. In a sample of 49 subjects in the online pretest, the two versions of the test were adequate in inducing different levels of positive affect (the null of equal scores on the positive affect scale was highly rejected on a t-test with a p-value of 0.02).

The procedure we discussed above is not new, has been validated, and has been used in several other studies (e.g., Barone, Miniard, and Romeo 2000; Swinyard 1993, 2003). To successfully complete the inducement phase in the lab, subjects in the lab were only told that this phrase corresponds to the results obtained from another subject pool (i.e., information that corresponded to the performance of subjects from our online test)[6]. Subjects that answered the hard version of the test, scored significantly lower in the positive affect scale (discussed in the next paragraph). There was no significant difference between subjects with respect to the negative affect scale.

2.3. The mood measurement phase

To find ways to measure mood, we turned to the psychology literature for guidance. Watson and Vaidya (2003) provided a comprehensive overview of the dimensionality of the mood construct as well as on ways to measure its dimensions. Mood is usually depicted as a circular scheme with four bipolar dimensions that are spaced 45 degrees apart. The positive affect and

[6] Another method for inducing moods is the use of film clips. However, an important limitation of the use of films is that there are no widely accepted sets of mood eliciting film stimuli, not to mention the challenge of finding film stimuli for culturally different or non-English speaking subjects.

negative affect dimensions are considered the most important measures of the higher order dimension.

The PANAS scale (Positive Affect Negative Affect Schedule; which was later subsumed into the PANAS-X) (Watson 1988) emerged as the standard measure of these constructs and has been widely used in the literature (Bono and Ilies 2006; de Ruyter and Bloemer 1998; Pelled and Xin 1999; Pocheptsova and Novemsky 2010; Pugh 2001). The terms comprising the PANAS-X Positive Affect scale are *active, alert, attentive, determined, enthusiastic, excited, inspired, interested, proud,* and *strong;* the items included in the Negative Affect scale are *afraid, ashamed, distressed, guilty, hostile, irritable, jittery, nervous, scared,* and *upset.* Subjects rated the extent to which they experienced each term right after inducement on a 5-point scale (1 = *very slightly or not at all,* 5 = *extremely*). In the lab the order of appearance of these terms was randomized. The scale has been thoroughly tested for reliability and validity (see Watson and Vaidya 2003).

2.4. The risk preferences phase

To elicit risk preferences we used the multiple price list (MPL) design devised by Holt and Laury (2002). In this design each subject is presented with a choice between two lotteries, A or B as illustrated in Table II. In the first row the subject is asked to make a choice between lottery A, which offers a 10% chance of receiving €2 and a 90% chance of receiving €1.6, and lottery B, which offers a 10% chance of receiving €3.85 and a 90% chance of receiving €0.1. The expected value of lottery A is €1.64 while for lottery B it is €0.475, which results in a difference of €1.17 between the expected values of the lotteries. Proceeding down the table to the last row, the expected values of the lotteries increase but increases much faster for lottery B.

For each row, a subject chooses A or B and one row is then randomly selected as binding for the payout.[7] The last row is a simple test of whether subjects understood the instructions correctly. A risk neutral subject should switch from lottery A to lottery B at the 5th row. In our experiments subjects undertook three risk aversion tasks: they made choices from Table II (the 1x table), a table where payoffs were scaled up by 10 (the 10x table) and a table similar to Table II but without the last three rows (the 1x-framed table). The order of appearance of the tables for each subject was completely randomized to avoid order effects (Harrison et al. 2005). The 10x table served as an elicitation vehicle of risk when larger payoffs are involved while the 1x-framed table was used as an alternate format since subjects could be drawn in the middle of the ordered table irrespective of their true value (Andersen et al. 2007). One of these tables was chosen at the end as binding for the payout. Thus, to infer risk preferences, subjects were asked to provide 27 binary choices from the risk preference task.

2.5. The time preferences phase

The experimental design for measuring discount rates is based on the experiments of Coller and Williams (1999), Harrison, Lau, and Williams (2002) and Andersen et al. (2008). Subjects are confronted with payoff tables similar to Table III and made choices from three tables with different time horizons: the 3-month time horizon table (Table III), the 6-month time horizon table (payment option B pays in 7 months) and the 12-month time horizon table (payment option B pays in 13 months). At the end of the experiment only one table and one row were randomly drawn as binding. Financial constraints precluded us from paying every single subject in each session and hence only one subject was randomly drawn as the winner.

[7] In every step that involved random drawings by the computer, we reassured subjects that the drawing was fair and that extra care was taken by the programmer to make sure that this is the case.

In Table III, option A offers 300 € in 1 month and option B offers 300 € +*x* € in 4 months, where *x* ranged from annual interests rates of 5% to 50% on the principal of 300 €, compounded semi-annualy to be consistent with national banking practices on savings accounts. The table also includes the anual and annual effective interest rates to facilitate comparisons between lab and field investments (Andersen et al. 2008). The tasks provided two future income options instead of one instant and one future option. This front-end delay on the early payment has two advantages: it holds the transaction costs of future options constant (see Coller and Williams 1999 for a discussion) and it avoids the passion for the present that decision makers exhibit when offered monetary amounts today or in the future. Future payments were guaranteed by means of a postdated check with a national bank serving as the third party guarantor. Thus subjects provided 30 binary choices for the time preference task that are used to infer time preferences.

2.6. The post-experiment phase

Subjects provided information about their age, household size and income. Experimental instructions are available at https://sites.google.com/site/risktimemood/.

3. Identification of risk and time preferences

The identification of risk and time preferences closely follows the framework of Andersen et al. (2008), so we will only repeat the basic information here. Andersen et al. (2008) discussed in detail how to put parametric structure on the identification of risk and time preferences, the theoretical issues involved, and the statistical specification.

