Annals of Finance (2024) 20:129–165
https://doi.org/10.1007/s10436-023-00437-y

RESEARCH ARTICLE

Skewness-seeking behavior and financial investments

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Received: 23 June 2023 / Accepted: 19 December 2023 / Published online: 26 February 2024

Abstract

Recent theoretical and empirical advancements highlight the pivotal role played by higher-order moments, such as skewness, in shaping financial decision-making. Nevertheless, contemporary experimental research predominantly relies on limited-outcome lotteries, an oversimplified representation distant from real-world investment dynamics. To bridge this research gap, we conducted a rigorously pre-registered experiment. Our study delves into individuals' preferences for investment opportunities, examining the influence of skewness of continuous probability distributions of returns. We document an inclination towards positively skewed outcome distributions. Furthermore, we uncovered a substitution effect between risk appetite and the sign of skewness. Finally, we unveiled a robust positive correlation between skewness-seeking behavior and a propensity for speculative behavior. Simultaneously, a distinct negative correlation surfaced between skewness-seeking behavior and the perceived risk associated with positive skewness.

Keywords Skewness · Risk-taking · Stochastic dominance · Experiment

JEL Classification C91 · D81 · G11

1 Introduction

Skewness is a measure of the asymmetry of a distribution, such as the distribution of returns on an investment. While the literature has traditionally focused on the first two moments of the distribution—expected return and variance—higher-order moments have increasingly been studied from multiple perspectives. Skewness, which is usually measured with the third standardized moment, has been indeed associated with several phenomena, effects, and anomalies, such as the long-shot anomaly on the horse track (Golec and Tamarkin 1998) and in online lotteries (Garrett and Sobel 1999), the

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volatility smile (Barberis and Huang 2008; Boyer and Vorkink 2014), the preference for lottery-like stocks (Barberis 2013; Boyer et al. 2010), the underperformance of IPOs (Green and Hwang 2012), the underperformance of high-skewness stocks (Amaya et al. 2015), and the conglomerate discount (Schneider and Spalt 2016). The common denominator of all these phenomena is that some individuals who find the combination of low probabilities and large outcomes particularly attractive overpay for access to these investments/gambles, which, as a result, tend to yield lower returns. In this context, skewness preference is a concept used to refer to the preference for a positively skewed distribution of outcomes—i.e., one with a long right tail—over a negatively skewed one.

The experimental literature includes several contributions concerning the topic of skewness preferences. Most of the literature has examined preferences over skewed distributions of outcomes using binary lotteries (Åstebro et al. 2015; Brünner et al. 2011; Dertwinkel-Kalt and Köster 2020; Ebert 2015; Ebert and Wiesen 2011; Mao 1970) and three-outcome lotteries (Bougherara et al. 2021, 2022; Grossman and Eckel 2015; Taylor 2020), departing significantly from continuous distributions, which are more appropriate representations of the outcomes that investors face on the markets. The results of these experiments may not be easily generalized to continuous distributions due to the presence of biases and heuristics that may affect judgment (Holzmeister et al. 2020; Summers and Duxbury 2006; Vrecko et al. 2009).

We designed and conducted an experiment to investigate the role of skewness in financial investments using continuous distributions of outcomes. The participants are shown the probability density function of the returns that they may obtain from a financial investment. The distributions all share the same positive expected return, and, for most of the rounds, they also share the same variance. Skewness is different across the different distributions, with the coefficient of skewness ranging in the [− 1, 1] domain and including the value 0 (symmetric distribution). The decision framework does not give subjects the possibility to choose a "safe alternative" (i.e., a certain outcome or a distribution without losses), but individuals can reduce the probability of experiencing a loss by choosing distributions with a lower skewness coefficient (and lower variance). Thus, the decision framework is a choice among different risky distributions of outcomes differing in skewness. In most rounds, subjects move one slider to change the skewness of the displayed distribution, as shown in Fig. 1. Only one distribution is shown at a time, and the movement of the slider changes the displayed distribution.

Consistent with previous experimental findings (see Sect. 2.2), we found evidence of preferences for outcome distributions with a positive skewness coefficient. Furthermore, we identified two channels of skewness preferences: the first is related to speculative behavior, and the second is related to risk perception. On the contrary, preferences over the skewness of the distribution of returns do not seem to be correlated with traditional risk preferences elicited with a multiple price list (MPL) à la Holt and Laury (2002).

Unlike previous findings (Amaya et al. 2015), we found that a negatively skewed environment encourages more risk-taking than a positively skewed one: subjects forced (by treatment) to choose a negatively skewed distribution chose distributions with a higher standard deviation than those forced to choose a positively skewed one.

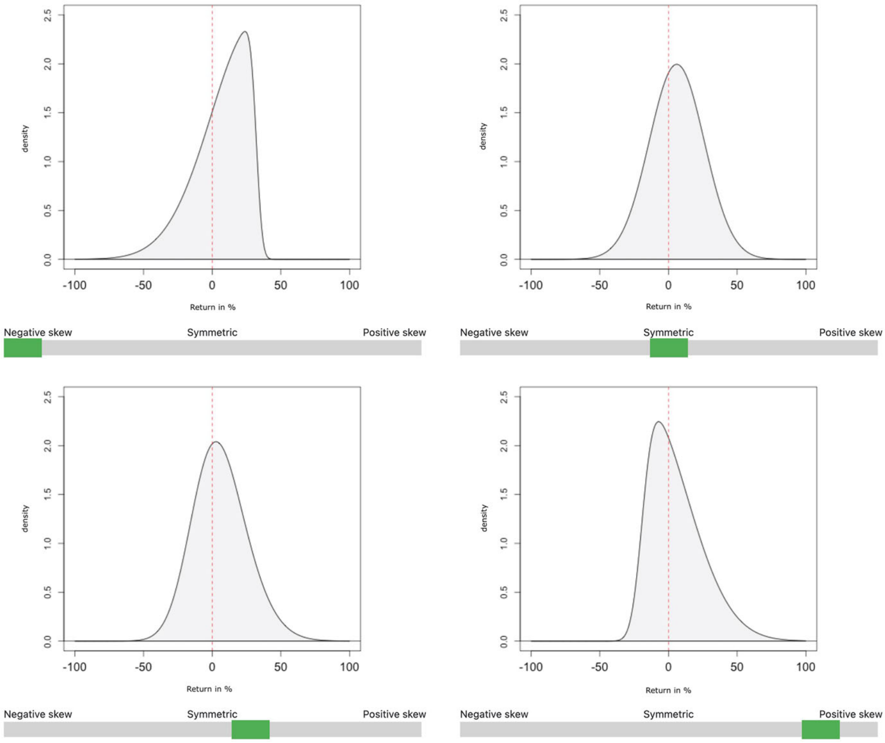

Fig. 1 Decision framework of the *Multiple-base* task. The green slider is moved to the left to reduce the skewness coefficient of the distribution or to the right to increase it. The range of the possible skewness coefficients is [− 0.95, + 0.95]. The four distributions displayed have skewness coefficients equal to − 0.95 (top-left), 0 (top-right), + 0.30 (bottom-left), and + 0.85 (bottom-right). The distributions all have the same mean and variance

A better understanding of the role of skewness preferences for investments is essential for advancing our understanding of decision-making under risk, and with our paper, we contribute to bridging the gap between real-world applications—whose underlying distribution of outcomes are continuous—and the current experimental literature, which is mostly focused on decisions on few-outcome lotteries. Considering the third distribution moment, in addition to the traditional first two, may open new opportunities to engineer financial products that better suit investors' needs and preferences. New products of this kind may represent an opportunity for subscribers of financial products and allow for a more efficient risk distribution in the financial system. Indeed, several empirical finance papers have highlighted the role of skewness in financial markets (An et al. 2020; Arditti 1967; Barberis et al. 2021; Boyer et al. 2010; Campbell et al. 2008; Conrad et al. 2014; Driessen et al. 2021; Harvey and Siddique 2000; Kraus and Litzenberger 1976; Schneider et al. 2020).

The remainder of the paper is organized as follows. In section two, we summarize some of the existing literature on the role of skewness in financial decisions, with a focus on the experimental literature; in section three, we describe the experimental design and the research questions; in section four, we report the main results; in section five, we discuss the main findings; finally, in section six we report our conclusions.

