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Emotional balance and probability weighting

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Abstract We find suggestive evidence that emotional balance has an impact on probability weighting incremental to demographic controls. Specifically, low negative affectivity (implying high emotional balance) tends to be a characteristic of those whose probability weighting functions exhibit lower curvature and more neutral elevation. In other words, emotional balance seems to push people in the direction of normative expected utility theory.

Keywords Emotional balance · Prospect theory · Negative affectivity · Probability weighting

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1 Introduction

We report the results of an experiment designed to explore whether a relationship exists between proxies for emotional balance and prospect theory's probability weighting function parameters. There is abundant evidence that emotion and mood affect financial decision-making. Emotion markers are present when markets heat up (Lo and Repin 2002). People are more likely to insure against emotionally vivid events (Johnson et al. 1993). The disposition effect, the tendency to hold on to losing investments too long, seems best explained by emotion (Summers and Duxbury 2007). Positive affect influences investment (MacGregor et al. 2000). Visceral factors seem to play an important role in intertemporal choice and lack of self-control (Loewenstein 1996, 2000). National stock markets may even be impacted via such triggers as sunlight, day length and changes thereto (Hirshleifer and Shumway 2003; Kamstra et al. 2000, 2003), sporting success (Edmans et al. 2007), and aviation disasters (Kaplanski and Levy 2010). While there is evidence suggesting that emotions can play a positive role in decision-making (Bechara et al. 1997), evidence to the contrary (Lo et al. 2005; Shiv et al. 2005) and the simplifying invocation of rationality by conventional finance have led to the presumption that financial decisions are not only best made cognitively and without mediation by possibly bias-inducing emotional forces but also usually are.

While decision-making has been traditionally viewed as a purely cognitive activity, and to the extent that emotions are considered, it is only through *anticipated* emotions (such as the regret that may be felt if a poor investment is made), in the "risk-as-feelings" view of Loewenstein et al. (2001), *immediate* visceral reactions concurrent with the decision itself may occur, and these may influence the cognitive process, leading to a feedback loop between cognition and emotion. If one subscribes to such a view, it is natural to suspect that emotion plays a role in decision-making under risk. Specifically, given that rationality and expected utility theory (EUT) go hand in hand, it is logical to consider the possibility that emotion is a key driver behind non-EUT-type behavior.[1] We focus our attention here on prospect theory (PT), as developed by Kahneman and Tversky (1979) and Tversky and Kahneman (1992). Loss aversion and probability weighting are the two most obvious markers of non-EUT-type behavior, and there is evidence that they are impacted by emotional forces. Dhar and Wertenbroch (2000) document this for loss aversion. Also, Rottenstreich and Hsee (2001) build a case for probability weighting. We focus on probability weighting here, not only because it is quite clear what the probability weighting function should look like under EUT but also because there is no unambiguous measure of loss aversion.[2] Rottenstreich and Hsee propose that the shape of PT's probability weighting function can be deconstructed such that the steep slopes at each end of the curve reflect emotional reactions from movements from near-certainty to certainty and impossibility to near-impossibility. In their experiments, they show that if an outcome is affect-rich (or emotion-laden) greater curvature for the weighting function (implying greater

[1] It is common to equate the EUT axioms with rationality (e.g., Wakker 2010; Edwards 1992).

[2] See Abdellaoui et al. (2008) for a discussion of different definitions of loss aversion.

steepness at the endpoints and less sensitivity in the mid-range) is required to explain behavior.

While the latter study suggests that probability weighting can be affected by emotional factors which are situation-dependent, probability weighting may also be influenced by emotional factors which are individual-dependent. There is abundant evidence that various emotional predispositions and financial tendencies have a significant heritable component (Larsen and Buss 2008; Barnea et al. 2010; Cesarini et al. 2010), suggesting a mechanism for heterogeneity. Bruhin et al. (2010) find that while most exhibit PT-type behavior, a substantial minority seems to follow EUT. Given the role played by probability weighting in financial decision-making and differences in emotional characteristics among individuals, heterogeneous financial behavior may in part be the result of cross-sectional differences in probability weighting function parameters arising from individual-specific emotional characteristics. We conjecture that an important individual difference in this context is the affective influence regulation, which we call emotional balance (EB). Individual differences in affective information processing exist (Barrett 1998; Gohm and Clore 2000). In particular, variation among individuals exists in terms of feeling intensity and the degree to which people allow their feelings to be integrated with their judgments and decisions. While emotion properly harnessed can facilitate decision-making, given free rein it can lead to poor choices. Logically, those who are better able to harness their emotions should make better decisions. Traders able to do so perform better (Lo et al. 2005). In the context of decision-making under risk, those with better emotional self-awareness and control over their feelings (i.e., those with greater EB) might be expected to act in a manner more closely resembling normative EUT-type preferences. In this study, we measure the degree of resemblance to EUT-type preferences by examining the curvature and elevation of the probability weighting function.

2 Background

2.1 PT

In our experiment, subjects are only asked to consider binary prospects, both of whose outcomes are either non-negative or non-positive. Let $P(z_1, q_1; z_2)$ denote a single-domain binary prospect, where z_1 and z_2 ($|z_1| > |z_2| \geq 0$) are the two possible outcomes (i.e., wealth changes) with probabilities q_1 and $1 - q_1$, respectively. According to the PT formulation of Tversky and Kahneman (1992), prospect value $V(P)$ can be expressed as

$$V(P) = w^{+}(q_1)v(z_1) + [1 - w^{+}(q_1)]v(z_2) \quad \text{if } z_1 > z_2 \geq 0 \tag{1a}$$

$$V(P) = w^{-}(q_1)v(z_1) + [1 - w^{-}(q_1)]v(z_2) \quad \text{if } z_1 < z_2 \leq 0 \tag{1b}$$

where $v(z)$ is a (reference point-dependent) value function, and $w^{+}(q)$ and $w^{-}(q)$ are non-linear probability weighting functions for the positive and negative domains, respectively. Agents choose among different prospects by maximizing prospect value $V(P)$.

Various functional forms have been used for $v(z)$, $w^{+}(q)$ and $w^{-}(q)$. Stott (2006) analyzed 256 model variants for PT to ascertain which ones conformed most closely to typical risk taking behavior in his data, concluding the following two-part power function (from Tversky and Kahneman 1992) worked best for the value function:

$$v(z) = z^{\alpha},\ 0 < \alpha \quad \text{if } z \geq 0 \tag{2a}$$

$$v(z) = -\lambda(-z)^{\beta},\ 0 < \beta, \lambda \quad \text{if } z < 0 \tag{2b}$$

where typically it is found that $0 < \alpha < 1$ and $0 < \beta < 1$, reflecting concavity for gains and convexity for losses; and $\lambda > 1$, because people are generally unwilling to take a fair bet on a coin flip. Nevertheless, since, here, we do not consider mixed prospects (i.e., those with both positive and negative outcomes), λ is not identified and can be ignored.

2.1.1 One-parameter probability weighting models

An appropriate probability weighting function must embody low-probability overweighting (to explain lotteries and insurance), probabilistic insensitivity in the mid-range (consistent with abundant evidence from the psychology literature), and high-probability (relative to certainty) underweighting (to account for the tendency to underweight almost certain outcomes relative to certain). Tversky and Kahneman (1992) specify the following inverted S-shaped functional form (which we denote as 'TK') which accomplishes this purpose:

$$w^{+}(q) = \frac{q^{\gamma}}{(q^{\gamma} + (1-q)^{\gamma})^{1/\gamma}}, \quad 0.28 \leq \gamma \tag{3a}$$

$$w^{-}(q) = \frac{q^{\delta}}{(q^{\delta} + (1-q)^{\delta})^{1/\delta}}, \quad 0.28 \leq \delta \tag{3b}$$

Monotonicity requires the lower bound 0.28. Mid-range probabilistic insensitivity, which is frequently observed, implies $\gamma, \delta < 1$.[3] EUT-type linearity is implied by $\gamma = 1$ (and $\delta = 1$), and curvature increases as γ (and δ) declines below this level.[4]

Stott (2006) found that the following probability weighting function (which we denote as 'P1'), suggested by Prelec (1998), actually fitted his data somewhat better than TK:

$$w^{+}(q) = \exp[-(-\ln(q))^{\gamma}], \quad 0 < \gamma \tag{4a}$$

$$w^{-}(q) = \exp[-(-\ln(q))^{\delta}], \quad 0 < \delta \tag{4b}$$

Again, probabilistic insensitivity implies $\gamma, \delta < 1$. In contradistinction to TK, Prelec (1998) developed P1 using an axiomatic approach, an implication of which is that

[3] Probabilistic insensitivity (implied by these parameters exceeding 1.0) entails mid-range probabilistic insensitivity coupled with over-sensitivity in the neighborhood of the endpoints.