Let the utility function be the constant relative risk aversion (CRRA) specification[8]:

$$U(M)=\frac{M^{1-r}}{1-r} \tag{0}$$

for $r\neq 1$, where r is the CRRA coefficient. In (0), r=0 denotes risk neutral behavior, r>0 denotes risk aversion behavior and r<0 denotes risk loving behavior.

In addition, if we assume that Expected Utility Theory (EUT) holds for the choices over risky alternatives and that discounting is exponential then the subject is indifferent between two income options M_t and $M_{t+\tau}$ if and only if:

$$U(M_t)=\frac{1}{(1+\delta)^{\tau}}U(M_{t+\tau}) \tag{0}$$

where $U(M_t)$ is the utility of monetary outcome M_t for delivery at time t, δ is the discount rate, τ is the horizon for delivery of the later monetary outcome at time $t+\tau$, and the utility function is separable and stationary over time. δ is the discount rate that equalizes the present value of the two monetary outcomes in the indifference condition (0).

The binary choices of the subjects in the risk preference tasks can be explained by different CRRA coefficients. For example, a subject that made four safe choices (i.e., choosing option A) and then switched to option B would have revealed a CRRA interval of -0.15 to 0.40. The intervals are

[8] One may argue that the risk aversion tasks are done over a different prize domain than the discount rate tasks. This would cause no problem for the assumption of the CRRA function, given that risk aversion is then constant. It would pose a problem however, if other forms are assumed. To allow for the possibility that the relative risk aversion is not constant we also tried a more flexible functional form by adapting the hybrid expo-power function of Saha (1993). The expo-power function can be defined as $u(M)=\left(1-\exp\left(-aM^{1-r}\right)\right)/a$, where M is income and a and r are parameters to be estimated. Relative risk aversion (RRA) is then $r+a(1-r)M^{1-r}$.
Given that the model did not converge for the joint estimation of risk and time preferences, we then estimated the model for risk aversion only. We allowed parameter a to be a separate linear function of the control variables that are used in latter estimations. The estimates indicate that there is no statistically significant deviation in a from zero for any of the variables controlled for, or for the constant. We can therefore conclude that there is no evidence to reject CRRA as a general characterization for this specific sample and this income domain. Similar conclusions were drawn in Harrison, Lau and Rutstrom (2007).

reported in Table II. Similarly, the binary choices in the time preference tasks can be explained by different discount rates. A subject that chose 300 € in 1 month would have revealed a discount rate higher than $(x/300)\cdot 100\%$; otherwise she would have revealed an annual discount rate of $(x/300)\cdot 100\%$ or less[9].

Andersen et al. (2008) explicitly write the likelihood function for the choices that subjects make in these tasks and jointly estimate the risk parameter *r* and the discount rate δ. The contribution to the overall likelihood from the risk aversion responses can be written for each lottery *i* as:

$$EU_i = \sum_{j=1,2}\left(p\left(M_j\right)\cdot U\left(M_j\right)\right) \qquad (0)$$

where $p(M_j)$ are the probabilities for each outcome M_j that are induced by the experimenter (i.e., columns 1, 3, 5 and 7 in Table II). To specify the likelihoods conditional on the model, a stochastic specification from Holt and Laury (2002) is used. The expected utility (EU) for each lottery pair is calculated for candidate estimate of *r* and the ratio:

$$\nabla EU = \frac{EU_B^{1/\mu}}{EU_A^{1/\mu} + EU_B^{1/\mu}} \qquad (0)$$

is then calculated where EU_A and EU_B refer to options A and B respectively, and μ is a structural noise parameter. The index in (0) is linked to observed choices by specifying that the option B is chosen when $\nabla EU > 1/2$.

The conditional log-likelihood can then be written as:

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[9] The fact that the whole experiment was computerized allowed us to impose monotonic preferences (i.e., subjects could only switch once to option B and could not go back and forth). We did not allow for indifference between A and B choices either. Subjects had to clearly state whether they preferred option A or B.

$$\ln L^{RA}\left(r,\mu;y,\mathbf{X}\right)=\sum_i\left(\left(\ln\left(\nabla EU\right)\mid y_i=1\right)+\left(\ln\left(1-\nabla EU\right)\mid y_i=-1\right)\right) \quad (0)$$

where $y_i=1(-1)$ denotes the choice of the option B (A) lottery in the risk preference task *i*.

The conditional log-likelihood for the time preference task can be written in a similar manner if we write the discounted utility of each option as:

$$PV_A=\frac{M_A^{1-r}}{1-r} \quad \text{and} \quad PV_B=\frac{1}{\left(1+\delta\right)^{\tau}}\frac{M_B^{1-r}}{1-r} \quad (0)$$

and the index of the present values as:

$$\nabla PV=\frac{PV_B^{1/\nu}}{PV_A^{1/\nu}+PV_B^{1/\nu}} \quad (0)$$

where ν is a noise parameter for the discount rate tasks. The log-likelihood will then be:

$$\ln L^{DR}\left(r,\delta,\nu;y,\mathbf{X}\right)=\sum_i\left(\left(\ln\left(\nabla PV\right)\mid y_i=1\right)+\left(\ln\left(1-\nabla PV\right)\mid y_i=-1\right)\right) \quad (0)$$

and the joint likelihood will be:

$$\ln L\left(r,\delta,\mu,\nu;y,\mathbf{X}\right)=\ln L^{RA}\left(r,\mu;y,\mathbf{X}\right)+\ln L^{DR}\left(r,\delta,\nu;y,\mathbf{X}\right) \quad (0)$$

Each parameter in equation (0) can be allowed to be a linear function of treatment effects. Equation (0) can be maximized using standard numerical methods. We used the routines made available as a supplemental material in Andersen et al. (2008) with appropriate modifications. For a more thorough and pedagogical treatise on maximum likelihood estimation of utility functions, see Appendix F in Harrison and Rutstrom (2008) or Harrison (2008). The statistical specification also takes into account the multiple responses given by the same subject and allows for correlation between responses.