2 Literature

2.1 Attitudes towards skewness

Skewness is a measure of the asymmetry of a distribution, and it is usually captured by the skewness coefficient, which is equal to the third standardized moment: $\widetilde{\mu}_3 = E\left[\left(\frac{X-\mu}{\sigma}\right)^3\right]$. Preference for skewness is a concept used to refer to the preference for a positively skewed distribution over a negatively skewed one. Arditti (1967) first related skewness to expected utility theory. His approach relied on approximating expected utility with a truncated Taylor series after three terms. Under three reasonable assumptions, he "proved" that utility should be increasing in skewness.[1] However, this approach neglected all the other higher moments of the distribution of outcomes. For this reason, it was criticized by Brockett and Kahane (1992) and Brockett and Garven (1998), who proved that, under EUT, utility is not necessarily increasing in skewness.[2]

An individual with a positive third-order derivative of the utility function, $U'''(w) > 0$ is said to be prudent, a concept introduced by Kimball (1990). Prudence is prevalent in several experimental works (Deck and Schlesinger 2010; Ebert and Wiesen 2011; Fairley and Sanfey 2020; Heinrich and Shachat 2020; Noussair et al. 2014). Skewness-seeking behavior is defined as the preference for a distribution of outcomes with a higher skewness coefficient over another with the same expected value, variance, and kurtosis (Ebert and Wiesen 2011). From a theoretical perspective, a prudent individual should be a skewness-seeker, but the opposite may not necessarily be true. Ebert and Wiesen (2011) provided experimental evidence in support of this.

2.2 Experimental evidence

One of the first studies of skewness preferences was Mao's (1970): he asked managers to decide between two binary lotteries with the same mean and variance but differing skewness. Managers were almost equally split between the alternatives if the investment represented a small portion of the company resources. However, when the lotteries represented the whole outcome of the company, they all picked the positively skewed distribution because of its better downside (i.e., a better outcome in the negative state). Brünner et al. (2011) studied skewness-seeking behavior using pairs of binary prospects with the same mean and variance but differing skewness and once again found evidence of skewness-seeking behavior, with about 60% of the subjects

[1] The three assumptions are (i) positive marginal utility of wealth, (ii) risk aversion, (iii) decreasing local risk aversion (Pratt 1964).

[2] The reason is that when the skewness of a lottery changes, the other moments may also change. The truncation of the Taylor series at the third term neglects all these other moments, ignoring a portion of the true utility of the lottery. Therefore, Arditti's approach should be seen as a *moment preferences approach* rather than an *expected utility theory approach*.

choosing the prospect with larger skewness more than half the time. Ebert and Wiesen (2011) used Mao lottery pairs (i.e., sets of two binary lotteries with the same mean, variance, and kurtosis, but different skewness) and found skewness-seeking behavior for about 75% of the subjects. Åstebro et al. (2015) tested skewness preferences with a variation of Holt and Laury's (2002) multiple price list format and found that subjects made, on average, skewness-seeking choices. Similarly, Ebert (2015) found that 64% of subjects make skewness-seeking choices, and Dertwinkel-Kalt and Köster (2020) found a preference for positive skewness.

Grossman and Eckel (2015) used a variation of Eckel and Grossman lotteries (2002, 2008) and found that more than 80% of the subjects were skewness-seeker. Taylor (2020) used a slight modification of Grossman and Eckel's (2015) design aimed at reducing the impact that loss aversion may have had on skewness-seeking behavior and indeed found that while this behavior was still prevalent, it was less frequently observed compared to Grossman and Eckel's study. Unlike the previous studies, both Grossman and Eckel (2015) and Taylor (2020) did not use binary prospects but three outcome prospects. Bougherara et al. (2021) found mostly skewness-avoidance in an experiment where they elicited certain equivalents of three-outcome prospects.[3] In a subsequent study with similar experimental settings, Bougherara et al. (2022) found mostly skewness-seeking behavior.

While using binary prospects seems to lead to skewness-seeking behavior, introducing other outcomes makes the situation less clear-cut. The impact of a shift from finite outcome prospects to continuous distributions is even more dramatic. Vrecko et al. (2009) found that the form used to represent an investment affects the decision: subjects were found to be skewness-seeker when a cumulative distribution function was used to represent the alternatives, whereas they were skewness-avoider when a probability density function was utilized instead. Skewness-avoidance in the *density treatment* was rooted in anchoring (Tversky and Kahneman 1974): the peak of the distribution would serve as an anchor for the estimation of the unknown mean (Summers and Duxbury 2006). As a result, when the expected value of the distribution is unknown, it is overestimated for negatively skewed distributions and underestimated for positively skewed ones (Vrecko et al. 2009). Consider Fig. 1: as the skewness coefficient increases, the distribution's mode decreases (moving to the left and passing from positive to negative territory), even if the expected return is the same for all four distributions. Thus, using probability density functions may discourage skewness-seeking behavior due to biased risk perception and incorrect estimation of the expected return. Holzmeister et al. (2020) elicited risk perception and investment propensity of continuous distributions represented by histograms of samples of 200 draws from such distributions.[4] The distributions differed in variance, skewness, and kurtosis, and they found that positively skewed distributions are generally perceived as riskier than negatively skewed ones by both financial professionals and laypeople, with this

[3] They found that subjects prefer highly negative skewed prospects over low negative skewed ones, and low positively skewed prospects over highly positive skewed ones, both for high and low variance. However, they preferred low positively skewed prospects over low negatively skewed prospects. Prospects had the same mean, variance, and kurtosis but differed in skewness.

[4] Thus, the pictures shown to the subjects resembled the original probability density functions that originated the samples.

phenomenon being driven by the higher probability of a loss. Likewise, investment propensity was negatively associated with risk perception, and thus, positively skewed distributions of outcomes were less likely to be chosen.

3 Methods

While positive skewness offers some downside protection and, therefore, should, at least to some extent, be associated with a lower level of risk, continuous distributions seem to lead subjects to believe the opposite. Moreover, among the studies reported in the previous section, some focus on decisions in a gains-only framework (Åstebro et al. 2015; Bougherara et al. 2022; Brünner et al. 2011), and some consider only positively skewed and symmetric distributions of outcomes (Åstebro et al. 2015; Grossman and Eckel 2015; Taylor 2020). Finally, all studies are characterized by significant heterogeneity in skewness preferences. For these reasons, the topic deserves further attention in a comprehensive framework: our pre-registered experimental design[5] aims at studying the preferences over skewed continuous distributions of outcomes, considering both gains and losses, as well as positive, zero and negative levels of skewness.

3.1 Research questions

The experiment aims to study skewness preferences under several perspectives using continuous distributions of outcomes. What we mean by skewness preferences are the choices over the third moment of the distribution of returns, in isolation from mean and variance. When we study the interactions between skewness preferences and risk-taking, we consider the joint choice over the second and third moments of the distribution. In other words, we operationalize the concept of skewness preferences with the choice of the third standardized moment (skewness coefficient), and the concept of risk-taking with the choice of the second central moment (variance). In line with Ebert and Wiesen (2011), we consider an individual to be a skewness-seeker if, among the choices available, she selects a positively skewed distribution instead of a negatively skewed distribution with equal mean, variance, and kurtosis.

Within our experimental setting, we address four main research questions about skewness preferences.

The first research question concerns the relationship between skewness and risk-taking: *"How do skewness and risk-taking interact?"*. We address this question with the *Skew-risk* and *Skew-risk-reference* tasks (see Sect. 4.1).

The second research question concerns skewness preferences: *"Do subjects exhibit skewness-seeking behavior when opportunities are shown using continuous distributions of outcomes?"*. We address this question with the *Binary-base*, *Multiple-base*, *Multiple-partial*, *Multiple-full* tasks (see Sects. 4.2 and 4.3).

[5] Link: https://osf.io/9q72b/?view_only=9b5327eedc4b46d187e34568d52d9f48.

The third research question regards the trade-off between skewness and expected return: *"Do subjects trade off skewness with expected returns, or do they exhibit mean—variance preferences?"*. We address this question with the two *Binary-adjustment* tasks (see Sect. 4.4).

The fourth research question is about the drivers of skewness preferences: *"What are the characteristics driving skewness preferences?"*. We address this question by combining the choices of the *Binary* and *Multiple* tasks with measures collected outside part one of the experiments, which concern speculative behavior, risk, and loss preferences (see Sect. 4.5).

3.2 Experimental design

The online experiment was programmed and executed with oTree (Chen et al. 2016). We present here the different parts of the experiment (see "Appendix A" for a detailed description). After an introductory non-incentivized part, participants were given a tutorial on the experimental framework. The tutorial reviewed the concepts of probability density function, variance, and skewness, and it offered the chance to see how changes in these moments would affect the distribution of outcomes. The tutorial was followed by a mandatory comprehension check, and then subjects were asked about their general aspirations about investments. Then, the first part of the experiment began: subjects played eight rounds, making incentivized decisions over distributions differing in skewness. In the second part of the experiment, subjects' risk preferences were elicited using a scaled version of Holt and Laury (2002) multiple price list, with one of the ten choices randomly selected for payment. Finally, a demographic and a financial-behavior questionnaire were administered.

