Reaching for Returns in Retail Structured Investment

Doron Sonsino, Yaron Lahav, Yefim Roth

Abstract: The growing market for retail structured investment products and empirical evidence for excessive pricing of such products, raise the hypothesis that private investors show increased risk appetite in structured investment contexts. A two-stage framed field experiment building on cumulative prospect theory is designed to test this hypothesis. Subjects' expectations regarding the future performance of an underlying index are elicited first. A bisection algorithm is then applied to derive the certainty equivalents of twenty simple individually-tailored deposits. The results support the increased risk appetite hypothesis, revealing that subjects reach for substantial gains and underweight tail loss events when evaluating the deposits. Similar results emerge in a follow-up experiment where the uncertain deposits are replaced by risky versions. While previous studies propose that misperception of complex terms and optimism contribute to the mispricing of structured instruments, the current experiments show that non-standard risk appetite manifests in the valuation of simple well-defined products, controlling for expectations.

Key words: Retail structured investment; Prospect theory; Reaching for returns; Probabilistic loss receptiveness; Exchangeability method.

JEL classifications: C90, D81, G11, G40

---

*Doron Sonsino (the corresponding author; email Sonsino.doron@gmail.com) is adjunct at the Economics Department of Ben-Gurion University. Yaron Lahav is from the Guilford Glaser Faculty of Business and Management at Ben-Gurion University. Yefim Roth is from the Department of Human Services at the University of Haifa. The work in process was presented in seminars at Gothenburg University's Centre for Finance, Haifa University, Uno College decision-making workshop, the Heidelberg 2018 meetings of the Society for Experimental Finance, the IAREP 2018 London meetings, the WEAI 2019 Tokyo meetings, and the Third Israel Behavioural Finance conference. We thank Priyodorshi Banerjee, Monica Capra, Adam Farago, Lior Gal, Tommy Gärling, Ori Haimanko, Erik Hajamarsson, Martin Holmén, Tomer Ifergane, Ido Kallir, Moshe Kim, Guy Mayraz, Moti Michaeli, Keren Stirin Tzur, Anna Rubinchik, Israel Waichman, Ro'i Zultan and other seminars and conferences participants for helpful communications. We thank Ido Erev for help in financing experiment 2 and the College of Management Academic Studies (COMAS) research authority for financing experiment 1.

1. Introduction

The lingering uncertainty and low interest rates have increased the retail demand for structured investment instruments to the point where finance research (Henderson and Pearson 2011; Célérier and Vallée 2017) and the industry (http://www.StructuredRetailProducts.com) specifically address the market for *retail-oriented structured products*. This paper deals with an especially popular class of retail-oriented structured instruments that provide capital protection while linking returns to the performance of particular risky assets (https://www.six-structured-products.com/en/knowhow/product-know-how/capital-protection-products/). A Web search in early 2020 brought hundreds of certificates, notes and deposits that combine full or limited capital protection with the possibility to gain from positive performance of stock indices, specific stocks, commodities and more. Products with 100% capital protection appear especially common, but 90% and 95% protection rates are also prevalent (Blümke 2009). The potential earnings from positive performance of the underlying asset are frequently capped in parallel, so the returns are bounded both ways (https://keyinvest-ch-en.ubs.com/know-how/capital-protection).

The first motivation for the current study comes from the similarity between structured deposits and choice theory's abstract concept of *uncertain prospects*. Formally, an uncertain prospect is a mapping from a space of uncertainty to consequences (Tversky and Kahneman 1992). Structured investment instruments, linking the return on investment to the performance of an underlying asset, closely match the formal definition. Given the growing retail interest in structured investment, this study aims at characterizing prospective investors' preferences over capital protecting instruments in light of Tversky and Kahneman's cumulative prospect theory under uncertainty (henceforth: CPT). We adopt the *framed field experiment* approach (Harrison and List 2004), devising field-like deposits whose return depends on the performance of the FTSE index over the twelve months following the experiment. The virtual deposits are evaluated by advanced business or economics students in an incentivized computerized experiment and a choice-based bonus is paid at the end of the investment period, about twelve months after the data collection.

In particular, the experiment consists of two main stages. At the first, the exchangeability method (Baillon 2008) is utilized to elicit median and quartile forecasts for the FTSE return over the investment period. At the second, the elicited forecasts are used to construct individually-tailored deposits. Subjects with a median FTSE forecast of 14%, for example, are presented with a deposit that pays 9% or 0% depending on whether FTSE increases by more than 14%. The deposits appear uncertain, linking the return on investment to the performance of an underlying index, but the likelihood of the underlying events is indirectly controlled through the first stage forecasts. The certainty equivalents of twenty deposits are elicited in short sequences of binary choice problems, and CPT is applied to test if typical characteristics of decision under uncertainty, such as risk aversion for gains, risk preference for losses, and loss aversion, hold in a retail structured investment context. Subjects' preferences over structured deposits are characterized in direct comparisons; e.g., attitude toward gain-domain risk is examined by comparing the certainty equivalents of (9% or 0%) and (6% or 3%) deposits, and loss aversion is tested by comparing the response to (9% or -8%) and parallel (1% or 0%) return combinations. Variants of the CPT model are estimated to summarize the data and gain more insight into the evaluation of retail-oriented deposits by prospective investors.

Additional motivation for the study, beyond exploring CPT under uncertainty, comes from empirical research suggesting that structured investment instruments are consistently overpriced. The overpricing shows in comparisons between the market price of products and the values implied by option pricing models (Bernard et al. 2011; Henderson and Pearson 2011; Schertler 2016). It also manifests in negative risk-adjusted returns to the investor (Entrop et al. 2016; Li et al. 2018). The overpricing generally increases with the complexity of the instrument (Célérier and Vallée 2017; Ghent et al. 2019), but it still displays for simple principal-protecting or index-tracking notes (Jørgensen et al. 2011; Deng et al. 2015). In the field, the overenthusiasm of investors for structured instruments may follow from misperception of complex terms (Bennet 2010; Castellano and Cerqueti 2013; Célérier and Vallée 2017; Kunz et al. 2017) and unrealistic optimism (Bernard et al. 2011; Hens and Rieger 2014; Hunt et al. 2015). The experiments of the current paper control for participants' expectations, testing if prospective investors exhibit non-standard preferences in evaluating well-defined simple structured deposits.

The results of two incentivized experiments, with uncertain and risky yearly deposits, indeed show that students with academic background in finance violate basic premises of prospect theory, reaching for substantial gains and accommodating the possibility of limited losses in a structured investment context. The increased risk preference reflects in high certainty equivalents, approaching and even exceeding the expected returns on the deposits. CPT estimations show that prospect theory explains the data well, but the parametric results are non-standard. A change in the shape of the utility function from convex to concave (Saha 1993) is essential to fit the certainty equivalents of deposits that fully protect the invested capital, while optimistic weighting of tail loss events robustly explains the strong willingness to invest in deposits that bring a loss in the least favourable market condition. When presented with a choice between risky structured deposits and investment in fixed annual interest rates, the subjects of experiment 2 prefer the deposit to its expected return in about 50% of the cases. In control problems presented to the same subjects in a post-experiment questionnaire, the risk-free alternative is preferred to the risky lottery in more than 75% of the cases. Comparisons with Tversky and Kahneman (1992) and recent CPT estimations reconfirm the idiosyncrasy of the elicited structured investment preferences, suggesting that context-specific appetite for substantial gains boosts the appeal of structured instruments even when the investment terms are simple and evidently clear.

2. Background

2.1: Retail-oriented Structured Investment Instruments

The expansion of the retail-oriented structured investment market shows in long lists of instruments offered by prominent banks and asset management firms (https://www.six-structured-products.com/en/search) and Web portals especially designated for retail clientele (e.g., http://www.StructuredRetailProducts.com). The experiments of the current paper refer to the subset of instruments that provide at least 90% capital protection and additionally cap the maximal return on the investment. Close to full capital protection is a key advantage for private investors who opt for structured products (Rieger and Hens 2012). The cap on maximal participation opens margins for the providers in managing or hedging the risks (e.g., Bernard et al. 2011; Deng et al. 2015).

Supplement A briefly surveys the retail structured investment market, bringing diverse examples from the field. A *FTSE100 3-year deposit plan* offered in early 2019 by an international asset management firm guarantees payback of the sterling investment capital, adding a fixed 15% return if the FTSE100 index increases during the investment period. An 18-month US dollar deposit offered by a leading Israeli bank in early 2020 builds on the performance of six international stocks. The invested capital is fully protected but the maximal return is capped at 33%. Close to full protection rates of 90% or 95% also appear common. A 4-year EURO STOXX 50 certificate issued by a leading Swiss bank in December 2019, for example, provides 90% capital protection while capping the total return at 26%. If the EURO STOXX 50 index falls by more than 10% during the investment period, the investor still receives 90% of the invested capital. If the index rises by more than 26%, the payback is limited to 126%. Following these examples, the current experiments focus on deposits that offer at least 90% capital protection, with the maximal annual return ranging between 6% and 22%.

Empirical studies commonly point at significant overpricing of structured instruments relatively to approximations of their fair values. Henderson and Pearson (2011) find that the offering price of 64 equity-linked notes issued by a leading US investment bank between 2001 and 2005 exceeded their fair value by about 8%. The mispricing is puzzling given that the notes are short termed (about 14 months average duration), issued for proceeds of about 2 billion US dollars, and traded at the AMEX exchange. Entrop et al. (2016) examine the returns on bonus certificates and discount certificates that are especially popular among German private investors, and find statistically significant negative alphas averaging at -3% and -10%, respectively. Schertler (2016) argues that competition affects the mispricing, showing that the overpricing of outstanding discount certificates increases when a duplicate certificate is issued by a lower credit-risk issuer. Célérier and Vallée (2017) find that the average yearly return on 7500 European structured products that matured between 2002 and 2011 was about 1.7% lower than the average risk-free rate for the respective maturities. Several papers argue that the mispricing of structured products increases with measures of product complexity (Entrop et al. 2016; Célérier and Vallée 2017; Ghent et al. 2019). Célérier and Vallée (2017), for example, find that the headline rate of structured instruments rises with the number of conditions or scenarios in the description of the product, arguing that banks design complex products to cater for yield-seeking investors. The present paper tests the *reaching for yield* hypothesis in framed field laboratory experiments using simplified yearly deposits with discrete return structures. The deposits are designed in light of Tversky and Kahneman's (1992) CPT to test if systematic deviations from standard characteristics of decision under uncertainty emerge in the context of structured investment.[1]

2.2: Cumulative Prospect Theory Under Uncertainty

A fundamental difficulty with modelling decision under uncertainty is that the likelihood of uncertain events is, by definition, unknown. Tversky and Kahneman's (1992) basic formulation of CPT assumes the existence of abstract gain and loss weighting functions that map uncertain events into numeric decision-weights. The decision-weights are applied to the respective gain and loss utilities to derive the value of the prospect. The operationalization of the theory, however, has been simplified by Fox and Tversky (1998) and Kilka and Weber (2001) that propose a two-step approach where the likelihoods of the uncertain events are judged first, and then transformed into decision-weights. The value of the 15% FTSE deposit of Section 2.1, following the two-step approach, is based on a subjective assessment $0 \leq P \leq 1$ of the likelihood that FTSE will increase during the investment period. The probability P is transformed to a decision-weight W(P) that is multiplied by the utility of 15% return to obtain the value of the deposit.

While the mathematical formulation of CPT is flexible enough to encompass a rich spectrum of preferences, the Tversky and Kahneman (1992; henceforth TK92) estimations and dozens of subsequent studies expose four major characteristics of decision-makers' preferences over uncertain prospects:

-Diminishing sensitivity to gains. The CPT utility function over gains is concave, and decision-makers are risk averse for gains of moderate to high probability.

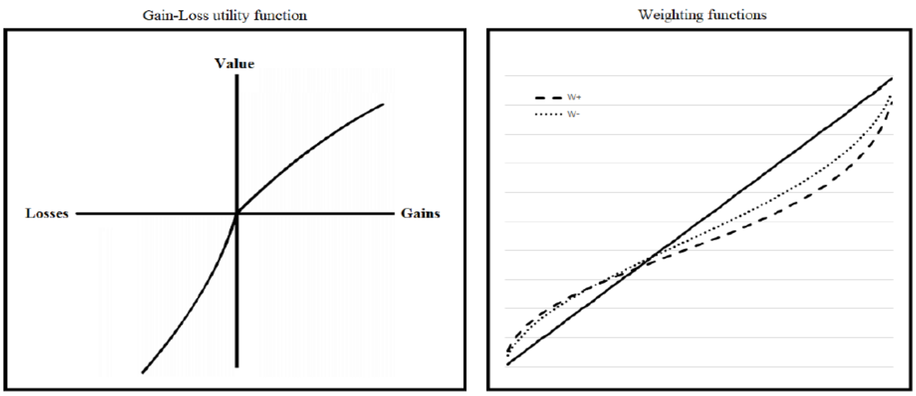
-Diminishing sensitivity to losses. The CPT utility function over losses is convex, and decision-makers are risk seeking for losses of moderate to high probability.