4. Estimation and results

Each subject in our experiment responded to 57 binary tasks (27 for the risk preference tasks and 30 for the time preference tasks). Data from subjects who chose lottery A over the last row of Table II were dismissed since this is a sign that they failed to comprehend the task. Therefore, 15 subjects were further dropped which resulted in a sample size of 86 subjects, with 2322 risk aversion choices and 2580 discount rate choices. As mentioned previously, since this paper has a twofold goal, we first analyze treatments 1 to 4 together and then examine treatments 1, 5 and 6.

4.1. Was the mood induction successful?

Figure I displays the kernel density estimates of the affect scores for positive and negative affect, respectively. The vertical lines depict mean estimates of the scores per treatment. Remember that a hard MENSA test aims to induce a negative mood to subjects and an easy MENSA test aims to induce a positive mood state through experience of failure and success, respectively. We are certain that our subjects experienced success or failure given that those exposed to the easy MENSA test in the lab answered on average 12.9 questions correctly (out of 16) while those exposed to the hard MENSA test answered only about 6 questions correctly.

It is obvious from panel A that the density function of positive affect for those exposed to the hard MENSA test is slightly shifted to the left implying lower scores for those exposed to the hard test. The density function of those exposed to the easy test has a slightly larger peak but is otherwise very close to the density function of the control group. One could tell a similar story based on the means (vertical lines) of the positive affect scores across treatments.

Panel B shows that both densities associated with the negative affect scores of those exposed to the easy and hard test are shifted right with respect to the control group. The density function of those exposed to the hard test is slightly more to the right but is practically indistinguishable from the density function of those exposed to an easy test. Comparing the means just reconfirms the above.

These results also hold up in a regression context. We run separate regressions for the positive affect and negative affect scales which are depicted in Table IV. The list of covariates includes dummies for those exposed to the easy and hard MENSA tests (the control treatments, where mood was not induced, serve as the base category). We used demographic variables as additional control variables. Variable description is exhibited in Table V.

Results are in agreement with Figure I. Subjects that were exposed to a *hard* test scored significantly lower (by almost 4 points) in the positive affect scale compared to subjects in a control group and those who took the *easy* test. No statistically significant differences are observed between those answering an easy test and those in the control group and the magnitude of the difference in the scores is negligible. Hence, our mood induction procedure was able to induce *lower* levels of positive affect to those that took the *hard* test.

On the other hand, both the *easy* and *hard* tests induced higher negative affect with respect to the control group by as much as 5 points, which is also evident in Figure I where both density functions are shifted to the right. The *Hard* coefficient is larger than the *Easy* coefficient by one point (i.e., those exposed to a hard test had on average higher levels of negative affect) although their difference is not statistically significant. So why did both procedures induce higher negative affect? One explanation could be that the quiz-type procedure resembles exams that associate negatively with students' mood (e.g., test anxiety). It is also important to remember that positive affect and negative affect are two dimensions of mood that can co-exist. The overall conclusion is that subjects that took the *hard* test had lower positive affect than subjects that took the *easy* test and there was no statistically significant difference in their negative affect level. They also exhibited less positive affect and higher negative affect than the control group.

4.2. Risk aversion and discount rates under induced mood states

We first analyze data from treatments 1 to 4 to examine whether mood states can affect risk and time preference elicitation. Also, since we alternated the order of the preference reversal task and the risk preference task after mood inducement, we are able to test the AIM vs. MMH issue; that is, examine the effect of an intervening cognitively demanding task before risk elicitation. Kim and Kanfer (2009) found that this procedure makes a significant difference when evaluating risk-taking judgments.

Table VI exhibits the maximum likelihood estimates of risk and time preferences. We allowed the δ and r parameters of equation (0) to be linear functions of treatment effects. We model r as a linear function of the treatment variables (*Positive mood*, *Negative mood*, *Task order*) as well as their interactions (*Positive* x *Order*, *Negative* x *Order*) in order to capture the differential effect of the order of the tasks and mood induction as predicted by AIM and MMH. The δ parameter is modeled as a linear function of the treatment variables alone (no interaction effects). One could in principle allow several variables to enter the linear specification of δ and r but this comes at the cost of convergence, at least with our data. Given our random assignment to treatments we can safely assume that our effects are causal. There are also no significant differences in the socio-demographic profile of our subjects between the treatments. We used chi-square and Fischer's exact tests to check the variables depicted in Table V (t-tests were used for the continuous variables like age and household size). None of the differences was statistically significant.

Panel A presents the maximum likelihood estimates allowing for risk aversion (joint estimation of risk and time preferences) and assuming an exponential discounting specification. Results in panel A show three things. The first is that mood does not significantly affect time preferences directly. While signs of the coefficients are in the expected direction, i.e., subjects in positive mood exhibit higher discount rates while subjects in negative mood exhibit lower discount rates, these are not statistically significant given the dispersions.