[4] Figure A1 of the Web-Appendix shows probability weighting functions based on the Tversky and Kahneman (1992) estimated parameters, as well as those estimated here.

$\gamma = \delta$, which we test below using our dataset. When it is justifiable to impose this condition we use upper-case gamma: $\Gamma = \gamma = \delta$. Note that for typical parametric values of TK and P1, the probability weighting function is below the 45-degree line for most (but far from all) of its range.[5]

2.1.2 Two-parameter probability weighting models

Two principal two-parameter weighting functions have also been proposed. The first (P2) is a straightforward extension of Prelec's (1998) one-parameter weighting function[6]:

$$w^{+}(q) = \{\exp[-\left(-\ln(q)\right)^{\gamma_1}]\}^{\gamma_2}, \quad 0 < \gamma_1, \gamma_2 \tag{5a}$$

$$w^{-}(q) = \{\exp[-\left(-\ln(q)\right)^{\delta_1}]\}^{\delta_2}, \quad 0 < \delta_1, \delta_2 \tag{5b}$$

Note that γ_1 and δ_1 are analogous to γ and δ from one-parameter models. The second (GE), usually attributed to Goldstein and Einhorn (1987), is as follows:

$$w^{+}(q) = \frac{\gamma_2 * q^{\gamma_1}}{\gamma_2 * q^{\gamma_1} + (1-q)^{\gamma_1}}, \quad 0 < \gamma_1, \gamma_2 \tag{6a}$$

$$w^{-}(q) = \frac{\delta_2 * q^{\delta_1}}{\delta_2 * q^{\delta_1} + (1-q)^{\delta_1}}, \quad 0 < \delta_1, \delta_2 \tag{6b}$$

The second parameter in the case of both models reflects elevation (or attractiveness) relative to the 45-degree line. Note that if the second parameter is set equal to unity, then $\gamma_1 = \gamma$ (and $\delta_1 = \delta$) with P2 collapsing to P1, and GE reducing to something very much like TK. Under P2, in the positive domain, the higher γ_2 is, the greater is the range for which the probability weighting function is below the 45-degree, and hence the more pessimistic the agent in question will be. On the other hand, in the negative domain under P2, optimism is implied by high values of δ_2, The opposite holds under GE: in the positive (negative) domain, the higher γ_2 (δ_2) is, the more optimistic (pessimistic) the agent in question will be.

There is a level of pessimism/optimism that is neutral (or EUT-type) in the sense that the probability weighting function is above the 45-degree line as often as it is below it, which, given monotonicity and a single inflection point, implies $w^{+}(0.5) = 0.5$ and $w^{-}(0.5) = 0.5$. First, it is easy to show that, provided $0.28 \leq \gamma < 1$ for TK and provided $0 < \gamma < 1$ for P1, the weighting function will always exhibit positive-domain pessimism because it is mathematically forced to intersect the 45-degree line below $q = 0.5$. Similarly, the weighting function will always exhibit negative-domain optimism when $0.28 \leq \delta < 1$ for TK and $0 < \delta < 1$ for P1. This in fact suggests that γ (δ) in one-parameter models is picking up both probabilistic

[5] For example, using TK and Tversky and Kahneman's (1992) median values of γ and δ, the intersections with the 45-degree line are at $q = .34$ (for γ) and $q = .38$ (for δ).

[6] Prelec (1998) imposes the constraint $\gamma = \delta$ for both his one-parameter and two-parameter models, showing this follows from his axiomatic approach. We find that both under P1 and P2 this constraint cannot be rejected for a majority of the subjects in our sample.

insensitivity and positive-domain pessimism (negative-domain optimism), where both behavioral tendencies increase with declines in γ (δ). The fact that one-parameter weighting functions actually fit the data well is a testament to the fact that pessimism for gains/optimism for losses is the norm. Two-parameter models are more subtle because they potentially allow for either optimism or pessimism in the two domains. In the case of GE, it can be shown that $\gamma_2 = 1$ (and $\delta_2 = 1$) always implies (and is implied by) 45-degree line intersection occurring at $q = 0.5$. Therefore, letting γ_2^N and δ_2^N denote, respectively, the values of γ_2 and δ_2 such that neutral pessimism/optimism is present, under GE $\gamma_2^N = \delta_2^N = 1$ regardless of the values of γ_1 and δ_1. Matters are more subtle in the case of P2 since it can be shown that

$$\gamma_2^N = [-\ln(0.5)]^{1-\gamma_1} \tag{7a}$$

$$\delta_2^N = [-\ln(0.5)]^{1-\delta_1} \tag{7b}$$

If $\gamma_1, \delta_1 = 1$, then $\gamma_2^N, \delta_2^N = 1$. When $\gamma_1, \delta_1 < 1$, clearly $\gamma_2^N, \delta_2^N < 1$ because $-\ln(0.5) = 0.693$.

2.2 Emotion and EB

In personality psychology, a five-factor model known as the “Big Five” has received much support (Larsen and Buss 2008). One of the five trait groupings is often termed “emotional stability,” with adjectives such as calm, composed, and poised characterizing one polar extreme, and adjectives such as anxious, excitable, and nervous the other. While all of us can be composed at times and at other times nervous, what makes emotional stability a trait is the tendency for people to vary in their *habitual* disposition in this realm. Those low on emotional stability or EB are said to exhibit “neuroticism” or “negative affectivity” (NA) (Watson and Clark 1984). A conventional instrument for measuring NA (and the one that we will use) also measures the so-called positive affectivity (PA). PA is associated with states high in pleasantness and activation, such as elation, enthusiasm, and pleasurable engagement. Another way to tease out EB is not to focus on innate tendencies, but rather on the ability of individuals to overcome their emotions. Emotional intelligence (EI), defined by Salovey and Mayer (1990) as “the ability to monitor one’s own and others’ feelings and emotions, to discriminate among them and to use this information to guide one’s thinking and actions,” captures this ability.

3 Hypotheses

Based on our previous discussion, it seems to be a reasonable conjecture that the higher the level of one’s EB, the less closely one’s probability weighting function conforms to PT and the more closely it conforms to EUT. The intuition is that people with higher levels of EB will be less influenced by their emotions when making decisions involving risk. Since EUT-type behavior requires probability weighting function linearity, this conjecture suggests the following two testable hypotheses:

Hypothesis 1 In the domain of gains, higher EB leads to γ and γ_1 values that are closer to unity. And in the domain of losses higher EB leads to δ and δ_1 values that are closer to unity.

Hypothesis 2 In the domain of gains, higher EB leads to γ_2 values closer to their neutral levels γ_2^N. And, in the domain of losses, higher EB leads to δ_2 values closer to their neutral levels δ_2^N.

Importantly, EUT is nested in the PT probability weighting functions: as $\gamma, \delta, \gamma_1, \delta_1, \gamma_2, \delta_2 \to 1$, probability weighting in conformity to EUT is approached.

4 Survey

4.1 Setup

The present experiment was conducted in a computer lab at McMaster University over three sessions from the fall of 2009 to the fall of 2010. 96 students were invited to participate. They were recruited via a mass e-mailing to all junior and senior undergraduate business students. All participants had taken at least basic courses in finance/economics and probability/statistics.

Prior to the start of the experiment, participants were provided with a set of instructions and were given about 20 min to read through them.[7] Next, the experimenters provided a recap, during which the procedural and technical questions were addressed. Then, subjects began to answer 100 questions via a web-based platform that was devised for this purpose. Brief instructions and questions were presented on their computer screen.