[1] Some empirical studies (see Choi and Kronlund 2017 and the references therein) illustrate that reaching for yields tilts the bond portfolios of institutional investors toward high-risk investment. Rajan (2006) particularly argues that convex incentives and low interest rates direct institutional investors to ignore tail risks that are easiest to conceal. The current experiments complementarily illustrate that neglect of tail risks shows in the preferences of private investors over structured products.

-Loss aversion. The disutility of loss exceeds the utility of a similar gain by a factor $\lambda > 1$. TK92 λ estimate is 2.25, proposing that the disutility of loss is more than twice the utility of a comparable gain. The utility of gains and losses assuming the TK92 estimates is depicted in the left panel of Figure 1.

-Overweighting of tail events. Decision-makers overweight low-probability tail events. The right panel of Figure 1 shows the weighting functions, transforming probabilities to decision-weights, assuming the TK92 estimates. The weighting functions for gains (w^+) and losses (w^-) are almost identical. The overweighting of tail events reflects in the concave segment of the function at the left.[2]

<u>Figure 1: Tversky and Kahneman's (1992) Utility and Weighting Functions</u>



Cumulative prospect theory has proved useful in resolving fundamental finance anomalies such as the equity premium puzzle, the disposition effect, and anomalous pricing of IPOs (Barberis and Thaler 2003). Studies that calculate the value of popular structured products assuming the TK92 benchmark estimates, however, paradoxically conclude that investors should prefer the risk-free rate or the market index to investing in structured instruments (Roger 2008; Jessen and Jørgensen 2012), and Erner et al. (2013) find close to zero correlation between individually elicited CPT parameters and the certainty equivalents of ten structured products. Together with the ample evidence regarding the overpricing of structured instruments, the weak results for standard CPT estimates again lead to the hypothesis that investors exhibit context-specific increased risk appetite when making structured investment choices. The current study aims at characterizing these preferences in laboratory experiments.[3]

[2] The TK92 weighting function is $w(p) = p^\gamma/(p^\gamma + (1-p)^\gamma)^{1/\gamma}$ with median estimates $\gamma = 0.61$ for gains and $\gamma = 0.69$ for losses. The Prelec (1998) function showed better fit in the current estimations.

[3] An alternative approach taken by Das and Statman (2013) illustrates that capital protecting instruments may fit in behavioural portfolios when investors maximize the expected return subject to keeping the probability of return smaller than a given threshold (e.g., -10%) below some predetermined level (0.05). Such behavioural demand explains the 8% overpricing of the equity-linked notes studied by Henderson and Pearson (2011).

3. Experiment 1: Method

3.1: Outline

The sessions were run in June 2017 at the laboratory of an Israeli college. Calls for registration were distributed among MBA, Econ MA, and advanced undergraduate students. Each session started with an oral presentation of detailed instructions (see Supplement B for the script). The first slides introduced the concept of retail-oriented structured investment instruments using recent field examples and explained that the experiment deals with characterizing prospective investors' tastes over simple structured deposits. We used the *FTSE all shares* index as the underlying asset, to detach from the local market.[4] The instructions explained that all the deposits of the experiment would build on the return of FTSE all shares in the twelve months between July 1st 2017 and June 30th 2018 (*the investment period*). A fact sheet with information regarding FTSE’s annual returns over the last ten years was distributed with the printed instructions. The structure of some exemplary deposits was explained in detail and the binary choice problems composing the experiment were introduced in examples. Subjects completed a short comprehension quiz before starting the program.

The computerized part of the experiment was programmed using Fischbacher’s (2007) Z-Tree and consisted of two main stages. In the first (Section 3.2), the exchangeability method was utilized to elicit median and quartile forecasts for the FTSE return in the investment period. In the second (Section 3.3), the certainty equivalents of twenty forecast-dependent deposits were elicited in short sequences of binary choice problems. The instructions explained that at the end of the investment period, one choice problem would be randomly selected to derive a choice-based participation bonus. The bonus formula was 40+300*R%, where R% denotes the realized return in the random problem. As the returns on the deposits took values between -10% and 22%, the bonus could range between 10 NIS and 106 NIS.[5] When done with the computerized part of the experiment, the participants filled in a demographics and personality questionnaire, collected a fixed participation fee, and left the laboratory. On average, the subjects took about 30 minutes on the computerized part of the experiment and the full sessions took 60−90 minutes. The sample consists of N=73 students (63% males), with 82% holding a BA and 67% pursuing an MBA or an MA in economics. The mean age at the time of participation was 28.8.

3.2: The Elicitation of Median and Quartile FTSE Forecasts

The *exchangeability method* has been applied in diverse decision experiments to partition spaces of uncertainty into equiprobable events (Baillon 2008; Abdellaoui et al. 2011; Menapace et al. 2015; Jiao

[4] Subjects were asked to report exposures to the UK economy at the end-of-session questionnaire. No one reported exposures.

[5] The exchange rate at the end of June 2018 was 3.65 NIS for 1 US dollar. Since the FTSE’s realized return in the investment period was significantly smaller than expected by the subjects (see 4.1 for details), the bonus amounts turned small averaging at 42.5 NIS. Subjects’ emails were collected in the consent form, and the bonus amounts were announced in emails that invited the subjects to collect their payoffs.

2020). We currently use the method to elicit median and quartile FTSE forecasts for the investment period.

To start the elicitation, each subject provides upper and lower bounds representing the most extreme values that FTSE can take over the investment period. Using L and H for the lower and upper bounds, the program begins iterating to divide the [L,H] interval into exchangeable events: [L,P50] and [P50,H]. Events are defined as exchangeable when the decision-maker is indifferent to permutations of their outcomes. Assuming the existence of probabilistic beliefs, the likelihoods of complementary exchangeable events must be 0.5 each, so P50 represents a median forecast for the FTSE return.

Specifically, the elicitation is based on sequentially defining tighter lower and upper bounds $\{L_t, H_t\}_{t=1,2\ldots T}$ for P50, up to the point where the distance between the upper and lower bounds is smaller than 1%. Following each update of the interval, the program uses the midpoint of the new interval to generate a binary choice problem between deposit A that pays 5% return when $FTSE \geq (L_t + H_t)/2$ and deposit B that pays 5% return when $FTSE < (L_t + H_t)/2$. If deposit A is preferred to deposit B, then the event $FTSE \geq (L_t + H_t)/2$ appears more likely than the complementary event $FTSE < (L_t + H_t)/2$, so the lower bound for P50 is updated to $(L_t + H_t)/2$. If deposit B is preferred to deposit A, then the event $FTSE < (L_t + H_t)/2$ appears more likely than the event $FTSE \geq (L_t + H_t)/2$, so the upper bound for P50 is updated to $(L_t + H_t)/2$. As a starting point the program takes the whole [L,H] interval as the range where P50 can fall.

If, for example, L=-5% and H=30%, the subject is first asked to choose between deposit A that pays 5% return if FTSE increases by at least 12.5% over the investment period and deposit B that brings the 5% return when FTSE's return falls below the 12.5% cutoff. If A is preferred to B, then the lower bound for P50 is updated to 12.5%. If B is preferred to A, the upper bound for P50 is changed to 12.5%. The updated interval is used to generate the next binary choice problem, which is presented on a new screen. The program proceeds, updating the bounds and generating binary choice problems, up to the stopping point where $H_T - L_T \leq 1\%$. The midpoint of the last interval is taken as the P50 estimate. A similar procedure is then used to divide the [L,P50] interval into the exchangeable events [L,P25] and [P25,P50] and finally divide the [P50,H] interval into the events [P50,P75], [P75,H]. A detailed example of the elicitations is provided in Supplement B.

3.3: The Individually-Tailored Deposits

For the second stage of the experiment, the program was fed with twenty prototype structured deposits, building on the P25, P50 and P75 forecasts (see Supplement B for the complete list). The elicited forecasts were substituted into the prototypes to determine the terms of each deposit on an individual basis. The prototype deposit paying (9% or 0%) depending on whether FTSE outperforms the P50 forecast, for example, was presented as paying 9% when FTSE ≥ 12% to subjects with P50=12%, while being presented as paying 9% when FTSE ≥ 2% in cases where P50=2%. The link between the two stages of the program was not exposed in the instructions, and the elicited median and quartile FTSE assessments were not announced on screen. We thus keep the deposits uncertain, while indirectly controlling the likelihood of the returns that the deposit may bring. Assuming that the subject holds consistent probabilistic beliefs regarding the performance of FTSE, the (9% or 0%) deposit pays the positive or zero returns with equal 0.5 probabilities, but the probabilities are not presented in the deposit's description. A possible weakness of this design is that large gaps may emerge between the underlying FTSE returns and the returns on the deposit. We therefore distributed the FTSE fact sheet that could serve as an anchor and reduce the risk of extreme forecasts. The instructions, in addition, guided participants to ignore the provider's risk-management considerations and assume the returns on each deposit are 100% guaranteed.[6]

The prototype deposits were organized in pairs to allow for direct characterization of preferences, beyond the CPT estimations. Gain-domain risk aversion was tested by comparing the certainty equivalents of (9% or 0%) and (6% or 3%) deposits, while loss aversion was tested by comparing the response to (9% or -8%) versus (1% or 0%) return combinations. The certainty equivalent of each deposit was elicited in a sequence of 3–5 binary choice problems, between the deposit and fixed return rates. The first problem always used a fixed rate of about 0.9*E(R), where E(R) represents the expected return on the deposit assuming the first-stage probabilities. The fixed rates were rounded to the nearest 0.5, so that the first problem for the (9% or 0%) deposit offered a choice between the deposit and a fixed return rate of 4% (Figure 2). The next problems in each elicitation were generated using a bisection algorithm, similar to the exchangeability method of stage 1. The fixed return rate was increased when the subject preferred the deposit to the fixed rate, and decreased if the subject preferred the fixed rate to the deposit (see Supplement B for details). The instructions directed subjects to make independent choices in each problem, assuming an investment budget of 100,000 NIS. The concept of an "equivalent fixed return rate" was introduced in words, explaining that the sequence of choice problems for each deposit is meant to elicit the equivalent rate for the deposit. We also explained that the equivalent rate

[6] The supplements to the paper are organized by section with Supplement B extending the discussions in Section 3 and addressing the methodological concerns more closely. The consistency of the FTSE forecasts was tested at the end of the program using three binary choice problems. One problem, for example, presented a choice between deposits A that pays 5% when FTSE<P50-3% and B that pays the 5% return when FTSE≥P50-3%. The consistency rate was 79%. In general, our consistency rates are similar to those of Baillon (2008) and related studies, and the results are robust to removal of subjects who violate consistency. To measure the gap between the underlying FTSE returns and the deposits' returns, we take a weighted average of the distances between the respective returns. The gap for the (9% or 0%) deposit, for example, is $0.5 * [(H + P50)/2 - 9] + 0.5 * [(P50 + L)/2 - 0]$. When the gaps are averaged across the twenty deposits, the median average gap (|gap|) is 3.3% (5%). Supplement B provides more details.

may be negative when the participant dislikes a given deposit to the extent of preferring to lose some fraction of the investment capital to investment in the deposit.

Figure 2: The First Choice Problem for the (9% or 0%) Deposit

Deposit no 5_

FTSE condition	Annual return on the deposit
FTSE ≥ 14%	9%
FTSE < 14%	0%

Choose one of the two investment alternatives:

□ Deposit 5 as presented on the top of this screen

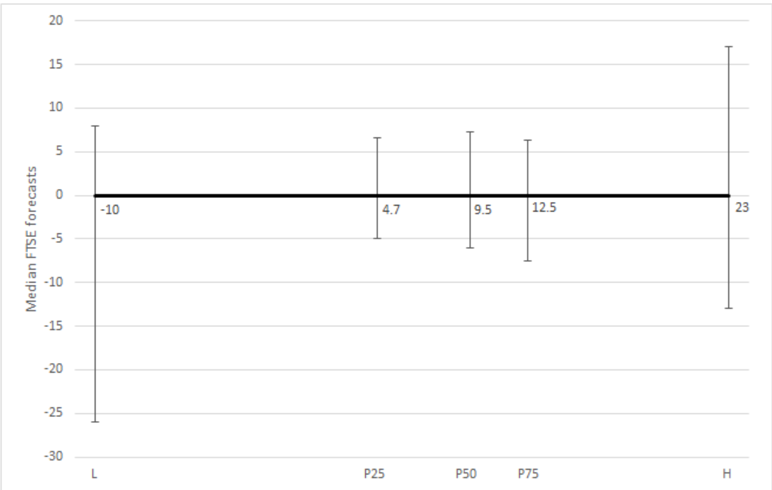
□ Fixed annual return of 4%

4. Experiment 1: Results

4.1: The FTSE Forecasts

The elicited FTSE forecasts were mostly positive. The median P50 was 9.3%, with only four subjects converging to negative median forecasts. In fact, FTSE all shares increased over the investment period by less than 5%, which is close to the median P25 forecast (4.7%). The FTSE forecast elicitations thus expose the familiar tendency of investors for unrealistic optimism (Sonsino and Regev 2013). Figure 3, however, illustrates that the forecasts are skewed to the left. The [L,P50] interval is about 50% longer than the [P50,H] interval, and P50 > (L+H)/2 for 71% of the participants. Forecasting studies show that investors tend to hedge their forecasts contrarily, so that forecasters with positive expectations tilt their confidence intervals to the left (De Bondt 1993; Grosshans and Zeisberger 2018). It is interesting to observe that similar patterns emerge in indirect elicitation of forecast statistics using the exchangeability method.