Second, with respect to risk preferences, positive mood has no statistically significant effect on relative risk aversion (RRA) coefficient while negative mood increases risk aversion (by 0.24) but only when there is no intervening task between mood induction and risk preference elicitation. This also means that mood affects time preferences indirectly by altering risk aversion. When we insert an intervening task (i.e., a cognitively demanding task), the effect becomes statistically insignificant. This finding supports the AIM model (versus the Mood Maintenance Hypothesis) but not the integrative explanation of Kim and Kanfer's (2009) which predicts that subjects in negative mood should be less risk averse when there is no intervening stage between mood induction and risk preference elicitation. Our results therefore question the intervening stage explanation offered by Kim and Kanfer (2009) which was based on the use of hypothetical elicitation of risk preferences.

Finally with respect to the order of the tasks, for subjects that we intervened with a cognitively demanding task, risk aversion increased when they were induced with positive mood or not induced at all (control treatment). The RRA coefficient was not affected when induced with negative mood. A t-test indicates that the effect of the order of the tasks was not significantly different between positive mood and control treatment.

4.3. Robustness checks

Basic insights gained over the previous section about the effect of mood on risk and time preferences clearly hinge upon certain assumptions about functional forms. In this section we examine how robust our results are when we deviate from these assumptions. We first consider an alternative discounting function assumed by hyperbolic discounting models[10], then introduce probability weighting under exponential and hyperbolic discounting models and then consider a mixture specification of EUT and probability weighting.

4.3.1. Hyperbolic discounting

When considering a hyperbolic discounting function, one would need to replace (0) with:

$$PV_A = \frac{M_A^{1-r}}{1-r} \qquad \text{and} \qquad PV_B = \frac{1}{(1+k\tau)} \frac{M_B^{1-r}}{1-r} \tag{0}$$

for $k > 0$. Panel B in Table VI shows estimates when considering this alternative discounting function. Not only do we get qualitatively similar results as compared to the exponential discounting model but many estimates also do not significantly change. Therefore, it appears that the issue of whether to use an exponential or hyperbolic discounting specification is not important, at least in our case.

4.3.2. Probability weighting

Up to now we have only assumed Expected Utility for risk. Since the Allais paradoxes (Allais 1953) for EUT and the Nobel-prize winning work of Kahneman and Tversky (1979), we know that EUT often fails and that one must account for probability weighting especially when using smaller scale payoffs. The weighting function proposed by Tversky and Kahneman (1992) has been extensively used in the literature and assumes weights of the form:

[10] As discussed in Andersen et al. (2008), the use of the quasi-hyperbolic specification is not possible due to the existence of a front end delay in our tasks.

$$w(p) = p^{\gamma} \Big/ \left[p^{\gamma} + (1-p)^{\gamma} \right]^{1/\gamma} \qquad (0)$$

In (0), when $\gamma = 1$, it implies that $w(p) = p$ and this serves as a formal test of the hypothesis of no probability weighting. Table VII exhibits the estimates when we assume probability weighting as in (0) and exponential discounting (panel A) or hyperbolic discounting (panel B) specification. A Wald test of the hypothesis that the parameter γ is equal to one, highly rejects the null under exponential discounting (p-value=0) and marginally rejects under hyperbolic discounting (p-value=0.099).

Note that results from the exponential and hyperbolic specification are similar. There are two notable differences with the results of the previous section that are worth discussing. The first one is with respect to the effect of the treatment variables on risk preferences. Results show that negative mood has no (statistically significant) effect on risk aversion. However, we find a statistically significant effect for subjects induced with positive mood when a cognitively demanding stage was intervened. Both results contrast with the results obtained under the specification linear in probabilities.

In addition, mood has no direct effect on elicited time preferences. This is in accordance with previous results from the specification linear in probabilities. Thus, mood only indirectly affects time preferences.

4.3.3. Mixture models

In the previous sections we found that inferences change depending on whether we assume a weighting probability function for risk or a specification linear in probabilities (but not when we assume an exponential or hyperbolic discounting function). The question that arises then is which model should we prefer? Up to now we have assumed only one data generating process at a time and have estimated each model separately in order to identify the effect of mood on risk and time preferences. Harrison and Rutström (2009) allowed more than one process to explain observed behavior instead of assuming that the data are generated by a single process. They estimated a model where some choices were allowed to be EUT-consistent and other choices were allowed to be Prospect Theory-consistent and found roughly equal support. A mixture model poses a different question to the data. As Harrison (2008) noted, "if two data-generating processes are allowed to account for the data, what fraction is attributable to each, and what are the estimated parameter values?"

Let π^{EUT} denote the probability that EUT is correct and $\pi^{PW} = 1 - \pi^{EUT}$ denote the probability that the model that assumes probability weighting is correct. We can replace (0) with:

$$\ln L\left(r^{EUT}, r^{PW}, \delta, \mu, \nu, \pi^{EUT}; y, \mathbf{X}\right) = \ln\left(\pi^{EUT} \times L^{RA-EUT} + \left(1 - \pi^{EUT}\right) \times L^{RA-PW}\right) + \ln L^{DR} \qquad (0)$$

where r^{EUT} is the RRA coefficient from the EUT part and r^{PW} is the RRA coefficient from the part assuming probability weighting. In (0) and (0) we model r as $r = \pi^{EUT} \times r^{EUT} + \left(1 - \pi^{EUT}\right) \times r^{PW}$.

Table VIII provides the maximum likelihood estimates under exponential and hyperbolic discounting respectively[11]. The mixing probability π^{EUT} is estimated to be 0.46 and 0.50 under exponential and hyperbolic discounting respectively. A Wald test of the null hypothesis that $\pi^{EUT} = \pi^{PW} = 0.5$, fails to reject the null (p-value=0.914 and 0.999 for exponential and hyperbolic discounting respectively). This means that EUT and probability weighting receive roughly equal support from our data. Note that a Wald test of the hypothesis about the parameter γ being equal to one highly rejects the null under both discounting specifications (p-value=0.00).

