On Skewness and Prudence

ABSTRACT

Skewness preferences are closely linked to downside risk aversion and prudence. However, using a sound experimental setup and controlling for the first four statistical moments and potentially distortionary effects of loss aversion a preference for skewness cannot be confirmed. In contrast to theoretical predictions, the preference for skewness does not increase with an increasing skewness of the considered lottery. Furthermore, the preference for left-skewed distributions is stronger for lotteries in the loss domain. However, more rational decision making increases the predisposition of right-skewed choices.

JEL Classification: C91, D81

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1 Introduction

Weighing risk against return has always been one of the key questions in economics and finance. Classic finance models and portfolio theory based on Markowitz (1952) assume that asset returns are normally distributed, implying that they do not exhibit any skewness or kurtosis. Risk is thus understood as the dispersion from the expected return, statistically measured as its standard deviation or variance. However, most asset classes exhibit a significant degree of skewness and (excess) kurtosis. Accordingly, higher moments have been integrated into the literature, for example in asset pricing (e.g. in the seminal works of Kraus and Litzenberger, 1976, Harvey and Siddique, 2000, and Dittmar, 2002), portfolio selection (among others Lai, 1991, Chunhachinda et al., 1997, Prakash, Chang and Pactwa, 2003, de Athayde and Flôres, 2004, Jondeau and Rockinger, 2006, and Proelss and Schweizer, 2014), and performance evaluation (Breuer and Gürtler, 2003).

From a theoretical perspective, expected utility maximizing investors with commonly assumed utility functions should have an aversion to even moments and a preference for odd moments, and thus should be skewness seeking (see Arditti, 1967, Tsiang, 1972, and Scott and Horvath, 1980). Beyond expected utility, if preferences are described according to cumulative prospect theory (Kahneman and Tversky, 1979, and Tversky and Kahneman, 1992), individuals may also have a preference for skewness as Ågren (2006) and Barberis and Huang (2008) have argued.

While there is broad theoretical evidence for a preference for skewness, it has only recently been tested whether individuals really behave as predicted using controlled laboratory experiments (see for example Vrecko, Klos and Langer, 2009, Ebert and Wiesen, 2011, and Åstebro, Mata and Santos-Pinto, 2015). Most of these studies confirm that individuals exhibit a preference for (positive) skewness. Among these studies, the experiment conducted by Ebert and Wiesen (2011) is the only one that uses a sound experimental setup in the sense that the proposed lottery pairs exhibit the same mean, variance and kurtosis. However, the lottery pairs do not strictly oppose pure gain lotteries vs. pure gain lotteries and pure loss lotteries vs. pure loss lotteries but in most cases the lottery pairs consist of a mixed lottery and a pure lottery (either in the gain or in the loss domain). This experimental setting may have a distorting impact in favour of the right-skewed distribution: If right- and left-skewed distributions with the same mean and variance are compared, more extreme outcomes of the left-skewed distribution occur in the loss domain which is perceived as value decreasing if individuals exhibit a pronounced degree of loss aversion. The first contribution of our study is therefore to test whether individuals exhibit a preference for skewness if the experimental design is adjusted for the first four statistical moments and if the potentially distorting effects of loss aversion are excluded by comparing either pure gain or pure loss lotteries.

Furthermore, skewness preferences are closely linked to downside risk aversion and the concept of prudence. For example, a decrease in skewness, i.e., an increase in downside risk, can be achieved by a mean variance preserving transformation that shifts probability mass from the right (i.e., the upper) to the left (i.e., the lower) part of the distribution (see Menezes, Geiss and Tressler, 1980). Within expected utility theory, an aversion to this downward shift of probability mass is captured by a positive third derivate of the utility function ($u''' > 0$), which is characterized as downside risk aversion and termed “prudence” by Kimball (1990). A positive third derivative implies a convex marginal utility function of the individual. As a result, the change of utility varies with the respective level of wealth: Whereas risk aversion represents a general aversion to risk (i.e., variance), prudence/downside risk aversion characterizes a preference regarding where and when to accept an additional risk, namely (in the case of a convex, declining marginal utility function) in a state of higher wealth in which the potential reduction in marginal utility is lower compared to a state of lower wealth in which the marginal utility is accordingly higher.

Beyond an expected utility context, Eeckhoudt and Schlesinger (2006) define prudence as a preference over lottery pairs in which an additional zero-mean risk and a sure loss have to be independently allocated to two states of an initial lottery. This definition does not require any assumption on the utility theoretic framework: Prudent individuals will simply allocate the additional zero-mean risk to the better outcome of the initial lottery by separating it from the sure reduction in wealth. In this context, preferences for prudence imply a preference for skewness that is not impacted by changes in kurtosis that may occur if the zero-mean risk itself exhibits positive or negative skewness that consequently translates into changes in kurtosis of the compound lottery (see Ebert and Wiesen, 2011). Prudent individuals will ceteris paribus always choose the distribution with the higher (positive) skewness – even if the kurtosis is less favourable. Hence, Eeckhoudt-Schlesinger lottery pairs[1] offer an opportunity to directly test prudence preferences in a laboratory experiment. First experiments to test whether individuals exhibit prudent behaviour have been conducted by Deck and Schlesinger (2010) and Ebert and Wiesen (2011) who also analyze the impact of different factors on the choice in favour of the prudent option. Among these, Ebert and Wiesen (2011) confirm that most individuals indeed exhibit a preference for skewness even if the kurtosis is unfavourable. However, given the factorial design testing for several factors, this impact is not quantified. Accordingly, for our experimental design in the prudence stage we use ES lottery pairs that statistically correspond to the lottery pairs applied in the skewness stage. The prudence stage consequently addresses the question to what extent individuals in fact exhibit prudent behaviour. In addition, factors that might have an impact in prudent decision making are analyzed. Thereby, the experimental design further contributes to the literature by using a set of lottery pairs with the same mean, variance and difference in skewness, but with varying kurtosis. This allows quantifying the impact of kurtosis on

[1] Henceforth referred to as ES lottery pairs.

prudence preferences in order to test for the "*kurtosis robustness*" characteristic of prudence (Ebert and Wiesen, 2011).

The paper is structured as follows: Section 2 provides an overview of the current literature on skewness and prudence preferences. Section 3 describes the methodology, experimental design and sample of our study. In section 4 we present our empirical results; section 5 concludes.

2 Preferences for Skewness and Prudence

2.1 Preferences for Skewness

Whereas ample theoretical and empirical support for skewness preferences in general exists, research concerning the question whether individuals exhibit a preference for skewness in individual decision making or analyzing the impact and implications of such a preference is scarce. Vrecko, Klos and Langer (2009) analyze how skewness preferences change when different presentation formats are used to display continuous return distributions. They find that most of the individuals in their sample (70%) choose the right-skewed option when the distribution is displayed as a cumulative distribution function (CDF) whereas roughly the same share of individuals opts for the left-skewed distribution when confronted with a probability density function (PDF). Even in the case of bar charts, which are rated as the best format in terms of decision usefulness by the individuals, a slight majority of subjects shows a preference for negative skewness. This preference occurs irrespective of an ascending or a randomized order of the states in the graph. The authors suggest that the preference for negative skewness with regard to the probability density presentation might be driven by a biased evaluation of the expected returns, i.e. individuals systematically underestimate expected returns in right-skewed and overestimate expected returns in left-skewed PDFs

(Vrecko, Klos and Langer, 2009).[2] Based on the design of Holt and Laury (2002), Åstebro, Mata and Santos-Pinto (2015) employ sets of lottery pairs that offer a “safe” option with symmetrical outcomes (and therefore a skewness of zero) and a “risky” lottery exhibiting skewness where the degree of skewness is varied across the treatments.[3] Whereas the “safe” lottery offers the higher expected pay-off in the beginning of the set, this difference decreases over the 10 choices, such that a rational decision maker is expected to switch once from the “safe” to the “risky” lotteries in the course of the respective treatment. The authors find that the higher the skewness of the risky lotteries, the higher the number of choices in favour of the “risky” option. Brünner, Levínský and Qiu (2011) also confirm a preference for skewness by applying a design of binary lotteries with identical first two moments. Similar to Åstebro, Mata and Santos-Pinto (2015), the experiment is limited to positive outcomes. Complexity is reduced, however, as each lottery only offers two potential outcomes.[4] The authors find that the share of subjects who prefer the prospect with the higher skewness in at least three out of four cases is 39% whereas the corresponding share of subjects preferring the prospect with the lower skewness is just 10%.

However, differences in kurtosis which may also have an impact on the respective decisions have generally been neglected. Ebert and Wiesen (2011) are the first to consider all (first) four moments and offer the most theoretically sound study on skewness seeking. In their experiment they test preferences using binary lottery pairs with identical mean, variance, and kurtosis but with a reverse-signed skewness (i.e., Mao-Lotteries; see Mao, 1970) and find a significant degree of skewness seeking: 77% of all choices are in favour of the right-skewed

[2] Wallmeier (2011) analyzes different presentation formats of risk and return characteristics of structured products in order to improve decision making of retail investors.

[3] See Holt and Laury (2002) which constitutes a common experimental design for testing for risk aversion. With respect to Åstebro, Mata and Santos-Pinto (2015)'s notation of “safe” lotteries, it should be noted that this notation is misleading, as these lotteries are of course risky, although less risky compared to the “risky” lottery. Likewise, the presented lottery of the “zero skew” treatment does indeed exhibit (negative) skewness (see Åstebro, Mata and Santos-Pinto, 2015).

[4] With regard to the first three moments, any distribution can be characterized by exactly one binary lottery. As the skewness of a binary lottery is a direct function of the underlying probability and vice versa, the outcomes can be calculated to match the given variance and mean.

option. Based on their individual decisions, 60% of the subjects are classified as skewness seeking (with at least 7 out of 8 decisions in favour of the right-skewed option), while only 4% of the individuals are classified as skewness avoiding (with at least 7 out of 8 decisions for the left-skewed option). However, the lotteries applied in the experimental stage on skewness seeking are designed so that their statistical properties correspond to the lotteries applied in a later stage of the experiment. Thus, the outcomes involve numbers with two decimal places and the associated probabilities are in most cases not common multiples of 5 or 10%, which does not facilitate assessment. More relevant, in six out of eight lottery pairs pure lotteries (containing either gains or losses) are compared with mixed lotteries comprising positive and negative outcomes (see Ebert and Wiesen, 2011, p. 1342). In the remaining two lottery pairs one outcome equals zero so that strictly speaking no mixed lotteries are compared either. As there are broad indications based on prospect theory that gains and losses are perceived differently or as Tversky and Kahneman (1992, p. 276) put it that "losses loom larger than gains", choices for the right-skewed option might be driven by loss aversion in the setting of Ebert and Wiesen (2011): Whenever both outcomes of the right-skewed option are positive (or not strictly negative), the left-skewed option always contains one negative outcome. Whenever the right-skewed lottery is mixed and comprises one positive and one negative outcome, the left-skewed lottery contains two losses or the outcome is in the best case zero which might bias decisions in favour of the right-skewed option.

As far as we are aware, up to now there has been no comprehensive experimental study testing for skewness seeking taking into account the first four moments and avoiding potential biases arising from loss aversion by applying choices between either pure (gains or losses) lotteries or choices between two mixed lotteries.

2.2 Preferences for Prudence

As the third derivative of the utility function – and the implied convexity of the marginal utility function – cannot be directly observed based on empirical data, most empirical studies focus on the precautionary savings motive (see for example Leland, 1968, Sandmo, 1970, Guiso, Jappelli and Terlizzese, 1992, Dynan, 1993, Carroll, 1994, Merrigan and Normandin, 1996, and Carroll and Samwick, 1997). However, for long, there has been no evidence that individual decision makers really exhibit prudent behaviour confirmed in a controlled laboratory setting. As far as we are aware, the first experimental study on prudence was conducted by Tarazona-Gomez (2004).

More recently, Eeckhoudt and Schlesinger (2006) defined prudence as a preference over a specific class of simple lottery pairs (ES-lottery pairs). Within each lottery, individual decision makers face two events: One is a sure reduction in wealth $(-k)$, the other the addition of an independent risk ε which exhibits an expected mean of zero to the initial wealth. Each event has to be allocated to one of two states that both occur at a probability of 50%. The resulting lottery pair, exhibiting the same mean and the same variance, is illustrated in Figure 1. Assuming that individuals are risk-averse, both events ($-k$ and ε) are associated with harm. A prudent individual exhibits a preference for the "disaggregation" of these two harms; consequently, the resulting lottery in which the additional zero-mean risk is attached to the better state is referred to as a prudent lottery; the lottery in which ε is located in the lower state is labeled as the imprudent lottery. This definition also helps to differentiate the implications of risk aversion and prudence: Whereas risk aversion characterizes a general aversion to taking an additional risk, prudence characterizes a preference concerning in which state to take the additional risk.

– Please insert Figure 1 about here –

Transferring the preferences over the ES lottery pairs into a dynamic two-period model, the link to precautionary saving is intuitive: When a prudent individual faces an independent risk, she increases her savings in order to take the additional risk in a better state in which her individual wealth is higher and therefore – within an expected utility framework – the loss in marginal utility is lower. However, by applying ES lotteries, the utility function does not have to be specified in order to identify an individual as prudent. If an individual prefers the prudent lottery (thereby allocating the additional zero-mean risk to the better outcome) over the imprudent lottery, she exhibits prudent behaviour – within or beyond expected utility.[5] The preferred disaggregation of the two harms $-k$ and ε implies that a prudent individual would rather face one harm for sure than contingently being hit by both harms at the same time. Eeckhoudt and Schlesinger (2006, p. 282), borrowing terminology from Kimball (1993, p. 590) propose an "mutually aggravating" characteristic of these two events in order to explain this preference. However, rather than focusing on the harms, it is instructive to point out that a prudent individual will always allocate the additional zero-mean risk to the better state, which characterizes the upper (right) part of the distribution – regardless of whether one outcome is connected to a loss, all outcomes are negative, or the distribution is completely located in the gain domain. Therefore, the term "disaggregation of harms" unnecessarily limits the concept of prudence; in favour of a more general understanding, the description as "proper risk apportionment", also applied by Eeckhoudt and Schlesinger (2006, pp. 283-284) is more appropriate: With regard to the respective moments, prudence can be referred to as proper risk apportionment of order three. The allocation of the additional risk to the upper part of the distribution is intuitively comprehensible, as the higher expected wealth in this state also provides a larger safety cushion to cover potential losses.