Figure 3: The FTSE Forecasts



Note. The bars represent the plus and minus 40% range around the median

4.2: The Certainty Equivalents in General

While risk and loss aversions imply that the certainty equivalents (henceforth: CEs) of the deposits should fall below their expected return, the elicited CEs approach and even exceed the expected return on the deposits. The hypothesis CE=E(R) cannot be rejected (at $p<0.05$) for eleven of the twenty deposits and in two of the remaining cases the certainty equivalents significantly exceed the expected return. When the certainty equivalents of the twenty deposits are averaged for each subject, about 40% of the participants show avg(CE)>avg(E(R)), exhibiting preference for risk over all their investment choices.[7] The hypothesis avg(CE)=avg(E(R)) cannot be rejected for Gain-Only deposits and for Gain-Loss deposits (see Table I). Closer look at the Gain-Loss deposits moreover shows that the hypothesis cannot be rejected for the four deposits that bring a loss when FTSE<P50 and for the four deposits that bring a loss when FTSE<P25 (see the bottom panel of Table I). The elicited CEs of the four deposits with a loss at FTSE<P25 are especially close to the expected return.

Table I: Comparing the Certainty Equivalents to the Expected Returns

	E(R)	Elicited CEs	Sign-test of CE=E(R)
All deposits	4.5%	3.8% (2.5%)	p=0.10 (29/44)
Gain-Only deposits	4.9%	4.7% (1.6%)	p=0.48 (33/40)
Gain-Loss deposits	4.1%	3.5% (3.3%)	p=0.10 (29/44)
Deposits with 0.5 loss	4.6%	3.6% (4.2%)	p=0.15 (29/42)
Deposits with 0.25 loss	4.1%	4.1% (2.4%)	p=0.99 (36/35)

Notes. E(R) denotes expected return and CE denotes certainty equivalent. The table reports the results of comparisons between the average CE (avg(CE)) and the average E(R) (avg(E(R)) on designated collections of deposits. The top row compares the average CE and average E(R) of all twenty deposits. The "Gain-Only" row compares the average CE and average E(R) of the nine deposits with no loss and the "Gain-Loss" row shows the results for the eleven deposits with at least one loss. The two bottom lines restrict the comparisons to the four deposits that bring a loss when FTSE < P50 (Deposits with 0.5 loss) and the four deposits that bring a loss when FTSE < P25 (Deposits with 0.25 loss). The E(R) column presents the average expected return on the respective deposits. The "elicited CEs" column reports the median avg(CE) for the 73 subjects, with the standard deviation in parentheses. The rightmost column shows the two-tailed significance level in a sign-test of the hypothesis avg(CE)=avg(E(R)). The parentheses disclose the number of subjects with avg(CE)>avg(E(R)) (left) and the number with avg(CE)<avg(E(R)) (right). More details are provided in Supplement C.

4.3: Preference for Riskier Gain-Only Structures, When the Expected Return is Low

Table II shows that subjects exhibit a preference for relatively riskier Gain-Only return structures when returns are low. Consider the deposits 1A and 1B first. Deposit 1A is low-risk, paying 6%, 4% or 3%

[7] We use "average", abbreviated as avg, for within-subject averages and "median" for the sample statistics. When discussing the median of average results (e.g., the median average CE of Gain-Only deposits), the average is omitted for convenience. Supplement C presents an extended version of Table I and other supplementary material for Section 4.

depending on whether FTSE exceeds the P75 forecast, falls between P50 and P75, or falls below P50. The riskier version 1B is constructed by shifting 3% from the weak state to the two stronger states, so the deposit respectively pays 9%, 7% or 0%. The expected return (4%) does not change, but the spread in payable returns increases from 3% to 9%. Aversion to risk implies that 1A should be preferred to 1B, but subjects show a clear preference for the riskier return structure. The median CE of the safer deposit 1A is lower than the 4% expected return, while the median CE of the riskier deposit 1B exceeds the expected return by 0.5% (median CEs 3.75% and 4.5%, respectively). Paired comparisons suggest that 63% of the subjects show preference for 1B over 1A, while only 23% show the opposite ranking. Equality of the CEs is rejected at $p<0.01$ in a sign test. Similar, but statistically weaker, results emerge in a comparison between deposits 2A and 2B, where the subjects show preference for a (9% or 0%) return structure over a (6% or 3%) design ($p<0.06$; see the table for details). We interpret the preference for more risky Gain-Only structures as reflecting an appetite for substantial enough "worthy" gains. Yearly return of 3% does not meet the implicit threshold for worthy return and an increase in possible gains from 6% to 9% has stronger effect than an equally likely decrease from 3% to 0%.[8]

Table II: Results for Gain-Only Deposits

Deposit	FTSE Condition	Return	E(R)	Elicited CEs	Sign-test
1A	*FTSE ≥ P75*	*6%*	4%	3.75% (1.1%)	p<0.01 (17/46)
	P50 ≤ FTSE < P75	*4%*			
	FTSE < P50	*3%*			
1B	*FTSE ≥ P75*	*9%*	4%	4.5% (2.1%)	
	P50 ≤ FTSE <P75	*7%*			
	FTSE < P50	*0%*			
2A	*FTSE ≥ P50*	*6%*	4.5%	4.25% (1.2%)	p<0.06 (20/35)
	FTSE < P50	*3%*			
2B	*FTSE ≥ P50*	*9%*	4.5%	5.0% (2.0%)	
	FTSE < P50	*0%*			
3A	*FTSE ≥ P50*	*20%*	10%	8.0% (4.6%)	p<0.01 (58/8)
	FTSE < P50	*0%*			
3B	*FTSE ≥ P50*	*10%*	5%	5.0% (3.1%)	
	FTSE < P50	*0%*			

Notes. The left panel of the table presents the terms of each deposit. E(R) is the expected return on the deposit. The "Elicited CEs" column presents the median CE of the deposit, with the standard deviation in parentheses. The rightmost column reports the results of applying a sign-test on the paired differences CE(jA)-CE(jB), for j=1,2,3. The parentheses disclose the number of subjects with CE(jA)> CE(jB) (left) and the number with CE(jA)<CE(jB) (right). Throughout the paper, the sign-test is used for one-sample hypotheses and the Pitman test is used for between-samples comparisons. Significance levels are two-tailed.

[8] The estimations of Section 5 formally capture the notion of "a threshold for substantial enough gains" using the inflection point of a convex-then-concave expo-power utility function (Saha 1993) or using the aspiration level of Diecidue and Van de Ven (2008).

4.4: Emergence of Risk Aversion, When the Expected Return is Higher

While the certainty equivalents of the deposits in pairs 1 and 2 of Table II were close to or even larger than the expected return, the results for deposit 3A, that pays 20% or 0% depending on whether FTSE exceeds the P50, show that gain-domain risk aversion emerges when returns are higher. The median certainty equivalent of the deposit is 8%, with almost 75% of the subjects (N=53) showing CEs smaller than or equal to the 10% expected return. The equality CE=E(R) is instantly rejected in a sign test (p=0.00). Risk neutrality emerges again, however, for deposit 3B that pays (10% or 0%) in the respective states (see table). More generally, the results for the nine Gain-Only deposits reveal that the deviations of the CEs from the E(R) change sign, from positive to negative, as the expected return increases. A fixed effects regression of (CE-E(R))/E(R) on E(R) and individual intercepts suggests that 1% increase in the expected return decreases the (CE-E(R))/E(R) ratio by 3.24% (T=-4.7; p<0.01). The median proportional deviation is negative -12.7% for the deposits with E(R)>4.5%, compared to positive +7.1% for the deposits with E(R)<4.5% (p<0.01). The subjects thus appear to switch from risk preference to risk aversion when the expected return on Gain-Only deposits increases. Intuitively, the change in risk attitudes connects with the appetite for substantial enough gains. When the expected return on the deposit is smaller than 4.5%, subjects show preference for more risky structures that bring 7% or 9% in the positive scenarios. When the expected return on the deposit increases, standard (default) risk aversion emerges.

Table III: Results for Deposits with a Single Loss

Deposit	FTSE Condition	Return	E(R)	Elicited CEs	Sign-test
4A	*FTSE ≥ P50*	*20%*	5%	4.0% (5.9%)	p<0.01 (12/50)
	FTSE < P50	*-10%*			
4B	*FTSE ≥ P50*	*20%*	7.5%	6.0% (5.6%)	
	FTSE < P50	*-5%*			
5A	*FTSE ≥ P50*	*7%*	3.75%	4.0% (1.6%)	p<0.03 (34/17)
	P25 ≤ FTSE < P50	*1%*			
	FTSE < P25	*0%*			
5B	*FTSE ≥ P50*	*7%*	3.75%	3.25% (1.4%)	
	P25 ≤ FTSE < P50	*3%*			
	FTSE < P25	*-2%*			
6A	*FTSE ≥ P50*	*10%*	5.25%	4.0% (2.6%)	p<0.02 (22/42)
	P25 ≤ FTSE <P50	*1%*			
	FTSE < P25	*0%*			
6B	*FTSE ≥ P50*	*10%*	5.25%	5.5% (2.6%)	
	P25 ≤ FTSE <P50	*9%*			
	FTSE < P25	*-8%*			

Note. The definitions are as in Table II.

4.5: Reduced Loss Aversion

Table III proceeds to discuss the results for deposits with a single loss. First, we use the data for deposits 4A and 4B to show that loss aversion is weaker than estimated in the early CPT studies. Deposit 4A pays 20% or -10% depending on whether FTSE exceeds the P50. The certainty equivalent of the deposit assuming the TK92 estimates is negative -0.81%, suggesting that TK92 decision-makers should prefer zero return to investment in this structure. The median elicited CE however is positive 4%, with 48% of the subjects showing CE≥5%, the expected return on the deposit. Similar results emerge for deposit 4B, paying (20% or -5%). The TK92 predicted CE for the deposit is 1.78%, but the median elicited CE is more than three times larger 6%.[9]

4.6: Willingness to Accommodate a Compensated Loss

In structured investment, possible gains must more-than-compensate for possible losses to keep the investment worthy. Deposit pairs 5 and 6 of Table III further examine the willingness to accommodate the possibility of a loss in such settings. Both pairs compare the certainty equivalents of a Gain-Loss deposit that brings a loss $L<0$ and a gain $G>|L|$ in two equiprobable states, to the certainty equivalents of a Gain-Only deposit that pays $G-|L|$ and 0 in the respective states. The results for the two pairs are different, illustrating that the willingness to accommodate a loss depends on the compensating gain.

The deposits of pair 5 bring 7% return when FTSE≥P50, but 5A is Gain-Only paying 1% or 0% in the lower quartile events, while 5B is Gain-Loss bringing returns of 3% or -2% in the respective states. The expected return on both deposits is similar, but the subjects show preference for 5A over 5B. The median CEs are 4% and 3.25%, and the paired comparisons reveal that 47% show preference for 5A while only 23% show preference for 5B ($p<0.03$). The increase in positive returns from 1% to 3% therefore does not compensate for the introduction of an equiprobable 2% loss.

The results for the deposits of pair 6 are opposite. Again, the two deposits pay similar positive (10%) return when FTSE exceeds the median forecast, but 6A is Gain-Only paying 1% or 0% in the lower quartile events, while 6B is Gain-Loss paying 9% or -8% in the respective states. While standard CPT estimates such as TK92 imply that 6A is preferred to 6B, the subjects reveal preference for the deposit with possible loss in this case. The median certainty equivalents of the two deposits are 4% and 5.5% and the paired comparisons show CE(6A)<CE(6B) for 58% while CE(6A)>CE(6B) for only 30%

[9] The results for these deposits match the findings in the Web survey-experiment of Lazar et al. (2017), where subjects reveal preference for a (5% or -3%) return structure over a parallel (2% or 0%) design. More generally, some recent CPT estimations that point to lower levels of loss aversion compared to TK92 and close to linear utility functions fit the elicited CEs of deposits 4A and 4B nicely. Zeisberger et al. (2012) median estimates in particular predict CEs of 4.4% and 6.8% respectively, but their estimates do not capture other features of the current results (see Supplement F).