Like Ebert (2015), we framed our alternative distributions in terms of returns rather than outcomes: the final payment from part one of the experiment was computed, compounding the returns obtained in two of the eight rounds. The distributions were skew-normal with parameters (ξ, ω, α) appropriately chosen so that the expected value would be equal to 6%, the standard deviation would be equal to 20%, and the skewness coefficient equal to some target level in the [1, 1] interval. The skew-normal distribution has been widely used in financial applications involving risk management, capital allocation in financial markets, and insurance (Adcock et al. 2015; Adcock and Azzalini 2020; Bernardi 2013; Bodnar and Gupta 2015; Vernic 2006) because it handles the asymmetry in a simple and flexible way.

We chose a graphical representation of outcomes, with the possibility to initially sample from the displayed distributions,[6] to make information provision easier to process for participants relative to a static numerical representation (on this see Kaufmann et al. (2013) and Bradbury et al. (2015)). Furthermore, we decided to present the probability density functions instead of histograms (like Holzmeister et al. (2020)) because their smoothness improves the comparability between different distributions.

In the *Binary-base* and *Binary-adjustment* tasks, subjects faced a binary decision between two distributions differing in skewness: they visualized both distributions (like those in Fig. 1) and clicked on a button to choose the distribution they preferred. In

6 Sampling was possible only in the first round.

the *Multiple-base*, *Multiple-partial*, and *Multiple-full* tasks, subjects made a decision among eleven distributions differing in skewness: they could visualize one distribution at a time and change the displayed distribution by horizontally dragging the slider placed below the distribution (see Fig. 1).

In the *Skew-risk* and *Skew-risk-reference* tasks, subjects could move two sliders to change the skewness and standard deviation levels. The skewness slider worked like in the previous tasks, while the standard deviation slider was vertical. The interface also provided some information about the probability of experiencing some outcomes (see Fig. 2).

Table 1 briefly summarizes the rounds and the associated tasks. For a full description of the tasks, please refer to "Appendix A".

3.3 Description of the sample

We collected 180 valid observations in the month of February 2022 on the platform Prolific.[7] Due to the complex nature of our tasks, we set some restrictions on the Prolific subject pool. Eligible subjects needed to be at least 21 years old, be fluent in English, have completed high school, and specialized in either a STEM subject or economics/finance. Moreover, the sample was gender-balanced. On average, subjects took 22 min (with a SD of 10 min) to complete the experiment and earned about £4.6. The final payment was composed of a fixed participation fee, a variable fee for part one (mean £1.1 and SD £0.31), and a variable fee for part two (mean £0.78 and SD £0.38).

4 Results

The experiment is designed so that the complexity of the decision framework increases throughout the rounds. Since these final rounds offer the most insightful results of this research, we will start commenting on them from the last rounds and move backward.

4.1 Skewness and risk-taking

In the *Skew-risk* (SR) and *Skew-risk-reference* (SRR) tasks, subjects could manipulate both skewness and standard deviation. In one round, they were assigned to the positive skewness treatment, meaning they could choose only a positively skewed distribution. In the other round, they were assigned to the negative skewness treatment, meaning they could choose only a negatively skewed distribution. The order was randomized at the subject level. For both treatments, the subjects could choose three levels of standard deviation: 0.16, 0.20, or 0.24, and five levels of skewness,[8] for a total of fifteen

[7] An observation is considered valid if the subject completed the study. This required passing the comprehension check. Forty-nine subjects did not pass the comprehension check or abandoned the study before starting it.

[8] The skewness coefficients of the distributions were 0.3, 0.5, 0.75, 0.85, and 0.95 for the positive treatment and -0.3, -0.5, -0.75, -0.85, and -0.95 for the negative treatment.

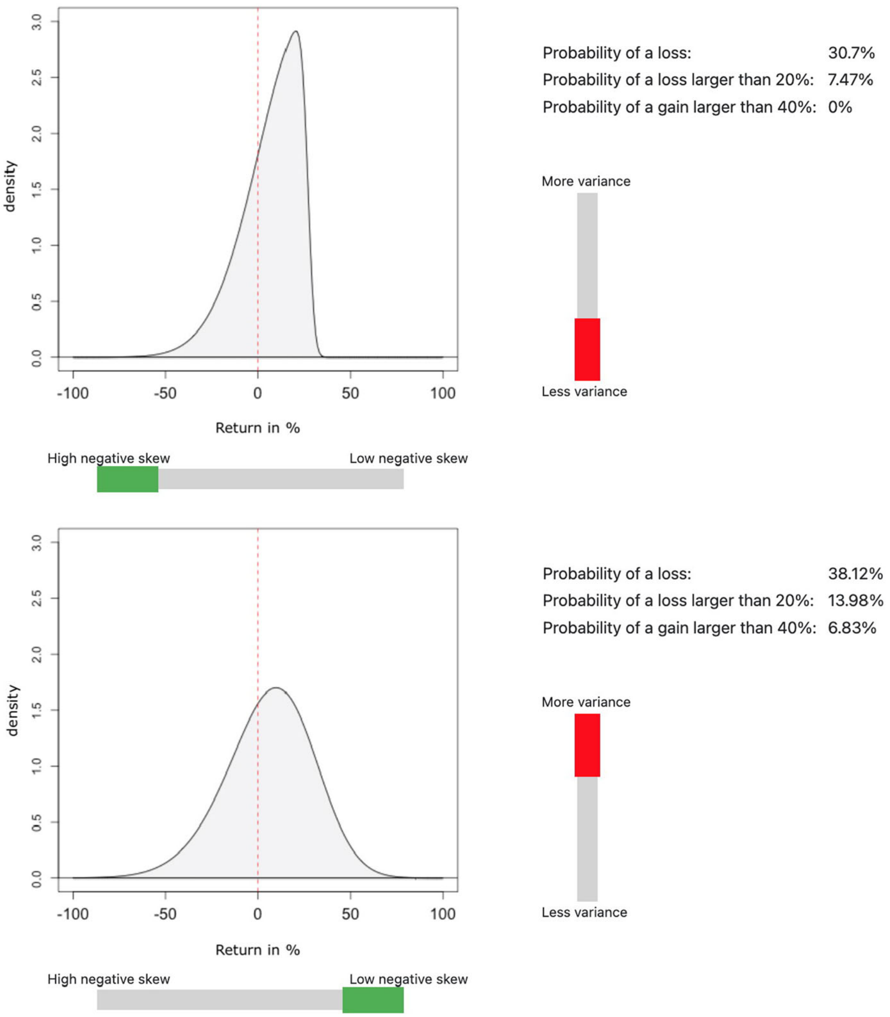

Fig. 2 Decision framework of the *Skew-risk* (SR) and *Skew-risk-reference* (SRR) tasks. The horizontal slider is used to change the skewness coefficient, and the vertical slider is used to change the standard deviation. The probability of experiencing a loss, a loss larger than 20%, and a gain larger than 40% update accordingly. The pictures show two of the available distributions in the negative treatment. The upper distribution is such that both skewness and variance are minimized, whereas they are both maximized in the lower distribution

possible distributions. Moreover, in the *Skew-risk-reference* (SRR) task, subjects were also provided with a reference point: their current return.[9]

We found that—as shown in Fig. 3—in both rounds, risk-taking (i.e., the level of chosen standard deviation) was significantly higher for the subjects assigned to

[9] The current return was a random draw from a distribution they had selected in one of the previous seven rounds. They were told their payoff of part one of the experiment would have been equal to the current return plus the realized return of the *Skew-risk-reference* task.