In addition to the simplicity that characterizes Eeckhoudt and Schlesinger (2006)'s approach to testing for a preference for prudence, it can be easily implemented in a laboratory setting to test whether subjects exhibit prudent behaviour in individual decision making. Deck and Schlesinger (2010) were the first to apply ES lotteries in an experimental study in order to

[5] The equivalence of preferences over this class of lotteries to $u''' > 0$ within an expected utility setting is shown by Eeckhoudt, Gollier and Schneider (1995) and Bigelow and Menezes (1995).

test for prudence preferences. Their experiment uses a coin to represent the additional zero-mean risk ε. Consequently, ε comprises the positive and the corresponding negative outcome that both occur at a probability of 50%. However, using a symmetric zero-mean risk (with an implied skewness of 0) leads to an identical kurtosis of the aggregated prudent and imprudent lottery, as the skewness of ε directly translates into the kurtosis of the aggregated lottery. In fact, all higher even moments are identical as shown by Roger (2011). As the mean and the variance of the lotteries are – by construction – the same, the options differ only in their skewness. In this special case, ES lotteries test for prudence preferences that coincide with preferences for skewness. However, as risk aversion is not exhaustively described by an aversion to variance, there also "seems to be more to prudence than skewness seeking" (Ebert and Wiesen, 2011, p. 1343). In order to exploit the full depth of prudence, Ebert and Wiesen (2011) apply zero-mean risks that are not symmetric. As a result, a positive skewness of the zero-mean risk directly translates into a higher kurtosis of the compound prudent lottery – in which the additional right-skewed distribution is added to the upper part of the distribution – as compared to the imprudent lottery. Vice versa, a left-skewed ε leads to a higher kurtosis of the imprudent lottery. Thus, whereas the prudent choice always exhibits higher skewness, the kurtosis may be higher, lower or – as for example in the case of a symmetrical ε – equal and therefore more or less favourable.[6] Ebert and Wiesen (2011) find that 65% of all choices are in favour of the respective prudent option. Classifying subjects as prudent if they choose the prudent option in at least 12 out of the 16 decisions, 47% of the participating individuals can be regarded as prudent, whereas only 8% of the subjects are to be classified as imprudent with at most 4 prudent choices. In the subsequent analysis Ebert and Wiesen (2011) find no significant differences depending on whether the zero-mean risk is allocated to an initial lottery in the loss domain (incorporating a sure loss) or in the gain domain in which a sure

[6] The higher kurtosis is generated if the less probable – and therefore more extreme – positive (negative) outcome of the zero-mean risk is allocated to the higher (lower) outcome of the initial lottery thereby "fattening" the tail. This is the case if a right-skewed ε is added to the upper part of the distribution (prudent choice) or if a left-skewed ε is added to the lower part of the distribution (imprudent choice).

gain is involved. Furthermore, the wealth level of the initial endowment does not have a significant impact, either. In addition to that, individuals make slightly more prudent choices if they allocate the zero-mean risk ε as compared to allocating the sure reduction in wealth $-k$. The most significant result refers to the skewness of the zero-mean risk: If the zero-mean risk is left-skewed, more subjects choose the prudent option (also exhibiting the lower kurtosis). Even if the zero-mean risk is right-skewed, subjects still predominantly choose the prudent option with the less favourable kurtosis as compared to the imprudent option, thus experimentally confirming the "kurtosis robustness feature of prudence" (Ebert, 2013, p. 274). However, the factorial design does not allow a further quantification of the impact of the degree of skewness of the additional risk ε on the tendency to make the prudent choice.

Accordingly, we experimentally analyze prudence in individual decision making with respect to the kurtosis robustness feature. Hence, the skewness of the zero-mean risk (and therefore the kurtosis of the compound prudent and imprudent lottery) is varied ceteris paribus, both for the gain and for the loss domain.

3 Data and Methodology

3.1 Design of Experiments

We use a controlled laboratory experiment to analyze the preferences for skewness and prudence in individual decision making. Both the Laboratory for Experimental Economics at the University of Bonn (BonnEconLab) and the WHU Behavioral Lab in Vallendar, where the experimental sessions took place, provide facilities in which each participant is shielded from outer influences as well as from other participants to prevent unintentional interaction during the experiment. In addition, an adjacent, separate room is available in both labs to grant anonymity during the pay-off procedure.

The experiment is implemented using the Bonn Experiment System (BoXS)[7] and consists of three stages: Skewness, prudence and certainty equivalents, of which only the first two stages are relevant for the paper at hand.[8] In order to test for skewness seeking, we use discrete distributions for the experimental setting as they are perceived to be more useful compared to continuous distributions within a decision making process. Moreover, discrete distributions are commonly used in previous studies, such that general comparability to other studies is ensured (see Vrecko, Klos and Langer, 2009). Information concerning the lotteries applied in this stage is provided in Appendix 1. Lottery pairs as proposed by Eeckhoudt and Schlesinger (2006) with symmetrical as well as asymmetrical zero-mean risks are applied to test for the "kurtosis robustness feature of prudence" – the preference for skewness regardless of whether the kurtosis is favourable or not (Ebert, 2013, p. 274). Further information with regards to the lotteries applied in the prudence stage is provided in Appendix 2. In both stages, figures of ballot boxes are used to achieve an intuitive visualization of the lotteries.

3.2 Experimental Procedure

In order to avoid potential biases within individual experimental sessions and to ensure consistency across the sessions as well as replicability of results, all experimental sessions follow the same standardized five step procedure:

1. Random assignment of subjects to computer terminals: Upon arrival subjects draw a number that determines their assignment to a computer. Thereby, communication between neighbouring participants is limited. All computer terminals in the experimental laboratories are additionally equipped with partition walls to prevent any

[7] BoXS is an open platform to program, conduct, and administrate experiments and is well suited to the requirements of our project. As the environment for the server and the clients is programmed in Java, BoXS can be used with every standard internet browser regardless of the underlying operating system. This also has the advantage that HTML elements can be easily integrated into the BoXS programming language which provides an easy and flexible way to define and adjust the layout of the experiment. In addition, elements such as pictures or videos can be easily integrated via the internet. As far as we are aware, these abilities are not provided by other solutions in an easy to implement way. For an overview of BoXS see Seithe (2012).

[8] The sequence of the experimental stages is randomized on an individual level.

interaction among subjects and to limit distractions so that subjects can fully concentrate on the computerized experiment.

2. Instructions read out loud: The instructions provide explanations of the tasks in all of the stages, also including the applied graphical presentations. For each stage, an example is discussed, which is also used to demonstrate the potential consequences in the payoff procedure. A printed version of the instructions is also made available at each terminal so that participants can follow the oral explanation at their own speed or revisit the instructions at a later stage of the experiment. Potential comprehension questions are clarified in one-on-one discussions.
3. Experimental stages: The experimental stages are conducted in an individually randomized order.
   a. As an introduction to each specific stage the relevant part of the instructions is repeated on screen.
   b. Subjects have to answer control questions to ensure that they understand the respective questions (including the outcomes and the underlying probabilities) and the associated payoffs.
   c. Having correctly answered the control questions, subjects are allowed to proceed with the questions in the respective experimental stage.
4. Socio-economic questionnaire: The computerized experiment concludes with a questionnaire concerning socio-economic variables. Anonymity and protection of personal data is ensured, as these details (as well as the individual decisions within the experiment) are only assigned to the number of the computer randomly drawn by participants at the beginning of the session, such that an assignment of the data to the individual participant is not possible after the experimental sessions have taken place.
5. Payoff procedure: Subjects are called into an adjacent room in a random order, one at a time, for the payoff procedure. Each participant receives a show-up fee of EUR 5.00,

a variable remuneration depending on her individual decisions within the experiment, and an additional $EUR\ 2.50$ for completing the socio-economic questionnaire (which was not announced before starting the questionnaire). The variable payoff is determined according to the random lottery incentive system. One question/lottery is randomly selected and played out in order to determine the individual payoff. This procedure is incentive compatible, as individuals have a strong incentive to make each decision carefully, given that any individual decision might determine the total (variable) payoff. In addition, no endowment effect occurs, which may have an impact in individual decision making and which hinders the between-subject comparison as the individual endowment, and therefore potentially the risk preferences, depend on the previous decisions. The random lottery incentive system is consequently commonly applied in experimental studies (e.g. by Tversky, Slovic and Kahneman, 1990, Holt and Laury, 2002, Stott, 2006, Harrison and Rutström, 2009, Deck and Schlesinger, 2010, or Dohmen and Falk, 2011; for a discussion of the random lottery incentive system see Starmer and Sugden, 1991, and Harrison and Rutström, 2008). In order to randomly select the question for the payoff procedure, a ballot box is used that is handled by each participant. The respective lottery is then played out according to the individual decision in this question. Blue and white marbles are used to simulate the lotteries drawn by the participant.

3.3 Subject Pool

Participants for the experimental sessions are recruited among students of the University of Bonn and WHU – Otto Beisheim School of Management. In total, 105 subjects participated in the experiment (46 in the BonnEconLab and 59 in the WHU Behavioral Lab, see Table 1). The respective experimental sessions lasted about 60-90 minutes for each individual participant, with approximately 10 minutes for the introduction and 50 minutes for the experiment itself. The subsequent payoff procedure lasted up to approximately 30 minutes (depending on the randomly determined order of subjects) until the payoff of the last participant was determined and processed. On average, subjects received a remuneration of EUR 16.26. Considering the average time of approximately 75 minutes that was required for subjects to participate in the experiment and receive the remuneration in the payoff procedure, this corresponds to an average hourly rate of EUR 13.00 and a median hourly rate of EUR 10.20, which is roughly in line with the opportunity costs of the participants.

– Please insert Table 1 about here –

With regards to the socio-economic characteristics, the ratio of male to female participants is about 2/3 to 1/3 with a higher share of female students among subjects in Bonn. The average age is 22.1 (median: 21 years) with participants from WHU being on average 3.1 years younger than subjects at the BonnEconLab. The subject pool recruited at the University of Bonn is furthermore more experienced at participating in laboratory experiments: Whereas most subjects in the WHU Behavioral Lab are participating in a controlled laboratory experiment for the first time, 59% of the participants recruited for the sessions in the BonnEconLab have already taken part at least five times. Reflecting the course offerings of the universities, all participants from the WHU study Business/Economics, compared to 15% of the subject pool from Bonn. The biggest group in Bonn is recruited from law students (22%).

– Please insert Table 2 about here –

4 Results

4.1 Preliminary Results

The stages testing for preferences for skewness and prudence yield ambiguous results: As 66% of all choices in the skewness stage are in favour of the left-skewed distribution, a preference for skewness cannot be confirmed. In the prudence stage, 65% of all choices are in favour of the prudent choice. In our experiments, each subject chooses on average 4.7 right-skewed options (33.7% of the 14 questions) and 6.5 prudent options (64.9% out of 10 decisions). Figure 2 shows the respective cumulative distribution function (CDF) of right-skewed and prudent choices per subject. The CDF of the binomial distribution which would result from random choices between the right-skewed (prudent) and the left-skewed (imprudent) option is added as a benchmark. As there are 14 questions in the skewness stage, the region ranging from 0 to 7 contains those subjects that made less right-skewed than left-skewed choices, i.e., subjects that are favouring left-skewed distributions. From Figure 2 it can be inferred that the share of individuals preferring the right-skewed option in only a few questions (i.e. the share of subjects favouring left-skewed distributions) is considerably higher than proposed by the binomial distribution. Accordingly, it can be concluded that subjects exhibit a preference against (positive) skewness. The right panel of Figure 2 shows the respective results for the prudent choices. In contrast to the findings in the skewness stage, the share of individuals choosing the prudent option to a large extent is considerably higher compared to the binomial distribution which implies that subjects exhibit a preference for the respective prudent choices. Both distributions are significantly different ($p = 0.000$) from the binomial and normal distribution as to the one-sample Kolmogorov-Smirnov test (Kolmogorov, 1933, and Smirnov, 1933) and therefore not the result of a random decision process.

– Please insert Figure 2 about here –

Figure 3 illustrates the correlation between right-skewed and prudent choices. Most subjects are located in the upper left corner, characterized by less right-skewed choices and more prudent choices. However, Spearman's rank correlation coefficient (Spearman, 1904) between skewed and prudent choices shows only a weak correlation of $\rho = 0.20$ which is statistically significant at the 5%-level ($p = 0.041$).