Questions were grouped into two major categories. One category consisted of 60 questions on risk attitude. These questions were very similar to the set employed in Tversky and Kahneman (1992). Specifically, we used their 56 non-mixed prospect questions along with four of their mixed prospect questions. The latter four questions, however, are not considered here. As discussed in the next section, these risk attitude questions were designed to elicit participants' preferences between risky prospects and a set of corresponding certain prospects, allowing for the elicitation of estimated certainty equivalents. From these certainty equivalents, estimation of the PT function parameters was possible. Further description of this category of questions is provided in Sect. 4.2.[8]

The second major category of questions, of which there were 32, was designed to tease out EB. Further details on this category of questions are provided in Sect. 4.3. To obviate potential ordering effects, two types of ordering of the two major categories of questions were used. Roughly half of the participants (randomly chosen) completed the experiment with the risk attitude questions coming before the EB questions, while roughly half answered the EB questions first. The final eight questions requested basic

[7] See Web-Appendix for the experimental instructions along with screen shots viewed by participants.

[8] These questions as well as all other categories of questions are provided in the Web-Appendix.

demographic data (such as age, gender, and education). Further discussion of these questions appears in Sect. 4.5.

The experiment lasted approximately 2 h, after which each participant received a $40 appearance fee. This worked out to $20 per hour, which is higher than the going rate for undergraduate employment.

4.2 Elicitation of risk attitude

The elicitation procedure was similar to that of Tversky and Kahneman (1992). In each of the 28 non-negative prospect questions, subjects were asked to express their preference between (i) a prospect with two possible non-negative outcomes the expected value of which was positive and (ii) a set of eight certain positive gains. These eight certain positive gains consisted of seven values which were evenly spaced between the two possible outcomes of the prospect, plus the higher of its two possible outcomes. These payoffs were displayed on the screen in ascending order. Subjects were required to choose (by clicking on) the number which represented the minimum certain gain that they found acceptable (i.e., preferred or were indifferent to) when compared to taking the prospect. After the selection was made, the screen then showed another set of eight certain gains. The purpose of this second set was to refine the estimated certainty equivalent. The eight gains in this set were evenly spaced between two values, one 10 % lower than the highest amount rejected in the previous selection and the other 10 % higher than the lowest amount accepted.

The 28 non-positive prospect questions were mirror images (i.e., only the sign of the outcomes was reversed) of the non-negative prospect questions. In each case, participants were required to express the preference between (i) a prospect with two possible non-positive outcomes the expected value of which was negative, and (ii) a set of eight certain losses. The process for eliciting certainty equivalents was similar to the case of non-negative prospects with once again a second step for refinement purposes.

Apart from the $40 appearance fee received by each participant, no additional financial incentives were received related to the prospect question responses. In some experimental studies (e.g., von Gaudecker et al. 2011), participants have also been paid according to randomized outcomes of the prospects examined. To avoid negative overall payoffs, the appearance fee is typically set at a high enough level such that it can cover the worse possible negative outcome. Nevertheless, some participants may combine the appearance fee with the potential outcome, thus altering the reference points and potentially influencing their aversion to negative outcomes. Moreover, at least in the negative domain, it appears that the presence of a financial incentive has no impact on preference revelation (Etchart-Vincent and l'Haridon 2011).

4.3 EB proxies and PA

EB is proxied by two instruments, one based on EI, the other on NA. As will be described, the proxy based on EI is SREIT, while the reverse proxy based on NA is also called NA (with lower values of NA indicating higher EB). Beginning with the latter, the International Positive Affectivity-Negative Affectivity Schedule-Short Form (I-PANAS-SF), proposed and tested for validity by Thompson (2007), yields in addition to the NA instrument another for PA (where we use NA and PA for both constructs and measures).[9] The essential idea is to elicit a reaction to a collection of affective adjectives (e.g., "upset" for NA; "attentive" for PA) by asking participants how often their feelings tend in the direction of the state under consideration. Using a 5-point Likert scale ranging from "1" (never) to "5" (always), and averaging over the five questions, both the NA and PA scales range from 1 to 5.

Turning to EI, the measure we utilize is an abbreviated version of Schutte et al.'s (1998) full 33-question SREIT (Self-Report Emotional Intelligence Test). Mayer et al. (2008) review criticisms levied against this and other EI metrics. SREIT is criticized for being "self-report" and combining EI with other traits. One problem with self-report instruments is that the quality of the data collected depends on the accuracy (and honesty) of participants' self-evaluation skills (Brackett and Mayer 2003). Nevertheless, factor analysis of the SREIT shows that it has good internal consistency and test–retest reliability (Schutte et al. 1998). And, SREIT has the benefit that it only requires a small number of questions compared to some of its competitors. Importantly, since NA and SREIT might be capturing quite different facets of EB, it is possible that both might have independent impact.

In part to keep the session duration manageable, we only drew from the SREIT questions pertaining to the areas of optimism and mood regulation, appraisal of emotions, and utilization of emotions, thus eliminating 11 questions from the original 33.[10] The deleted questions, from the area of social skills, were deemed of little relevance for the present research since the effect of emotions on financial decision-making typically occurs in a solitary environment and involves intrapersonal rather than interpersonal skills and abilities. Once again, questions were answered by means of a 5-point Likert scale ranging from strong disagreement ("1") to strong agreement ("5") and averaging was performed (with several questions, as is common in surveys, "reverse-scored").

4.4 Implications of our hypotheses

All else equal, provided $\gamma, \delta, \gamma_1, \delta_1 \leq 1$, we expect NA to be negatively correlated with these parameters. Thus, high-NA individuals are likely to have risk attitudes that depart more from EUT than low-NA individuals. All else equal, provided $\gamma, \delta, \gamma_1, \delta_1 \leq 1$, we expect SREIT to be positively correlated with these parameters. Thus, low-SREIT individuals are likely to have risk attitudes that depart more from EUT than high-SREIT individuals. Further, we expect low-NA/high-SREIT individuals to have γ_2 and δ_2 values close to their neutral equivalents. We do not contend that PA is a proxy for EB so

[9] It is based on the PANAS instrument developed by Watson et al. (1988), who show that NA and PA are by and large uncorrelated, internally consistent and stable over time.

[10] The 33 questions from Schutte et al. (1998) were subjected to factor analysis by Petrides and Furnham (2000), who identified four factors, which they labeled optimism/mood regulation (9), appraisal of emotions (9), social skills (11), and utilization of emotions (4), where the number of questions with the highest loading on a particular factor is in brackets. Our questionnaire omits the 11 "social skills" questions, leaving us with 22 questions.

our views on any potential impact are more tentative. Nevertheless, it seems reasonable to expect that a high level of PA is suggestive of an ability to channel emotions effectively, thus enhancing decision-making potentially moving people closer to EUT-type behavior.

4.5 Demographic control variables

The survey asked several basic demographic questions providing us with several control variables. These variables are gender (SEX), age (YRS), and relevant education (EDU). The latter was defined to be the sum of answers to four questions, namely the number of finance/economics courses previously and currently enrolled in and the number of probability/statistics courses previously and currently enrolled in. Age and relevant education might be expected to engender wisdom and lead one closer to an EUT stance.

Fehr-Duda et al. (2006) have recently explored the relationship between gender and probability weighting, finding that women tend to have higher levels of probabilistic insensitivity than do men, which means that γ, δ, γ_1, and δ_1 are usually lower for women. They argue that this, rather than the shape of the value function, probably accounts for the typical finding that men are less risk averse than women. Further, they show that women tend to be more pessimistic in the gain domain. In the P2 model, this would mean that for women, γ_2 is higher. Using a representative sample from the general public, Booij et al. (2010) also document a significant gender effect on the elevation of the probability weighting function in the positive domain.

5 Results

5.1 Descriptive statistics for SREIT, NA, PA, and demographic controls

The distributions of the two EB proxies are reasonably symmetric, and there appears to be enough variability for us to ascertain (potential) impact.[11] SREIT values are clustered between 3.25 and 4.25 with the majority of observations between 3.5 and 4.00 and a mean and median of 3.75 and 3.77, respectively. On the other hand, most values of NA are between 1.5 and 3, and the mean and median are, respectively, 2.42 and 2.40. As for PA, with a mean (median) of 3.60 (3.60), it also exhibits reasonable variability with a standard deviation just a little lower than that of NA (0.45 vs. 0.56). As for the three demographic control variables, SEX (an indicator variable where male = 1), YRS (participant age in years), and EDU (number of relevant courses), the average age was 21 with little dispersion, the average number of courses was 9.70, and the gender mix was quite balanced (with 48 % of the subjects being male).

Not surprisingly, some of the explanatory variables are significantly correlated.[12] Beginning with the emotion-based variables, SREIT and PA are positively correlated

[11] See the Web-Appendix (Table A1; Fig. A3) for a table (with more detail) and frequency distributions.