Table 1 Description of the tasks

Round	Task	Description
1	*Binary-base*	Binary decision between 2 distributions differing in skewness
2/3	*Binary-adjustment*	Binary decision between 2 distributions differing in skewness and expected return
4	*Multiple-base*	Decision among 11 distributions differing in skewness
5	*Multiple-partial*	Decision among 11 distributions differing in skewness with one piece of information
6	*Multiple-full*	Decision among 11 distributions differing in skewness with three pieces of information
7	*Skew-risk*	Decision among 15 distributions differing in skewness and standard deviation
8	*Skew-risk-reference*	Decision among 15 distributions differing in skewness and standard deviation, with the provision of a reference point

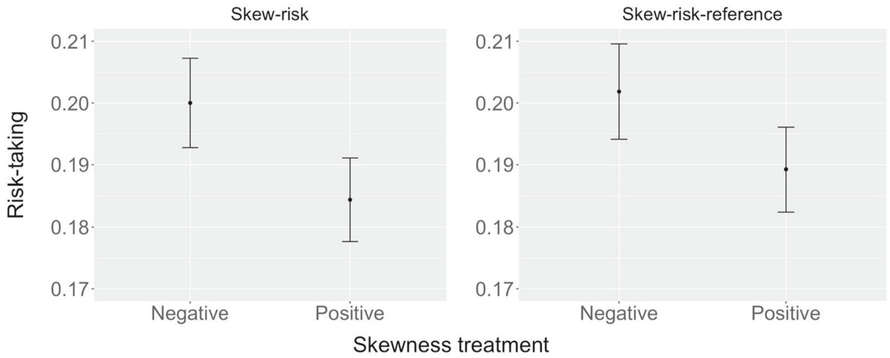

Fig. 3 Average standard deviation, distinguishing by task and skewness treatment. Subjects assigned to the negative treatment took more risk

the negative treatment than for those assigned to the positive treatment (p-value of Wilcoxon rank sum test is 0.002 in the SR task, and 0.018 in the SRR task).

Furthermore, we analyzed the level of skewness and standard deviation within treatment. Although the level of these two variables was positively correlated in both tasks (controlling for treatment), Kendall's Tau correlation coefficient was significantly different from zero only in the two treatments of the *Skew-risk-reference* task.[10]

[10] $\tau = 0.13$ in the SR-positive task, $\tau = 0.11$ in the round SR-negative task, $\tau = 0.30$ in the SRR-positive task, $\tau = 0.34$ in the SRR-negative task. The correlation test with the null hypothesis that the correlation coefficient is equal to zero is rejected only for the two treatments of the SRR task. In "Appendix C" we argue that there is actually stronger evidence of a positive correlation between skewness and risk-taking than Kendall's τ suggests, even in the SR task.

4.2 Analysis of skewness preferences

In the *Binary-base* task, the choice was between two alternatives. Depending on the randomly assigned treatment, the choice could be between (1) a positively skewed and a symmetric distribution, (2) a negatively skewed and a symmetric distribution, or (3) a positively and a negatively skewed distribution. All investments had the same expected return and volatility but differed in skewness (equal to − 0.75, 0, and 0.75, depending on the distribution). Subjects could generate random samples from the displayed distributions to enhance familiarity with probability density functions.[11] In the *Multiple-base* task, the choice was between eleven alternatives differing in skewness—five positively skewed, one symmetric, and five negatively skewed—and the choice was made dragging a slider.[12]

Like in Brünner et al. (2011), higher skewness implies third-degree stochastic dominance. Thus, in an EUT framework, for any decision maker with utility function $U(w)$ such that $U\prime(w) > 0$, $U''(w) < 0$, and $U'''(w) > 0$, the distribution with higher skewness coefficient should be preferred (Levy 1992). Menezes et al. (1980) define downside risk as *"a leftward transfer of risk, keeping mean and variance the same"*. Given two distributions with densities f(x) and g(x), if f dominates g by third-degree stochastic dominance (TSD), and they have the same mean and variance, then f has less downside risk than g, and it is more right-skewed than g (Menezes et al. 1980). Thus, the downside risk is decreasing in skewness in our framework, and a sufficient condition to prefer the distribution with a higher skewness coefficient is $U'''(w) > 0$, or downside risk aversion (Menezes et al. 1980, theorem 2). Finally, our distributions satisfied the skewness comparability criteria (Chiu 2010). "Appendix B" expands on skewness comparability, third-degree stochastic dominance, and downside risk increase.

In our settings, an individual is considered a skewness-seeker if she selects a positively skewed distribution over a negatively skewed one. Our definition is consistent with Ebert and Wiesen's concept of skewness-seeking behavior: indeed, in the *Multiple* tasks and in the *positive–negative* treatment of the *Binary-base* task, every time an individual selects a positively skewed distribution, she is revealing she prefers it over another distribution with the same mean, variance, and kurtosis, but opposite skewness coefficient.

In the *Binary-base* task, the proportion of subjects who did select the distribution with the larger skewness coefficient was not significantly different from 50%, neither at the aggregate level nor dividing by the three treatments. Therefore, we did not find

[11] The possibility to sample had the purpose of enhancing subjects' understanding of the potential outcomes distributions and their differences. We acknowledge that our experiment focuses on continuous distributions, but the samples are discrete. However, we do not believe that the possibility to sample undermines our results because (i) it is limited to one round, (ii) each sample included 10 outcomes per distribution and could be repeated several times, (iii) the continuous distributions still represent the core of the visual cues provided during the round.

[12] Expected return and variance were constant across alternatives, while skewness differed. Skewness coefficients were -0.95, -0.85, -0.75, -0.50, -0.30, 0, 0.3, 0.5, 0.75, 0.85, 0.95. Kurtosis was the same for each couple of distributions with the same absolute level of skewness.

evidence of the prevalence of prudence or skewness-seeking behavior.[13] Moreover, we cannot reject the hypothesis that choices were made randomly in this task.

In the *Multiple-base* task, we found evidence of skewness-seeking behavior: the proportion of subjects investing in a positively skewed alternative was significantly different from 50% and equal to about 68%.[14] Moreover, we can reject the hypothesis that choices were made randomly (p-value of Chi-squared test < 0.001).

4.3 Skewness preferences and information set manipulations

In the *Multiple-base* task, subjects could decide among eleven investment opportunities differing in skewness. Still, they had no numerical information about them, except that they all had the same expected return and volatility. All they could do was infer some information from the probability density functions. In the *Multiple-partial* task, subjects faced the same decision environment but received one piece of information regarding the displayed distributions. Depending on the treatment, they may visualize (1) the probability of a loss, (2) the probability of a loss larger than 20% ("large loss"), or (3) the probability of a gain larger than 40% ("large gain"). As they moved the slider, the distribution displayed changed, as well as the displayed probability and the area associated with the displayed probability, as shown in Fig. 4.

First, we reject the hypothesis that choices were random (Chi-squared test, p-value < 0.001). If subjects could perfectly (and somewhat unrealistically) infer probabilities from the pictures of the distributions, then none of the treatments should impact their decisions, which should be equal to the decision of the *Multiple-base*. On the contrary, if subjects had no understanding of the distributions, they would rely just on the probabilities shown and pick an edge choice—either the most positively or the most negatively skewed alternative—optimizing for the probabilities displayed. Assuming subjects fall somewhere in between, that is, they have some understanding of the probability density functions, and they incorporate the new piece of information, we should expect the "probability of a loss" treatment to reduce skewness-seeking. In contrast, the other two treatments should increase it. Statistical tests do indeed indicate that treatments were effective in orienting decisions. Since the median skewness level across treatments is statistically different (Kruskal–Wallis test, p-value < 0.001), we perform a pairwise comparison of the three treatments using a Wilcoxon rank sum test and find that the difference in median skewness is not statistically significant only between the "probability of a large gain" and "probability of a large loss" (p-value $= 0.23$; all other p-values < 0.001). Two-sample Kolmogorov–Smirnov tests

[13] We can test for skewness-seeking behavior only in the *positive–negative* treatment because, in the other two treatments, the two distributions did not have the same kurtosis.