– Please insert Figure 3 about here –

Furthermore, we take a closer look at the contingent choices of subjects which should be correlated from a theoretical point of view, as the left-skewed Mao-Lottery exhibits a higher downside risk compared to the right-skewed option and all prudent choices also exhibit the higher skewness. As prudence has been characterized as a preference for skewness that is robust to changes in kurtosis, this criterion is stricter than a pure preference for skewness. Consequently, prudent individuals should always have a preference for skewness, whereas skewness seeking individuals may not necessarily have a preference for prudence. As can be seen from Table 3, the share of skewness seeking subjects is stable within a range of 6-9% across prudent, imprudent, and neutral individuals. However, whereas the majority of the total subject pool can be classified as not skewness seeking, this is not the case for the prudent individuals who tend to be at least indifferent with regards to skewness. Similarly, the majority of skewness seeking individuals can also be classified as prudent, and this share is considerably higher than among the skewness avoiding individuals. Based on the experimental results, the level of skewness seeking seems to be able to predict whether an individual has a preference for prudence, whereas different preferences for prudence seem at least to be an indicator of whether an individual has an aversion to skewness.

– Please insert Table 3 about here –

4.2 Preference for Skewness

4.2.1 Impact of the Degree of Skewness

Subjects should exhibit a preference for skewness and this preference should tend to be stronger, the higher the skewness of the considered distribution. Thus, the share of right-skewed choices should be above 50% and increase with the skewness of the respective lottery. Figure 4 (left panel) and Table 4 show the observed right-skewed choices in the experiment according to the probability of the lower outcome, which is congruent with an increasing skewness of the lottery. It can be clearly seen that the share of right-skewed choices does not exceed 50%. In addition, as the graph is neither strictly increasing nor strictly decreasing, no clear trend can be observed with respect to the impact of the skewness of the respective lottery. With the exception of the lottery with the lowest (positive) skewness, subjects opt for even more left-skewed options if lotteries with losses are regarded. For lotteries with a probability of 75% of the lower outcome, both graphs exhibit a slight kink.

– Please insert Figure 4 and Table 4 about here –

To shed further light on the relevant factors for the choice in favour of the right-skewed options, we use a binary choice model and consider different statistical characteristics of the lotteries as well as the impact of the participants' characteristics on the propensity to choose the right-skewed distribution. More precisely, we include the probability of the lower outcomes of the right-skewed lottery ($L_A\, p_1$) which corresponds to the probability of the higher outcome of the left-skewed lottery and which is positively correlated to the skewness of the lottery, the variance (Var), the difference in skewness between the two lotteries ($\Delta\, Skew$), the initial endowment for the respective decision (w_0), a dummy variable ($4\ balls$) for the number of balls used in the urn that equals 1 if 4 instead of 10 balls are used in the urn (to represent the probabilities 25%/75%), a dummy variable to control for gender of the participants that is 1 for females and 0 otherwise (Fem) and a dummy variable to control for location that is 1 if the sessions took place in Bonn and 0 otherwise ($Bonn$). In addition, dummy variables are used for pure gain ($Gain$) or pure loss ($Loss$) lotteries, which implies that mixed lotteries serve as a basis if both variables equal 0 in the logistic regressions (Berkson, 1944, and McFadden, 1974). The log-likelihood is maximized over all 1,470 decisions in the sample. As 14 decisions are made by each participant, standard errors are clustered per subject in order to account for potential correlation.

Table 5 presents the coefficients for marginal effects at the means (MEM, panel A), average marginal effects (AME, panel B) and the logit coefficients (panel C). All model specifications are at least significant at the 1% level. The reduced number of balls in the urn does not have a significant impact on the propensity to choose the right-skewed option; thus, the slight kink in the share of right-skewed choices at 75% in Figure 4 is not due to some methodological artefacts. Similarly, the gender of the participants does not exert any significant influence on skewness preferences. In contrast, if the experimental sessions took place in Bonn, the propensity to opt for the right-skewed lottery decreases by 9.4%, although no further causal rationale can be found for this observed behaviour. Whereas gain lotteries are not considered differently than mixed lotteries, preferences change significantly if lotteries with losses are involved: In this case, the probability of choosing the right-skewed lottery L_A decreases by 16.6%, such that in the loss domain even more individuals choose the left-skewed option which exhibits the higher maximum loss compared to the corresponding right-skewed lottery. This effect is even aggravated by an increase in the initial endowment, which is provided to cover potential losses for the following decision; the higher endowment further decreases the propensity to choose the right-skewed option by about 3% across all model specifications. Consequently, the higher the potential loss, the stronger the preference for the left-skewed option, in which the extreme loss occurs at a smaller probability.

Considering the impact of the statistical characteristics of the respective lotteries, the logit estimation reveals that the variance has a highly significant positive impact on the potential right-skewed choice. However, if the variance increases by 1,000, the probability of choosing the right-skewed lottery increases by just 0.7% - 1.2%. As the variance of all pure lotteries (10 out of 14) maximally ranges up to 2,400 (see Table A1 in the appendix) this effect is rather limited for most of the lotteries. With respect to the difference in skewness ($\Delta\, Skew$) and the probability of the lower outcome of the right-skewed choice ($L_A\, p_1$) which is positively correlated to its skewness, it can be observed that neither of the two has a significant impact if only one factor is considered within the regression. However, if both variables are used as regressors, both are highly significant ($p < 0.01$). Given the statistical characteristics of binary lotteries, the probability $L_A\, p_1$ is in a non-linear way correlated to the skewness of the lottery (and therefore to the difference in skewness between the Mao lotteries $\Delta\, Skew$) and its variance. Thus, the total marginal effect consists of the direct marginal effect and the indirect effect, which in the case of MEM can be calculated as

$$MEM(x)^{total} = \sum_i \; MEM\{g_i(\bar{x})\}\frac{dg_i(x)}{dx} x = \bar{x}, \tag{1}$$

where $g(x)$ refers to the mathematical transformation of x (see Bartus, 2005). In the following, we consider a change in $L_A\, p_1$: If $L_A\, p_1$ increases, the probability of the right-skewed choice $p(y = 1)$ decreases by 29.5% for each 10% change. However, as $\Delta\, Skew$ is also dependent on $L_A\, p_1$, there is an indirect effect via $\Delta\, Skew$ and the variance Var on $p(y = 1)$. The indirect effect via $\Delta\, Skew$ equals the derivative $d\Delta\, Skew/dL_A\, p_1$ times the marginal effect of 0.184 (see Table 5, panel A). Accordingly, the indirect effect with respect to variance equals $d\mathrm{Var}/L_A\, p_1$ times the marginal effect of 0.007/1,000. As the skewness of a binary lottery is

$$Skew(p_1) = \frac{2p_1 - 1}{\sqrt{p_1(1-p_1)}}, \tag{2}$$

the derivative of $\Delta\, Skew$ with regard to p_1 is

$$d\left(\frac{4p_1 - 2}{\sqrt{p_1 - p_1^2}}\right)/dp_1 = \frac{4}{\sqrt{p_1 - p_1^2}} + \frac{(2p_1-1)^2}{\sqrt{(p_1 - p_1^2)^3}}. \tag{3}$$

Accordingly, the partial derivative of the variance of a distribution with two outcomes

$$Var(p_1) = p_1(1 - p_1)(x_2 - x_1)^2 \tag{4}$$

yields

$$dVar(p_1)/dp_1 = (1 - 2p_1)(x_2 - x_1)^2. \tag{5}$$

Based on the mean values of the respective parameters ($\overline{L_A\, p_1} = 0.75$, $\overline{x_2} = 88.7143$ and $\overline{x_1} = -31.2857$), the total marginal effect on the propensity to choose the right-skewed option can be calculated as the sum of the direct marginal effect of $= -2.95$ (related to a change of 100%), the indirect marginal effect via the change in $\Delta\, Skew$ of $12.3168 \times$

$0.184 = 2.2663$ and the indirect marginal effect via the change in variance of $-7{,}200 \times 0.007/1{,}000 = -0.0504$. The total marginal effect if $L_A\, p_1$ increases by one – which implicitly leads to a higher skewness of the lottery – therefore adds up to -0.7341. This decrease in the probability of a right-skewed choice of 7.341% for a 10% increase of $L_A\, p_1$ confirms the observable choices according to the respective probabilities shown in Figure 4 and is far more realistic than the decline of 29.5% proposed by an isolated consideration of the direct marginal effect that neglects the mathematical interdependencies between the variables.

In summary, our analysis shows that the average decision maker does not exhibit a preference for skewness and, furthermore, that the propensity to choose the right-skewed distribution even declines if the respective skewness increases. In addition, subjects tend to choose significantly less right-skewed options if losses are involved.

– Please insert Table 5 about here –

4.2.2 Impact of Decision Time

The median decision maker took on average 13.3 seconds for each question within the skewness stage. The decision time is measured from the appearance of the question on the computer screen until the desired option is selected. If subjects change their choice the decision time is measured until the final choice is selected. Subjects exhibit a broad range of time needed for their decisions ranging from 5.0 to 86.7 seconds on average for each decision in this stage. Dividing the subject pool in two subgroups of faster and slower decision makers with median decision times of 9.0 and 22.3 seconds per question reveals that the average numbers of right-skewed choices of each subgroup exhibits a considerable difference: Whereas the faster deciding subjects make 29.7% (4.2) right-skewed choices on average, the decision makers of the slower deciding group make 37.7% (5.3) right-skewed choices. This difference is statistically significant ($p = 0.0117$) as to the Wilcoxon rank-sum test

(Wilcoxon, 1945, and Mann and Whitney, 1947). Comparing the fastest and slowest deciding quartile (with median decision times of 7.4 and 33.1 seconds per question; see Table 6), the discrepancy of the chosen number of right-skewed options widens even further: Whereas the fastest quartile (Q1) opts for only 26.4% right-skewed choices, the median decision maker of the slowest quartile (Q4) chooses 43.1% right-skewed alternatives (statistically significant at $p = 0.0032$). Furthermore, the null hypothesis that the number of right-skewed choices chosen by the slowest subjects (Q1) follows the same distribution as the ones obtained by the individuals with a medium decision time (Q2 and Q3) has to be rejected at a 5% level of significance. This suggests that subjects choose significantly more right-skewed options when they take more time for the decision (even though subjects in the fastest deciding quartile on average still opt for more left-skewed than right-skewed choices). As it can be assumed that a shorter decision time is an indication for a more intuitive decision whereas a longer decision time may reflect a more rational decision, this result suggests that intuitive decision makers have a stronger tendency towards the left-skewed lottery. The cumulative distribution function of right-skewed choices of each subgroup is provided in Figure 5.

– Please insert Table 6 and Figure 5 about here –

We perform an OLS regression in order to obtain a quantitative indication of the correlation between decision time and the number of right-skewed choices based on the individual decisions in the sample. The results of the regression are provided in Table 7 (panel A). The estimated coefficient of 0.0632 ($p = 0.0010$) for the required decision time suggests that a longer decision time of approximately 16 seconds increases the number of right-skewed choices by 1. This linear regression presumes that decision time is the only factor driving the individual decisions for more or less right-skewed choices. Of course, this is a monocausal model and has to be treated with caution, as all other factors and characteristics of the respective lotteries are neglected.

In summary, subjects that take more time for the decision, hence making a less intuitive and supposedly more rational decision, show a higher tendency to behave in accordance with economic theory which proposes a preference for skewness. This finding is in line with Wilcox (1994) who provides experimental evidence that subjects with faster decision times are more likely to exhibit lottery pricing anomaly. Beyond that, the required decision time is (as far as we are aware) not taken into account in most other experimental studies.

– Please insert Table 7 about here –

4.2.3 Discussion of Results in the Skewness Stage

The preference for negative skewness we find in the experimental session differs from the results of other studies on skewness preferences. Our results are in stark contrast to Ebert and Wiesen (2011) who classify 60% of their participants as skewness-seeking. As we compare pure gain with pure gain and pure loss with pure loss lotteries whereas Ebert and Wiesen (2011) use mixed lotteries in the skewness stage, these contrasting results might be attributed to the different experimental setup.

The observed aversion to positive skewness might be also supported by the graphical presentation of the lotteries: In order to facilitate intuitive decision making and to use a presentation that is familiar to subjects, a ballot box is used in this experimental study. However, a ballot box also places a greater focus on probabilities than on associated outcomes and – for example if there are 8 white versus 2 blue balls – very clearly points out the lower likelihood of drafting a blue ball. This might be more obvious to participants compared to, for example, a non-graphical presentation. A potential impact of the presentation format can also be found in Zeisberger, Vrecko and Langer (2012) who also find a preference for negative skewness when probability density functions are used to present the distribution. In the case of binary lotteries, however, the chosen presentation is appropriate from a theoretical perspective, as the skewness of binary lotteries is a pure function of the underlying probabilities and is therefore not influenced by the actual outcomes. An opportunity for future research would be to further analyze the impact of the applied presentation on skewness preferences; this becomes notably relevant in the case of multiple outcome lotteries or continuous distributions.[9]

Although this is the first study that explicitly eliminates any potential impact from loss aversion in its experimental design, this factor cannot be used to explain a preference for negative skewness: As the left-skewed lottery of a mixed or pure Mao lottery pair in the loss domain always exhibits the more extreme loss as compared to the right-skewed lottery, the consideration of loss aversion would favour the right-skewed lottery – unless the loss aversion were actually a "loss preference". In this case, individual decision makers would associate a higher value with gains than with the corresponding losses, which is a behaviour that is not confirmed in other experimental studies. When subjects were asked in the pay-off procedure why they favoured the left-skewed option in their choice, they often stated that they compared the absolute pay-offs of the more likely outcomes of the lotteries. This heuristic favours the left-skewed distribution as the higher probability is associated with the higher outcome, whereas the higher probability is associated with the respective lower outcome in a right-skewed lottery. This approach leads to an overweighting of larger probabilities, as the smaller probabilities are simply neglected. Several participants also explicitly expressed that they assumed they would not receive an outcome if the associated probability was too low. An indication for applying this heuristic decision rule can also be seen in the observed correlation of the required decision time and the number of right-skewed choices as the quartile with the shortest decision time exhibits the highest share of left-skewed choices (73.6%). It is reasonable to assume that the fastest decision making processes are more the result of a heuristic approach than of rational consideration of the associated utility and value of the