(p<0.02). The increase in positive returns from 1% to 9% therefore more-than-compensates for the equiprobable 8% loss.[10]

At the level of interpretation, the difference in the results for deposit pairs 5 and 6 plausibly connects to the appetite for substantial gains discussed in 4.3. The results in 4.3 suggest that increase in gains from 6% to 9% has stronger impact than decrease from 3% to 0%. Currently, the increase in gains from 1% to 9% in the structural shift from 6A to 6B shows a stronger impact per unit of loss compared to the increase from 1% to 3% in the shift from 5A to 5B.[11]

Table IV: Results for Deposits with Two Losses

Deposit	FTSE Condition	Return	E(R)	Elicited CEs	Sign-test
7A	*FTSE ≥ P50*	*14%*	4.5%	2.0% (4.2%)	p=0.27 (22/31)
	P25 ≤ FTSE < P50	*-4%*			
	FTSE < P25	*-6%*			
7B	*FTSE ≥ P50*	*14%*	4.5%	2.75% (4.1%)	
	P25≤ FTSE < P50	*0%*			
	FTSE < P25	*-10%*			
8A	*FTSE ≥ P75*	*22%*	3%	2.25% (6.0%)	p=0.81 (32/35)
	P50 ≤ FTSE <P75	*-2%*			
	FTSE < P50	*-4%*			
8B	*FTSE ≥ P75*	*22%*	3%	2.75% (5.5%)	
	P50≤ FTSE < P75	*0%*			
	FTSE < P50	*-5%*			

Note. The definitions are as in Table II.

4.7: Mixed Results for Deposits with Two Losses

The decreasing sensitivity to loss component of CPT implies that decision-makers would prefer a single large loss of -10% over two smaller losses of -4% and -6% (Thaler 1985). Deposit pair 7 of Table IV tests if this feature holds in the valuation of simple experimental deposits. The deposits 7A and 7B similarly pay 14% when FTSE exceeds the median forecast, but 7B brings a loss of -10% in the least favourable 0.25 event, while 7A brings smaller losses of -4% and -6% in the two least favourable 0.25 events. The median CEs in Table IV apparently point to a preference for the single-loss deposit, but the paired comparisons suggest that 30% show preference for 7A while 42% show preference for 7B, so that equality cannot be rejected (p=0.27). Similar inconclusive results are observed for deposits 8A−8B

[10] Note that 6A dominates 5A in the return distribution, but the median CEs are equal. A closer look reveals that 23 subjects violated dominance with CE(5A)>CE(6A). N=12 preferred deposit 5A to the initial fixed rate of 3.5%, while preferring the initial fixed rate of 4.5% to deposit 6A. Supplement D shows that the results are robust to removal of cases where subjects violate dominance.

[11] The difference may also be attributed to decreasing sensitivity to marginal loss, so that 8% loss brings smaller average disutility compared to 2% loss, but Section 4.7 shows that the data does not support decreasing sensitivity.

which also differ only in splitting a single loss into two smaller losses.[12] Interestingly, only 38% of the subjects exhibit consistency in the sense of showing preference for the single loss or the two losses in both problems. The consistency rates for the Gain-Only deposit pairs 1 and 2 are significantly larger, with 59% of the subjects exhibiting consistent preference for the riskier or the safer deposit in both pairs (see Supplement C for details). The CPT estimations of the next section assume linearity with respect to losses, so that preference for a single large loss or a split into two smaller losses mostly follows from noise in the choice process. Relaxing the linearity assumption does not improve the fit of the estimations.

5. Experiment 1: Estimations

5.1: Simplified Version of CPT

Since the structured deposits of the current experiments build on a maximum of four exchangeable events, we introduce a restricted CPT version for quadruple deposits.

Quadruples $\mathrm{D} = (\mathrm{r}_1, \mathrm{r}_2, \mathrm{r}_3, \mathrm{r}_4)$ are used to represent *quadruple deposits* that pay return $\mathrm{r_i}$ in the event $\mathrm{E_i}$, where the returns are ranked in decreasing order so that $\mathrm{r}_1 \geq \mathrm{r}_2 \geq \mathrm{r}_3 \geq \mathrm{r}_4$ and $\mathrm{E}_1, \mathrm{E}_2, \mathrm{E}_3, \mathrm{E}_4$ are the four exchangeable events by the first stage of the experiment (E_1 is the event $\mathrm{P75} \leq \mathrm{FTSE} \leq \mathrm{H}$ etc). Deposits that build on only two or three events are split into quadruples in the obvious way; e.g., deposit 1A of Table II is presented as $(6\%, 4\%, 3\%, 3\%)$. At least one return (r_1) is positive, and when some returns are negative $\mathrm{m} \in \{2,3,4\}$ denotes the smallest index for which $\mathrm{r_m} < 0$. When all the returns are positive, $\mathrm{m} \equiv 5$.

***Definition**: CPT under uncertainty holds (for quadruple deposits) if there exists a strictly increasing continuous utility function $u: \mathcal{R} \to \mathcal{R}$ satisfying $u(0) = 0$, a parameter $\lambda > 0$, and two strictly increasing weighting functions $W^+, W^-: [0,1] \to [0,1]$ satisfying W(0)=0 and W(1)=1, such that each quadruple deposit $D = (r_1, r_2, r_3, r_4)$ is evaluated through the equation*

[12] The hypothesis CE=E(R) is rejected for deposits 7A (p<0.01) and 7B (p<0.03), but cannot be rejected for deposits 8A and 8B (p>0.64). The predicted CEs of these four deposits assuming TK92 or the more recent CPT estimates of Booij et al. (2010) or L'Haridon and Vieider (2019) are either negative or smaller than 1%. The Zeisberger et al. (2012) CPT estimates produce much larger CEs ranging between 2.9% and 3.8%. A closer look at the data shows that 20%−30% of the subjects converged to negative CEs in each of the 7A, 7B, 8A and 8B elicitations. The valuation model for non-attractive deposits may be different, but the current experiments were not designed to test such hypotheses.

$$(\mathbf{1})\quad V(D) = \sum_{i=1}^{m-1} \big(W^{+}(0.25 * i) - W^{+}(0.25 * (i-1))\big) * u(r_i)$$

$$+ \sum_{j=m}^{4} \big(W^{-}(0.25 * (5-j)) - W^{-}(0.25 * (4-j))\big) * \lambda * u(r_j).$$ [13]

The formula is easily understood by splitting the calculation into three steps. First, the utility function u is applied to the deposit's possible gains and losses. Then, the utility of losses is multiplied by the loss aversion factor λ, defining the *overall disutility of loss r* as the product $\lambda * u(r_j)$ for $r_j < 0$. Finally, the value of the deposit is calculated as a weighted sum of the overall utilities, where the weights are derived from the weighting functions W^{+} and W^{-} and depend on the probability of the respective gain/loss and the accumulated probability of larger gains/losses.

Applying the valuation function (1) to Deposit 7A of Table IV, for example, gives

$$\mathrm{V(7A)} = \mathrm{W}^{+}(0.25) * \mathrm{u}(14) + \big(\mathrm{W}^{+}(0.5) - \mathrm{W}^{+}(0.25)\big) * \mathrm{u}(14) +$$
$$\big(\mathrm{W}^{-}(0.5) - \mathrm{W}^{-}(0.25)\big) * \lambda * \mathrm{u}(-4) + \mathrm{W}^{-}(0.25) * \lambda * \mathrm{u}(-6),$$

which reduces to

$$\mathrm{W}^{+}(0.5) * \mathrm{u}(14) + \big(\mathrm{W}^{-}(0.5) - \mathrm{W}^{-}(0.25)\big) * \lambda * \mathrm{u}(-4) + \mathrm{W}^{-}(0.25) * \lambda * \mathrm{u}(-6).$$

$\mathrm{W}^{+}(0.5)$ represents the subjective weight that the decision-maker assigns to the 14% gain. When $\mathrm{W}^{+}(0.5) > 0.5$, the investor overweights the 14% return, exhibiting optimistic weighting of the respective event. When $\mathrm{W}^{+}(0.5) < 0.5$, the investor underweights the 14% return, exhibiting pessimistic weighting of the gain. $\mathrm{W}^{-}(0.25)$ similarly represents the subjective weight of the -6% outcome. Since the utility of loss is negative, $\mathrm{W}^{-}(0.25) > 0.25$ represents pessimistic weighting of the event, while $\mathrm{W}^{-}(0.25) < 0.25$ conversely exhibits optimistic weighting of the 6% loss. The dependency of weights on the ranking of payoffs can be seen in the fact that the weight of the -4% outcome $\big(\mathrm{W}^{-}(0.5) - \mathrm{W}^{-}(0.25)\big)$ may be different from the weight of the -6% outcome, although the probabilities of the two outcomes are identical.

5.2: Structural Assumptions

For the estimations, parametric utility and weighting functions must be selected. In background work, we examined diverse alternatives, comparing the results of aggregate and individual estimations. Two observations robustly emerged for the models with close to maximum likelihood. The next sections

[13] The CPT definition assumes a reference point of zero. Supplement D reports the results of estimating the reference point on an individual basis. The median estimated reference point is 0.82% and a likelihood ratio test rejects the model with endogenous reference points for the model with a zero reference point at p<0.01.

report the results for relatively simple parametric versions of the model that exhibit the two observations neatly. Supplement D presents the results of estimating richer specifications.

Gain-domain utility:

We first assume the power utility model for gains

$$(\mathbf{2}) \quad u(r) = r^{\rho_G} \text{ for return } r > 0 \text{ and parameter } \rho_G > 0,$$

but given the mixed results regarding the attitude toward gain-domain risk (sections 4.3–4.4), we also estimate the two-parameter expo-power utility function (Saha 1993) that allows for a switch in the curvature from convex to concave or vice versa:

$$(\mathbf{3}) \quad U(r) = \frac{1}{\alpha_G} * \left(1 - EXP(-\alpha_G * r^{\rho_G})\right)$$

for return $r > 0$ and parameters $\alpha_G \neq 0$; $\rho_G > 0$.[14]

Loss-domain utility

Joint estimation of a loss-side curvature parameter (such as ρ_L, assuming power utility $u(r) = -|r|^{\rho_L}$ for losses) and a loss aversion parameter λ is considered problematic, as the likelihood function is frequently flat with respect to these parameters (Nilsson et al. 2011). Following the preparatory work, where linearity with respect to losses could not be rejected in the best-fitting models, we assume linear utility with respect to losses ($u(r) = r$ for $r < 0$), focusing on the estimation of λ (but see Supplement D for models that relax this assumption).

The event-weighting function

We adopt the one-parameter weighting function of Prelec (1998) using PR_G and PR_L for the gain and loss event-weighting parameters, respectively:

$$(\mathbf{4}) \quad \begin{cases} W^+(p) = EXP\left[-\left(-LN(p)\right)^{PR_G}\right] \\ W^-(p) = EXP\left[-\left(-LN(p)\right)^{PR_L}\right], \end{cases}$$

for $PR_G > 0, PR_L > 0$.[15]

[14] The expo-power function converges to power utility when $\alpha_G \to 0$ and reduces to the exponential utility when $\rho_G = 1$. Recent studies utilize the function to explain context-dependent risk attitudes (Baltussen et al. 2016), insurance choices (Collier et al. 2017) and agricultural decisions (Gregg and Rolfe 2017). Saha's (1993) formulation assumes $\alpha * (1 - \rho) > 0$ to preclude a change in the sign of the second derivative, but we currently adopt the function especially to capture such change.