[12] While the independent variables are clearly correlated, their degree of correlation is not severe enough so that multicollinearity is a problem.

(0.38), and both are negatively correlated with NA (−0.17 vs. SREIT and −0.34 vs. PA). All three of these pairwise correlations are significant at (or close to) 10 %. While the (negative) correlation between NA and SREIT is not surprising since they are the EB proxies employed here, given previous research to the contrary (Watson et al. 1988) the negative correlation between NA and PA is somewhat unexpected. It is also worth noting that YRS is positively correlated with SREIT, which is logical if EI is something that can be honed with time. And, SEX is significantly and positively correlated with the two EB measures (i.e., positively vs. SREIT and negatively vs. NA), which means that at least in our sample males exhibit higher levels of EB. This suggests that Fehr-Duda et al.'s (2006) gender effect may be in part an EB effect.

5.2 PT parameter estimation

PT's value function and probability weighting function parameters α_k, β_k, γ_k, and δ_k (and $\gamma_{1,k}$, $\delta_{1,k}$, $\gamma_{2,k}$ and $\delta_{2,k}$ for the two-parameter models) were estimated for each of the four considered models for subject k by maximum likelihood. More specifically, let $c_{k,j}$ and $\varepsilon_{k,j}$ denote the imputed certainty equivalent of subject k and its measurement error (both expressed in dollars) in answering prospect question j. As previously discussed, each binary prospect j $[P_j(z_{j,1}, q_{j,1}; z_{j,2})$ where $|z_{j,1}| > |z_{j,2}|]$ is characterized by its two dollar outcomes and the probability of the high-absolute value outcome being realized. Equating the values of the elicited certain equivalents and the risky prospect in question leads to

$$w_k^+\left(q_{j,1}\right) v_k\left(z_{j,1}\right) + \left[1 - w_k^+\left(q_{j,1}\right)\right] v_k\left(z_{j,2}\right) = v_k\left(c_{k,j} + \varepsilon_{k,j}\right) \text{ if } z_{j,1} > z_{j,2} \geq 0 \tag{8a}$$

$$w_k^-\left(q_{j,1}\right) v_k\left(z_{j,1}\right) + \left[1 - w_k^-\left(q_{j,1}\right)\right] v_k\left(z_{j,2}\right) = v_k\left(c_{k,j} + \varepsilon_{k,j}\right) \text{ if } z_{j,1} < z_{j,2} \leq 0 \tag{8b}$$

Note that the error above stems from several sources. Most obviously, confusion and/or inattention will induce subjects to provide inaccurate certainty equivalents. In addition, the elicitation procedure imputes certainty equivalents from revealed preferences, leading to some estimation error. Finally, there is modeling error. To the extent that subjects have preferences that do not precisely conform to PT as parameterized, error arises.

On the assumptions of homoscedastic and normally distributed proportional measurement errors ($\varepsilon_{k,j}/c_{k,j}$), the maximum likelihood estimates of the parameters of subject k are computed based on the choices made by the subject in answering the 56 non-mixed (28 non-negative and 28 non-positive) questions. To facilitate the estimation, reasonable restrictions on the parameter values are imposed. Specifically, all parameters were assumed to lie between 0.0001 and 2.0 with the exception of TK's probability weighting function parameters (γ and δ) which must be bounded below by 0.28 to ensure monotonicity. Any corner solutions were considered to be invalid estimation results and were excluded in the regression analysis presented below. These occurrences were viewed to be quite likely the result of subject confusion/inattention.

5.3 Model selection

Probability weighting function model suitability was judged on the basis of the Akaike information criterion (AIC).[13] One-parameter models (TK and P1) prove superior 71 % of the time and two-parameter models (P2 and GE) 29 % of the time. Of the one-parameter models, P1 does better than TK (39 % vs. 31 %) so the former is stressed in the subsequent analyses.[14]

While the data here point in the direction of a one-parameter approach (as in, e.g., Stott 2006), since other research (e.g., Fehr-Duda et al. 2006) favors a two-parameter approach and it is of interest to explore the impact of EB on elevation, it is useful to also present results for a two-parameter model. P2 is selected as the preferred two-parameter model since it outperforms GE when only two-parameter models are considered and P1 is nested in P2 which is useful for comparison purposes. Nevertheless, while in what follows, we stress results based on P1 and P2, robustness checks using the other models are discussed in Sect. 5.7.

5.4 Central tendency and dispersion of PT parameters

To obtain a sense of typical parameter estimates along with dispersion, refer to Table 1.[15] Besides presenting results of estimations without parametric restrictions, we also report results based on imposing the restrictions $\gamma = \delta = \Gamma$ for P1 and $\gamma_1 = \delta_1 = \Gamma_1$ for P2, consistent with the approach of Prelec (1998). Focusing on central tendency, median values of α and β are below 1.0, suggesting concavity in the positive domain and convexity in the negative. Typical probability weighting functions for the two preferred models are consistent with previous research with probabilistic insensitivity implied by the fact that median values of γ, δ, Γ, γ_1, δ_1 and Γ_1 are always below 1.0. Based on Sect. 2.1 and median values of γ_1, δ_1, and Γ_1 from the current sample, $\gamma_2^N = 0.891$ (using γ_1) or 0.883 (using Γ_1) and $\delta_2^N = 0.886$ (using δ_1) or 0.883 (using Γ_1). Since Table 1 indicates that median $\gamma_2 = 0.934$ (or 0.949 if $\gamma_1 = \delta_1$) while median $\delta_2 = 1.037$ (or 1.002 if $\gamma_1 = \delta_1$), the inference to be drawn is that the typical subject is too pessimistic in the positive domain and too optimistic in the negative domain. These typical tendencies push people in the direction of risk aversion for gains and risk seeking for losses.[16]

As for dispersion in probabilistic insensitivity, while most estimates of γ, γ_1, δ, and δ_1 are between 0.5 and 1.0, there are quite a few people above and below this range.[17] Consistent with EUT, a number of subjects have estimates within 10 % of unity (16 for

[13] See Table A2 of Web-Appendix.

[14] If we restrict ourselves to one-parameter models, it is essentially a dead heat.

[15] From this point on the paper deals with estimates of PT parameters, not the true parameters. As a verbal abbreviation, however, we still speak of parameters when we really mean their estimates, but no confusion is likely to ensue from this. See the Web-Appendix for frequency distributions of the probability weighting function parameters (Fig. A4) as well as for the value function parameters α and β (Fig. A5).

[16] Using the P1 and P2 median values of γ, δ, γ_1, δ_1, γ_2 and δ_2 it is apparent (see Fig. A1 of the Web-Appendix) that these lead to probability weighting functions not unlike those estimated by Tversky and Kahneman (1992).

[17] In Fig. A4 of Web-Appendix, we also report frequency distributions for Γ, Γ_1, $\gamma_2$and δ_2.

Table 1 PT parameter descriptive statistics

	Obs	Mean	Median	Min	Max	SD
P1 parameters						
γ	76	0.7550	0.6962	0.3070	1.5521	0.2600
α	76	0.9018	0.9044	0.1215	1.9067	0.3102
δ	59	0.8061	0.7130	0.3040	1.6760	0.3396
β	59	0.6899	0.7199	0.0640	1.5169	0.3421
$\Gamma = \gamma = \delta$	71	0.5882	0.6318	0.0004	1.4046	0.3539
$\alpha(\gamma = \delta)$	71	0.8046	0.8480	0.0232	1.8939	0.3476
$\beta(\gamma = \delta)$	71	0.6144	0.6597	0.0359	1.4648	0.3435
P2 parameters						
γ_1	80	0.6911	0.6853	0.0030	1.8374	0.3327
γ_2	80	1.0053	0.9335	0.3586	1.9202	0.3756
α	80	0.8335	0.7869	0.1928	1.7809	0.3470
δ_1	62	0.6474	0.6707	0.0009	1.6248	0.3606
δ_2	62	1.2765	1.0369	0.4911	1.9497	0.3511
β	62	0.7449	0.7515	0.1494	1.4540	0.3116
$\Gamma_1 = \gamma_1 = \delta_1$	56	0.6191	0.6595	0.0151	1.1488	0.3030
$\gamma_2(\gamma_1 = \delta_1)$	56	1.0531	0.9492	0.3992	1.9497	0.4019
$\delta_2(\gamma_1 = \delta_1)$	56	1.0677	1.0020	0.5154	1.8639	0.2825
$\alpha(\gamma_1 = \delta_1)$	56	0.7588	0.7555	0.0276	1.9695	0.3658
$\beta(\gamma_1 = \delta_1)$	56	0.6932	0.6869	1.1206	1.6184	0.3393

Note: For number of observations, see discussion in text

γ; 14 for γ_1; 14 for δ; and 11 for δ_1). Moreover, some subjects are at least 10 % above unity (5 for γ; 5 for γ_1; 3 for δ; and 5 for δ_1), suggesting a non-PT-type irrationality with probabilistic over-sensitivity.