[9] Wallmeier (2011) recommends putting more weight on the probabilities of the outcomes rather than the payoff itself when educating retail investors about risk and return of structured products.

respective lotteries. Thus, heuristic decision making can offer an explanation for the observed aversion to skewness that notably occurs in the case of fast/intuitive decision making. However, even among the slowest-deciding subjects, the majority of choices still favours the left-skewed option. This might be an indication that individual decision makers follow a rational and utility-maximizing decision process to a much lesser extent than presumed by expected utility and non-expected utility theory models. In contrast, individuals reduce complexity and simplify their decision making processes by applying heuristic decision rules adapted to the specific setting.[10]

4.3 Preference for Prudence

4.3.1 Impact of the Degree of Skewness of the Zero-Mean Risk

As individuals are expected to exhibit a preference for prudence, the share of prudent choices should in general exceed 50%. Figure 4 (right panel) shows that the share of prudent choices is higher in the case of sure losses than in the gain domain: On average, the share of prudent choices is 67.8% in the case of sure losses (ES 1 – ES 5) and 61.9% in the case of sure gains (ES 6 – ES 10) which is very well in line with the results of Ebert and Wiesen (2011) who document 66.3% prudent choices if a sure loss is involved and 63.9% if a sure gain is considered. If the zero-mean risk is added to an initial lottery involving a sure loss, the share of prudent choices is above 50% across all states. Furthermore, it shows little variation and consistently lies within a narrow range of 66% to 70%. If a sure gain is considered, the share of prudent choices exhibits a considerably higher variation: The share of prudent choices globally increases with the skewness of the zero-mean risk. For the zero-mean risk exhibiting the highest negative skewness ($p_1 = 10\%$), the share of prudent choices is slightly below 50%. If the zero-mean risk ε exhibits a higher (positive) skewness (resulting from the

[10] This behaviour is in line with the hypothesis "people do not maximize" repeatedly expressed by the German Nobel laureate Reinhard Selten – for example during the annual conference of the *Gesellschaft für experimentelle Wirtschaftsforschung* in Luxembourg in October 2010.

probability of the lower outcome of $p_1 = 80\%$ and $p_1 = 90\%$), the share of prudent choices reaches the highest values with 74% and 70% respectively, although in these cases the compound prudent lotteries exhibit the highest kurtosis in the sample. Hence, we are able to partly confirm the "kurtosis robustness feature of prudence" (Ebert, 2013, p. 274). In the case of an initial lottery in the loss domain, the prudence preferences are almost not at all impacted by changes in the kurtosis of the compound lotteries induced by the skewness of the zero-mean risk. If a sure gain is involved, the choices are on average in favour of the prudent lottery. Even more, the share of prudent choices increases with increasing skewness of the zero-mean risk. The increasing kurtosis of the prudent lottery, therefore, seems not to have a deterrent impact on the individual decision maker. An explanation for this result might be provided by the skewness of the zero-mean risk itself: If ε risk is strongly right-skewed, a loss will be realized at a higher probability (e.g., $p_1^{ES\,6} = 90\%$; $p_1^{ES\,8} = 80\%$). If this zero-mean risk is allocated to an initial lottery in the gain domain, the compound imprudent lottery consequently still exhibits a significant probability of resulting in a loss (of 40%/45% in this case). In contrast, the corresponding prudent lotteries do not include any losses, the worst outcome of the compound prudent lottery is zero. Loss aversion can therefore provide an explanation for the high share of prudent choices if the zero-mean risk is highly right-skewed; if ε is strongly left-skewed, the loss is accordingly associated with a lower probability (e.g., $p_1^{ES\,7} = 10\%$). Consequently, even in the imprudent option the probability of facing a loss is limited (5% in this case). The observed share of prudent choices is accordingly lower. In the loss domain, losses cannot be generally avoided. Even if the prudent option is chosen, a loss can occur. In general, the imprudent lottery always exhibits the more extreme loss that can occur. To avoid the aggregation of losses, the prudent option has to be chosen regardless of the skewness of the zero-mean risk. Loss aversion can consequently provide an explanatory motive why prudence preferences (notably in the gain domain) increase with increasing skewness of the zero-mean risk although the increasing kurtosis of the compound prudent lottery is generally perceived as utility decreasing.

To shed further light on the impact of the statistical characteristics of the lotteries at hand as well as the individual characteristics of the individual decision maker, we use logistic regressions in analogy to the analysis of the skewness stage. As prudence is also characterized as a preference for skewness that is robust to changes in kurtosis, a special focus is laid on the skewness of the zero-mean risk ε which directly translates into the kurtosis of the compound (prudent and imprudent) lottery: A positive skewness of the zero-mean risk translates into a higher (lower) kurtosis of the compound prudent (imprudent) lottery. A higher skewness of the zero-mean risk consequently leads to a higher $\Delta\, Kurt$, i.e., the difference between the kurtosis of the prudent choice and the kurtosis of the imprudent choice. Therefore, the probability of the lower outcomes of the zero-mean risk ($\varepsilon\, p_1$) and its skewness ($\varepsilon\, Skew$) are considered as well as the difference between the two outcomes ($\varepsilon\, \Delta\, X$) and the initial endowment for the respective decision (w_0) which is granted in order to cover potential losses. In addition, we include a dummy variable which equals 1 if the additional zero-mean risk is allocated to an initial lottery in the loss domain and 0 otherwise ($Loss$), a dummy variable to control for gender of the participants that is 1 for females and 0 otherwise (Fem) and a dummy variable to control for location that is 1 if the sessions took place in Bonn and 0 otherwise ($Bonn$).

The results of the logistic regressions for the marginal effects of the independent variables are provided in Table 8. The respective model specifications separately test for the impact of $\varepsilon\, p_1$ (1a), $\varepsilon\, Skew$ (1b) and the impact of both variables (1c); all model specifications are highly significant. Moreover, the preference for prudence is stronger if the zero-mean risk is allocated to an initial lottery that also covers losses; this effect is significant at a 5%-level and stable throughout the regression models (1a) – (3c). The propensity to choose the prudent option consequently increases by 6.0% if the initial lottery is in the loss domain. As the dummy variable Fem is not significant, no gender effect can be found. However, the logistic regression reveals a location effect that is weakly significant at the 10%-level and leads to a higher preference for prudence within the experimental sessions conducted in Bonn. Interestingly, this effect works in the opposite direction as the location effect observed in the skewness stage: Whereas the subject pool of the experimental sessions conducted in Bonn exhibits a significantly lower propensity to choose the right-skewed option, the propensity to opt for the prudent option is higher. As the prudent choice implies the higher skewness, this behaviour is not consistent and cannot be explained from a rational point of view. In general, the results of the logistic regression models document a prudence preference that is also affected by the probability of the lower outcome of the zero-mean risk $\varepsilon\, p_1$ and the resulting skewness $\varepsilon\, Skew$. Whenever $\varepsilon\, p_1$ is solely used as regressor (such as in model specifications (1a), (2a) and (3a)), or whenever $\varepsilon\, Skew$ is solely used as regressor (see models (1b), (2b) and (3b)), each of these variables has a highly significant, positive impact on the propensity to choose the prudent option. If the probability of the lower outcome of the zero-mean risk increases (which implicitly leads to an increasing skewness of ε) or if the direct effect of an increase in skewness is considered, both lead to an increasing preference for prudence. However, if $\varepsilon\, p_1$ and $\varepsilon\, Skew$ are jointly used in the regression models (as in (1c), (2c) and (3c)), the effects cannot be clearly separated and allocated to the two variables anymore; hence, both variables lose their significant impact on the propensity of choosing the prudent option $p(y = 1)$.

Considering the regression models in which $\varepsilon\, p_1$ is used as the sole variable to describe the symmetry of the zero-mean risk (i.e., (1a), (2a) and (3a)), a clear preference for prudence can be shown. As the considered variables themselves are non-negative and all significant coefficients exhibit a positive sign in these models, the latent variable z, which is the weighted sum (i.e., a linear combination) of the independent variables, is also positive. Thus, based on the logistic distribution (see Berkson, 1944)

$$p_m(y = 1|z_m) = \left(\frac{1}{1+e^{-z_m}}\right)^{y_m} \left(1 - \frac{1}{1+e^{-z_m}}\right)^{1-y_m} \tag{6}$$

we get $p(y = 1|z > 0) > 0.5$ which results in a prudent choice. Furthermore, an increasing skewness of ε leads to a higher propensity to choose the prudent option. Evaluated at mean values, an increase of the probability of the lower outcome of ε by 10% increases the probability of a prudent choice by 1.7% which is stable throughout the different model specifications (1a), (2a) and (3a). If $\varepsilon\, Skew$ is used as sole regressor that reflects the potential asymmetry of the zero-mean risk (as in regression models (1b), (2b) and (3b)), the constant term also becomes significant. As all other significant coefficients are positive, the only reduction in z could consequently arise from a negative skewness of ε.

In order to evaluate the absolute impact of the contrary effects it is instructive to consider the estimated coefficients of the respective regression models (see Table 8, panel C): Subjects will choose the imprudent option if $p(y = 1|z) < 0.5$ which is the case if $z < 0$. With respect to regression (1b), z_{1b} will become negative if $0.492 + 0.120 \times \widehat{\varepsilon\, Skew}_{1b} < 0$ which is true if $\widehat{\varepsilon\, Skew}_{1b} < -4.1167$ and equivalent to $\widehat{\varepsilon\, p1}_{1b} < 5.03\%$. Analogously, $\widehat{\varepsilon\, p1}_{2b} < 2.28\%$ and $\widehat{\varepsilon\, p1}_{3b} < 3.30\%$ can be calculated.

With regards to the regression models considering the skewness of the zero-mean risk, the results suggest that subjects have a general preference for prudence unless the zero-mean risk exhibits a strong negative skewness, which is caused by a very low probability of the lower outcome of ε. Considering the compound lottery, this implies that subjects exhibit a preference for skewness that is in general robust to changes in kurtosis. Therefore, the mathematical characteristic of this prudence definition can be confirmed in general. However, the direction of the effect does not conform with the common assumption of a preference for skewness and an aversion to kurtosis: The higher the skewness of the zero-mean risk and consequently the higher the kurtosis of the prudent option, the higher the propensity of subjects to opt for the prudent option with the increasingly unfavourable kurtosis, whereas the mean and the variance as well as the difference in skewness between the prudent and the imprudent option remain the same. In contrast, a strongly left-skewed zero-mean risk increases the propensity to choose the imprudent option. This implies that subjects favour the compound lottery with the lower skewness and the higher kurtosis. This result is also indicated in Figure 4 (right panel) as in the gain domain the share of prudent choices increases with an increasing probability of the lower outcome (and therefore the implied skewness) which simultaneously leads to a higher kurtosis of the compound prudent lottery. If ε is allocated to a distribution in the loss domain, the robustness of this finding even increases, as z increases by the coefficient of the dummy variable (0.263 to 0.265) which is significant at the 5%- level. As a result, the skewness of the zero-mean risk might move up to $\varepsilon\,\widehat{Skew}_{1b}^{L} > -6.6928$ or even $\varepsilon\,\widehat{Skew}_{2b}^{L} > -8.7747$. This implies that the probabilities of the lower outcome (the loss) have to be $\widehat{\varepsilon\,p1}_{1b}^{L} > 2.09\%$, $\widehat{\varepsilon\,p1}_{2b}^{L} > 1.25\%$ and $\widehat{\varepsilon\,p1}_{3b}^{L} > 1.59\%$, respectively, such that (ceteris paribus) $p(y = 1) > 0.5$. If the probability of the loss does not occur at such a low probability, subjects exhibit a preference for prudence and thus their skewness preference is robust to changes in the kurtosis. This again corresponds to the correlation of the share of prudent choices and the probability of the lower outcome of ε shown in Figure 4: The share of prudent choices remains in a narrow range of 66% to 70% regardless of the varying skewness of the zero-mean risk.

– Please insert Table 8 about here –

4.3.2 Impact of Decision Time

Whereas subjects need a median decision time of 13.3 seconds for each question in the skewness stage, the higher complexity of the experimental design applied in the prudence stage accordingly leads to a longer median decision time of 24.1 seconds. In contrast to the observed decision pattern in the skewness stage, the average share of prudent choices is similar across the quartiles and lies within a range from 63.3% to 66.2% (see Table 6, panel B); the null hypothesis that the share of prudent choices of the respective quartiles follows the same distribution cannot be rejected at common levels of significance.

Analogous to the analysis of the right-skewed options in the skewness stage, the influence of the average decision time on the number of prudent choices is analyzed in a linear regression model. As the coefficient of the average decision time per question is highly insignificant ($p = 0.9830$) it can be deduced that the required decision time does not have a significant influence on the choices in the prudence stage. In addition, the estimated coefficient of 0.0003 implies that a longer decision time of 56 minutes would be necessary in order to increase the number of prudent choices by 1 (see Table 7, panel B). Thus, the impact would be very limited. Figure 5 (right panel) displays the cumulative distribution functions of the prudent choices: In contrast to the observed correlation in the skewness stage, the decision time does not have an impact on the choices in the prudence stage. As argued before, subjects might have a tendency for the left-skewed option if they decide intuitively and choose more right-skewed choices the longer they think about the respective decisions. As the experimental design in the prudence stage is per se more complex than the comparison of two simple lotteries (as in the skewness stage), the design itself already requires a more complex cognitive decision process in order to evaluate the presented options. Decisions might consequently be made less intuitively; this is also supported by the decision times, which are considerably longer than in the skewness stage. Therefore, the explanatory approach suggested in the skewness stage – subjects behave according to the economic theory and choose more right-skewed options when they take more time and come to a more rational decision – can partly be transferred to the prudence stage if the higher complexity in the experimental design is seen as hindering intuitive decision making and already per se resulting in a higher need for a rational decision process.