[11] While one could also extend the mixture model we estimated above to allow more than one data generating process for time preferences (i.e., a mixture of exponential and hyperbolic discounting) along with a mixture of risk preferences, we encountered convergence problems that made the model inestimable.

Results are qualitatively and quantitatively similar when assuming exponential or hyperbolic discounting[12]. With respect to the effect of mood on risk preferences, results boil down to this: negative mood has a positive and statistically significant effect on risk preferences as explained by EUT. Negative induced mood makes subjects more risk averse but only when a cognitively demanding task is not intervened between mood induction and risk preference elicitation. This finding is consistent with AIM but not the integrative explanation of Kim and Kanfer's (2009). In addition, while positive mood increases risk aversion under probability weighting (which is consistent with results from Table VII) the effect is not statistically significant. All in all, our results offer support for AIM alone and not for MMH.

A significant difference with the non-mixture models of Table VI and VII is that negative mood has a direct effect on time preferences as well. Subjects induced into negative mood have lower discount rates by 0.1.

With respect to the order of the tasks, having a cognitively demanding task before risk preference elicitation increases risk aversion for subjects in the positive mood and control treatments but not for those in the negative mood treatment.

4.4. Risk aversion, discount rates and mood: Are there gender differences?

To test for gender differences on choice under risk, we ran gender-specific sessions represented by Treatments 5 and 6 in Table I. We did not alternate the order of the tasks as done in Treatments 1 to 4, since we have tested and demonstrated this effect in the previous section. To explore for gender differences, we compared Treatments 1, 5 and 6 and used the data from these treatments

[12] If one insists on discriminating between choice models (e.g., hyperbolic vs. exponential discounting), a test for non-nested specifications would be appropriate. We used the Vuong (1989) as well as the Clarke (2003) tests to answer the question whether a mixture specification with hyperbolic discounting or a mixture specification with exponential discounting is favored and found support for the former.

only. Table IX shows the maximum likelihood estimates from these treatments using a mixture specification of EUT and probability weighting for risk and exponential discounting specification for risk preferences[13]. We allowed r^{EUT} and r^{PW} of equation (0) to be linear functions of treatment effects (namely the *Positive*, *FemTreat* and *MaleTreat* variables), gender, and the interaction between gender and positive mood inducement dummy. The discount factor δ was modeled without an interaction term. The mixing probability π^{EUT} is estimated to be 0.512. Therefore, the complementary probability π^{PW} is 0.488. A Wald test of the null hypothesis that $\pi^{EUT} = \pi^{PW} = 0.5$, fails to reject the null (p-value=0.956). Thus, it appears that there is equal support for EUT and the probability weighting specification. Note that a Wald test of the hypothesis about the parameter γ being equal to one highly rejects the null (p-value=0.00).

The first thing we note from Table IX is that none of the treatment variables has a direct statistically significant effect on time preferences while several variables affect time preferences indirectly through risk aversion. Positive mood has a gender specific effect for females but only under probability weighting. In specific, females (but not males) induced in positive mood exhibit lower risk aversion levels (by 0.37 points) under the probability weighting specification as compared to negative mood inducement. In addition, the level of risk aversion does not differ between males and females when induced with positive mood under probability weighting, but males induced into positive mood exhibit lower risk aversion (by 0.46 points) under EUT. Males also exhibit lower risk aversion (by 0.55 points) when induced under negative mood but this effect is significant for choices consistent with probability weighting and not for choices consistent with EUT.

[13] A mixture model of EUT and probability weighting with hyperbolic specification for time preferences would not converge with our data.

Furthermore, the peer environment had an effect on risk preference elicitation. It appears that subjects behave differently when they are in mixed gender sessions and the effect differs for choices consistent with either EUT or probability weighting. Females reduce their level of risk aversion by 0.35 when placed in all female sessions but this effect is statistically significant only for choices consistent with probability weighting. In contrast, males increase their level of risk aversion by 0.38 when placed in all male session for choices consistent with EUT, and there is no significant difference for choices consistent with probability weighting. A t-test indicates, however, that the reduction in risk aversion (as compared to mixed sessions) does not differ significantly between all male sessions and all female sessions (p-value=0.573) for choices consistent with EUT while the null is rejected (p-value=0.038) for choices consistent with EUT. These differences exist despite the fact that subjects made decisions that they knew did not depend on other subjects in the session.

5. Conclusions

Our objective in this study is to assess the effect of mood states on risk and time preferences. Our paper differs from previous studies in two important ways. First, we simultaneously elicited measures of risk and time preferences and jointly estimated the parameters of interest using structural econometric methods. Credible estimates of risk and time preferences have been found to rely on the joint estimation of risk and time preferences (Andersen et al. 2008). Yet, none of the previous studies jointly elicited these preferences when examining mood effects. Second, instead of choosing either a EUT or probability weighting model, we utilized a more flexible mixture specification that can determine which parts of the decisions are consistent with which model. Third, a vast majority of the studies that examined the effect of mood states on risk or time preferences was conducted in hypothetical contexts. We conducted our risk and time elicitation tasks non-hypothetically. Our results generally suggest that negative mood states (but not positive mood) can significantly affect time preferences both directly and indirectly (the indirect effect comes from the effect on risk aversion coefficients). In contrast to the negligible effect of positive mood, we find that negative mood has a direct negative effect on time preferences. Thus, we cannot reconfirm the result of Ifcher and Zarghamee (2010) which suggests that mild positive affect significantly increases the present value of a future payment. Our finding seemed surprising at first, given the many similarities in the experimental procedures followed (e.g., paid for recruitment, real elicitation context, student sample etc.) in their study and ours. However, Ifcher and Zarghamee (2010) did not consider the simultaneous determination of risk and time preferences and did not use mixture specifications. Thus, in contrast to our work, they implicitly assumed risk neutrality in eliciting time preferences and did not employ a more flexible model.