[15] The Prelec one-parameter function reduces to linear weighting when $PR_i = 1$. It has a fixed point at p*=1/e. The function is inverse S-shaped, overweighting probabilities smaller than p* and underweighting probabilities larger than p* when PR_i<1. It is S-shaped, underweighting probabilities smaller than p* and overweighting

5.3: Error Model

To construct the likelihood function, we adopt a version of the Fechner model with heteroskedastic errors as assumed in Blavatskyy and Pogrebna (2010), Wilcox (2011) and others. Using $V_\Theta(D_j)$ for the CPT value of deposit D_j and $V_\Theta(R_j)$ for the value of fixed return R_j assuming the parameters Θ, let $\Delta_{\mathrm{j},\Theta} = V_\Theta(D_j) - V_\Theta(R_j)$ (the subscript Θ is omitted henceforth). Assume an error term $\epsilon_j \sim N(0, \sigma * K_j)$ such that deposit D_j is preferred to the fixed rate R_j if $\Delta_\mathrm{j} + \epsilon_j > 0$, the fixed rate R_j is preferred to deposit D_j if $\Delta_\mathrm{j} + \epsilon_j < 0$, and the probability of choosing each of the two alternatives is 0.5 when $\Delta_\mathrm{j} + \epsilon_j = 0$. The parameter σ captures the general noisiness of choice, while K_j is the heteroskedastic adjustment for choice problem j. Specifically, let $K_j = u(max_{D_j}) - u(min_{D_j})$ where max_{D_j} and min_{D_j} are the maximal and minimal returns on deposit D_j. Using the customary $\Phi_{[0,\sigma * K_j]}(z)$ to represent the probability of $\varepsilon_j \le z$, the log likelihood function is formulated as follows:

$$(\mathbf{5}) \qquad LL = \sum_{j \text{ } where \text{ } D_j \text{ } is \text{ } preferred \text{ } to \text{ } R_j} \log\left(\Phi_{[0,\sigma \cdot K_j]}\left(V(D_j) - V(R_j)\right)\right) +$$

$$\sum_{j \text{ } where \text{ } R_j \text{ } is \text{ } preferred \text{ } to \text{ } D_j} \log\left(1 - \Phi_{[0,\sigma \cdot K_j]}\left(V(D_j) - V(R_j)\right)\right)$$

The estimations assuming the power utility model of equation (2) maximize the log-likelihood function (5) with respect to the five parameters $\Theta = (\rho_G, \lambda, PR_G, PR_L, \sigma)$. Adopting the expo-power utility model (3) expands the set to $\Theta = (\alpha_G, \rho_G, \lambda, PR_G, PR_L, \sigma)$.

5.4: The Estimation Results

The complete data set for the estimations consists of 6542 binary choices between given deposits and fixed rates. The number of choices for each subject varies between 86 and 93. Table V presents the results of four estimations. Models (a)–(c) adopt the power utility function, estimating the model at increasing levels of detail. Model (a) ignores preference heterogeneity, pooling all the parameters across the sample, except for the noise σ which is estimated individually. The results for this model represent the estimates that account best for the 6542 choices throughout the experiment. Model (b) takes a first step toward individual estimations, estimating ρ_G, PR_G and σ at the individual level, but still pooling the loss-side parameters PR_L and λ. Model (c) proceeds to full-fledged individual estimations, building on the 86–93 binary choices of each participant to estimate the five parameters that maximize the individual likelihood function. Model (d) also runs the estimations at the individual level, but moves from the single-parameter power utility to the two-parameter expo-power function.

probabilities larger than p* when PR_i>1. The model was also estimated using the two-parameter Prelec (1998) function and other parametric weighting functions. Supplement D reports some results, showing robustness.

Table V: Estimation Results – Experiment 1 (N=73)

	(a)	(b)	(c)	(d)
-2LL	7592	7141	6683	5927
AIC	7761	7583	7413	6803
ρ_G	1.14*** (1.07,1.26)	1.29*** (61/12)	1.21*** (49/24)	1.50*** (56/17)
α_G	-	-	-	0.0078*** (54/19)
λ	1.78*** (1.45,2.10)	2.75** (1.25,4.25)	2.31*** (73/0)	2.16*** (54/19)
PR_G	0.57*** (0.44, 0.70)	0.71*** (0/73)	0.79*** (19/54)	0.69*** 22/51
PR_L	2.05*** (1.8,2.3)	1.62*** (1.33,1.90)	1.20*** (55/18)	1.68*** 51/22
σ	0.38	0.31	0.23	0.20
ρ1	0.44	0.66	0.70	0.73
ρ2	-	0.90	0.96	0.96

Notes. The columns present the results of four CPT estimations following the basic structure of Section 5.2. Models (a)−(c) assume the power utility function. Model (d) assumes expo-power utility. Model (a) pools all the parameters across the sample, except for the noise σ. Model (b) pools λ and PR_L, estimating ρ_G, PR_G, and σ on an individual basis. Models (c) and (d) estimate all the parameters on an individual basis. Shaded cells represent parameters that are estimated at the individual level. Non-shaded cells represent parameters that are estimated in the aggregate. The asterisks report the results of testing the benchmark hypotheses $\rho_G = 1$ (linearity of the power utility function), $\lambda = 1$ (loss neutrality), $PR_G = 1$ (linear weighting of gain events), $PR_L = 1$ (linear weighting of loss events) and $\alpha_G = 0$ (curvature of expo-power utility). The standard T-test is used for parameters estimated on an aggregate basis, and the sign-test is used for parameters estimated on an individual basis. Aggregate estimates are shown with the 90% confidence interval in parentheses. The individual level estimations are summarized presenting the median estimate with the number of subjects with parameters exceeding (left) and falling below (right) the hypothesized benchmark in parentheses. Three asterisks *** mean that the hypothesis is rejected at p<0.01; ** and * are used for p<0.05 and p<0.1. The bottom rows of the table summarize the correlations between the elicited and predicted CEs. $\rho1$ is the Pearson correlation between the twenty elicited CEs and the respective predicted CEs. The correlation is calculated for each subject and the table presents the sample median. For $\rho2$ we average the twenty elicited and predicted CEs for each subject and calculate the Pearson correlation between the 73 averages.

To compare the fit of the different models, the upper two rows of Table V present the log-likelihood (-2LL) and AIC scores of each model. The -2LL of model (a) is 7592. For comparison note that the log-likelihood score assuming random choice between the deposit and the fixed rate ($\sigma \rightarrow \infty$) is 9069, and the score of the expected-return model with individual estimation of σ is 7643. The hypothesis that the subjects maximize expected returns is thus instantly rejected in a likelihood ratio test (p=0.00). The log-likelihood scores, moreover, significantly decrease as more parameters are estimated at the individual level (p<0.01 in all three comparisons).[16] The best fit (-2LL =5927) is found for model (d), which adopts the expo-power utility function for gains. When the Pearson correlation between the predicted CEs and

[16] While models (a)−(c) are sequentially nested, model (c) is a special case of model (d) only at the limit when $\alpha_G \rightarrow 0$. We therefore use likelihood ratio tests for comparing models (a)−(c) while using the Clarke and Vuong tests, applying the Clarke (2007) correction for the larger number of parameters in model (d), for comparing models (c) and (d). For a comprehensive discussion of Clarke and Vuong tests see Harrison and Swarthout (2019).

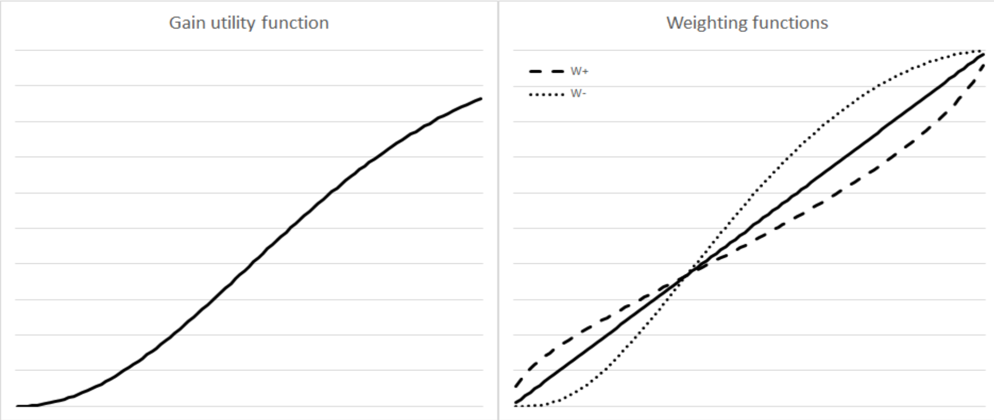
elicited CEs is calculated for each subject, the median correlation for model (d) is 0.73, with 77% of the correlations exceeding 0.5. When the elicited CEs and predicted CEs are averaged across the twenty deposits for each subject, the correlation between the average elicited CEs and the average predicted CEs is almost perfect 0.96. The correlational analysis thus suggests that CPT successfully fits subjects' individual preferences over the twenty deposits, while also effectively capturing between-subject heterogeneity. While CPT fits the data well, the estimation results are clearly non-standard. The results are summarized next in two observations.[17]

Observation 1: Reaching for substantial gains

In section 4.3 we interpreted the preference for a (9% or 0%) return structure over a parallel (6% or 3%) design as revealing an appetite for substantial gains. The estimations indeed suggest that the gain-domain utility function in the models that summarize the data most effectively is convex, at least for low levels of gain. The ρ_G estimates in models (a)–(c) range between 1.14 and 1.29, and the hypothesis $\rho_G = 1$ is rejected at p<0.01 in each of the estimations. The individual level estimations of model (c), for example, suggest that the gain-domain utility function is convex for 49 subjects and concave for only 21. The median ρ_G is 1.21. The fit of the estimations, however, significantly improves when the power utility function is replaced by the more flexible expo-power utility. The expo-power function, assuming the median estimates of column (d), has an inflection point switching from convexity to concavity at a return level of 12.2%. A closer look at the individual estimates shows that about two-thirds of the subjects (N=46) change from convex to concave utility. The median inflection point for these subjects is 6.4% (see Supplement D for details). Returning to the complete sample, the model (d) estimations suggest that increase in returns from 3% to 6% brings more utility than an initial 3% return to almost two-thirds of the subjects (N=46), while increase in returns from 9% to 12% brings less utility than an increase from 6% to 9% to N=45. The estimated expo-power utility functions thus capture the switch from risk preference to risk aversion as the expected return on Gain-Only deposits increases. The change in curvature is illustrated in the left panel of Figure 4.

[17] The binary choice problems generated by the bisection model are nested in the sense that later choices imply preceding choices under monotonicity (the subject may prefer some deposit to a fixed rate of 2% and then again prefer the deposit to a fixed rate of 3%). As a robustness test, the model was also estimated using the choice problems that determine the CE of the deposit. Robustness was also tested in randomized split-sample tests where one of the deposits of each pair is used for the estimations and the ten-deposit estimates are utilized to predict the CEs of the remaining ten deposits. Following a comment by an anonymous reviewer, we also tested robustness using models that account for complexity aversion in the sense of Sonsino et al. (2003). Observations 1 and 2 were consistently supported. Details are provided in Supplement D.

Figure 4: The Model (d) Utility and Weighting Functions



Observation 2: Probabilistic loss-receptiveness

Within CPT, loss aversion can manifest in asymmetry of the (gain vs. loss) utility functions or in asymmetry of the weighting functions (Schmidt and Zank 2008). Harrison and Ross (2017) accordingly draw a distinction between *utility loss aversion* and *probabilistic loss aversion*. Utility loss aversion can be locally measured at $x > 0$ by comparing the overall disutility of -*x* loss ($-\lambda * u(-x)$) to the utility of *x* gain ($u(x)$). In TK92, the gain and loss utility functions are symmetric ($u(x) = x^{0.88}$ and $u(-x) = -|x|^{0.88}$), so the parameter λ serves as a global measure of loss aversion. λ, however, loses its universal meaning when the gain and loss utility functions differ. In the power utility model with $\rho_L > \rho_G$, the overall disutility of loss may exceed the utility of gain even if $\lambda < 1$ (Nilsson et al. 2011). Utility loss aversion thus depends on all three parameters (ρ_G, ρ_L, λ). Moreover, probabilistic loss aversion (Schmidt and Zank 2008) may emerge when loss events are overweighted relative to comparable gain events. In TK92, the weighting of gains and losses is almost identical, so probabilistic loss aversion does not play a significant role. When the gain and loss weighting functions are different, however, choices that appear as loss-averse may arise even if the gain and loss utility functions are symmetric and $\lambda = 1$ (Pachur and Kelen 2013). Assuming the Prelec (1998) one-parameter weighting function, attitude to loss is affected by (PR_G, PR_L) in addition to the utility curvature and loss aversion parameters.

We now use the estimation results to test for utility loss aversion and probabilistic loss aversion in the models that account best for the choices along the experiment.

To test for utility-based loss aversion we calculate the gain-loss utility ratios (GLRs) $-\lambda * u(-r)/u(r)$ for return levels *r* between 1% and 10% (the range of losses on the deposits). If losses loom larger than gains, the GLRs should exceed 1. Indeed, the (median) ratios implied by the estimates of models (a)-(d) fall between 1.1 and 2.75. The model (d) median ratios are 1.2 for r=5% and 1.1 for r=10%. The ratios, however, are smaller than 1 for more than 40% of the subjects, so the hypothesis that the overall disutility of 5% or 10% loss equals the utility of a similar gain cannot be rejected.