4.3.3 Discussion of Results in the Prudence Stage

The implication of prudence as skewness preference that is not impacted by changes in kurtosis can be partly confirmed: A majority of choices favours the prudent choice exhibiting the higher skewness regardless of the kurtosis of the compound lottery. However, the experimental results reveal that prudence preferences actually increase when the kurtosis of the prudent lottery (induced by the (positive) skewness of the zero-mean risk) increases, although an increasing kurtosis is typically associated with a declining utility in the most commonly assumed utility functions. This result does not support the experimental findings of Ebert and Wiesen (2011) who indicate that the average share of prudent choices is significantly higher when left-skewed zero-mean risks are involved compared with a right-skewed ε (69% vs. 62%). However, the experimental design in our study has the advantage that it specifically allows a ceteris paribus analysis of the impact of the skewness of the zero-mean risk and consequently of the kurtosis of the compound lotteries. This is possible because all lottery pairs in the prudence stage exhibit the same variance, the same difference in skewness and the same expected value of 90 Taler either as a gain or as a loss.

Disentangling prudence preferences and the kurtosis robustness feature of prudence shows that if the zero-mean risk is allocated to an initial lottery including a sure loss, the share of prudent choices is not impacted by the kurtosis of the compound lottery but remains in a narrow range between 66% and 70%. In contrast, if the initial lottery includes a sure gain, the share of prudent choices varies between 49% and 74% and even increases from 49% to 70% according to the increasing skewness of ε, although the kurtosis of the compound prudent lottery increases as well. Therefore, the kurtosis, which is perceived as utility decreasing in commonly assumed utility functions, seems not to be a deterrent or determining factor for the prudence preferences. The ES lottery pairs ES 6 and ES 8 with highly right-skewed zero-mean risks and consequently one of the highest kurtosis among the prudent lotteries are even associated with the highest share of prudent choices in the prudence stage. However, the skewness of the zero-mean risk in itself may provide a motive for opting for the prudent choice. If the zero-mean risk is strongly right-skewed, a loss will be realized at a high probability (e.g., $p_1^{ES\,6} = 90\%$; $p_1^{ES\,8} = 80\%$; see Table A2). Even when allocated to an initial lottery in the gain domain, the imprudent option is associated with a significant risk of resulting in a loss. If the zero-mean risk is strongly left-skewed, (e.g., $p_1^{ES\,7} = 10\%$) the probability of suffering a loss in the imprudent option is considerably lower (5% in this case). Accordingly, the share of prudent choices is smaller. In general, the highest possible loss can be minimized if the zero-mean risk is allocated to the better state of the initial lottery, whereas the loss might add up in the imprudent choice. In the case of ES lotteries in the loss domain (ES 1 – ES 5), the prudent choice is therefore the strategy to avoid the aggregation of losses. However, in all of these lottery pairs, a loss cannot be excluded in neither the prudent nor the imprudent option. This holds true regardless of the skewness of the zero-mean risk and can therefore provide an explanation for why the share of prudent choices is not affected by the skewness of ε/the kurtosis of the compound lotteries in the loss domain. This indicates that loss aversion may play a relevant role in prudence preferences as well, a factor that is not sufficiently considered in current experimental research projects.

5 Conclusion

Based on the experiment conducted with 105 participants at the BonnEconLab and at the WHU Behavioral Lab, a preference for skewness cannot be confirmed as about two-thirds of all choices in the skewness stage are in favour of the left-skewed option. Accordingly, 51% of subjects are classified as skewness-averse; only 34% of all choices are in favour of the right-skewed option and only a minority of 6% of the individuals can be seen as skewness-seeking.

In contrast to the theoretical predictions, the preference for skewness does not increase with an increasing skewness of the considered lottery. When the marginal effect of a change of the underlying probabilities is analyzed in a logistic regression model (thereby also considering the indirect marginal effect via the change in skewness and variance), it becomes apparent that the propensity to choose the right-skewed option actually decreases when the probability of the lower outcome of the lottery (which is positively correlated to the skewness of the lottery) increases. In addition, it can be seen that the preference for the left-skewed option further increases (by 17% on average) when lotteries in the loss domain are considered – although in this case participants even tend to choose the distribution containing the more extreme loss as compared to the right-skewed alternative.

Examining the required time for each decision in the skewness stage reveals that the fastest- and slowest-deciding quartiles exhibit a significant difference in the share of right-skewed choices. While the fastest-deciding individuals opt for just 26.5% right-skewed options, the slowest-deciding quartile opts for considerably more: 43.1%. Keeping in mind the limitations of this monocausal analysis, an OLS regression confirms that on average, every additional 16 seconds used in the individual decisions increases the number of right-skewed choices by 1. This suggests that less intuitive and presumably more rational decision making at least reduces the observed preference for the left-skewed distribution.

To shed further light on the skewness-seeking puzzle, a potential direction for future research would be to develop experimental designs that restrict the applicability of the heuristic decision-making processes. This could be achieved for example by continuous distributions or at least distributions with multiple outcomes. Alternatively, multiple drawings from a (right and left-skewed) distribution could be applied; these could, for example, be simulated as two shares in an experimental asset market.

The significant differences in our results as to decision time show that considering different types of decision making adds a valuable perspective that could increase our understanding of individual decision making: While this is to some extent present in the popular science literature,[11] a consideration or differentiation between intuitive/"gut feeling" decision making versus intellectual/rational decision making is not commonly used in current experimental research projects. Most studies assume that decision makers all follow a similar decision process, neglecting personal traits and characteristics that may also have an impact on the analyzed results. In order to account for different types of decision making, decision times should also be monitored and considered in experimental research projects.

Based on the experimental data elicited in the prudence stage, a preference for prudence can be confirmed, as 65% of all choices are in favour of the prudent alternative. Consequently, the majority of subjects (54%) can be classified as prudent individuals whereas only 13% can be seen as imprudent. Analyzing the potential impact of the factors favouring the prudent choice, no significant differences in the prudence preferences of the considered subgroups can be identified. These preferences are similar across all subgroups. Based on a binary choice model and estimating marginal effects at the means, a clear preference for prudence can be shown as all significant coefficients are positive – whereas the only negative coefficient (the dummy variable for a potential gender effect) does not have a significant impact. Prudent behaviour is even stronger if the zero-mean risk is allocated to an initial lottery in the loss domain. This behaviour has been indicated in experimental studies before. For example, Ebert and Wiesen (2011) find a higher share of prudent choices if losses are involved but this difference is not statistically significant compared to lottery pairs including a sure gain. This experimental result is in accordance with economic theory: Reflecting that prudence does not imply a general aversion to risk, but a preference to take this risk in a better state, it is intuitive that this preference is even stronger when the worse state is associated with a loss. In addition, the analysis of the binary choice models indicates that prudence preferences are stronger if the probability of the lower outcome of the zero-mean risk ε –

[11] As for example prominently in the title of "Thinking, fast and slow" by Kahneman (2011).

which is positively correlated to its skewness – increases. This consequently translates into a higher kurtosis of the (compound) prudent lottery.

It can be observed that the share of prudent choices increases as the skewness of ε increases, which is equivalent to an increasing probability of the lower state of the zero-mean risk that is always associated with a loss. Loss aversion can therefore provide an explanatory motive that might override a potential aversion to kurtosis or kurtosis robustness feature. Future research should therefore further explore the interrelation between prudence preferences and loss aversion, e.g. by using a similar experimental design with varying initial wealth levels.

The quartiles of subjects based on the required decision time do not exhibit significant differences in the observed prudent behaviour. Accordingly, the OLS regression model shows that decision time does not have a significant impact on the prudent/imprudent decision. Compared to the lottery pairs used in the skewness stage, the Eeckhoudt and Schlesinger (2006) lottery pairs applied in the prudence stage are already per se more complex, such that a higher cognitive effort is required to assess and evaluate the respective lottery. Therefore, the decision making process might be already less intuitive and heuristic, such that the decision time does not have an impact on the prudent decision. Although more than 40 years have gone by since Tversky and Kahneman (1974) initiated a whole new strand of research, the usage of heuristics when making judgements under uncertainty is far from being completely understood. Accordingly, there is ample room for research in the next 40 years.

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Figure 1: Eeckhoudt-Schlesinger Lottery Pair
This figure presents an example of a Eeckhoudt-Schlesinger (ES) lottery pair. Left panel: prudent lottery; right panel: imprudent lottery. Source: Own presentation based on Eckhoudt and Schlesinger (2006), Deck and Schlesinger (2010), and Ebert and Wiesen (2011).

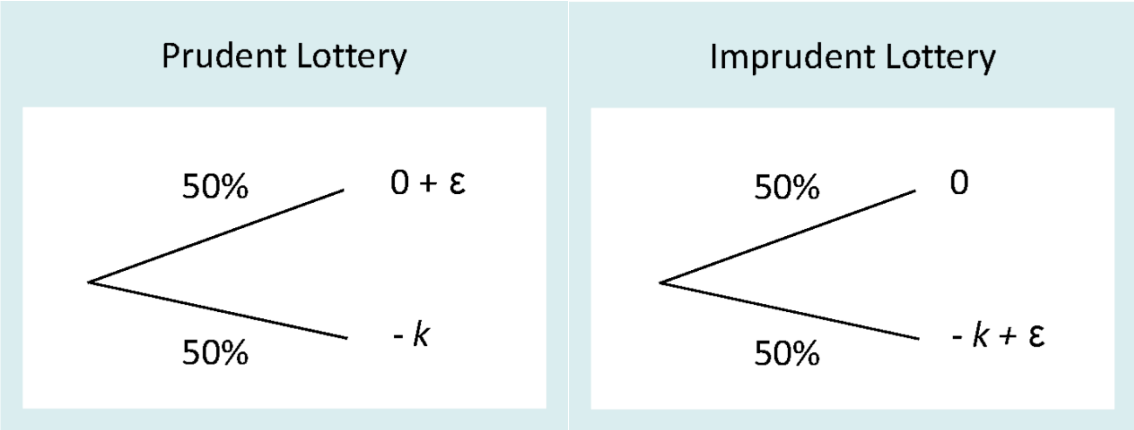

Figure 2: Cumulative Share of Right-Skewed and Prudent Choices per Subject
This figure presents the cumulative distribution functions of right-skewed (left panel) and prudent (right panel) choices per subject.

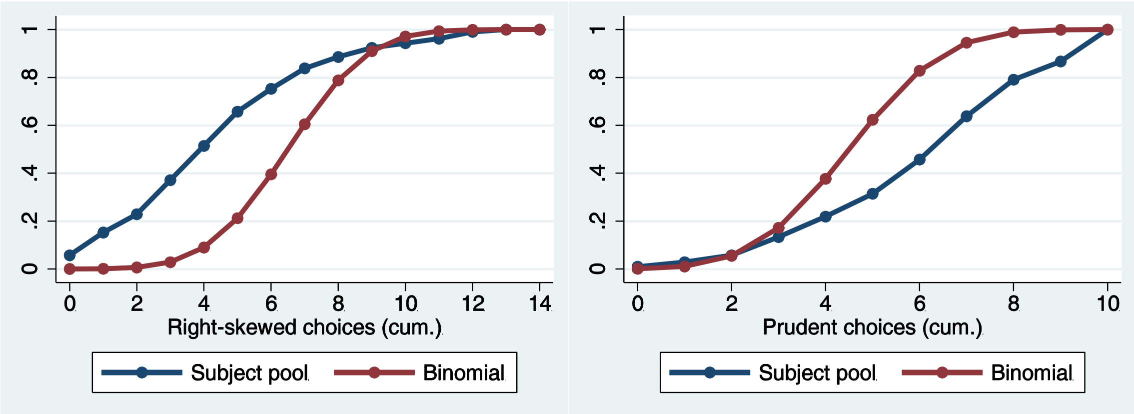

Figure 3: Correlation of Right-Skewed and Prudent Choices per Subject

This figure presents the distribution of right-skewed and prudent choices per subject. The size of the circles corresponds to the frequency at which the respective combination occurs.

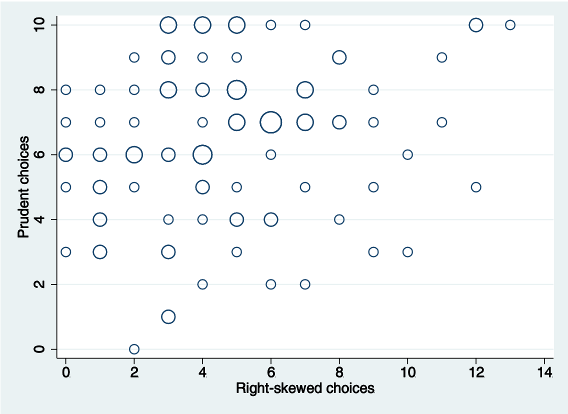

Figure 4: Right-Skewed and Prudent Choices per Subject

This figure presents the average percentage of right-skewed (left panel) and prudent (right panel) choices per subject as to degree of skewness and degree of the zero-mean risk, respectively.