While some of the aforementioned dispersion may be driven by estimation error, much of it likely arises from natural subject heterogeneity. Bruhin et al. (2010) document substantial heterogeneity in PT parameter estimates for Swiss and Chinese subjects. While in their study, about 20 % of participants display behavior close to what EUT would predict ($\alpha = \beta = \gamma = \delta = 1$ or $\alpha = \beta = \gamma_1 = \delta_1 = \gamma_2 = \delta_2 = 1$ for the small-stakes prospects in their survey), the other 80 % conform to PT (though there is some dispersion in parameter values). Our data are not dissimilar in this regard: under P1, $\alpha = \beta = \gamma = \delta = 1$ could not be rejected for 29 % of the subjects.

5.5 P1 probability weighting function parameter regressions

Next, we present regressions of the P1 probability weighting function parameters on the EB proxies, PA, and demographic controls.[18] Consistent with our previous discussion

[18] While α and β are not relevant to our hypotheses, we also ran regressions of these parameters on the same set of variables (both with and without the constraint that $\gamma = \delta$). The principal finding was that in the negative domain, males were closer to EUT in the sense that β was higher (i.e., typically closer to linearity).

of P1, we first test the condition $\gamma = \delta$, finding that it cannot be rejected for 63 % of the subjects. Table 2 displays regressions of Γ (or transformations thereof). Tables 3 and 4 do the same for γ and δ. Our principal expectation is that SREIT and NA exert an impact on γ, δ, and Γ, but it is important to note that the impact is not likely to be unidirectional. If all γ, δ, or Γ values were less than or equal to 1.0, we would expect higher parameter values to point in the direction of EUT with the sign on the coefficient of SREIT (NA) anticipated to be positive (negative), but, as discussed in the previous section, in a minority of cases γ, δ, or Γ values exceed 1.0. We deal with this issue in two ways. First, we exclude γ, δ, or Γ values that are in excess of 1.0 (Panels A and B). Second, $\gamma^* = abs\,(1-\gamma)$, $\delta^* = abs\,(1-\delta)$ and $\Gamma^* = abs\,(1-\Gamma)$ are substituted for γ, δ, and Γ respectively (Panels C and D), now with the expectation that the sign of SREIT's coefficient is negative and that of NA positive. As for the other independent variables, in line with the discussion in Sects. 4.3 to 4.5, our expectation is that the coefficient of SEX (male = 1) is positive (negative) in the Panel A and B (Panel C and D) regressions; and, more tentatively, those of PA, YRS, and EDU (all of which we conjectured to be positively related to EUT-type behavior) are positive (negative) in the Panel A and B (Panel C and D) regressions.

Because of the danger that some participants may have been subject to inattention or confusion, we also filter out the lowest 5 % of observations when γ, δ, or Γ is the dependent variable (Panel B) and both the lowest and highest 5 % of observations when γ^*, δ^*, or Γ^* is the dependent variable (Panel D). In each panel, three regressions are shown: the first (reg. 1) uses the three emotion-based variables as regressors; the second (reg. 2) also incorporates the demographic controls; and the third (reg. 3) begins with all variables and eliminates them in a stepwise fashion, until only those at a significance level of 10 % or better remain. All regressions are stress-tested for heteroscedasticity, and when homoscedasticity is rejected at 10 % using one of three tests *p* values are calculated based on heteroscedastic-consistent standard errors.[19]

From Table 2 it is apparent that both NA and SEX impact Γ as expected. Beginning with the latter, reminiscent of Fehr-Duda et al. (2006), males are more likely to have probability weighting functions resembling EUT. When Γ below 1.0 is used as the dependent variable, males on average have a value 0.136–0.218 higher. When Γ^* is the dependent variable, male Γ's are 0.131–0.211 closer to unity. As for the EB proxies, while SREIT is never significant, NA, as expected, always tends to move inversely with Γ^* and positively with Γ^*, and in most cases (regs. A1, B1, B2, B3, C1, D1, D2, and D3) the coefficient is statistically significant. Even after controlling for gender and other relevant demographic variables, low EB as proxied by high NA leads to high probabilistic insensitivity. Notably, PA also matters in one case (reg. C3). It was argued earlier that high PA is likely to lead to enhanced decision-making and this is consistent with the finding that high PA is associated with Γ-values close to unity.

It is useful to investigate whether these tendencies are equally prevalent in both domains. Clearly, in our sample they are not. Table 3 shows that in the domain of gains only SEX matters: when γ below 1.0 is used as the dependent variable, males on average have a value 0.120–0.184 higher, and when the dependent variable is γ^*

[19] These are White's test statistic for heteroscedasticity of unknown form, a redundant variable *F* test and White's LM test for model misspecification.

Table 2 P1 Γ and Γ* regressions

Regression	Constant	SREIT	NA	PA	SEX	YRS	EDU	Obs	R^2	$\bar{R}^2$
Panel A: Γ above 1.0 trimmed										
Emotion variables	0.876	−0.173	−1.220*	−0.053				60	0.061	0.011
	(0.191)	(0.911)	(0.075)	(0.957)						
Above & controls	1.138	−0.526	−0.990	0.066	20.935***	−1.519	−0.043	58	0.196	0.101
	(0.189)	(0.753)	(0.141)	(0.948)	(0.010)	(0.591)	(0.962)			
Stepwise	0.391***				21.796***			61	0.141	0.126
	(0.000)				(0.003)					
Panel B: Γ above 1.0 & lowest 5 % trimmed										
Emotion variables	0.723	0.688	−1.485**	−0.255				57	0.113	0.063
	(0.249)	(0.640)	(0.021)	(0.775)						
Above & controls	1.269	0.317	−1.360**	−0.355	13.597*	−2.489	0.585	55	0.209	0.111
	(0.126)	(0.843)	(0.037)	(0.712)	(0.083)	(0.358)	(0.556)			
Stepwise	0.725***		−1.134**		15.374**			58	0.168	0.138
	(0.000)		(0.043)		(0.029)					
Panel C: Γ*										
Emotion variables	0.723	−0.570	1.097*	−0.888				70	0.096	0.055
	(0.205)	(0.683)	(0.092)	(0.327)						
Above & controls	0.411	−0.290	0.911	−0.888	−18.910**	1.379	0.488	68	0.207	0.129
	(0.596)	(0.844)	(0.156)	(0.350)	(0.013)	(0.612)	(0.579)			

Table 2 continued

Regression	Constant	SREIT	NA	PA	SEX	YRS	EDU	Obs	R^2	$\bar{R}^2$
Stepwise	1.138***			−1.607**	−21.067***			71	0.175	0.151
	(0.000)			(0.033)	(0.002)					
Panel D: Γ* with 10 % trimming										
Emotion variables	0.586	−0.578	1.333**	−0.722				62	0.132	0.087
	(0.297)	(0.688)	(0.043)	(0.424)						
Above & controls	0.136	−0.240	1.151*	−0.635	−13.069*	1.986	0.204	60	0.201	0.111
	(0.858)	(0.879)	(0.089)	(0.518)	(0.094)	(0.452)	(0.835)			
Stepwise	0.198		1.264**		−13.934**			63	0.157	0.129
	(0.195)		(0.028)		(0.045)					

Notes: p values are in parentheses below coefficient estimates; see text for variable definitions