[14] An individual is considered a skewness-seeker if she selects a positively skewed distribution over a negatively skewed distribution with the same mean, variance, and kurtosis. We can classify an individual as a skewness-seeker or skewness-avoider only if she selected one of the ten non-symmetric distributions. We cannot classify subjects who selected the symmetric distribution; therefore, we call them *skewness-neutral. In the* Multiple-base *task, 66% of the subjects selected a positively skewed alternative, 31% selected a negatively skewed alternative, and 3% chose the symmetric distribution. The 68% of skewness-seeker subjects refers to the proportion of subjects for whom we can make a classification, i.e., those who selected a distribution with a non-zero skewness coefficient.*

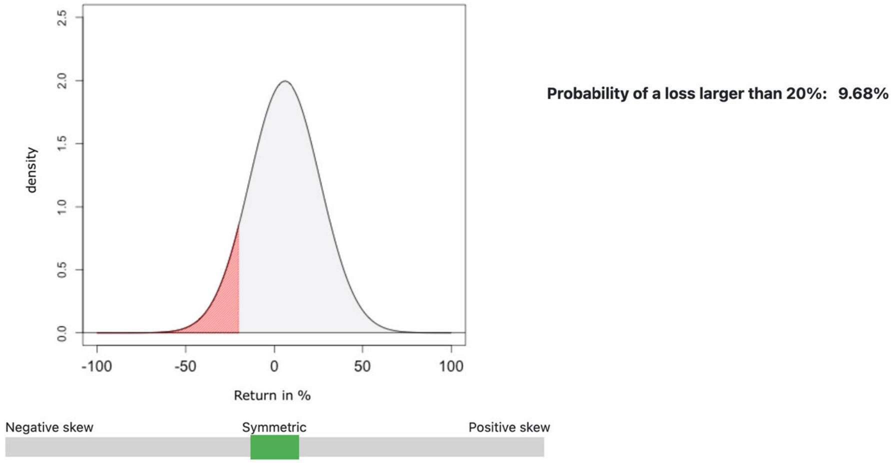

Fig. 4 Decision framework of the *Multiple-partial* task. In this treatment, the probability of experiencing a loss larger than 20% is shown

on the distribution of skewness choices across the treatments confirm the previous results (p-value $= 0.42$ for the "probability of a large gain" and "probability of a large loss" comparison; all other p-values < 0.001). Despite the effectiveness of the treatments in orienting decisions, the choices in the *Multiple-partial* task were still consistent with those made in the *Multiple-base* task: for all three treatments, subjects previously classified as skewness-seeker were still more skewness-seeking than the others (Wilcoxon rank sum test, p-value < 0.01 for all three treatments).

In the *Multiple-full* task, subjects were again asked to choose one of the eleven distributions, but they were provided with all three pieces of information of the *Multiple-partial* task. This task was more complex than the previous because the three probabilities displayed provided contrasting cues: the probability of a large gain and the probability of a loss increased in skewness, while the probability of a large loss decreased in skewness. The increase in the complexity was indeed perceived by the subjects, who moved the slider (i.e., explored the environment) significantly more times. We can reject the hypothesis that decisions were affected by the treatment assigned in the *Multiple-partial* task (Kruskal–Wallis test, p-value $= 0.63$) and that the choices were random (Chi-squared test, p-value < 0.014). This suggests that subjects incorporated new information when making their decision. We found that even if the skewness-seeker group was still the largest, the proportion of skewness-seeker reduced significantly from the *Multiple-base* to the *Multiple-full* task. The prevalence of skewness-seeking behavior largely disappeared: skewness-seeker were not significantly more than 50% of the sample anymore (Proportion test, p-value $= 0.69$); they were about 52% versus 48% skewness-avoider.[15] Subjects classified as skewness-seeker and skewness-avoider based on the *Multiple-base* task were still, on average,

[15] The proportion of subjects that we cannot classify, i.e., those who selected the symmetric distribution, rose from 3% in the *Multiple-base* to 11% in the *Multiple-full* task. Thus, the 52%-48% division reported above refers to the remaining 89% of the subjects.

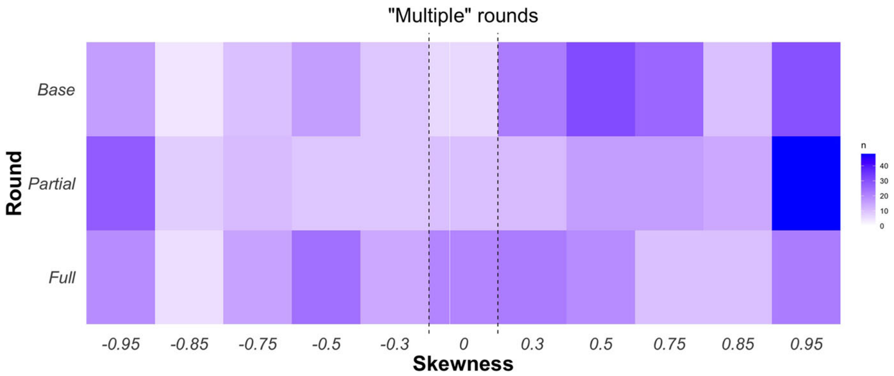

Fig. 5 Heatmap of the choices in the *Multiple-base*, *Multiple-partial* and *Multiple-full* tasks. The intensity of the color of each cell represents the number of subjects who selected the distribution with the skewness coefficient indicated on the x-axis in the task indicated on the y-axis. A darker color indicates more subjects selected that distribution

skewness-seeker and skewness-avoider, respectively. Still, the median skewness chosen for both groups was closer to zero. This process resulted in a more uniform (but not random) distribution of choices (see the bottom row of Fig. 5).

4.4 Trade-off between skewness and expected return

In the two *Binary-adjustment* tasks, subjects faced the same decision environment of the *Binary-base* task. In one round, they could receive a bonus if they decided to invest in the opportunity they had not selected in the *Binary-base* task ("bonus treatment"). In contrast, in the other, they would pay a penalty if they decided to invest in the opportunity they had selected in the *Binary-base* task ("penalty treatment"). Both treatments were played during the two consecutive rounds, with the order of treatments being randomly assigned at the subject level. The value of the adjustment (bonus/penalty) ranged between 0 and 1%, extremes included, with 0.10% increments. In the first three columns of Table 2, we report the generalized linear mixed-effect models analyzing the probability of changing distribution with respect to the *Binary-base* task. The results show that subjects traded off skewness with expected returns: the probability of changing increases in the magnitude of the adjustment. Moreover, subjects were less likely to change when the shift would have been from a positively to a negatively skewed distribution (or vice versa) than when the change involved a symmetric distribution: the further away the new level of skewness from the initial favorite level, the less likely the subjects to change, given the adjustment.

4.5 Determinants of skewness preferences

We now combine the decisions taken in several tasks to study the determinants of skewness preferences. Considering the decisions in the three *Binary* tasks (see Table 2, Models 4 and 5), we find that, in general, the higher the upside score, the more likely

Table 2 Models of skewness choices in the *Binary* tasks

	Model 1	Model 2	Model 3	Model 4	Model 5
Intercept	− 1.64*	0.13	− 2.61***	− 1.24	− 0.27
	(0.79)	(1.42)	(0.78)	(1.25)	(0.55)
Adjustment	2.41***	2.38***	2.44***		
	(0.64)	(0.64)	(0.64)		
Upside	0.49*	0.49*	0.55*	0.44*	0.08*
	(0.23)	(0.23)	(0.24)	(0.20)	(0.04)
Round 3	1.02***	1.02***	1.01***		
	(0.30)	(0.30)	(0.30)		
Treatment penalty	0.67*	0.67*	0.68*		
	(0.29)	(0.29)	(0.29)		
Treat Pos and Neg	− 0.98*	− 0.97*		− 0.21	0.41***
	(0.45)	(0.44)		(0.40)	(0.07)
Treat Pos and Symm	− 0.40	− 0.38		− 0.49	0.67***
	(0.43)	(0.43)		(0.38)	(0.07)
Skewness-seeker			− 0.40		
			(0.37)		
Return most skewed					0.42***
					(0.07)
Return least skewed					− 0.47***
					(0.07)
Perceived gap				0.05*	
				(0.02)	
Controls	Yes	Yes	Yes	Yes	Yes
AIC	442.26	440.21	449.56	251.22	836.30
BIC	485.00	482.96	476.76	279.95	887.80
Log Likelihood	− 210.13	− 209.11	− 217.78	− 116.61	− 406.15
Num. obs	360	360	360	180	540
Num. groups: participant	180	180	180		180
Var: participant (Int)	2.02	1.98	2.34		0.08
Deviance				233.22	
Var: Residual					0.19

In Models 1–3 (GLMM), we study the probability of changing distribution in the *Binary-adjustment* tasks with respect to the *Binary-base* task. In Model 4 (GLM), we model the probability of choosing the distribution with the largest skewness coefficient in the *Binary-base*, and in Model 5 (LMM) we model the skewness coefficient of the chosen distribution in the *Binary-base* and *Binary-adjustment* tasks. Significance levels are 5% (*), 1% (**) and 0.10% (***)

a subject to pick the distribution with the higher skewness coefficient in a binary choice. The upside score is an indicator of the willingness to achieve better upside opportunities or speculative gains, which is computed based on the answers given in the final questionnaire.

Furthermore, we pool together the decisions made in the three *Multiple* tasks (Table 3). The upside score was a driver of skewness preferences also in these tasks.