The estimated weighting functions additionally point to strong asymmetry in the weighting of gains and losses. The PR_G estimates are significantly smaller than 1 while the PR_L estimates significantly exceed 1, in all four estimations. The model (d) median PR_G estimate is 0.69 and equality to 1 is rejected (51 subjects with $PR_G < 1$; N=22 with $PR_G > 1$; p<0.01). With $PR_G = 0.69$, $W^+(0.25) = 0.29$ and $W^+(0.5) = 0.46$, suggesting that subjects overweight the maximal return that the deposit may bring when the probability is 0.25, while underweighting the maximal return when the probability is 0.5. The median PR_L estimate, however, is 1.68, more than twice larger than the median PR_G. Equality to 1 is rejected again (51 subjects with $PR_L > 1$; N=22 with $PR_L < 1$; p<0.01). With $PR_L = 1.68$, $W^-(0.25) = 0.18$ and $W^-(0.5) = 0.58$, suggesting that subjects strongly underweight the maximal loss that the deposit may bring when the probability is 0.25, while overweighting the maximal loss when the probability is 0.5. The gain and loss weighting functions are contrasted in the right panel of Figure 4. As the graph illustrates, subjects exhibit probabilistic loss receptiveness, overweighting gains while discounting losses, when p=0.25. This reverses to probabilistic loss aversion, overweighting losses while discounting gains, at p=0.5. Individual level calculations confirm that $W^+(0.25)/W^-(0.25) > 1$ and $W^+(0.5)/W^-(0.5) < 1$ for about two-thirds of the subjects (N=49). The median ratios for the complete sample are 1.46 and 0.81.[18]

5.5: Alternative Models

While CPT with non-standard parameters appears to fit the experimental data well, it is possible that alternative models of choice can similarly approximate the data, raising competing explanations for the results. The next paragraphs briefly summarize the results of estimating three such alternative models. More details on the estimated models and the results of the estimations are provided in Supplement D.

Alpha MaxMin: The two-step design of the experiment assumes that the forecasts elicited in the first stage of the experiment still apply when subjects evaluate the individually-tailored deposits of the second stage. If this assumption is violated, the willingness to invest in the deposits may respond to *ambiguity over probabilities* (Camerer and Weber 1992; see Trautmann and van de Kuilen 2015 for a survey of experimental results). Leading models of decision under ambiguity assume the uncertainty manifests in terms of multiple priors over the space of uncertainty. To test if multi-prior models can convincingly explain the results, we estimate versions of the alpha MaxMin model of Ghirardato et al. (2004), which has shown the best fit in studies comparing the descriptive power of different models

[18] We are not aware of evidence connecting to the strong underweighting of 0.25 losses, except for Roberts et al. (2008) where environmental survey participants appear to significantly underweight 0.2−0.3 probability of bad lake-water quality.

(Hey et al. 2010; Baillon and Bleichrodt 2015; Carbone et al. 2017). In the best-fitting alpha MaxMin estimation, the strong willingness to invest in the deposits shows in a median alpha estimate of 0.5, suggesting that subjects assign similar weight to the most optimistic and the (symmetrically) most pessimistic return distributions in their set of priors.[19] The AIC score of the best alpha MaxMin model, however, is almost 200 points larger than the score of model (d) and a Clarke test for comparison of non-nested models rejects the alpha MaxMin model in favour of the CPT model (d) at $p<0.01$.

Aspiration Utility Theory: The switch from risk preference with respect to small gains to risk aversion with respect to larger gains (Table II) and the results for deposit pairs 5−6 (Table III) suggest that the subjects may be responding to implicit aspiration levels. Aspiration levels of 7%−8%, for example, may explain the preference for (9% or 0%) over (6% or 3%) and also explain the preference for 6B=(10%,10%,9%,-8%) over 6A=(10% ,10%,1%, 0%). Following Diecidue and Van de Ven (2008) we apply aspiration utility theory, estimating the aspiration level on an individual basis together with the other parameters of the model. The estimated aspiration level is strictly positive for 80% of the subjects with median 4% and interquartile range [1%,5%]. However, the fit scores of the model do not reach those of model (d) and tests for the comparison of non-nested models reject aspiration utility for CPT.

Range-dependent utility: The intriguing results for deposit pairs 5 and 6 also raise the possibility that the range of returns, which varied between the deposits in each pair and between the two pairs, affects the evaluations. We thus estimate the range-dependent utility model of Kontek and Lewandowski (2018), adopting the parsimonious basic framework proposed in Baucells et al. (2019). The log likelihood score of our best-fitting range-dependent utility model is similar to the score of model (c) in spite of the smaller number of parameters, but again the fit scores of model (d) are better and the Clarke (2007) test rejects range-dependent utility for CPT model (d) at $p<0.01$.

To summarize, the results of the three additional estimations illustrate that intuitions that motivate other theories of decision under uncertainty may also shed light on the observed preferences over the deposits, but the explanatory power of CPT in the current study is stronger.[20] In particular, the switch in curvature of the utility function and the possibility of asymmetric weighting of tail gain and loss events appear to be essential for fitting the current data well. The deposits of this study, however, were designed in light

---

[19] But similar alpha values emerge in standard applications; see Dimmock et al. 2015.

[20] Heuristic-based (non-compensatory) theories of choice also fail to explain the current results. For example, neither the priority heuristic (Brandstätter et al. 2006) nor the Pwin heuristic (Venkatraman et al. 2014) can explain the preference for 1B over 1A (Table II).

of CPT, and it is possible that the stronger performance of CPT follows from the particular set of deposits being tested (see Loomes 2010).

5.6: Discussion

Misperception of complex terms and excessive optimism have been invoked as plausible explanations for the overpricing of retail-oriented structured products. Experiment 1 still illustrates that prospective investors show non-standard risk appetite in the valuation of simple well-defined products, controlling for the likelihoods of the distinct returns that the investment may yield. To illustrate the departure from benchmark preferences, we run an additional set of estimations assuming the TK92 parameters and estimating the noise σ on an individual basis. The log-likelihood score of the TK92 model is 7857 compared to a score of 7592 in the (comparable) aggregate estimations of model (a), so TK92 is instantly rejected for model (a) in a likelihood ratio test (p=0.00). The increased risk-taking relative to TK92 shows clearly in direct comparisons of the predicted and observed choice rates. TK92, for example, predict that subjects will prefer deposit 1B of Table II to a fixed rate of 3.5% (the fixed rate starting the elicitations for this deposit) in 53% of the cases, while in fact the deposit was preferred to this fixed rate by 74% of the subjects. The TK92 estimations, to take one more example, predict that subjects will prefer deposit 4A (Table III) to a fixed rate of 4.5% in 32% of the cases, while in fact 48% of the subjects preferred the deposit to this fixed rate. Over all the choices between the risky deposits and the 0.9*E(R) fixed rate, the TK92 estimations predict a risk aversion rate of 59%, while our subjects prefer the risk-free rate only 42% of the time.

Prospect theory, with parameters around the canonical TK92 estimates, has proved useful in resolving paradoxes regarding the pricing of basic financial assets such as stocks and bonds. Benartzi and Thaler (1995) show that TK92 investors may mix stocks and bonds in their portfolios, although stocks historically pay 6% larger yearly return. Barberis and Huang (2008) illustrate that overweighting of tail probabilities, as in TK92, explains the overpricing of stocks with positively skewed return in equilibrium. Barberis et al. (2016) more generally argue that investors tilt their portfolios toward stocks with high TK92 valuations to the point that these stocks bring negative risk-adjusted returns. Attempts to utilize the TK92 estimates, or standard CPT estimates, to shed light on the pricing of structured instruments, however, show weak or paradoxical results (Roger 2008; Jessen and Jørgensen 2012; Erner et al. 2013). The current experiment indeed suggests that the CPT preferences of structured instruments investors strongly depart from TK92. Subjects reach for substantial enough gains while underweighting the possibility of tail losses when evaluating simple synthetic deposits. The results propose that context-specific appetite for returns may contribute to the mispricing of structured instruments and explain their weak performance.[21]

[21] Exploring the roots of the non-standard preferences is beyond the scope of the current experiments. Intuitively, we suspect that the combination of a synthetic structure, where limited tail losses show up with larger capped

To test the robustness of experiment 1's results and put the increased risk appetite hypothesis to an additional test, we ran a follow-up experiment about one year after the first experiment on a different group of participants. The instructions still referred to the growing retail-oriented structured investment market, and bonuses were again paid at the end of a twelve months investment period. The deposits, however, were presented in terms of probability distributions over annual returns and the subjects were required to choose between each risky deposit and its expected return upfront, at the first step of the CE elicitation.

6. Experiment 2

6.1: Method

Experiment 2 used risky annual deposits that were similar in design to the uncertain deposits of experiment 1. The deposit paying (9% or 0%) depending on whether FTSE≥P50 was now presented as an annual deposit paying 9% or 0% with equal 0.5 probability. Deposit 7A of Table IV, to take another example, was presented as paying 14%, -4% or -6% with probabilities 0.5, 0.25, 0.25. The data was collected in June 2018, and the investment period was the twelve months between July 1st 2018 and June 30th 2019. The assumed investment budget was 100,000 NIS. The instructions still introduced the concept of retail-oriented structured deposits using uncertain deposits, but then explained that for simplicity the experimental deposits would be presented in terms of probability distributions over yearly returns. The forecast elicitations stage was dropped from the program. The CE elicitation algorithm was kept intact, except for starting each elicitation with a choice between the deposit and its expected return. In the case of the (9% or 0%) deposit, the first binary choice problem of experiment 2 presented a choice between the deposit and a fixed annual return rate of 4.5%, compared to a choice between the deposit and a fixed rate of 4% (about 0.9 of the expected return) in experiment 1. Seven of the ten deposit pairs of experiment 1 were used again in experiment 2. The three other pairs were slightly modified (see Supplement E for details). In addition, the printed questionnaire that subjects filled at the end of the session, now presented two binary choice problems to control for risk preferences outside the structured investment context. The first problem presented a choice between a lottery paying (5000 NIS with probability 0.75) and a certain payoff of 3750 NIS. The second problem presented a choice between a lottery paying (+5000 or -3000 with equal 0.5 probability) and a certain payoff of 1000. The participants

gains, and the predetermined yearly investment horizon, underlie the non-standard risk appetite exposed in the experiments and these factors similarly affect the valuation of capital protecting instruments in the field. A related open problem is why preferences over stocks and bonds strongly differ from preferences over structured instruments. Here we conjecture that the difference follows from distinct evaluation processes, as structured instruments are evaluated based on their published terms (although selecting an appropriate underlying asset plays an important role; see Entrop et al. 2016), while stocks or bonds are mostly selected based on private assessments and fundamental or technical information.

in experiment 2 (N=61) were undergraduate university students who had completed at least one course in finance. The incentivization method was identical to the one used in experiment 1.[22]

6.2: Results

To start the analysis, we examine the first problem of each elicitation where the subject chose between the structured deposit and its expected return. Across the 1220 binary choice problems (61 subjects making twenty choices each), the proportion of cases where subjects prefer the expected return to the deposit (52%) is close to the proportion where the deposit is preferred to its expected return (48%). Similar results emerge when cases where the subject prefers the deposit to its expected return first, but prefers the fixed rate to the deposit in all subsequent problems, or vice versa (prefers the expected return to the deposit first, but prefers the deposit to the fixed rate in all subsequent steps) are classified as "approximately risk neutral". About 33% of the elicitations classify as approximately risk neutral, 34% as strongly risk-averse, and 33% as strongly risk-seeking. The sample also appears equally split at the individual level, with 31 subjects preferring the expected return to the deposit in the majority of problems (at least eleven problems) and 28 preferring the deposit to its expected return in most problems. Table VI shows that, as in experiment 1, the hypothesis CE=E(R) cannot be rejected for Gain-Only and Gain-Loss deposits, and the certainty equivalents of the deposits with a single 0.25 loss are especially close to the expected return.

Table VI: Comparing the Certainty Equivalents of Experiment 2 to the Expected Returns

	E(R)	Elicited CEs	Sign-test of CE=ER
All deposits	4.6%	4.5% (1.9%)	p=0.80 (29/32)
Gain-Only deposits	4.9%	5.1% (1.5%)	p=0.99 (31/30)
Gain-Loss deposits	4.4%	4.0% (2.4%)	p=0.52 (27/33)
Deposits with 0.5 Loss	5.2%	4.9% (3.4%)	p=0.70 (28/32)
Deposits with 0.25 Loss	4.2%	4.2% (2.1%)	p=0.99 (29/30)

Note. The table presents the results for the 61 participants of Experiment 2. The definitions are as in Table I.

The certainty equivalents of the fourteen deposits replicated from experiment 1 were larger in experiment 2 (median avg(CE) 4.6% in experiment 2 compared to 3.9% in experiment 1), but Pitman tests could not reject equality (p values exceeding 0.08 in all fourteen comparisons with an average p=0.43).[23] Accordingly, the main results of experiment 1 appear again in experiment 2. Table VII

[22] The average bonus amount was 50 NIS (about 15 US dollars).