Table 3 P1 γ and γ^* regressions

Regression	Constant	SREIT	NA	PA	SEX	YRS	EDU	Obs	R^2	$\bar{R}^2$
Panel A: γ above 1.0 trimmed										
Emotion variables	0.577	0.616	−0.349	−0.162				60	0.021	−0.032
	(0.147)	(0.534)	(0.460)	(0.799)						
Above & controls	0.662	0.441	−0.076	0.018	14.034***	−1.195	0.371	57	0.170	0.070
	(0.144)	(0.689)	(0.871	(0.977)	(0.007)	(0.496)	(0.518)			
Stepwise	0.605***				12.042***			62	0.112	0.098
	(0.000)				(0.008)					
Panel B: γ above 1.0 & 5 % lower estimates trimmed										
Emotion variables	0.779**	0.161	−0.358	−0.195				57	0.014	−0.042
	(0.041)	(0.864)	(0.419)	(0.748)						
Above & controls	1.005**	−0.541	−0.023	0.183	18.359***	−1.577	0.698	54	0.292	0.202
	(0.013)	(0.577)	(0.953)	(0.745)	(0.000)	(0.297)	(0.162)			
Stepwise	0.614***				14.092***			59	0.179	0.165
	(0.000)				(0.001)					
Panel C: γ^*										
Emotion variables	0.407	−0.327	0.481	−0.276				74	0.038	−0.003
	(0.245)	(0.712)	(0.278)	(0.647)						
Above & controls	0.293	−0.359	0.419	−0.254	−9.591**	0.736	0.199	71	0.110	0.027
	(0.513)	(0.717)	(0.342)	(0.683)	(0.048)	(0.671)	(0.723)			
Stepwise	0.346***				−8.982**			76	0.056	0.043
	(0.000)				(0.040)					
Panel D: γ^* with 10 % trimming										
Emotion variables	0.189	−0.113	0.550	−0.014				66	0.032	−0.015
	(0.577)	(0.896)	(0.209)	(0.981)						
Above & controls	−0.050	0.060	0.349	−0.103	−13.168***	1.470	0.019	63	0.174	0.085
	(0.903)	(0.949)	(0.406)	(0.861)	(0.006)	(0.350)	(0.971)			
Stepwise	0.331***				−11.279***			68	0.102	0.089
	(0.000)				(0.008)					

Notes: p values are in parentheses below coefficient estimates; see text for variable definitions

male γ's are 0.090–0.132 closer to unity. Table 4, which is for the domain of losses, reasserts a role for the EB variables. NA, as in the case of Table 2, is highly significant in virtually all cases, once again in the anticipated direction. In addition, SREIT is significantly negative in the untrimmed δ^* regressions. Notably, when stepwise regression is performed, we find that NA, SREIT, and SEX all have the expected impact on the absolute difference between δ and unity. While SEX only matters in untrimmed regressions, NA is a driving force in both untrimmed and trimmed regressions.

To review, gender and EB (as proxied by NA) are the most important determinants of probabilistic insensitivity in our data. In the domain of gains, only gender matters, with males exhibiting probabilistic insensitivities closer to EUT. The major finding in the negative domain is the consistent tendency for low-NA individuals to display EUT-type behavior. In other words, EB and rationality seem to go hand in hand when confronting risky decisions involving losses.

5.6 P2 probability weighting function parameter regressions

While in one-parameter models elevation and probabilistic insensitivity coalesce, two-parameter models such as P2 provide the advantage of being able to separate out these two quite different behavioral tendencies. To review the previous discussion, γ_1 (and δ_1) now measures probabilistic insensitivity, while γ_2 (andδ_2) measures elevation.[20] The condition $\gamma_1 = \delta_1$ can be rejected only 37 % of the time.[21] Therefore, as previously, we will present results for Γ_1 as well as for γ_1 and δ_1. Regressions of Γ_1, γ_1, δ_1, γ_2 and δ_2 on the independent variables are performed and presented as previously described.[22] The Γ_1, γ_1, and δ_1 regressions (see Tables A3–A5 of the Web-Appendix) are broadly similar to those presented in Tables 2, 3, 4. One difference however is salient. While previously SEX was the key driver in the domain of gains and NA in the domain of losses, now SEX dominates in both domains. For example, while NA is significant in several of the δ_1 regressions, only SEX remains significant in the stepwise regressions. Recalling that γ, δ, or Γ confounds probabilistic insensitivity and elevation, this suggests that EB might be primarily acting on elevation, while SEX matters mostly for probabilistic insensitivity.

In Tables 5 and 6, $\gamma_2, \delta_2, \gamma_2^* = abs\left(\gamma_2^N - \gamma_2\right)$ and $\delta_2^* = abs\left(\delta_2^N - \delta_2\right)$ are the dependent variables. Values for γ_2 and $\delta_2$will vary depending on whether or not the $\gamma_1 = \delta_1$ condition is imposed, so regression results are presented both with and without this restriction. Further, 10 % filtering is used throughout.[23] To interpret, higher levels of γ_2 point toward higher gain-domain pessimism and higher levels of δ_2 point toward higher loss-domain optimism. Recalling that there is a neutral level for the

[20] These two parameters do not quite cleanly decompose these two behavioral tendencies. See Fehr-Duda et al. (2006) for a discussion.

[21] This is the same percentage rejection as the $\gamma = \delta$ test under P1.

[22] It should be noted that results for γ_2 and δ_2 will vary depending on whether or not the $\gamma_1 = \delta_1$ condition is imposed.

[23] Results without 10 % filtering are broadly similar, but weaker (see Tables A6 and A7 of the Web-Appendix).

Table 4 P1 δ and δ^* regressions

Regression	Constant	SREIT	NA	PA	SEX	YRS	EDU	Obs	R^2	$\bar{R}^2$
Panel A: δ above 1.0 trimmed										
Emotion variables	0.881*	−0.006	−1.256**	0.125				41	0.178	0.112
	(0.085))	(0.997)	(0.016)	(0.660)						
Above & controls	0.931	−0.434	−1.060*	0.380	8.290	−0.676	0.681	41	0.258	0.127
	(0.139)	(0.706)	(0.050)	(0.600)	(0.153)	(0.705)	(0.301)			
Stepwise	0.788***		−0.874*		9.668*			42	0.183	0.142
	(0.000)		(0.052)		(0.017)					
Panel B: δ above 1.0 & 5 % lower estimates trimmed										
Emotion variables	1.002**	0.008	−1.174**	−0.244				39	0.148	0.075
	(0.039)	(0.995)	(0.022)	(0.721)						
Above & controls	1.316**	−0.181	−1.065**	−0.205	4.358	−1.748	0.584	39	0.215	0.068
	(0.047)	(0.874)	(0.047)	(0.793)	(0.469)	(0.346)	(0.367)			
Stepwise	0.840***		−0.815*					40	0.085	0.061
	(0.000)		(0.068)							
Panel C: δ^*										
Emotion variables	0.871**	−1.976**	0.979*	−0.070				58	0.154	0.107
	(0.031)	(0.042)	(0.058)	(0.912)						
Above & controls	0.921*	−1.346	0.703	−0.418	−13.014**	−0.044	−0.171	58	0.247	0.159
	(0.088)	(0.170)	(0.170)	(0.519)	(0.016)	(0.981)	(0.798)			
Stepwise	0.807**	−1.595*	0.814*		−12.258**			58	0.240	0.198
	(0.022)	(0.072)	(0.082)		(0.016)					
Panel D: δ^* with 10 % trimming										
Emotion variables	0.342	−1.231	1.173**	0.401				52	0.146	0.092
	(0.405)	(0.197)	(0.016)	(0.518)						
Above & controls	0.023	−1.141	1.002**	0.378	−4.287	1.731	−0.030	52	0.184	0.075
	(0.969)	(0.251)	(0.048)	(0.588)	(0.437)	(0.336)	(0.963)			
Stepwise	0.083		0.903**					53	0.081	0.063
	(0.425)		(0.039)							

Notes: p values are in parentheses below coefficient estimates; see text for variable definitions