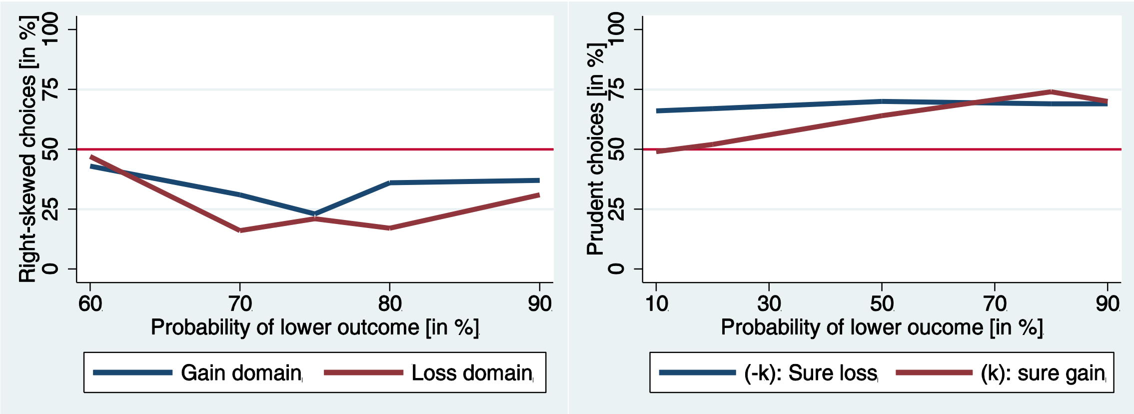

Figure 5: Cumulative Distribution Functions of Right-Skewed and Prudent Choices (Decision Time)
This figure presents the cumulative distribution functions of the right-skewed (left panel) and prudent (right panel) choices as to decision time for the respective quartiles.

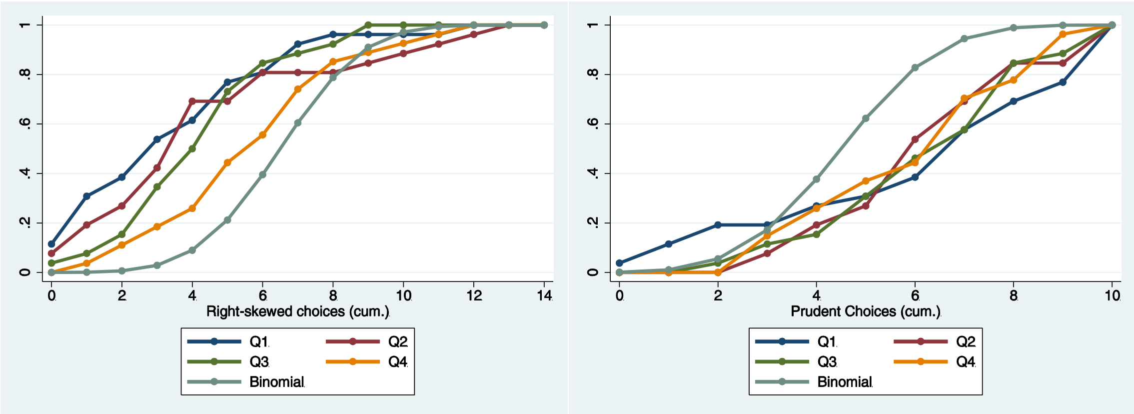

Table 1: Overview of Experimental Sessions
This table presents information on the date, location, and number of participants as well as the average pay-off for the experimental sessions. The test sessions are not included.

Date	Location	Participants (N)	∅ Pay-off (EUR)
September 22	BonnEconLab	16	17.07
September 23	BonnEconLab	14	17.05
September 24	BonnEconLab	16	18.00
October 5	WHU Behavioral Lab	16	15.26
October 6	WHU Behavioral Lab	13	14.21
October 6	WHU Behavioral Lab	13	11.70
October 7	WHU Behavioral Lab	12	18.74
October 7	WHU Behavioral Lab	9	18.00
Total		105	16.26

Table 2: Overview of Socio-Economic Characteristics of the Participants

This table presents information on socio-economic characteristics of the participants. The test sessions are not included. Statistics for participants in Bonn and Vallendar are reported separately as well as total. Percentage terms in all cases relate to the overall number of 105 subjects. Monthly disposable income (panel G) net of rent.

	Bonn		Vallendar		Total	
Panel A: Gender						
Male	25	(24%)	42	(40%)	67	(64%)
Female	21	(20%)	17	(16%)	38	(36%)
Total	46	(44%)	59	(56%)	105	(100%)
Panel B: Age						
17-20	8	(8%)	40	(38%)	48	(46%)
21-25	31	(30%)	19	(18%)	50	(48%)
26-30	7	(7%)	0	(0%)	7	(7%)
Total	46	(44%)	59	(56%)	105	(100%)
Panel C: Nationality						
German	45	(43%)	59	(56%)	104	(99%)
Other EU	1	(1%)	0	(0%)	1	(1%)
Other	0	(0%)	0	(0%)	0	(0%)
Total	46	(44%)	59	(56%)	105	(100%)
Panel D: Marital Status						
Married	1	(1%)	0	(0%)	1	(1%)
Unmarried	45	(43%)	59	(56%)	104	(99%)
Total	46	(44%)	59	(56%)	105	(100%)
Panel E: Profession of Father						
Employee	20	(19%)	18	(17%)	38	(36%)
Civil servant	10	(10%)	7	(7%)	17	(16%)
Self-employed	7	(7%)	21	(20%)	28	(27%)
Entrepreneur	0	(0%)	6	(7%)	6	(6%)
Not working	2	(2%)	3	(3%)	5	(5%)
Retiree	7	(7%)	4	(4%)	11	(10%)
Total	46	(44%)	59	(56%)	105	(100%)
Panel F: Profession of Mother						
Employee	23	(22%)	29	(28%)	52	(50%)
Civil servant	5	(5%)	6	(6%)	11	(10%)
Self-employed	7	(7%)	11	(10%)	18	(17%)
Entrepreneur	0	(0%)	1	(1%)	1	(1%)
Not working	11	(10%)	12	(11%)	23	(22%)
Retiree	0	(0%)	0	(0%)	0	(0%)
Total	46	(44%)	59	(56%)	105	(100%)
Panel G: Monthly Disposable Income						
< EUR 250	17	(16%)	5	(5%)	22	(21%)
≥ EUR 250; < EUR 500	22	(21%)	31	(30%)	53	(50%)
≥ EUR 500; < EUR 750	5	(5%)	15	(14%)	20	(19%)
≥ EUR 750	2	(2%)	8	(8%)	10	(10%)
Total	46	(44%)	59	(56%)	105	(100%)
Panel H: Investment Objectives						
Only capital preservation important	0	(0%)	0	(0%)	0	(0%)
Capital preservation more important	18	(17%)	14	(13%)	32	(30%)
Both	16	(15%)	16	(15%)	32	(30%)
Capital growth more important	11	(10%)	29	(28%)	40	(38%)
Only capital growth important	1	(1%)	0	(0%)	1	(1%)
Total	46	(44%)	59	(56%)	105	(100%)
Panel I: Saving Behaviour in View of Increasing Uncertainty						
Decrease savings	3	(3%)	7	(7%)	10	(10%)
Unchanged savings	25	(24%)	33	(31%)	58	(55%)
Increase savings	18	(17%)	19	(18%)	37	(35%)
Total	46	(44%)	59	(56%)	105	(100%)

(continued)

Table 2: Overview of Socio-Economic Characteristics of the Participants – *continued*

Panel J: Self-Assessed Loss Aversion						
Missed gains much more severe	2	(2%)	3	(3%)	5	(5%)
Missed gains somewhat severe	1	(1%)	3	(3%)	4	(4%)
Equally severe	1	(1%)	3	(3%)	4	(4%)
Realized losses somewhat more severe	8	(8%)	21	(20%)	29	(28%)
Realized losses much more severe	34	(32%)	29	(28%)	63	(60%)
Total	46	(44%)	59	(56%)	105	(100%)
Panel K: Field of Study						
Economic sciences	7	(7%)	59	(56%)	66	(63%)
Law	10	(10%)	0	()	10	(10%)
Mathematics/natural sciences	9	(96%)	0	()	9	(9%)
Linguistics	6	(6%)	0	()	6	(6%)
Agricultural/nutritional sciences	5	(5%)	0	()	5	(5%)
Medical sciences	1	(1%)	0	()	1	(1%)
Other humanities	4	(4%)	0	()	4	(4%)
Not specified/other	4	(4%)	0	()	4	(4%)
Total	46	(44%)	59	(56%)	105	(100%)
Panel L: Aspired University Degree						
Bachelor	10	(10%)	57	(54%)	67	(64%)
Master	7	(7%)	2	(2%)	9	(9%)
Master (Magister)	2	(2%)	0	(0%)	2	(2%)
Master (Diplom)	10	(10%)	0	(0%)	10	(12%)
State examination (Staatsexamen)	13	(12%)	0	(0%)	13	(12)
Doctoral degree	2	(2%)	0	(0%)	2	(2%)
Not specified/other	2	(2%)	0	(0%)	2	(2%)
Total	46	(44%)	59	(56%)	105	(100%)
Panel M: Number of Semesters						
1	4	(4%)	48	(46%)	52	(50%)
2-6	18	(17%)	10	(10%)	28	(27%)
7-10	15	(14%)	1	(1%)	16	(15%)
> 10	3	(3%)	0	(0%)	3	(3%)
Not specified	6	(6%)	0	(0%)	6	(6%)
Total	46	(44%)	59	(56%)	105	(100%)
Panel N: Experience in Experimental Studies						
No experience	3	(3%)	55	(52%)	58	(55%)
1-2 experiments	7	(7%)	4	(4%)	11	(10%)
3-5 experiments	9	(9%)	0	(0%)	9	(9%)
5-10 experiments	14	(13%)	0	(0%)	14	(13%)
> 10experiments	13	(12%)	0	(0%)	13	(12%)
Total	46	(44%)	59	(56%)	105	(100%)

Table 3: Contingent Classification of Participants According to Third-Order Risk Preferences
This table presents the contingent classification of participants as to their choices concerning skewness seeking and prudence. Panel A presents the contingent choice of skewness given a subject's prudence preference. Panel B presents the contingent choice of prudence given a subject's skewness preference. Percentage terms in all cases relate to row total.

Panel A: Contingent Choice of Skewness for given Level of Prudence								
	Skewness Seeking		Neutral		Not Skewness Seeking		Total	
Prudent	5	(9%)	30	(53%)	22	(39%)	57	(100%)
Neutral	2	(6%)	9	(26%)	23	(68%)	34	(100%)
Imprudent	1	(7%)	4	(29%)	9	(64%)	14	(100%)
Panel B: Contingent Choice of Prudence for given Level of Skewness								
	Prudent		Neutral		Imprudent		Total	
Skewness Seeking	5	(63%)	2	(25%)	1	(13%)	8	(100%)
Neutral	30	(70%)	9	(21%)	4	(9%)	43	(100%)
Not Skewness Seeking	22	(39%)	23	(43%)	9	(17%)	54	(100%)

Table 4: Share of Right-Skewed and Prudent Choices per Lottery Pair

This table presents the share of right-skewed and prudent choices per lottery pair. Panel A presents the results for the skewness stage. The number in brackets refers to the notation of the respective Mao lottery pair of Table A1 in the appendix. An increasing probability of the smaller outcome (p_1) of the right-skewed lottery (A) corresponds to an increasing degree of skewness of lottery A and thus an increasing degree of skewness between the right-skewed lottery and the equivalent left-skewed lottery. Panel B presents the results for the prudence stage. The number in brackets refers to the notation of the respective ES lottery pair of Table A2 in the appendix. An increasing probability of the smaller outcome of the zero-mean risk $p_1(\varepsilon)$ corresponds to an increasing degree of skewness of the zero-mean risk and thus a higher kurtosis of the aggregated prudent lottery.

Panel A: Share of Right-Skewed Choices per Mao Lottery Pair											
p_1 (Lottery A)	60%		70%		75%		80%		90%		Ø
Gain lotteries ($PMAO_G$)	43%	(5)	31%	(4)	23%	(3)	36%	(2)	37%	(1)	34.1%
Loss lotteries ($PMAO_L$)	47%	(5)	16%	(4)	21%	(3)	17%	(2)	31%	(1)	26.5%
Mixed lotteries (MAO_M)					49%	(1)					42.4%
					51%	(2)					
					40%	(3)					
					30%	(4)					
Total											33.7%
Panel B: Share of Prudent Choices per ES Lottery Pair											
$p_1(\varepsilon)$	10%		20%		50%		80%		90%		Ø
Sure loss	66%	(2)	67%	(4)	70%	(5)	69%	(3)	69%	(1)	67.8%
Sure gain	49%	(7)	52%	(9)	64%	(10)	74%	(8)	70%	(6)	61.9%
Total											64.9%