Table 3 Models of the level of skewness chosen in the *Multiple-base*, *Multiple-partial*, and *Multiple-full* rounds

	Model 1	Model 2	Model 3	Model 4
Intercept	0.33	0.60*	0.27	0.53*
	(0.28)	(0.26)	(0.28)	(0.27)
Risk perception	− 0.15***	− 0.15***	− 0.13***	− 0.15***
	(0.03)	(0.03)	(0.03)	(0.03)
Upside	0.11**			
	(0.04)			
Call pref		0.15*	0.41***	0.20*
		(0.07)	(0.12)	(0.09)
Put pref and high loss (5%)			0.32**	
			(0.12)	
Put pref and high loss (10%)				0.09
				(0.10)
No information shown	0.21***	0.21***	0.21***	0.21***
	(0.05)	(0.05)	(0.05)	(0.05)
P large gain shown	0.48***	0.48***	0.49***	0.48***
	(0.08)	(0.08)	(0.08)	(0.08)
P large loss shown	0.57***	0.56***	0.56***	0.56***
	(0.08)	(0.08)	(0.08)	(0.08)
P loss shown	− 0.52***	− 0.52***	− 0.52***	− 0.52***
	(0.08)	(0.08)	(0.08)	(0.08)
Controls	Yes	Yes	Yes	Yes
AIC	1000.61	1002.31	999.81	1006.23
BIC	1056.40	1058.10	1059.89	1066.31
Log Likelihood	− 487.30	− 488.15	− 485.90	− 489.12
Num. Obs	540	540	540	540
Num groups: participant	180	180	180	180
Var: participant (Int)	0.11	0.11	0.11	0.11
Var: Residual	0.25	0.25	0.25	0.25

The four specifications test the speculative channel in different ways. Significance levels are 5% (*), 1% (**) and 0.10% (***)

Moreover, risk perception of positive skewness was a driver of decisions: the higher the risk perception (of positively skewed distributions vis-a-vis negatively skewed distributions), the lower the skewness level and the lower the likelihood of choosing a positively skewed distribution. In the *Multiple-partial* and *Multiple-full* tasks, subjects were given different pieces of information about the distributions. We conjecture that subjects gave different weights to the three probabilities and, depending on these weightings, made a decision in the *Multiple-full* task. We use information collected in the aspirations phase to classify subjects into three groups, with each group expected to give more weight to one of the three probabilities. On the aspirations page, we asked subjects whether they would rather combine ownership of a stock with a financial instrument that enhances returns in case the stock performs well (i.e., a call option) or with a financial instrument that reduces losses in case the stock performs badly (i.e., a put option). We assume that those who chose the call option are relatively more focused on the upside, while those who chose the put option are relatively more focused on the downside. Therefore, more upside-focused subjects are expected to give more weight to the probability of a large gain, so they are expected to be relatively more skewness-seeker. As for the downside-focused subject, we distinguish between subjects concerned about avoiding losses and subjects concerned about avoiding large losses. Hence, we consider the maximum self-reported threshold for losses in an investment: those who are willing to bear a loss up to a given low threshold τ are expected to give more weight to the probability of a loss, so they are expected to be relatively less skewness-seeker.

The others, who can tolerate losses larger than τ, are expected to attribute more weight to the probability of a large loss, so they are expected to be relatively more skewness-seeker. A natural threshold could be 10%, that is the mid-point between the two loss levels provided, 0% and 20%. Since the probability of a loss has been found to be salient in risky decisions (Holzmeister et al. 2020; Zeisberger 2022), we also used a 5% threshold, which is closer to the salient value of 0%.

The regressions in Table 3 are consistent with our conjectures. Skewness preferences seem to be ultimately driven by two channels: first, the speculative channel (operationalized through the "Upside score" and the "Call preference" dummy) indicates that speculators tend to choose more positively skewed distributions than non-speculators. The second channel is the risk perception of positively skewed distributions versus negatively skewed distributions, a variable that we label "Risk perception".

While risk perception plays an important role in skewness preferences, traditional risk preferences do not seem to play a role within our framework. In part two of the experiment, we elicited risk preferences using a modified version of the multiple price list[16] (Holt and Laury 2002), and classified subjects as risk-averter, risk-neutral, and risk-seeker. We found no systematic difference in skewness preferences across the tasks among the three groups. This result is not surprising since skewness concerns downside risk preferences, and both risk lovers and risk averters can be downside risk averse (Menezes et al. 1980). Indeed Haering et al. (2020) did not find differences across these two groups in their preferences for higher-order odd moments, including skewness.

5 Discussion

5.1 Risk perception

Risk perception plays a relevant role in explaining skewness preferences. Within our framework, the relationship between skewness and risk would depend on the operationalization of the latter. Volatility σ was constant across the distributions, and the

[16] The payoffs of the low-risk lottery were £0.6 and £0.8, while the payoffs of the high-risk Lottery were £0.1 and £1.2.

behavioral risk measure $\sigma_B{}^2$ (Davies and De Servigny 2012)[17] was decreasing in skewness, as well as semi-variance. The probability of experiencing a loss—which, according to Holzmeister et al. (2020), is the main channel through which skewness translates into risk perception—was increasing in skewness. Finally, since the skewness comparability criteria (Chiu 2010; Oja 1981; Van Zwet 1964) were satisfied, a distribution with a higher skewness coefficient could be considered a downside risk decrease with respect to any other distribution with a lower skewness coefficient (see "Appendix B" for more details).

In the *Multiple* tasks, risk perception was correlated with actual choices. In particular, in the *Multiple-full*, i.e., when information became "fully available", the median skewness level for subjects who perceived positive skewness as less risky was significantly higher than zero ($p < 0.003$), while it was significantly lower than zero for subjects who perceived positive skewness riskier ($p < 0.032$). Only about 35% of our subjects perceived positively skewed distributions as riskier than negatively skewed distributions, while 26% perceived them as safer, and the remaining 39% of the subjects believed they bear about the same risk. This result aligns with the idea that risk can be measured in different ways, but it contrasts with previous literature specifically focused on risk perception and skewness of continuous distributions (Holzmeister et al. 2020). This difference could stem from the elicitation procedure: while the measurement of risk perception was a key element of Holzmeister et al.'s study—elicited for every distribution—we only asked our subjects at the end of the study to indicate their level of agreement with the statement that positively skewed distributions are riskier than negatively skewed ones. Our subjects had thus already experienced the treatments and were aware of the relationship between skewness and the probability of losses, large losses, and large gains. However, at least part of the risk perception was already formed before the visualization of pieces of information about probabilities, as risk perception was significantly correlated with choices made before probabilities were provided (*Multiple-base* task). Like Holzmeister et al. (2020), we found that investment propensity and risk perception are inversely related.

5.2 Skewness and risk-taking: substitutes or complements

Most experimental evidence indicates a positive relationship between skewness and risk-taking (Åstebro et al. 2015; Brünner et al. 2011; Dertwinkel-Kalt and Köster 2020; Ebert and Wiesen 2011; Ebert 2015). Grossman and Eckel (2015) also found that risk-taking increases as skewness available increases, but Taylor (2020) while confirming this result, attributed part of this effect to loss aversion.

The justification of the positive relationship between skewness and risk-taking can be found in Amaya et al. (2015): *"As positive asymmetry increases, volatility is welfare increasing as it implies a larger probability of an extremely good state of the economy. The opposite is true for the case of negative skewness since higher volatility increases the likelihood of a left tail event"*. Behavioral components may enhance this mechanism: according to Åstebro et al. (2015), skewness-seeking behavior is driven by

[17] A risk measure directly incorporating higher order moments — like skewness and kurtosis — which interact with traditional risk preferences.

optimism and likelihood insensitivity. Similarly, Dertwinkel-Kalt et al. (2020) relate skewness-seeking behavior to salience theory (Bordalo et al. 2012). On the contrary, Bougherara et al. (2021) found that variance and skewness do not interact in a positively skewed environment, while the difference between the certain equivalent of a highly negatively skewed prospect and a low negatively skewed prospect is higher when variance is higher. Differently, Bougherara et al. (2022) did not find a significant interaction between skewness and risk-taking.

We contribute to this literature with two findings. First, we show that subjects took more risk when forced (by the treatment) to choose negatively skewed distributions. Such distributions have a longer left tail and a shorter right tail, so the probability of obtaining large positive outcomes is relatively lower. A subject interested in improving her upside may be forced to increase risk-taking because changing only skewness may not be satisfactory enough. This is unnecessary in a positively skewed environment, where increasing skewness may be sufficient. Since a satisfactory upside may be achieved either by increasing the skewness coefficient in a positively skewed environment or increasing variance in a negatively skewed environment, we claim that the direction of skewness—positive or negative—and risk-taking can be seen as substitutes.