Table 5 P2 γ_2 and γ_2^* regressions with 10 % trimming

Regression	Constant	SREIT	NA	PA	SEX	YRS	EDU	Obs	R^2	$\bar{R}^2$
Panel A: γ_2 ($\gamma_1 = \delta_1$)										
Emotion variables	2.692***	−2.346	−0.746	−1.660				49	0.134	0.076
	(0.000)	(0.169)	(0.398)	(0.141)						
Above & controls	3.031***	−2.061	−0.764	−1.869	−0.694	−1.834	0.321	48	0.143	0.018
	(0.003)	(0.296)	(0.421)	(0.134)	(0.948)	(0.599)	(0.795)			
Stepwise	1.735***			−1.921**				50	0.080	0.061
	(0.000)			(0.047)						
Panel B: γ_2^* ($\gamma_1 = \delta_1$)										
Emotion variables	1.632***	−1.312	−0.844	−1.824**				49	0.1626	0.1068
	(0.003)	(0.315)	(0.216)	(0.038)						
Above & controls	1.855**	−1.635	−0.672	−1.765*	7.079	−1.057	0.216	48	0.1865	0.0675
	(0.016)	(0.281)	(0.358)	(0.067)	(0.390)	(0.692)	(0.820)			
Stepwise	0.934***			−1.809**				50	0.1157	0.0973
	(0.001)			(0.016)						
Panel C: γ_2 ($\gamma_1 \neq \delta_1$)										
Emotion variables	1.673**	−1.208	−0.374	−0.388				70	0.023	−0.022
	(0.010)	(0.388)	(0.649)	(0.673)						
Above & controls	1.281*	−0.091	−0.806	−1.083	−12.080	2.294	−0.836	67	0.082	−0.010
	(0.067)	(0.954)	(0.277)	(0.278)	(0.142)	(0.355)	(0.371)			
Stepwise	0.991***							72	0.000	0.000
	(0.000)									
Panel D: γ_2^* ($\gamma_1 \neq \delta_1$)										
Emotion variables	1.633***	−2.108**	−0.649	−1.149*				70	0.200	0.163
	(0.000)	(0.020)	(0.159)	(0.061)						
Above & controls	1.640***	−1.464	−0.742	−1.339**	−1.272	−0.247	−0.975	67	0.226	0.148
	(0.001)	(0.157)	(0.125)	(0.041)	(0.810)	(0.878)	(0.110)			
Stepwise	1.297***	−2.729***						70	0.147	0.135
	(0.000)	(0.001)								

Notes: p values are in parentheses below coefficient estimates; see text for variable definitions

Table 6 P2 δ_2 and δ_2^* regressions with 10 % trimming

Regression	Constant	SREIT	NA	PA	SEX	YRS	EDU	Obs	R^2	$\bar{R}^2$
Panel A: δ_2 ($\gamma_1 = \delta_1$)										
Emotion variables	0.860*	0.150	1.028	−0.283				50	0.074	0.013
	(0.095)	(0.902)	(0.114)	(0.715)						
Above & controls	0.642	−0.504	1.109	0.053	4.385	0.950	0.935	49	0.116	−0.010
	(0.349)	(0.707)	(0.109)	(0.949)	(0.529)	(0.690)	(0.260)			
Stepwise	0.795***		0.1090*					50	0.071	0.051
	(0.000)		0.0618							
Panel B: $\delta_2^*(\gamma_1 = \delta_1)$										
Emotion variables	0.635	−0.953	0.765	−0.641				50	0.095	0.036
	(0.228)	(0.451)	(0.249)	0.422						
Above & controls	0.265	−1.483	0.728	−0.323	1.402	1.839	0.626	49	0.128	0.003
	(0.706)	(0.287)	(0.303)	(0.706)	(0.845)	(0.454)	(0.462)			
Stepwise	−0.022		1.049*					50	0.059	0.039
	(0.881)		(0.091)							
Panel C: δ_2 ($\gamma_1 \neq \delta_1$)										
Emotion variables	0.535	−0.483	1.728**	0.928				56	0.105	0.053
	(0.467)	(0.765)	(0.027)	(0.324)						
Above & controls	0.414	−0.662	1.426*	0.878	−7.913	1.158	0.786	55	0.136	0.028
	(0.664)	(0.713)	(0.089)	(0.387)	(0.361)	(0.687)	(0.491)			
Stepwise	0.722***		1.610**					56	0.087	0.070
	(0.000)		(0.027)							
Panel D: $\delta_2^*(\gamma_1 \neq \delta_1)$										
Emotion variables	0.153	−1.169	1.599**	0.536				56	0.110	0.058
	(0.830)	(0.457)	(0.035)	(0.556)						
Above & controls	0.468	−0.890	1.333*	0.233	−10.710	−1.137	0.462	55	0.148	0.042
	(0.611)	(0.608)	(0.099)	(0.811)	(0.202)	(0.682)	(0.674)			
Stepwise	−0.101		1.645**					56	0.096	0.079
	(0.562)		(0.020)							

Notes: p values are in parentheses below coefficient estimates; see text for variable definitions

second parameter reflecting neither excessive pessimism nor excessive optimism, this neutral level is a function of the first parameter, and that the typical subject is too pessimistic in the positive domain and too optimistic in the negative domain; our expectation for the EB proxies is that NA/SREIT should be positively/negatively correlated with both γ_2 and δ_2, in expectation that EB should push people closer to the neutral pessimism/optimism level. Further, the expectation is that NA/SREIT should be positively/negatively related to both γ_2^* and δ_2^* in expectation that the gap between the second parameter and its neutral level should contract with EB. As for the other independent variables, as we have said before, either drawing on past research or reasonable conjecture, we would expect all else equal higher levels of PA, SEX, YRS and EDU to lead to EUT-type behavior.

In Table 5, when $\gamma_1 = \delta_1$ is imposed, PA is significantly negative in the γ_2 regressions, suggesting higher levels reduce excessive pessimism. In the γ_2^* regressions, SREIT and PA coefficients have the anticipated sign and in many cases are statistically significant. Higher levels of EB as proxied by SREIT point in the direction of neutral elevation. And, higher PA also indicates EUT-type behavior. As seen in Table 6, however, it is NA—not SREIT and PA— that matters in the domain of losses. This variable's coefficient always has the anticipated sign, and in many of the regressions it is statistically significant. As expected, subjects who are typically already too optimistic become even more optimistic when they have high levels of NA. As it were, these people are suffering from wishful thinking. This would have the effect of increasing risk seeking in the negative domain. Further, higher levels of NA are associated with larger absolute differences between δ_2 and its pessimism/optimism neutral level.

In short, there is solid evidence in both domains that EB leads to EUT-type behavior in that excess optimism and pessimism is moderated. When 10 % filtering is done, in all cases of statistical significance, the sign of the coefficient lines up with expectations. In the positive domain, SREIT and PA have impact, while in the negative domain NA is the driver.

5.7 Robustness check I: alternative probability weighting functions

We check the robustness of our findings by repeating the analyses using results generated by the two competing models, namely the TK one-parameter model and the GE two-parameter model. Regression results when TK parameter value estimates are used as dependent variables (see Web-Appendix for comparable Tables A8–A10) are broadly similar to those reported in Tables 2, 3, 4 where P1 is the model of choice. While there are fewer instances of statistical significance for NA, the essential story remains: high levels of NA (i.e., low EB) are associated with lower values of γ, δ, and Γ when values above unity are filtered out. Further, low levels of NA lead to γ, δ, and Γ values closer to unity. In the case of P1, there were a few cases of statistical significance for SREIT and PA, but the same is not true with TK.

Turning to a comparison of two-parameter models, regression results when GE parameter value estimates are used as dependent variables are also broadly similar to those reported in Tables 5 and 6 where P2 is the model of choice, but once again there are fewer instances of statistical significance for the emotion-based variables.[24] As before, high PA leads to values of γ_2 that are closer to unity. Recall that under GE, high levels of γ_2 suggest optimism while high levels of δ_2 suggest pessimism. We find that high NA leads to low δ_2 (i.e., more optimism), a result that is analogous to the reported positive relationship between the two variables under P2.

5.8 Robustness check II: additional filters

Results previously presented generally utilized a 10 % outlier screen (i.e., 5 % on both sides). We repeat the relevant estimations for 5 and 15 % filters and our findings are broadly similar (see Tables A16–A22 in the Web-Appendix). For example, refer back to the stepwise regression displayed in Panel D of Table 2 (where Γ^* is the regressor) where we saw that both NA and SEX were significant at 5 % in the anticipated direction using 10 % trimming. This also holds with 5 % trimming. With 15 % trimming, while NA remains significant at 5 %, the significance level of SEX declines to 10 %.