Table 5: Logistic Regressions for Right-Skewed Choices

This table presents the results of the logistic regressions for right-skewed choices. Panel A presents coefficients for the logit estimation of marginal effects at mean values of the independent variables. Panel B presents coefficients for the logit estimation of average marginal effects. Panel C presents the logit coefficients. The underlying units of the respective variables are provided in squared brackets if differing from 1. LL log-likelihood. AIC Akaike information criterion (Akaike, 1974). BIC Schwarz' Bayesian information criterion (Schwarz, 1978). $McK-Z\ R^2$ McKelvey-Zavoina R^2 (McKelvey and Zavoina, 1975). Clustered standard errors in parenthesis. Coefficients significant at $^{a}\ p < 0.10$, $^{b}\ p < 0.05$, $^{c}\ p < 0.01$.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Pannel A: Marginal Effects at the Means (MEM)							
$L_A\ p_1$ [10%]	-0.029^{a}		-0.022		-0.249^{c}	-0.284^{c}	-0.286^{c}	-0.295^{c}
	(0.017)		(0.018)		(0.047)	(0.061)	(0.061)	(0.061)
Var [1000]		0.008^{c}	0.011^{c}	0.011^{c}	0.012^{c}	0.012^{c}	0.012^{c}	0.007^{c}
		(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
$\Delta\ Skew$		-0.004		-0.004	0.156^{c}	0.179^{c}	0.180^{c}	0.184^{c}
		(0.012)		(0.012)	(0.030)	(0.038)	(0.038)	(0.038)
w_0 [100]			-0.033^{c}	-0.034^{c}	-0.028^{b}	-0.029^{b}	-0.030^{b}	
			(0.012)	(0.012)	(0.013)	(0.013)	(0.013)	
$4\ balls$						0.032	0.032	-0.036
						(0.034)	(0.034)	(0.043)
Fem							-0.012	-0.012
							(0.041)	(0.041)
$Bonn$							-0.094^{b}	-0.094^{b}
							(0.044)	(0.044)
$Gain$								-0.083
								(0.054)
$Loss$								-0.166^{c}
								(0.052)
$Constant$	YES	YES^{c}	YES	YES^{c}	YES^{c}	YES^{c}	YES^{c}	YES^{c}
	Panel B: Average Marginal Effects (AME)							
$L_A\ p_1$ [10%]	-0.029^{a}		-0.021		-0.242^{c}	-0.275^{c}	-0.275^{c}	-0.283^{c}
	(0.017)		(0.017)		(0.044)	(0.058)	(0.058)	(0.058)
Var [1000]		0.008^{c}	0.010^{c}	0.011^{c}	0.012^{c}	0.011^{c}	0.011^{c}	0.007^{c}
		(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
$\Delta\ Skew$		-0.004		-0.004	0.151^{c}	0.173^{c}	0.173^{c}	0.173^{c}
		(0.012)		(0.011)	(0.029)	(0.036)	(0.036)	(0.036)
w_0 [100]			-0.032^{c}	-0.033^{c}	-0.027^{b}	-0.029^{b}	-0.029^{b}	
			(0.012)	(0.012)	(0.012)	(0.013)	(0.013)	
$4\ balls$						0.031	0.031	-0.035
						(0.033)	(0.033)	(0.041)
Fem							-0.012	-0.012
							(0.039)	(0.039)
$Bonn$							-0.090^{b}	-0.090^{b}
							(0.042)	(0.042)
$Gain$								-0.080
								(0.052)
$Loss$								-0.159^{c}
								(0.049)
$Constant$	YES	YES^{c}	YES	YES^{c}	YES^{c}	YES^{c}	YES^{c}	YES^{c}

(continued)

Table 5: Logistic Regressions for Right-Skewed Choices – *continued*

				Panel C: Logit Coefficients				
$L_A\, p_1$ [10%]	-0.128[a]		-0.098		-1.125[c]	-1.282[c]	-1.295[c]	-1.339[c]
	(0.078)		(0.081)		(0.221)	(0.286)	(0.286)	(0.289)
Var [1000]		0.037[c]	0.048[c]	0.048[c]	0.055[c]	0.053[c]	0.053[c]	0.031[c]
		(0.008)	(0.009)	(0.009)	(0.009)	(0.010)	(0.010)	(0.011)
$\Delta\, Skew$		-0.020		-0.017	0.704[c]	0.808[c]	0.816[c]	0.834[c]
		(0.053)		(0.053)	(0.142)	(0.179)	(0.179)	(0.181)
w_0 [100]			-0.149[c]	-0.153[c]	-0.126[b]	-0.133[b]	-0.134[b]	
			(0.056)	(0.056)	(0.057)	(0.057)	(0.058)	
$4\ balls$						0.145	0.147	-0.165
						(0.154)	(0.156)	(0.194)
Fem							-0.056	-0.056
							(0.185)	(0.186)
$Bonn$							-0.425[b]	-0.427[b]
							(0.201)	(0.202)
$Gain$								-0.377
								(0.244)
$Loss$								-0.754[c]
								(0.237)
$Constant$	0.284	-0.809[c]	0.014	-0.677[c]	5.848[c]	6.718[c]	6.990[c]	7.736[c]
	(0.571)	(0.167)	(0.601)	(0.173)	(1.276)	(1.637)	(1.623)	(1.673)
LL	-937.860	-923.863	-919.590	-920.591	-911.350	-910.981	-903.678	-899.535
$Wald\ \chi^2$	2.724	24.450	30.815	30.344	45.474	45.342	59.835	66.129
$Prob > \chi^2$	0.099	0.000	0.000	0.000	0.000	0.000	0.000	0.000
AIC	1.279	1.261	1.257	1.258	1.247	1.248	1.240	1.236
BIC	-8830.429	-8851.132	-8852.384	-8850.381	-8861.571	-8855.017	-8855.035	-8856.028
$McFadden\ R^2$	0.002	0.017	0.021	0.020	0.030	0.031	0.038	0.043
$McK-Z\ R^2$	0.004	0.027	0.035	0.033	0.050	0.051	0.064	0.074

Table 6: Right-Skewed and Prudent Choices (Decision-Time)

This table presents the decision times and number of right-skewed and prudent choices for the respective quartiles (upper part) and the results of the Wilcoxon rank sum test (see Wilcoxon, 1945, and Mann and Whitney, 1947) for equality of the quartiles (lower part). Panel A presents the median decision time as well as the share of right-skewed choices. Panel B presents the median decision time as well as the share of prudent choices.

	Panel A: Right-Skewed Choices				*Panel B: Prudent Choices*			
	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
Median decision time	7.4	10.4	17.7	33.1	14.8	19.2	27.4	51.1
Choices	26.4%	33.0%	32.1%	43.1%	64.6%	65.4%	66.2%	63.3%
	p-Values of Wilcoxon Rank-Sum Test							
	Q1	0.4533	0.1749	0.0032	Q1	0.6571	0.8390	0.5414
	Q2		0.5421	0.0319	Q2		0.7738	0.8362
	Q3			0.0328	Q3			0.6405

Table 7: Impact of Decision Time on Right-Skewed and Prudent Choices

This table presents the regression results for the impact of decision time on right-skewed (panel A) and prudent choices (panel B).

	Coef.	Std. Error	t-value	p-value	95% Conf. Interval	
			Panel A: Right-Skewed Choices			
Time [sec.]	0.0632	0.0185	3.42	0.0010	0.0265	0.0999
Constant	3.5351	0.4460	7.93	0.0000	2.6504	4.4197
			Panel B: Prudent Choices			
Time [sec.]	0.0003	0.0137	0.02	0.9830	-0.0269	0.0275
Constant	6.4773	0.4572	14.17	0.0000	5.5705	7.3841

Table 8: Logistic Regressions for Prudent Choices

This table presents the results of the logistic regressions for prudent choices. Panel A presents coefficients for the logit estimation of marginal effects at mean values of the independent variables. Panel B presents coefficients for the logit estimation of average marginal effects. Panel C presents the logit coefficients. LL log-likelihood. AIC Akaike information criterion (Akaike, 1974). BIC Schwarz' Bayesian information criterion (Schwarz, 1978). $McK - Z\,R^2$ McKelvey-Zavoina R^2 (McKelvey and Zavoina, 1975). Clustered standard errors in parenthesis. Coefficients significant at $^a\ p < 0.10$, $^b\ p < 0.05$, $^c\ p < 0.01$.

	(1a)	(1b)	(1c)	(2a)	(2b)	(2c)	(3a)	(3b)	(3c)	(4)
				Pannel A: Marginal Effects at the Means (MEM)						
$\varepsilon\, p_1$	0.172^c		0.331	0.170^c		0.345	0.171^c		0.347	0.348
	(0.050)		(0.268)	(0.049)		(0.270)	(0.049)		(0.271)	(0.272)
$\varepsilon\, Skew$		0.027^c	-0.026		0.027^c	-0.029		0.027^c	-0.029	
		(0.008)	(0.042)		(0.008)	(0.042)		(0.008)	(0.042)	
$\varepsilon\, \Delta\, X$				-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
				(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
w_0										0.000
										(0.000)
$Loss$	0.060^b	0.060^b	0.060^b	0.060^b	0.060^b	0.060^b	0.060^b	0.060^b	0.060^b	0.002
	(0.029)	(0.029)	(0.029)	(0.029)	(0.029)	(0.029)	(0.030)	(0.030)	(0.030)	(0.093)
Fem							-0.003	-0.003	-0.003	-0.003
							(0.045)	(0.045)	(0.045)	(0.045)
$Bonn$							0.078^a	0.078^a	0.078^a	0.078^a
							(0.046)	(0.046)	(0.046)	(0.046)
$Constant$	YES	YES^c	YES	YES	YES^b	YES	YES	YES^a	YES	YES

(continued)

Table 8: Logistic Regressions for Prudent Choices – *continued*

					Panel B: Average Marginal Effects (AME)					
$\varepsilon\ p_1$	0.170^{c}		0.326	0.168^{c}		0.340	0.168^{c}		0.340	0.341
	(0.048)		(0.263)	(0.047)		(0.265)	(0.048)		(0.265)	(0.266)
$\varepsilon\ Skew$		0.027^{c}	-0.026		0.027^{c}	-0.028		0.027^{c}	-0.028	
		(0.008)	(0.041)		(0.008)	(0.042)		(0.008)	(0.042)	
$\varepsilon\ \Delta\ X$				-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
				(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
w_0										0.000
										(0.000)
$Loss$	0.059^{b}	0.059^{b}	0.059^{b}	0.059^{b}	0.059^{b}	0.059^{b}	0.059^{b}	0.059^{b}	0.059^{b}	0.002
	(0.029)	(0.029)	(0.029)	(0.029)	(0.029)	(0.029)	(0.029)	(0.029)	(0.029)	(0.091)
Fem							-0.003	-0.003	-0.003	-0.003
							(0.045)	(0.045)	(0.045)	(0.045)
$Bonn$							0.077^{a}	0.077^{a}	0.077^{a}	0.077^{a}
							(0.044)	(0.044)	(0.044)	(0.044)
$Constant$	YES	YES^{c}	YES	YES	YES^{b}	YES	YES	YES^{a}	YES	YES
					Panel C: Logit Coefficients					
$\varepsilon\ p_1$	0.756^{c}		1.457	0.750^{c}		1.520	0.755^{c}		1.529	1.533
	(0.220)		(1.180)	(0.218)		(1.190)	(0.218)		(1.197)	(1.201)
$\varepsilon\ Skew$		0.120^{c}	-0.115		0.119^{c}	-0.127		0.120^{c}	-0.127	
		(0.035)	(0.185)		(0.035)	(0.186)		(0.035)	(0.187)	
$\varepsilon\ \Delta\ X$				-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001
				(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
w_0										0.001
										(0.002)
$Loss$	0.263^{b}	0.263^{b}	0.263^{b}	0.263^{b}	0.263^{b}	0.263^{b}	0.265^{b}	0.265^{b}	0.265^{b}	0.009
	(0.130)	(0.129)	(0.130)	(0.130)	(0.130)	(0.130)	(0.130)	(0.130)	(0.130)	(0.408)
Fem							-0.015	-0.015	-0.015	-0.015
							(0.200)	(0.200)	(0.200)	(0.200)
$Bonn$							0.345^{a}	0.345^{a}	0.345^{a}	0.345^{a}
							(0.200)	(0.200)	(0.200)	(0.200)
$Constant$	0.114	0.492^{c}	-0.236	0.399	0.767^{b}	0.023	0.257	0.627^{a}	-0.122	-0.124
	(0.150)	(0.120)	(0.590)	(0.344)	(0.333)	(0.650)	(0.358)	(0.350)	(0.658)	(0.660)

(continued)

Table 8: Logistic Regressions for Prudent Choices – *continued*

LL	-671.989	-672.318	-671.888	-671.647	-671.992	-671.525	-668.285	-668.632	-668.163	-668.163
$Wald\ \chi^2$	17.543	17.263	17.607	18.297	18.096	18.273	24.228	23.853	24.327	24.327
$Prob > \chi^2$	0.000	0.000	0.001	0.000	0.000	0.001	0.000	0.000	0.000	0.000
AIC	1.286	1.286	1.287	1.287	1.288	1.289	1.284	1.285	1.286	1.286
BIC	-5939.525	-5938.867	-5932.770	-5933.253	-5932.564	-5926.539	-5926.063	-5925.370	-5919.352	-5919.352
$McFadden\ R^2$	0.013	0.012	0.013	0.013	0.013	0.014	0.018	0.018	0.018	0.018
$McK - Z\ R^2$	0.022	0.021	0.022	0.023	0.022	0.023	0.031	0.030	0.032	0.032

Appendix

Appendix 1: Definitions and Design of the Lotteries – Skewness Stage

Analogous to Ebert and Wiesen (2011) the following definitions and notations will be used:

Definition 1. *A binary lottery $L(p_1, x_1, x_2)$ is a lottery with two potential outcomes $x_1 < x_2$ and the associated probability p_1 for the smaller outcome x_1 and $(1 - p_1)$ for the higher outcome x_2.*

Binary lotteries exhibit some statistical specifics: All (standardized) higher central moments are a pure function of the probabilities of the respective outcomes. Consequently, the skewness of a binary lottery condenses to

$$Skew(X) = \frac{2p_1 - 1}{\sqrt{p_1 \times (1 - p_1)}}. \tag{A1}$$

Definition 2. *A pair of binary lotteries L_A and L_B with the same mean, variance, and kurtosis is referred to as a Mao-lottery pair.*[12]

In the case of binary lotteries there is exactly one other lottery that matches these criteria. The corresponding Mao-lottery can be virtually constructed by mirroring the lottery in the mean of the lottery, resulting in $\mu(L_a) = \mu(L_B)$. As the absolute difference between the two outcomes of the lottery stays the same, the variance of the binary lottery pair $[p_1 \times (1 - p_1)(x_2 - x_1)^2]$ remains unchanged, as do the kurtosis and all higher even (standardized) central moments, such that $\sigma^2(L_A) = \sigma^2(L_B)$, $Kurt(L_A) = Kurt(L_B)$ and $sCM_k(L_A) = sCM_k(L_B)$ for all even k. Considering that the probability of the smaller outcome of lottery A determines the probability of the Mao-equivalent lottery $p_1^B = 1 - p_1^A$, the skewness of the lottery will be inverted: $Skew(L_A) = -Skew(L_B)$. Mao-lotteries are therefore appropriate for testing for preferences for skewness as characterized by the 3rd central moment. Even more, a preference for all higher odd (standardized) central moments is implicitly tested, as all higher

[12] The reference to Mao (1970) is already used by Menezes, Geiss and Tressler (1980). Mao (1970) surveyed executives with one (mixed) lottery pair of this class to analyze the impact of semi-variance in investment decisions.

odd (standardized) central moments of a Mao-lottery are inverted accordingly: $sCM_k(L_A) = -sCM_k(L_B)$ for all odd $k \geq 3$. In the following, L_A represents the right-skewed lottery, whereas L_B refers to the left-skewed lottery. Consequently, the probability of the smaller outcome is $p_1^A > 0.5$ and $p_1^B < 0.5$.