Considering the robust finding in the literature of the general effect of risk and time preferences on human behavior and health outcomes (e.g., Benhabib and Bisin 2005; Bernheim and Rangel 2004; Fudenberg and Levine 2009), the issue examined in our study has significant implications for assessment of the potential mechanisms through which risk and time preferences affect behavior and health outcomes. Our study supports the argument offered in Ifcher and Zarghamee (2010) that affect should be neutralized before elicitation of time preferences and that uncontrolled affect may be partially responsible for the wide range of time preference values estimated in past time preference studies. It is possible that mood effects could be responsible for the divergence of findings in risk preference elicitation studies as well. This issue is important in economics considering the large literature devoted to estimating and analyzing risk preferences.

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Table I. Experimental design

Treatments	Mood inducement	Subject pool	Order of Tasks
1	Yes, Positive-Negative	Mixed	Preference Reversals – Risk Preferences
2	Yes, Positive-Negative	Mixed	Risk Preferences – Preference Reversals
3	No	Mixed	Preference Reversals – Risk Preferences
4	No	Mixed	Risk Preferences – Preference Reversals
5	Yes, Positive-Negative	Females	Preference Reversals – Risk Preferences
6	Yes, Positive-Negative	Males	Preference Reversals – Risk Preferences

Table II. Sample payoff matrix in the risk aversion experiments

Lottery A				Lottery B				EV^A (€)	EV^B (€)	Difference (€)	Open CRRA interval if subject switches to Lottery B	
p	€	*p*	€	*p*	€	*p*	€					
0.1	2	0.9	1.6	0.1	3.85	0.9	0.1	1.640	0.475	1.17	-∞	-1.71
0.2	2	0.8	1.6	0.2	3.85	0.8	0.1	1.680	0.850	0.83	-1.71	-0.95
0.3	2	0.7	1.6	0.3	3.85	0.7	0.1	1.720	1.225	0.50	-0.95	-0.49
0.4	2	0.6	1.6	0.4	3.85	0.6	0.1	1.760	1.600	0.16	-0.49	-0.15
0.5	2	0.5	1.6	0.5	3.85	0.5	0.1	1.800	1.975	-0.18	-0.15	0.14
0.6	2	0.4	1.6	0.6	3.85	0.4	0.1	1.840	2.350	-0.51	0.14	0.41
0.7	2	0.3	1.6	0.7	3.85	0.3	0.1	1.880	2.725	-0.85	0.41	0.68
0.8	2	0.2	1.6	0.8	3.85	0.2	0.1	1.920	3.100	-1.18	0.68	0.97
0.9	2	0.1	1.6	0.9	3.85	0.1	0.1	1.960	3.475	-1.52	0.97	1.37
1	2	0	1.6	1	3.85	0	0.1	2.000	3.850	-1.85	1.37	+∞

Note: Last four columns showing expected values and implied CRRA intervals were not shown to subjects.

Table III. Payoff table for 3 month horizon in discount rate experiments

Payoff alternative	Payment option A in € (Pays amount below in 1 month)	Payment option B in € (Pays amount below in 4 months)	Annual interest rate in %	Annual effective interest rate in %
1	300	304	5	3.4
2	300	308	10	6.8
3	300	311	15	10.1
4	300	315	20	13.5
5	300	319	25	16.9
6	300	323	30	20.3
7	300	326	35	23.6
8	300	330	40	27.0
9	300	334	45	30.4
10	300	338	50	33.8

Table IV. Regression results for positive and negative affect

	Positive affect		Negative affect	
	Coef.	Std.Error	Coef.	Std.Error
Constant	**43.577****	**17.847**	**45.698*****	**13.765**
Easy	0.549	1.711	**3.917*****	**1.319**
Hard	**-3.776****	**1.703**	**5.013*****	**1.313**
Age	-0.078	0.944	**-1.796****	**0.728**
Gender	0.566	1.394	**2.277****	**1.075**
Hsize	-0.187	0.671	-0.325	0.518
$Educ_2$	-1.287	2.485	0.908	1.916
$Educ_3$	-3.092	2.756	**3.779***	**2.126**
$Educ_4$	-2.239	3.858	**5.124***	**2.976**
$Educ_5$	-1.917	4.926	**7.057***	**3.799**
$Income_2$	-4.826	2.990	1.320	2.306
$Income_3$	-5.018	3.187	3.394	2.458
$Income_4$	-0.334	3.164	0.387	2.440
R-squared	0.187		0.254	
Adj. R-squared	0.076		0.153	

Note: ***, **, * = Significance at 1%, 5%, 10% level.

Table V. Variable description

Variable	Variable description	Mean	SD
Age	Subject's Age	20.523	1.636
Gender	Dummy, 1=male	0.442	0.500
Hsize	Household size	4.279	1.059
$Educ_1$*	Dummy, 1st year student	0.221	0.417
$Educ_2$	Dummy, 2nd year student	0.128	0.336
$Educ_3$	Dummy, 3rd year student	0.349	0.479
$Educ_4$	Dummy, 4th year student	0.186	0.391
$Educ_5$	Dummy, 5th year student	0.116	0.322
$Income_1$*	Dummy, Household's economic position is good, very good or above average	0.070	0.256
$Income_2$	Dummy, Household's economic position is average	0.512	0.503
$Income_3$	Dummy, Household's economic position is below average	0.221	0.417
$Income_4$	Dummy, Household's economic position is bad or very bad	0.198	0.401
Positive mood (*Hard*)	Dummy, Subject is induced into positive mood (exposed to hard MENSA test)	0.384	0.489
Negative mood (*Easy*)	Dummy, Subject is induced into negative mood (exposed to easy MENSA test)	0.349	0.479
*Control**	Dummy, Subject's mood is not induced	0.267	0.445
Task order	Dummy, Preference reversal task is conducted first	0.686	0.467
FemTreat	Dummy, only females in the session	0.186	0.391
MaleTreat	Dummy, only males in the session	0.198	0.401
*Mixed**	Dummy, mixed gender sessions	0.616	0.489

* Removed for estimation purposes.