Secondly, we find that—especially when a reference point is provided—skewness and risk-taking are positively correlated: individuals react to the reference point by selecting a corner distribution more often. We define a corner distribution as a distribution where skewness and standard deviation are either maximized or minimized within the available set of distributions, like those shown in Fig. 2. In this sense, skewness and risk-taking acted synergically as complements to achieve a goal: in the maximization case, subjects maximized the probability of a large gain, whereas in the minimization case, they minimized the probability of a loss.[18] For each heatmap in Fig. 6, the top-right and bottom-left squares represent the corner distributions: for both treatments, they were more frequent in the *Skew-risk-reference* tasks (heatmaps on the right) than in the *Skew-risk* tasks (heatmaps on the left).

5.3 Skewness preferences

We defined skewness-seeking behavior as the preference for a positively skewed distribution over a symmetric and a negative one when multiple alternatives with the same mean, variance, and kurtosis were available. Our definition is consistent with Ebert and Wiesen (2011): when a subject picked a positively skewed distribution in the *Multiple* tasks, she was not indeed picking another distribution with the same mean, variance, and kurtosis, but negative skewness coefficient. In the *Binary-base* task, subjects faced a binary decision, and skewness-seeking could only be tested for the treatment where

[18] We did not find a specific relationship between the level of the reference point and the choices of skewness and standard deviation. Indeed, several subjects would have maximized/minimized both anyway (like they did in the *Skew-risk* task when there was no feedback). There is not a unanimous theoretical relationship between the level of the reference point and the reaction: for instance, a large current return may be consistent with both the house money effect (Thaler and Johnson 1990), which would suggest an increase in risk-taking, and with prospect-theory-like preferences (Tversky and Kahneman 1992), which would suggest a decrease in risk-taking.

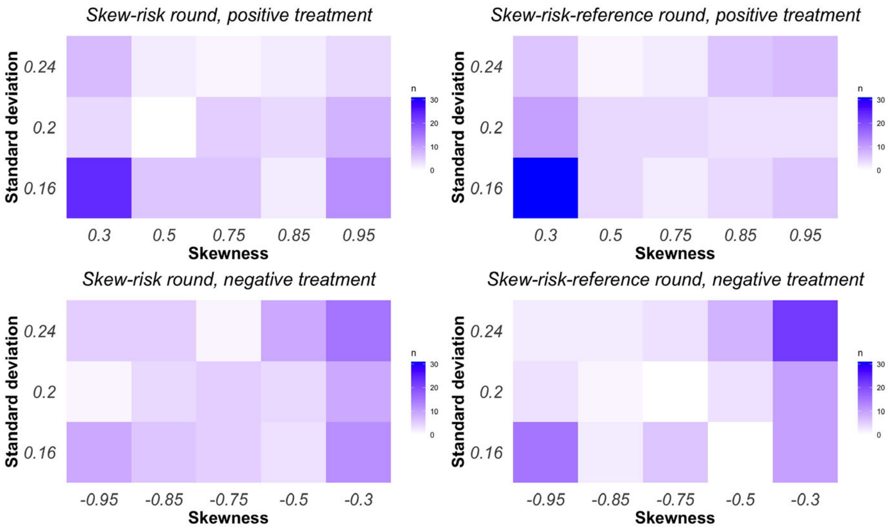

Fig. 6 The four heatmaps show the distribution of the skewness and standard deviation levels chosen in the *Skew-risk* and *Skew-risk-reference* rounds, distinguishing for assigned skewness treatment. The title of each heatmap indicates the task and the treatment. The possible levels of skewness are represented on the x-axis, and the possible levels of standard deviation on the y-axis. The intensity of the color of a square is related to the number of subjects who selected that combination of skewness and standard deviation. A Darker square indicates that more individuals chose that combination

a positively and a negatively skewed distribution were available. In the other two treatments, only prudence could be tested. In the *Binary-base* task, in none of the three treatments, we found evidence of subjects choosing the distribution with the largest skewness coefficient with a probability significantly larger than 50%. Therefore, we rejected the prevalence of both prudence and skewness-seeking behavior. However, a few considerations are worth mentioning. Firstly, our results already contrast Vrecko et al. (2009) and Holzmeister et al. (2020), who found evidence of skewness-avoidance when probability density functions are used. Secondly, the preference for skewness may not arise immediately: in Brünner et al. (2011), the proportion of skewness-seeker in the first two rounds was about 40%, while in the last rounds, it was around 67%, and since the order of the rounds was randomized, they attributed this phenomenon to some form of learning. Finally, since Ebert and Wiesen (2011) suggest that prudent individuals are mostly skewness-seeker, but the opposite is not necessarily true, we could see the proportion of prudent individuals in the *Binary-base* task as a lower bound for skewness-seeker since the imprudent skewness-seeker should be more than the prudent skewness-avoider. Indeed, when we tested for skewness-seeking behavior in the *Multiple-base*, 80% of prudent decision-makers (i.e., those who made a prudent choice in the *Binary-base* task) were skewness-seeker. At the same time, only 55% of imprudents were skewness-seekers.[19] Overall, in the *Multiple-base* task, about

[19] If we exclude from our sample the subjects for whom we cannot make a classification, the proportions rise to 84% of prudent skewness-seeker and 56% of imprudent skewness-seeker.

two-thirds of the subjects were skewness-seekers, a proportion in line with the existing experimental literature. Considering the five pairs of distributions with the same mean, variance, and kurtosis, the proportion of skewness-seeker in each pair ranged between 65 and 72%. The prevalence of skewness-seeking behavior can be attributed to at least two elements. First, compared to the *Binary-base* task, subjects earned some additional experience with distributions differing in skewness, and the round properly allowed the testing of this behavior. Second, in the *Multiple-base* task, subjects could visualize only one distribution at a time, and by dragging the slider, they could change the displayed distribution: the impact of increasing skewness on the probability density function became extremely evident and salient. Thus, the "dynamic" presentation of the alternatives may have made the comparisons easier compared to the traditional "static" presentation.

Furthermore, we found that skewness is traded off directly with the expected return, suggesting that it may play a major role in financial decisions. Ebert and Karehnke (2021) discuss skewness-seeking behavior in the context of binary lotteries and analyze the order of skewness preferences under different theories. In the expected utility (EUT) framework, skewness preferences are shown to be second or third order, whereas in the cumulative prospect theory (CPT) framework (Tversky and Kahneman 1992), skewness preferences are first order. Therefore, our results do not conform well to EUT, while they could be consistent with CPT. Indeed, thanks to the introduction of probability weighting, CPT allows skewness to play a more prominent role. Moreover, the different parametrizations of the value function as well as the probability weighting function do not define *ex-ante* a single relationship between skewness and utility, allowing individuals to be both skewness-seeker or skewness-avoider (Barberis 2012). Our findings of significant heterogeneity in skewness preferences are consistent with this view.

Since subjects traded off skewness for returns in the two *Binary-adjustment* tasks, mean–variance preferences do not fit their preferences well, and skewness must also be considered. However, a linear relationship like the one suggested by Arditti (1967) does not seem consistent with our results, either. Indeed, our results also suggest a convoluted relationship between variance, skewness, and the skewness environment (i.e., the direction of skewness of the available options). Consider the classification of the subjects into the three groups skewness-seeker, skewness-avoider, and skewness-neutral based on their decisions in the *Multiple-full* task, and analyze their choices in the two subsequent rounds: the *Skew-risk* and *Skew-risk-return* tasks. Not surprisingly, for both treatments, the subjects in the skewness-seeker group were significantly more skewness-seeking than those in the skewness-avoider (p-value of Wilxon rank sum test < 0.001), indicating the robustness of skewness preferences in both directions. The few skewness-neutral subjects were somewhere between the two groups for both treatments.[20] However, there is a difference between the groups in the level of variance in the two treatments: while they all take about the same risk in the positive treatment (p-value of Kruskal–Wallis test equal to 0.63), subjects in the skewness-seeker group

[20] However, the reliability of the statistical tests is hampered by the limited power due to the small size of the subsample of skewness-neutral subjects.

take significantly more risk in the negative treatment than those in the skewness-avoider group (p-value of Kruskal–Wallis test and subsequent pairwise Wilcoxon test < 0.05). Furthermore, both skewness-seeker and skewness-avoider select a distribution with higher variance in the negative treatment (p-values of the paired Wilcoxon tests < 0.001 and < 0.05 for the first and second group, respectively). Interpreting these results under a *moment-preferences* light suggests that individuals exhibit heterogeneous preferences for the third moment of the distribution. These preferences, combined with the availability of alternatives with skewness in the preferred direction, influence the decisions involving the second moment. First, in general, regardless of skewness preferences, individuals take more risk in a negatively skewed environment than in positively skewed environments. This is because, in this environment, the upside opportunities are more limited. Therefore, increasing variance is a solution to the bounded upside. This is not necessary in a positively skewed environment because the positive skewness alone can allow a more satisfactory upside, and only a limited number of subjects seek to maximize both skewness and variance. Second, in a negatively skewed environment, skewness-seekers are more aggressive than skewness-avoiders in taking more risks by increasing variance. This is probably because one reason to be a skewness-avoider is to reduce the probability of a loss, and increasing risk-taking would harm this objective. The specification of a theoretical model to account for these phenomena is beyond the scope of this paper, and it is left to future research.