Definition 3. *A Mao-lottery pair is a pure Mao-lottery pair if all outcomes of both lotteries are associated with strictly positive ($x_1 > 0$) or strictly negative pay-offs ($x_2 < 0$). Mixed Mao-lotteries combine outcomes in the gain and in the loss domains or are weakly positive ($x_1 = 0$) or weakly negative ($x_2 = 0$). Thus, pure Mao-lotteries exhibit $sgn(x_1) \times sgn(x_2) = 1$ whereas mixed Mao-lotteries exhibit $sgn(x_1) \times sgn(x_2) = -1 \vee sgn(x_1) \times sgn(x_2) = 0$.*

In the following, pure Mao-lottery pairs are labeled as $PMAO_G$-lotteries within the gain domain with strictly positive outcomes and $PMAO_L$-lotteries within the loss domain with strictly negative outcomes. Mixed Mao-lotteries are referred to as MAO_M-lotteries. In this stage, subjects decide between 5 $PMAO$-lottery pairs in the gain domain, 5 $PMAO$-lottery pairs in the loss domain, and 4 mixed Mao-lottery pairs. All lotteries are characterized by either a mean of $+90$ or -90 [Taler] and are designed so that all outcomes are round numbers and all probabilities that are either multiples of 10% or 25% are covered. An overview of the lottery pairs and their statistical characteristics is provided in Table A1. To encourage intuitive decision making, ballot boxes are chosen for the graphical presentation of the lotteries. This design is consistently used across all experimental stages. For each individual, the following aspects were randomized: (1) the order of the domains of the lotteries ($PMAO_G$, $PMAO_L$, MAO_M), (2) the order of the respective lottery pairs within each domain, and (3) the respective presentation of the right/left-skewed lottery on the right-hand/left-hand side.

All right-skewed lotteries stochastically dominate the equivalent left-skewed Mao-lottery by third-degree stochastic dominance, but neither by first-degree stochastic dominance nor by second-degree stochastic dominance. A commonly assumed risk-averse expected utility theory decision maker exhibiting decreasing absolute risk aversion (DARA), for example implied by a power utility function with $u(x) = x^r$ and $0 < r < 1$, will maximize her utility by choosing the right-skewed lotteries. The median cumulative prospect theory decision maker of Tversky and Kahneman (1992) will accordingly opt for the respective right-skewed options across all domains.[13]

Table A1: Mao Lotteries and Their Statistical Characteristics

This table presents the lotteries used for the skewness stage of the experimental sessions and their statistical characteristics. $PMAO_G$ denotes pure Mao-lotteries within the gain domain with strictly positive outcomes. $PMAO_L$ denotes pure Mao-lotteries within the loss domain with strictly negative outcomes. MAO_M denotes mixed Mao-lotteries. $\Delta\, Skew = Skew(L_A) - Skew(L_B)$. w_0 denotes the initial endowment.

	Lottery A			Lottery B			Statistical Characteristics				
Lottery Pairs	p_1	x_1	x_2	p_1	x_1	x_2	$Mean$	Var	$\Delta\, Skew$	$Kurt$	w_0
$PMAO_G 1$	90%	85	135	10%	45	95	90	225	5.33	8.11	0
$PMAO_G 2$	80%	80	130	20%	50	100	90	400	3.00	3.25	0
$PMAO_G 3$	75%	75	135	25%	45	105	90	675	2.31	2.33	0
$PMAO_G 4$	70%	66	146	30%	34	114	90	1,344	1.75	1.76	0
$PMAO_G 5$	60%	50	150	40%	30	130	90	2,400	0.82	1.17	0
$PMAO_L 1$	90%	-95	-45	10%	-135	-85	-90	225	5.33	8.11	180
$PMAO_L 2$	80%	-100	-50	20%	-130	-80	-90	400	3.00	3.25	180
$PMAO_L 3$	75%	-105	-45	25%	-135	-75	-90	675	2.31	2.33	180
$PMAO_L 4$	70%	-114	-34	30%	-146	-66	-90	1,344	1.75	1.76	180
$PMAO_L 5$	60%	-130	-30	40%	-150	-50	-90	2,400	0.82	1.17	180
$MAO_M 1$	75%	0	360	25%	-180	180	90	24,300	2.31	2.33	180
$MAO_M 2$	75%	-180	180	25%	-360	0	-90	24,300	2.31	2.33	360
$MAO_M 3$	75%	55	195	25%	-15	125	90	3,675	2.31	2.33	90
$MAO_M 4$	75%	-125	15	25%	-195	-55	-90	3,675	2.31	2.33	270

[13] Assuming the following CPT parameters: $\alpha = 0.88$, $\beta = 0.88$, $\gamma = 0.61$, $\delta = 0.69$ and $\lambda = 2.25$. See Tversky and Kahneman (1992).

Appendix 2: Definitions and Design of the Lotteries – Prudence Stage

Analogous to Eeckhoudt and Schlesinger (2006) and Ebert and Wiesen (2011) the following definitions and notations will be used:

Definition 4. *An ES lottery pair is a pair of lotteries resulting from the allocation of a sure reduction in wealth* $(-k)$ *and a zero-mean risk* ε *to the two states of an initial binary lottery. The aggregated lottery pair is thus:* $L_A(p_1, -k, \varepsilon)$ *and* $L_B(p_1, -k + \varepsilon, 0)$*, where* p_1 *refers to the lower outcome of the lottery which will always contain the sure loss of* $-k$*.*

Definition 5. *An individual is prudent if she prefers* L_A *over* L_B *and thereby implicitly allocates the independent zero-mean risk to the upper part of the distribution.* L_A *is accordingly referred to as the prudent choice, whereas* L_B *is referred to as the imprudent choice.*

As the prudent and the imprudent lottery include the same components, the mean and the variance of both lotteries are consequently the same, whereas the skewness of L_A and L_B differ according to the allocation of ε. The lotteries are designed so that the expected means of all lotteries either sum up to $+90$ or to -90 [Taler] and are therefore statistically equivalent to the Mao-lotteries applied in the skewness stage.

In order to construct ES lottery pairs that additionally exhibit the same variance and the same difference in skewness, ε – which is added to the respective initial lottery – is required to add the same variance across all questions. Therefore, the outcomes of the respective zero-mean risk are adjusted such that the variance (which reduces to $\frac{p_1}{(1-p_1)}(x_1)^2$ in the case of a binary lottery with an expected mean of zero) remains constant. As a result, this design is adequate not just to test whether individuals exhibit a preference for prudence in general, but also to analyze the impact of a variation of the skewness of the zero-mean risk (and therefore of the kurtosis of the compound lottery pairs) on the preference for the right-skewed, prudent choice, which can be ceteris paribus analyzed in the gain and in the loss domain. The variance and the difference in skewness of all ES lottery pairs are designed to exactly match the statistical properties of the lotteries MAO_M1 and MAO_M2 applied in the skewness stage. Therefore, a further comparison of these lotteries exhibiting the same first three moments is possible.

In total, subjects have to choose between 5 ES lottery pairs in the loss domain (thereby allocating the zero-mean risk ε to either 0 or to a sure loss $(-k)$ of 180) and between 5 ES lottery pairs in the gain domain (where ε is to be allocated to either 0 or to a sure gain of (k) of 180). Table A2 gives an overview of the ES-lotteries and their respective statistical properties. At the beginning of each question, subjects receive an initial endowment sufficient to cover the maximum loss arising from the imprudent lottery. As the zero-mean risk is allocated to the lower part of the distribution in this case, the maximum loss always occurs in the imprudent option.

In addition to the statistical requirements discussed above, the lotteries are designed such that all outcomes are round numbers and all associated probabilities are multiples of 10% or 25%. This is done not just for computational convenience, but also to enable an intuitive presentation of the compound prudent and imprudent lotteries. Similarly to the presentation applied by Ebert and Wiesen (2011), the ballot boxes already used to present the right and left-skewed lotteries in the skewness stage are applied to present the zero-mean risk ε. The initial lottery determining the upper and lower state, which each occur at a probability of 50%, are represented by the two sides of a 1 Euro coin. This provides an intuitive and illustrative presentation familiar to the participants. By choosing option A or option B, subjects decide on the allocation of the ballot box (ε) to the two states, the upper or lower part of the distribution. If an ES lottery is chosen to determine the compensation for a participant, the relevant state for the chosen option is determined by a coin toss. The two states are accordingly marked by the two sides of the coin.

Within the prudence stage, both the order of the (gain or loss) domain and the appearance of the prudent (imprudent) option on the right or left-hand side of the screen are individually randomized for each subject. To avoid confusion within the selection of the preferred option, “Option A” (“Option B”) always refers to the option on the left (right) hand side.

Based on the construction of the ES lotteries, each prudent lottery exhibits the same mean and variance, but a higher skewness than the imprudent lottery. Accordingly, each prudent option dominates the imprudent option by third order stochastic dominance but neither by second order stochastic dominance nor by first order stochastic dominance. Therefore, the imprudent option is characterized by an increasing downside risk (or higher 3rd degree risk as defined by Menezes, Geiss and Tressler, 1980, and Ekern, 1980) compared to the prudent option.

A common expected utility theory maximizer with a simple DARA utility function of $u(x) = x^r$ will choose the prudent option if she is risk-averse ($r < 1$). In addition, the prudent option will be preferred if the individual is extremely risk loving ($r > 2$). In this case, the high exponent of the power utility function leads to an increased sensitivity towards more extreme (positive and negative) outcomes. As the highest positive outcome of the prudent option is always higher than the highest positive outcome of the corresponding imprudent option – and vice versa the lowest outcome of the imprudent choice is always lower than the lowest outcome of the corresponding prudent option – the prudent option will be preferred with an increasing exponent of $r > 2$. Accordingly, if individuals simply adopt gambling behaviour and heuristically try to achieve the highest possible outcome, they will opt for the prudent option as well as for the right-skewed lottery in the skewness stage. A cumulative prospect theory decision maker characterized by Tversky and Kahneman (1992) median parameters will opt for the prudent choice in 9 out of 10 cases. Only in the first question (ES 1) will she choose the imprudent option. In this question, the zero-mean risk is extremely right-skewed, which implies that ε will result in a loss at a high probability of 90%. If the zero-mean risk is allocated to the better state ("0"), the CPT decision maker will suffer a loss with an overall probability of 95%. As this loss is further aggravated by a loss aversion of $\lambda = 2.25$, the rational CPT decision maker achieves a higher value by choosing the imprudent option.[14] If the same ε is to be allocated to the gain domain (ES 6), the CPT decision maker will opt for the prudent option again as no overall loss can occur in this compound lottery.

[14] Assuming the following CPT parameters: $\alpha = 0.88$, $\beta = 0.88$, $\gamma = 0.61$, $\delta = 0.69$ and $\lambda = 2.25$. See Tversky and Kahneman (1992).

Table A2: ES Lotteries and Their Statistical Characteristics

This table presents the ES lotteries used for the prudence stage of the experimental sessions and their statistical characteristics. $\Delta\, Skew = Skew(L_A) - Skew(L_B)$. $\Delta\, Kurt = Kurt(L_A) - Kurt(L_B)$.

	Additional Zero-Mean Risk									Statistical Characteristics			
	k	p_1	x_1	p_2	x_2	$Mean$	Var	$Skew$	$Kurt$	$Mean$	Var	$\Delta\, Skew$	$\Delta\, Kurt$
ES 1	-180	90%	-60	10%	540	0	32,400	2.67	8.11	-90	24,300	2.31	9.48
ES 2	-180	10%	-540	90%	60	0	32,400	-2.67	8.11	-90	24,300	2.31	-9.48
ES 3	-180	80%	-90	20%	360	0	32,400	1.50	3.25	-90	24,300	2.31	5.33
ES 4	-180	20%	-360	80%	90	0	32,400	-1.50	3.25	-90	24,300	2.31	-5.33
ES 5	-180	50%	-180	50%	180	0	32,400	0.00	1.00	-90	24,300	2.31	0.00
ES 6	180	90%	-60	10%	540	0	32,400	2.67	8.11	90	24,300	2.31	9.48
ES 7	180	10%	-540	90%	60	0	32,400	-2.67	8.11	90	24,300	2.31	-9.48
ES 8	180	80%	-90	20%	360	0	32,400	1.50	3.25	90	24,300	2.31	5.33
ES 9	180	20%	-360	80%	90	0	32,400	-1.50	3.25	90	24,300	2.31	-5.33
ES 10	180	50%	-180	50%	180	0	32,400	0.00	1.00	90	24,300	2.31	0.00