μ

Table VI. Estimates of risk and time preferences

		CRRA coefficient (r)		Individual discount rate (δ for exponential, k for hyperbolic)	
		Estimate	Std. Error	Estimate	Std. Error
A. Exponential discounting					
Positive mood	*Task order=1*	-0.078	0.061	0.039	0.030
	Task order=0	0.004	0.101		
Negative mood	*Task order=1*	-0.076	0.098	-0.043	0.038
	Task order=0	0.241**	0.100		
Task order	*Positive mood*	0.234**	0.084	-0.035	0.026
	Negative mood	-0.001	0.082		
	Control	0.315**	0.107		
Constant		0.591**	0.113	0.129**	0.039
μ		0.080**	0.016		
ν				0.028**	0.009
B. Hyperbolic discounting					
Positive mood	*Task order=1*	-0.081	0.064	0.041	0.031
	Task order=0	0.004	0.101		
Negative mood	*Task order=1*	-0.080	0.106	-0.043	0.040
	Task order=0	0.244**	0.099		
Task order	*Positive mood*	0.237**	0.086	-0.035	0.027
	Negative mood	-0.003	0.088		
	Control	0.321**	0.105		
Constant		0.581**	0.112	0.133**	0.039
μ		0.082**	0.017		

ν	0.029**	0.009

Note: **, * = Significance at 5%, 10% level. This table presents several conditional marginal effects. For example, "*Positive mood*, *Task order*=1" refers to the marginal effect of *Positive mood conditional* on *Task order* taking the value of 1. In other words, "*Positive mood*, *Task order*=1" captures the effect of positive mood in the treatments that intervened a cognitively demanding task before risk preference elicitation. Likewise, "*Task order, Positive mood*" refers to the effect of *order of the tasks* for subjects induced into *Positive mood*.

Table VII. Estimates of risk and time preferences assuming probability weighting

		CRRA coefficient (r)		Curvature of the probability weighting function (γ)		Individual discount rate (δ for exponential, k for hyperbolic)	
		Estimate	Std. Error	Estimate	Std. Error	Estimate	Std. Error
A. Exponential discounting							
Positive mood	*Task order=1*	0.300**	0.141			0.015	0.064
	Task order=0	0.096	0.090				
Negative mood	*Task order=1*	0.069	0.142			-0.102	0.083
	Task order=0	0.334	0.538				
Task order	*Positive mood*	0.151	0.153			0.134	0.099
	Negative mood	-0.319	0.514				
	Control	-0.053	0.104				
Constant		0.306**	0.062	0.375**	0.143	0.285**	0.100
μ		0.085**	0.017				
ν						0.079**	0.034
B. Hyperbolic discounting							
Positive mood	*Task order=1*	0.286	0.215			0.022	0.107

	Task order=0	0.090	0.125				
Negative mood	*Task order=1*	0.064	0.134			-0.099	0.117
	Task order=0	0.282	1.035				
Task order	*Positive mood*	0.141	0.191				
	Negative mood	-0.274	0.956			0.135	0.106
	Control	-0.055	0.104				
Constant		0.299**	0.119	0.354	0.393	0.299	0.208
μ		0.081	0.066				
ν						0.083	0.073

Note: **, * = Significance at 5%, 10% level. This table presents several conditional marginal effects. For example, "*Positive mood*, *Task order*=1" refers to the marginal effect of *Positive mood conditional* on *Task order* taking the value of 1. In other words, "*Positive mood*, *Task order*=1" captures the effect of positive mood in the treatments that intervened a cognitively demanding task before risk preference elicitation. Likewise, "*Task order, Positive mood*" refers to the effect of *order of the tasks* for subjects induced into *Positive mood*.

Table VIII. Mixture specification of Expected Utility and probability weighting

		CRRA coefficient $\left(r^{EUT}\right)$		CRRA coefficient $\left(r^{PW}\right)$		Curvature of the probability weighting function $\left(\gamma\right)$		Individual discount rate (δ)	
		Estimate	Std. Error	Estimate	Std. Error	Estimate	Std. Error	Estimate	Std. Error
A. Exponential discounting									
Positive mood	*Task order=1*	0.035	0.104	0.214	0.306			0.031	0.043
	Task order=0	0.049	0.157	0.061	0.118				
Negative mood	*Task order=1*	-0.037	0.148	0.075	0.128			-0.098**	0.047
	Task order=0	0.478**	0.104	-0.010	0.102				
Task order	*Positive mood*	0.417**	0.159	-0.018	0.120			-0.056	0.041
	Negative mood	-0.084	0.139	-0.085	0.180				
	Control	0.431**	0.110	-0.171	0.299				
Constant		0.388**	0.165	-1.611**	0.339	0.138	0.113	0.200**	0.068
π		0.463	0.343	0.537	0.343				
μ		0.042	0.039						
ν								0.039**	0.018
B. Hyperbolic discounting									