6 Conclusion

In this exploratory study investigating whether a relationship exists between emotional balance and probability weighting, we report mixed results. Our expectation was that the curvature of the probability weighting function would be greater (i.e., lower γ, δ, and Γ assuming all values are below unity) for those with lower levels of emotional balance (i.e., lower emotional intelligence and higher negative affectivity). While the coefficient signs for negative affectivity were always consistent with this in the positive domain, nothing approaching statistical significance was apparent. In the negative domain, however, and also over both domains when we imposed the constraint $\gamma = \delta$ (which could not be rejected for a majority of subjects), the evidence was stronger that higher emotional balance individuals had lower curvature with negative affectivity being the dominant driver. There were also suggestive results that elevation is impacted by emotional balance. In the positive domain, high emotional intelligence (and positive affectivity) was associated with neutral elevation, while in the negative domain low negative affectivity was associated with neutral elevation.

Previous work has established a role for gender. We too find that women are more likely to have probability weighting function curvature. While emotional balance variables and gender are correlated in our sample, both were shown to have independent impact. Thus, emotional balance is not proxying for gender. It is also notable that the strongest results for emotional intelligence exist in the positive domain while the strongest results for negative affectivity are present in the negative domain. One explanation is that losses are more affective. Importantly, emotional intelligence arguably embodies a cognitive element as conscious control is being exerted by those high in emotional intelligence. On the other hand, more innate tendencies are reflected in negative affectivity as opposed to the attempt to regulate these tendencies.

[24] See Web-Appendix for comparable tables (A14, A15). In the same Web-Appendix, Tables A11–A13 for GE are comparable to Tables A3–A5 for P2.

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References

Abdellaoui, M., Bleichrodt, H., & Paraschiv, C. (2008). Loss aversion under prospect theory: A parameter-free measurement. *Management Science*, *53*, 1659–1674.

Barnea, A., Cronqvist, H., & Siegel, S. (2010). Nature or nurture: What determines investor behavior? *Journal of Financial Economics*, *98*, 583–604.

Barrett, L. F. (1998). Discrete emotions or dimensions? The role of valence focus and arousal focus. *Cognition and Emotion*, *12*, 579–599.

Bechara, A., Damasio, H., Tranel, D., & Damasio, A. R. (1997). Deciding advantageously before knowing the advantageous strategy. *Science*, *275*, 1293–1295.

Booij, A. S., van Praag, B. M. S., & van de Kuilen, G. (2010). A parametric analysis of prospect theory's functionals for the general population. *Theory and Decision*, *68*(1–2), 115–148.

Brackett, M., & Mayer, J. (2003). Convergent, discriminant, and incremental validity of competing measures of emotional intelligence. *Personality and Psychology Bulletin*, *29*, 1147–1158.

Bruhin, A., Fehr-Duda, H., & Epper, T. (2010). Risk and rationality: Uncovering heterogeneity in probability distortion. *Econometrica*, *78*, 1375–1412.

Cesarini, D., Johannesson, M., Lichtenstein, P., Sandewall, O., & Wallace, B. (2010). Genetic variation in financial decision-making. *Journal of Finance*, *65*, 1725–1754.

Dhar, R., & Wertenbroch, K. (2000). Consumer choice between hedonic and utilitarian goods. *Journal of Marketing Research*, *37*, 60–71.

Edmans, A., Garcia, D., & Norli, O. (2007). Sports sentiment and stock returns. *Journal of Finance*, *62*, 1967–1998.

Edwards, W. (Ed.). (1992). Utility theories: Measurements and applications. Kluwer Academic Publishers, Dordrecht, the Netherlands.

Etchart-Vincent, N., & l'Haridon, O. (2011). Monetary incentives in the loss domain and behavior towards risk: An experimental comparison of three reward schemes including real losses. *Journal of Risk and Uncertainty*, *42*, 61–83.

Fehr-Duda, H., de Gennaro, M., & Schubert, R. (2006). Gender, financial risk and probability weights. *Theory and Decision*, *60*, 283–313.

Gohm, C. L., & Clore, G. L. (2000). Individual differences in emotional experience: Mapping available scales to processes. *Personality and Social Psychology Bulletin*, *26*, 679–697.

Goldstein, W. M., & Einhorn, H. J. (1987). Expression theory and the preference reversal phenomena. *Psychological Review*, *94*, 236–54.

Hirshleifer, D., & Shumway, T. (2003). Good day sunshine: Stock returns and the weather. *Journal of Finance*, *58*(3), 1009–1032.

Johnson, E. J., Hershey, J., Meszaros, J., & Kunreuther, H. (1993). Framing, probability distortions and insurance decisions. *Journal of Risk and Uncertainty*, *7*, 35–51.

Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. *Econometrica*, *47*, 263–291.

Kamstra, M. J., Kramer, L. A., & Levi, M. D. (2000). Losing sleep at the market: The daylight saving anomaly. *American Economic Review*, *90*, 1005–1011.

Kamstra, M. J., Kramer, L. A., & Levi, M. D. (2003). Winter blues: A SAD stock market cycle. *American Economic Review*, *93*, 724–743.

Kaplanski, G., & Levy, H. (2010). Sentiment and stock prices: The case of aviation disasters. *Journal of Financial Economics*, *95*, 174–201.

Larsen, R. J., & Buss, D. M. (2008). *Personality psychology* (3rd ed.). New York: McGraw-Hill.

Lo, A. W., & Repin, D. V. (2002). The psychophysiology of real-time financial risk processing. *Journal of Cognitive Neuroscience*, *13*, 323–339.

Lo, A. W., Repin, D. V., & Steenbarger, B. N. (2005). Fear and greed in financial markets: A clinical study of day traders. Working paper.

Loewenstein, G. F. (1996). Out of control: Visceral influences on behavior. *Organizational Behavior and Human Decision Processes*, *65*, 272–292.

Loewenstein, G. F. (2000). Emotions in economic theory and economic behavior. *American Economic Review*, *90*, 426–432.

Loewenstein, G., Weber, E. U., Hsee, C. K., & Welch, N. (2001). Risk as feelings. *Psychological Bulletin*, *127*, 267–286.

MacGregor, D. G., Slovic, P., Dreman, D., & Berry, M. (2000). Imagery, affect, and financial judgment. *Journal of Psychology and Financial Markets*, *1*, 104–110.

Mano, H. (1994). Risk-taking, framing effects and affect. *Organizational Behavior and Human Decision Processes*, *57*, 59–82.

Mayer, J. D., Roberts, R. D., & Barsade, S. G. (2008). Human abilities: Emotional intelligence. *Annual Review of Psychology*, *59*, 507–536.

Petrides, K. V., & Furnham, A. (2000). On the dimensional structure of emotional intelligence. *Personality and Individual Differences*, *29*, 313–320.

Prelec, D. (1998). The probability weighting function. *Econometrica*, *66*, 497–528.

Rottenstreich, Y., & Hsee, C. K. (2001). Money, kisses and electric shocks: On the affective psychology of risk. *Psychological Science*, *12*, 185–190.

Salovey, P., & Mayer, J. D. (1990). Emotional intelligence. *Imagination, Cognition and Personality*, *9*, 185–211.

Schutte, N. S., et al. (1998). Development and validation of a measure of emotional intelligence. *Personality and Individual Differences*, *25*, 167–177.

Shiv, B., Loewenstein, G., Bechara, A., Damasio, A., & Damasio, H. (2005). Investment behavior and the dark side of emotion. *Psychological Science*, *16*, 435–439.

Stott, H. P. (2006). Cumulative prospect theory's functional menagerie. *Journal of Risk and Uncertainty*, *32*, 101–130.

Summers, B., & Duxbury, D. (2007). Unraveling the disposition effect: The role of prospect theory and emotions. Working paper.

Thompson, E. R. (2007). Development and validation of an internationally reliable short-form of the positive and negative affect schedule. *Journal of Cross-cultural Psychology*, *38*, 227–242.

Tversky, A., & Kahneman, D. (1992). Advances in prospect theory: Cumulative representation of uncertainty. *Journal of Risk and Uncertainty*, *5*, 297–323.

von Gaudecker, H.-M., van Soest, A., & Wengström, E. (2011). Heterogeneity in risky choice behavior in a broad population. *American Economic Review*, *101*, 664–694.

Wakker, P. P. (2010). *Prospect theory for risk and ambiguity*. Cambridge, UK: Cambridge University Press.

Watson, D., & Clark, L. A. (1984). Negative affectivity: The disposition to experience aversive emotional states. *Psychological Bulletin*, *96*, 465–490.

Watson, D., Clark, L. A., & Tellegen, A. (1988). Development and validation of brief measures of positive and negative affect: The PANAS scales. *Journal of Personality and Social Psychology*, *54*, 1063–1070.