[23] The greater risk-taking in experiment 2 cannot be attributed to the change from uncertainty to risk since the two experiments differed in several features.

reports the results for four pairs of risky deposits. The preference for more risky Gain-Only structures when returns are low, can be seen in the results for deposit pair R1. The median CEs of the (20% or -10%) and (20% or -5%) deposits approach the expected returns, and the equality CE=E(R) cannot be rejected in either case (p>0.31). The Gain-Loss return structure (9% or -7%) is preferred to the Gain-Only structure (2% or 0%) by the results for deposit pair R3, and the inconclusive results regarding a preference for integration or separation of losses emerges again for deposit pair R4.

Table VII: Results for Selected Experiment 2 Deposits

Deposit	Probability	return	E(R)	Elicited CE	Sign test
R1A	*0.25*	*6%*	4%	3.5% (0.8%)	p<0.01 (13/32)
	0.25	*4%*			
	0.5	*3%*			
R1B	*0.25*	*9%*	4%	5.0% (2.1%)	
	0.25	*7%*			
	0.5	*0%*			
R2A	*0.5*	*20%*	5%	4.5% (4.7%)	p<0.01 (9/48)
	0.5	*-10%*			
R2B	*0.5*	*20%*	7.5%	7% (4.9%)	
	0.5	*-5%*			
R3A	*0.5*	*10%*	5.5%	5.0% (1.9%)	p<0.01 (16/36)
	0.25	*2%*			
	0.25	*0%*			
R3B	*0.5*	*10%*	5.5%	5.75% (2.5%)	
	0.25	*9%*			
	0.25	*-7%*			
R4A	*0.5*	*14%*	4.5%	3.0% (3.3%)	p=0.10 (17/29)
	0.25	*-4%*			
	0.25	*-6%*			
R4B	*0.5*	*14%*	4.5%	4.0% (3.5%)	
	0.25	*0%*			
	0.25	*-10%*			

Note. The definitions are as in Table II

Table IIX presents the estimation results for experiment 2. The results for models (a)-(c) point to a close to linear utility function for gains and smaller λ estimates compared to experiment 1, but the results for model (d), which again shows the best fit levels, are close to those of experiment 1.[24] The asymmetric weighting of gains and losses reemerges in all four models. The model (d) results, in particular, show $PR_L > PR_G$ for 39 subjects and $PR_L < PR_G$ for 20, so symmetric weighting is rejected at p=0.02. The

[24] Equality of the experiment 1 and experiment 2 model (d) estimates cannot be rejected (p>0.11 in all six comparisons with average p=0.44; see Supplement E for details). The $W^+(0.25)/W^-(0.25)$ ratios are significantly smaller in experiment 2 (p<0.04), but equality of the $W^+(0.5)/W^-(0.5)$ ratios cannot be rejected (p=0.48). Comparisons of the log likelihood scores reveal slightly stronger fit of the model in experiment 2 (median -2LL 78 vs. 81; p<0.04).

median $W^+(0.25)/W^-(0.25)$ is 1.26 compared to median $W^+(0.5)/W^-(0.5)$ of 0.87. Again, TK92 (with -2LL score 6422) is rejected for the estimated CPT models.

Table IIX: Estimation Results – Experiment 2 (N=61)

	(a)	(b)	(c)	(d)
-2LL	5884	5409	4965	4571
AIC	6014	5779	5575	5303
ρ_G	1.01 (0.95,1.07)	1.03 (31/30)	1.08^{**} (39/22)	1.44^{***} (42/19)
a_G	-	-	-	0.0024^{**} (40/21)
λ	1.06 (0.85,1.26)	1.07 (0.77, 1.37)	1.02 (31/30)	1.71 (37/24)
PR_G	0.86^{*} (0.73,0.99)	0.90^{***} (6/55)	0.71^{***} (14/47)	0.65^{***} (19/42)
PR_L	1.14 (0.93,1.36)	1.17^{*} (0.97,1.38)	1.20^{**} (39/22)	1.18^{*} (38/23)
σ	0.27	0.24	0.19	0.16
ρ1	0.60	0.73	0.72	0.77
ρ2	-	0.91	0.98	0.96

Note. The definitions are as in Table V.

Interestingly, the non-standard preferences do not appear in the binary choice problems of the post-experiment questionnaire. About 72% of the subjects preferred the 3750 certain-payoff to the lottery paying 5000 with probability 0.75, while 79% preferred a certain payoff of 1000 to the 50-50 lottery with outcomes +5000 or -3000. The proportion of risk-averse choices thus roughly increases from about 50% in the choices between deposits and their expected returns to 75% in the auxiliary control problems. It is still interesting to note that the auxiliary measures show predictive power for the choices between deposits and fixed returns. The median avg(CE) of subjects who preferred the certain 3750 payoff to the (5000 with probability 0.75) lottery is 3.8%, compared to median CE of 5.8% for subjects who preferred the lottery to the certain payoff (samples of 44 and 17; $p<0.01$). The median Gain-Loss CE of subjects who preferred the certain 1000 to the (+5000, -3000) lottery is 3.5% compared to 4.9% for subjects who preferred the lottery (N=48 and N=13; $p=0.03$).

7. Concluding discussion

Research on mispricing of structured investment instruments surprisingly reveals that even simple capital protecting notes are overpriced relative to estimates of their fair value (Jørgensen et al. 2011; Deng et al. 2015). The results of the current paper advance a demand-based explanation for such mispricing, showing that the structured investment context boosts the appetite for risk of prospective investors in two main channels. An appetite for substantial gains leads to violations of the mean-variance principle when the investment capital is protected but the expected return is low. Probabilistic loss receptiveness displays in strong underweighting of losses that realize under the most pessimistic scenarios for the underlying asset. The non-standard results connect to the foundational literatures on domain-specific risk preferences (Weber et al. 2002) and the susceptibility of risk attitudes to context and affect (Loewenstein et al. 2001; Rottenstreich and Hsee 2001). The results here, however, are especially non-typical and we are not aware of previous research pointing, for example, to such strong asymmetry in the weighting of 0.25 gains and losses.

Our evidence for reduced loss aversion in the context of structured investment connects to a growing research stream illustrating that attitude to loss is context-dependent and loss aversion may reduce in educated or calculated decision-making. Sensitivity to context emerges, for example, in studies illustrating that loss aversion varies with the distribution of payoffs in the environment (Harinck et al. 2007; Mukherjee et al. 2017).[25] The effects of education can be seen in a representative survey of the Dutch population (Booij and Van de Kuilen 2009), and in a multinational study of almost 3000 subjects from 80 countries which finds that loss aversion reduces with GPA scores (L'Haridon and Vieider 2019). Diverse studies illustrate that loss aversion attenuates in thoughtful decision. In Ert and Erev (2008), the rejection of mixed gain-loss gambles is more frequent in hallway questionnaires compared to laboratory experiments; Vieider (2009) finds that loss aversion declines when subjects justify their choices in post-experiment interviews; and Sokol-Hessner et al. (2009) show that loss aversion almost disappears when laboratory subjects assume the role of professional traders. Loss aversion is generally lower among stock market participants (Dimmock and Kouwenberg 2010), and an Australian survey finds reduced loss aversion among financially literate respondents (Bateman et al. 2015). In the context of structured investment decisions, Lazar et al. (2017) report preference for (5% or -3%) yearly deposits over parallel (2% or 0%) deposits in a Google Forms survey-experiment, and Sonsino et al. (2017) illustrate that loss aversion only manifests for losses exceeding thresholds around 5% in valuation-by-tranche of composite structured deposits.[26] The current experiments additionally imply that attitudes toward a loss may vary depending on the overall terms of the deposit. The appetite for substantial gains may offset loss aversion, so that a (10%,10%,9%,-8%) return structure appears more appealing than a Gain-Only (10%,10%,1%,0%) design.

[25] In retail structured instruments, possible losses must be accompanied by increased gain possibilities to keep the instrument appealing. It is plausible that loss aversion would play smaller role in such contexts. For an anecdotal reference, see the March 3rd 2013 commentary at https://www.whatinvestment.co.uk/ where David Thorpe reports not regretting a loss of 32% on a structured instrument as "*the investment had offered appropriate potential compensation for the risks accepted*".

[26] In valuation by tranche (VBT) of a (75% GOLD 25% DJIA) certificate, the valuation function V is applied to each tranche separately, weighting the values of the respective tranches (0.75*V(GOLD)+0.25*V(DJIA)), instead of rationally valuating the reduced-form (V(0.75*GOLD+ 0.25*DJIA)). Sonsino et al. (2017) reject the rational model for VBT. The reduced loss-aversion is seen in the results of estimating the VBT model.

Cumulative prospect theory, assuming the TK92 parameters, has been applied in several previous structured investment studies. Hens and Rieger (2014) show that the expected utility from investment in structured instruments does not cover the fees, but loss aversion and optimistic beliefs open space for designing attractive products. Bernard and Boyle (2008) specifically illustrate that overweighting of low-probability events, where the structured product brings the maximal (capped) return, may explain the demand for relatively complex products. Breuer and Perst (2007) conversely show that overweighting of extreme events may reduce the appeal of popular products such as reversed convertible bonds. Some studies paradoxically argue that utility-maximizing investors should not invest in structured products, as direct investment in the underlying asset or the risk-free rate, depending on individual risk preference, would increase their utility (Roger 2008; Jessen and Jørgensen 2012). While the aforementioned studies build on the TK92 estimation results, Erner et al. (2013) run a two-step experiment where CPT is estimated, using standard elicitation procedures, for each subject individually, and the certainty equivalents of ten structured products are elicited later, in a separate session. The correlations between the predicted certainty equivalents, assuming the individually estimated CPT parameters, and the elicited certainty equivalents are surprisingly low (ranging between -0.03 and 0.07 for seven of ten products), and the insignificant correlations reemerge in various robustness checks. The weak results lead the authors to conclude that the predictive power of standard CPT parameters for the attractiveness of structured financial products is dubious. The results of the current study, where CPT is estimated on an individual basis from about 90 choices between structured deposits and given risk-free rates, still suggest that prospect theory may effectively characterize private investors' preferences over structured instruments. Our estimated CPT parameters strongly depart from the benchmark TK92 estimates and also clearly diverge from more recent estimations such as Booij et al. (2010), Zeisberger et al. (2012) and L'Haridon and Vieider (2019) (see Supplement F for details), but CPT, with the non-standard estimates, works well, capturing individual preferences and between-subject variability.

The results of the experiments may prove valuable in the engineering of retail-oriented investment instruments. Reversed Convertible Bonds, for example, allow for the possibility of receiving a pre-determined coupon on the investment capital, but may bring a heavy loss when the price of the underlying asset falls below the knock-in level (Breuer and Perst 2007). The current results suggest that RCB investors may strongly respond to an increase in the value of the fixed coupon, while a wise choice of the knock-in level can protect the provider without heavily damaging the appeal of the instrument. As far as risk management considerations permit, awareness to the non-standard preferences of retail investors may prove valuable to providers, also promoting the enhanced regulation of the market (https://www.esma.europa.eu/; http://FCA.org.UK; http://Finra.org).

References

Abdellaoui, M., Baillon, A., Placido, L., and Wakker, P. (2011). The rich domain of uncertainty: Source functions and their experimental implementation. *American Economic Review, 101*(2), 695-723.

Baillon, A. (2008). Eliciting subjective probabilities through exchangeable events: An advantage and a limitation. *Decision Analysis, 5*(2), 76-87.

Baillon, A., and Bleichrodt, H. (2015). Testing ambiguity models through the measurement of probabilities for gains and losses. *American Economic Journal: Microeconomics*, *7*(2), 77-100.

Baltussen, G., van den Assem, M. J., and van Dolder, D. (2016). Risky choice in the limelight. *Review of Economics and Statistics*, *98*(2), 318-332.

Barberis, N., Mukherjee, A., and Wang, B. (2016). Prospect theory and stock returns: An empirical test. *The Review of Financial Studies*, *29*(11), 3068-3107.

Barberis, N., and Huang, M. (2008). Stocks as lotteries: The implications of probability weighting for security prices. *American Economic Review*, *98*(5), 2066-2100.

Barberis, N., and Thaler, R. (2003). A survey of behavioral finance. *Handbook of the Economics of Finance*, *1*, 1053-1128.

Bateman, H., Stevens, R., Lai, A., (2015). Risk information and retirement investment choice mistakes under prospect theory. *Journal of Behavioral Finance*, *16*(4), 279–296.

Baucells, M., Lewandowski, M., and Kontek, K. (2019). Range Utility Theory for Uncertain Cash-flows. *SSRN 3466617*.

Benartzi, S., and Thaler, R. H. (1995). Myopic loss aversion and the equity premium puzzle. *The quarterly journal of Economics*, *110*(1), 73-92.