Positive mood	*Task order=1*	0.038	0.121	0.267	0.264			0.033	0.047
	Task order=0	0.064	0.163	0.074	0.146				
Negative mood	*Task order=1*	-0.045	0.179	0.094	0.136			-0.101*	0.052
	Task order=0	0.500**	0.134	-0.029	0.127				
Task order	*Positive mood*	0.418**	0.192	-0.035	0.158			-0.052	0.049
	Negative mood	-0.101	0.162	-0.105	0.191				
	Control	0.444**	0.145	-0.228	0.274				
Constant		0.342**	0.143	0.322*	0.177	0.156**	0.063	0.217**	0.059
π		0.500	0.306	0.500	0.306				
μ		0.049	0.024**						
ν								0.043**	0.016

Note: **, * = Significance at 5%, 10% level. This table presents several conditional marginal effects. For example, "*Positive mood*, *Task order*=1" refers to the marginal effect of *Positive mood conditional* on *Task order* taking the value of 1. In other words, "*Positive mood*, *Task order*=1" captures the effect of positive mood in the treatments that intervened a cognitively demanding task before risk preference elicitation. Likewise, "*Task order, Positive mood*" refers to the effect of *order of the tasks* for subjects induced into *Positive mood*.

Table IX. Mixture specification of Expected Utility and probability weighting under exponential discounting (gender differences)

		CRRA coefficient $\left(r^{EUT}\right)$		CRRA coefficient $\left(r^{PW}\right)$		Curvature of the probability weighting function (γ)		Individual discount rate (δ)	
		Estimate	Std. Error	Estimate	Std. Error	Estimate	Std. Error	Estimate	Std. Error
Positive mood	*Males*	0.029	0.163	-0.078	0.137			0.052	0.076
	Females	0.205	0.268	-0.366*	0.192				
Females only session		-0.115	0.148	-0.347**	0.161			-0.027	0.081
Males only session		0.377*	0.194	-0.188	0.185			-0.039	0.093
Gender	*Positive mood*	-0.457**	0.232	-0.267	0.202			-0.056	0.139
	Negative mood	-0.281	0.310	-0.555**	0.120				
Constant		0.650**	0.287	0.971**	0.060	0.325**	0.077	0.212	0.137
π		0.512**	0.212	0.488**	0.212				
μ		0.048**	0.007						
ν								0.056**	0.021

Note: **, * = Significance at 5%, 10% level. This table presents several conditional marginal effects. For example, "*Positive mood*, *Males*" refers to the marginal effect of *Positive mood conditional* on *Gender* being male. In other words, "*Positive mood*, *Males*" captures the effect of positive mood for males. Likewise, "*Gender, Positive mood*" refers to the effect of *gender* for subjects induced into *Positive mood*.

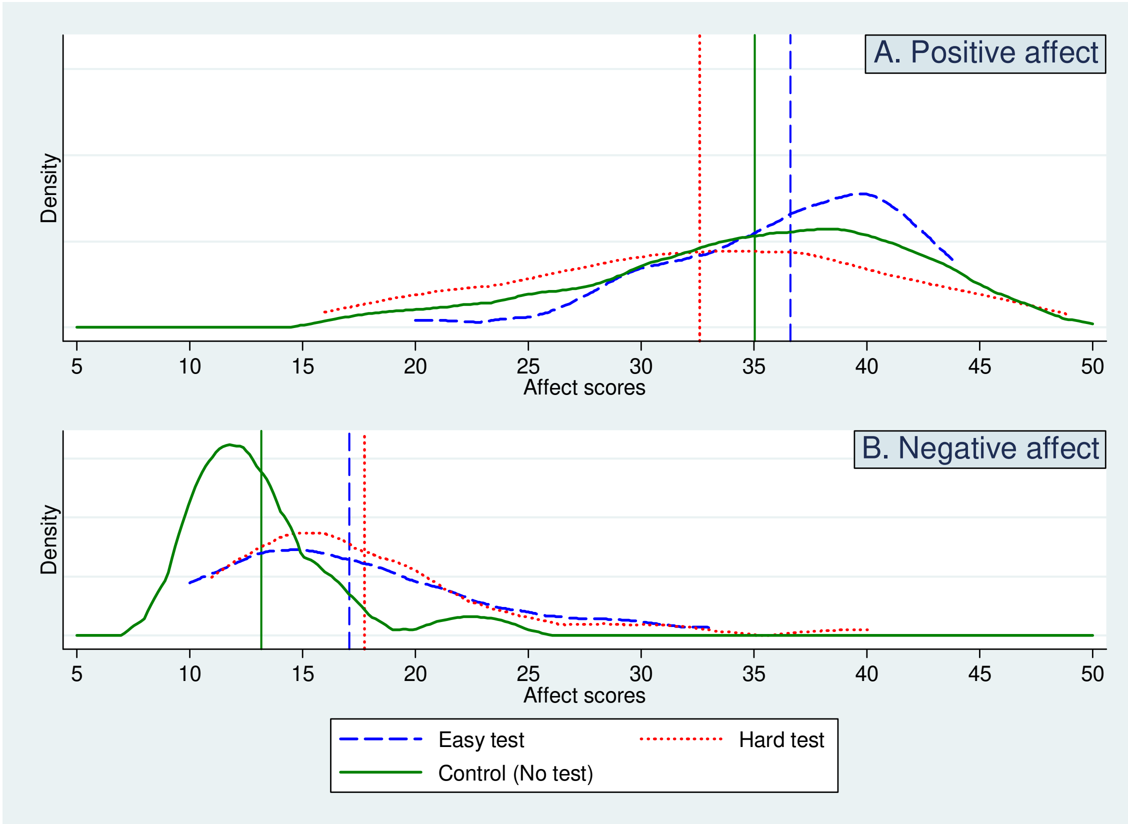

Figure I. Kernel density estimates for affect scores