Bennet, M. (2010). Complexity and its discontents: recurring legal concerns with structured products. *NYUJL & Bus.*, *7*, 811-844.

Bernard, C., and Boyle, P. (2008). Structured investment products with caps and floors. Working paper.

Bernard, C., Boyle, P. P., and Gornall, W. (2011). Locally capped investment products and the retail investor. *The Journal of Derivatives*, *18*(4), 72-88.

Blavatskyy, P. R ,.and Pogrebna, G. (2010). Models of stochastic choice and decision theories: Why both are important for analyzing decisions. *Journal of Applied Econometrics*, *25*(6), 963-986.

Blümke, A. (2009). How to invest in structured products: a guide for investors and asset managers. *John Wiley and Sons*.

Booij, A. S., and Van de Kuilen, G. (2009). A parameter-free analysis of the utility of money for the general population under prospect theory. *Journal of Economic Psychology*, *30*(4), 651-666.

Booij, A. S., Van Praag, B. M., and 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.

Brandstätter, E., Gigerenzer, G., and Hertwig, R. (2006). The priority heuristic: Making choices without trade-offs. *Psychological Review*, *113*(2), 409-432.

Breuer, W., and Perst, A., (2007). Retail banking and behavioral financial engineering: The case of structured products. *Journal of Banking and Finance*, *31*(3), 827–844.

Camerer, C., and Weber, M. (1992). Recent developments in modeling preferences: Uncertainty and ambiguity. *Journal of risk and uncertainty*, *5*(4), 325-370.

Carbone, E., Dong, X., and Hey, J. (2017). Elicitation of preferences under ambiguity. *Journal of Risk and Uncertainty*, *54*(2), 87-102.

Castellano, R., and Cerqueti, R. (2013). Roots and effects of financial misperception in a stochastic dominance framework. *Quality and Quantity*, *47*(6), 3371-3389.

Célérier, C., and Vallée, B. (2017). Catering to investors through security design: Headline rate and complexity. *The Quarterly Journal of Economics*, *132*(3), 1469-1508.

Choi, J., and Kronlund, M. (2017). Reaching for yield in corporate bond mutual funds. *The Review of Financial Studies*, *31*(5), 1930-1965.

Clarke, K. A. (2007). A simple distribution-free test for nonnested model selection. *Political Analysis*, *15*(3), 347-363.

Collier, B. L., Schwartz, D., Kunreuther, H. C., and Michel-Kerjan, E. O. (2017). *Risk preferences in small and large stakes: Evidence from insurance contract decisions* (No. w23579). National Bureau of Economic Research.

Das, S. R., and Statman, M. (2013). Options and structured products in behavioral portfolios. *Journal of Economic Dynamics and Control*, *37*(1), 137-153.

De Bondt, W. P. (1993). Betting on trends: Intuitive forecasts of financial risk and return. *International Journal of Forecasting*, *9*(3), 355-371.

Deng, G., Dulaney, T., Husson, T., McCann, C., and Yan, M. (2015). Ex post structured-product returns: Index methodology and analysis. *The Journal of Investing*, *24*(2), 45-58.

Diecidue, E., and Van De Ven, J. (2008). Aspiration level, probability of success and failure, and expected utility. *International Economic Review*, *49*(2), 683-700.

Dimmock, S. G., and Kouwenberg, R. (2010). Loss aversion and household portfolio choice. *Journal of Empirical Finance*, *17*(3), 441-459.

Dimmock, S. G., Kouwenberg, R., Mitchell, O. S., and Peijnenburg, K. (2015). Estimating ambiguity preferences and perceptions in multiple prior models: Evidence from the field. *Journal of Risk and Uncertainty*, *51*(3), 219-244.

Entrop, O., McKenzie, M., Wilkens, M., and Winkler, C. (2016). The performance of individual investors in structured financial products. *Review of Quantitative Finance and Accounting*, *46*(3), 569-604.

Erner, C., Klos, A., and Langer, T. (2013). Can prospect theory be used to predict an investor’s willingness to pay? *Journal of Banking and Finance*, *37*(6), 1960-1973.

Ert, E., and Erev, I. (2008). The rejection of attractive gambles, loss aversion, and the lemon avoidance heuristic. *Journal of Economic Psychology*, *29*(5), 715-723.

Fischbacher, U. (2007). z-Tree: Zurich toolbox for ready-made economic experiments. *Experimental Economics*, *10*(2), 171-178.

Fox, C. R. and Tversky, A. (1998). A belief-based account of decision under uncertainty. *Management Science, 44*(7), 879-895.

Ghent, A. C., Torous, W. N., and Valkanov, R. I. (2019). Complexity in structured finance. *The Review of Economic Studies*, *86*(2), 694-722.

Ghirardato, P., Maccheroni, F., and Marinacci, M. (2004). Differentiating ambiguity and ambiguity attitude. *Journal of Economic Theory, 118*(2), 133-173.

Gregg, D., and Rolfe, J. (2017). Risk behaviours and grazing land management: A framed field experiment and linkages to range land condition. *Journal of Agricultural Economics*, *68*(3), 682-709.

Grosshans, D., and Zeisberger, S. (2018). All's well that ends well? On the importance of how returns are achieved. *Journal of Banking and Finance, 87*, 397-410.

Harinck, F., Van Dijk, E., Van Beest, I., and Mersmann, P. (2007). When gains loom larger than losses: Reversed loss aversion for small amounts of money. *Psychological Science*, *18*(12), 1099-1105.

Harrison, G. W., and List, J. A. (2004). Field experiments. *Journal of Economic literature*, *42*(4), 1009-1055.

Harrison, G. W., and Ross, D. (2017). The empirical adequacy of cumulative prospect theory and its implications for normative assessment. *Journal of Economic Methodology*, *24*(2), 150-165.

Harrison, G. W., and Swarthout, J. T. (2019). Cumulative prospect theory in the laboratory: A reconsideration. Center for the Economic Analysis of Risk. Working Paper.

Henderson, B. J., and Pearson, N. D. (2011). The dark side of financial innovation: A case study of the pricing of a retail financial product. *Journal of Financial Economics*, *100*(2), 227-247.

Hens, T., and Rieger, M. O. (2014). Can utility optimization explain the demand for structured investment products? *Quantitative Finance*, *14*(4), 673-681.

Hey, J. D., Lotito, G., and Maffioletti, A. (2010). The descriptive and predictive adequacy of theories of decision making under uncertainty/ambiguity. *Journal of Risk and Uncertainty, 41*(2), 81-111.

Hunt, S., Stewart, N., and Zaliauskas, R. (2015). Two plus two makes five? Survey evidence that investors overvalue structured deposits. *FCA Occasional Paper*, (9).

Jessen, P., and Jørgensen, P. L. (2012). Optimal investment in structured bonds. *Journal of Derivatives*, *19*(4), 7-28.

Jiao, P. (2020). Payoff-Based belief distortion. Forthcoming, *The Economic Journal.*

Jørgensen, P. L., Nørholm, H., and Skovmand, D. (2011). Overpricing and hidden costs of structured products for retail investors: Evidence from the Danish market for principal protected notes. *SSRN 1863854*.

Kilka, M., and Weber, M. (2001). What determines the shape of the probability weighting function under uncertainty? *Management Science*, *47*(12), 1712-1726.

Kontek, K., and Lewandowski, M. (2018). Range-dependent utility. *Management Science*, *64*(6), 2812-2832.

Kunz, A. H., Messner, C., and Wallmeier, M. (2017). Investors' risk perceptions of structured financial products with worst-of payout characteristics. *Journal of Behavioral and Experimental Finance*, *15*, 66-73.

L'Haridon, O., and Vieider, F. M. (2019). All over the map: A worldwide comparison of risk preferences. *Quantitative Economics*, *10*(1), 185-215.

Lazar, M., Levkowitz, A., Oren, A ,.and Sonsino, D. (2017). A note on receptiveness to loss in structured investment. *Journal of Behavioral and Experimental Economics*, 69, 92-98.

Li, X., Subrahmanyam, A., and Yang, X. (2018). Can financial innovation succeed by catering to behavioral preferences? Evidence from a callable options market. *Journal of Financial Economics*, *128*(1), 38-65.

Loewenstein, G. F., Weber, E. U., Hsee, C. K., and Welch, N. (2001). Risk as feeling. *Psychological Bulletin*, *127(2)*, 267-286.

Loomes, G. (2010). Modeling choice and valuation in decision experiments. *Psychological Review*, *117*(3), 902-924.

Menapace, L., Colson, G., and Raffaelli, R. (2015). Climate change beliefs and perceptions of agricultural risks: An application of the exchangeability method. *Global Environmental Change*, *35,* 70-81.

Mukherjee, S., Sahay, A., Pammi, V. C., and Srinivasan, N. (2017). Is loss-aversion magnitude-dependent? Measuring prospective affective judgments regarding gains and losses. *Judgment and Decision Making*, *12*(1), 81-89.

Nilsson, H., Rieskamp, J., and Wagenmakers, E. J. (2011). Hierarchical Bayesian parameter estimation for cumulative prospect theory, *Journal of Mathematical Psychology*, *55*(1), 84-93.

Pachur, T., and Kellen, D. (2013). Modeling gain-loss asymmetries in risky choice: The critical role of probability weighting. In *Proceedings of the Annual Meeting of the Cognitive Science Society* (Vol. 35, No. 35).

Prelec, D. (1998). The probability weighting function. *Econometrica*, 497-527.

Rajan, R. G. (2006). Has finance made the world riskier? *European Financial Management*, *12*(4), 499-533.

Rieger, M. O., and Hens, T. (2012). Explaining the demand for structured financial products: Survey and field experiment evidence. *Zeitschrift für Betriebswirtschaft*, *82*(5), 491-508.

Roberts, D. C., Boyer, T. A ,.and Lusk, J. L. (2008). Preferences for environmental quality under uncertainty. *Ecological Economics*, *66*(4), 584-593.

Roger, P. (2008). Capital protected notes for loss averse investors: A counterintuitive result. *SSRN 1106749*.

Rottenstreich, Y., and Hsee, C. K. (2001). Money, kisses, and electric shocks: On the affective psychology of risk. *Psychological Science*, *12*(3), 185-190.
Saha, A. (1993). Expo-power utility: A 'flexible' form for absolute and relative risk aversion. *American Journal of Agricultural Economics, 75*(4), 905-913.

Schertler, A. (2016). Pricing effects when competitors arrive: The case of discount certificates in Germany. *Journal of Banking and Finance*, *68*, 84-99.

Schmidt, U., and Zank, H. (2008). Risk aversion in cumulative prospect theory, *Management Science*, *54*(1), 208–216.

Sokol-Hessner, P., Hsu, M., Curley, N. G., Delgado, M. R., Camerer, C. F., and Phelps, E. A. (2009). Thinking like a trader selectively reduces individuals' loss aversion. *Proceedings of the National Academy of Sciences*, *106*(13), 5035-5040.

Sonsino, D., Benzion, U., and Mador, G. (2002). The complexity effects on choice with uncertainty–Experimental evidence. *The Economic Journal*, *112*(482), 936-965.

Sonsino, D., and Regev, E. (2013). Informational overconfidence in return prediction–More properties. *Journal of Economic Psychology*, *39*, 72-84.

Sonsino, D., Rosenboim, M., and Shavit, T. (2017). The valuation "by-tranche" of composite investment instruments. *Theory and Decision*, *82*(3), 353-393.

Thaler, R. H. (1985). Mental accounting and consumer choice. *Journal of Behavioral Decision Making*, *4*(3), 199-214.

Trautmann, S. T., and Van De Kuilen, G. (2015). Ambiguity attitudes. *The Wiley Blackwell handbook of judgment and decision making*, *1*, 89-116.

Tversky, A., and Kahneman, D. (1992). Advances in prospect theory: Cumulative representation of uncertainty. *Journal of Risk and Uncertainty*, *5*(4), 297-323.

Venkatraman, V., Payne, J. W., and Huettel, S. A. (2014). An overall probability of winning heuristic for complex risky decisions: Choice and eye fixation evidence. *Organizational Behavior and Human Decision Processes*, *125*(2), 73-87.

Vieider, F. M. (2009). The effect of accountability on loss aversion. *Acta Psychologica*, *132*(1), 96-101.

Weber, E. U., Blais, A. R., and Betz, N. E. (2002). A domain-specific risk-attitude scale: Measuring risk perceptions and risk behaviors. *Journal of Behavioral Decision Making*, *15*(4), 263-290.

Wilcox, N. T. (2011). 'Stochastically more risk averse:' A contextual theory of stochastic discrete choice under risk. *Journal of Econometrics*, *162*(1), 89-104.

Zeisberger, S., Vrecko, D., and Langer, T. (2012). Measuring the time stability of prospect theory preferences. *Theory and Decision*, *72*(3), 359-386.