We conclude this section by showing that subjects exhibited consistency in their revealed preferences throughout the rounds: we conduct seemingly unrelated regressions (SUR) of the skewness levels of the six tasks in which the distributions had the same expected return (i.e., all the tasks except the two *Binary-adjustment* tasks), and analyze the correlation matrix of the residuals. The residuals are all positively correlated. This correlation is statistically significant in most cases, indicating that unobservable idiosyncratic traits influenced the decisions over the rounds (see "Appendix C" for more details), confirming once again the fact that preferences over the third moment consistently play a first-order role in financial decisions.

6 Conclusions

Our experiment investigated preferences for continuous distributions differing in skewness. Our results are manifold, and they concern two main areas: the analysis of skewness preferences and the interactions between skewness and risk-taking.

In our main settings—choice across multiple distributions based solely on the plots of the probability density functions—we found the prevalence of skewness-seeking behavior, with a proportion of skewness-seeker consistent with the existing literature. While previous contributions adopted mainly binary lotteries, we highlight this behavior using continuous distributions defined on choice supports that include gains and losses and giving the possibility to choose positively skewed, symmetric, and negatively skewed distributions. Consistent with the literature, our results suggest that a positively skewed distribution may be more attractive than a negatively skewed distribution because of its longer right tail, which represents the speculative channel, and its shorter left tail, which may represent the risk channel. Indeed, we show that several subjects perceive positively skewed distributions as safer than negatively skewed ones. Skewness preferences would, therefore, represent a kind of meta-preferences summarizing the view of the subject of the *skewness trade-off*. In other words, the choices represent each subject's synthesis of the features inferred from the probability density functions and the probabilities provided. This synthesis results from a weighting process of the (un)desirable characteristics. Quantification of the weights, as well as the identification of other sources, is beyond the scope of the paper, and it is left for future research.

Finally, we found a twofold relationship between skewness and risk-taking. First, the environment in which decisions are made significantly affects risk-taking: individuals are more risk-taking in a negatively skewed environment than in a positively skewed one. This finding, in sharp contrast to the existing literature, is related to the idea that since negatively skewed distributions have a relatively short right tail, the only way to increase the probability of large gains is to resort to more risk-taking, thus increasing the dispersion parameter. Thus, volatility can be seen as a substitute for positive skewness. Furthermore, our findings reveal that when participants are presented with a reference point, the choices regarding skewness and standard deviation become positively correlated. These choices work in tandem, either to maximize the potential for substantial gains or to minimize the risk of losses. This intriguing observation hints at a connection between our research and Prospect Theory (Tversky and Kahneman 1992), opening up possibilities for future exploration.

Funding Open access funding provided by Università degli Studi di Trento within the CRUI-CARE Agreement.

Declarations

Conflict of interest On behalf of all authors, the corresponding author states that there is no conflict of interest.

Appendix A: Experimental design

Introduction to the experiment

In the description of the study, we told subjects: "In this study, we will ask you to make investment decisions. On top of the fixed payment, you will earn a bonus payment.

The experiment will take between 20 and 25 min. We recommend the use of the Web Browser Chrome."

As they clicked on the link we provided, they had to enter their Prolific ID, and after the "Welcome page", in which they were briefly introduced to the content of the experiment, subjects had to complete an interactive tutorial, which included the meaning of a probability density function and the concepts of variance and skewness. Subjects could use two sliders—like those they would use in the subsequent rounds—to manipulate these variables and learn the impact they had on the probability density function.

Afterward, they were administered a comprehension check: unless they answered all questions correctly, they could not move forward. However, they could try to answer as many times as they wished. The comprehension check page is shown in Fig. 7.

The tutorial served as a refresher of the previously acquired skills related to the interpretation of probability density functions. The comprehension check served the purpose of making sure that all subjects had a clear idea of what the distributions represented.

Aspirations

Before starting part one, subjects were asked about their aspirations for gains in a stock market investment, the maximum loss they would be willing to bear for a stock market investment, and whether they would rather combine the ownership of stocks with *"an option that increases your gains when the stock performs very well"* (i.e., a call option) or with *"an option that reduces your losses when the stock performs very bad"* (i.e., a put option).

Summary of the rounds

In each of the eight rounds of part one, the subjects chose one of the available distributions differing in skewness. The tasks are now described in depth.

Binary-base task (Round 1): binary choice between two distributions differing in skewness. There are three possible treatments that affect the skewness of the alternative: (– 0.75, 0), (– 0.75, + 0.75), (0, + 0.75). The treatment received in this task influences the available options in the two subsequent rounds. Both distributions are shown at the same time. Only in this round, subjects can draw samples of 10 observations from the two distributions.

Binary-adjustment tasks (Rounds 2/3): binary choice between the two distributions presented in the *Binary-base* task. In the penalty treatment, the distribution chosen in the *Binary-base* task receives a random penalty that reduces its expected return, keeping its variance and skewness unchanged, while in the bonus treatment the distribution not chosen in the *Binary-base* task receives a random bonus, which increases its expected return, keeping its variance and skewness unchanged.

The order of the penalty/bonus treatment and the magnitude of the adjustments to the expected return are randomized at the subject level. The bonus and penalty

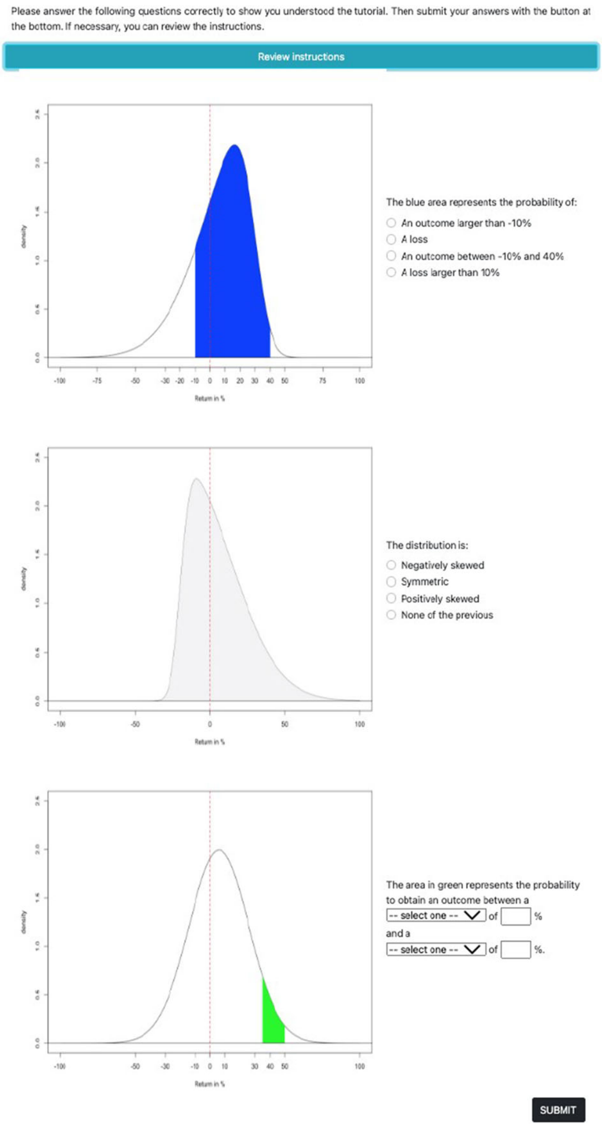

Fig. 7 Comprehension check page

range between 0 and 1%, with 0.10% increments. Like in the *Binary-base* task both distributions are shown at the same time.

Multiple-base task (Round 4): multiple choice among eleven distributions with the same expected return and variance, but differing in skewness with no additional information. Skewness levels are − 0.95, − 0.85, − 0.75, − 0.50, − 0.30, 0, + 0.30, + 0.50, + 0.75, + 0.85, + 0.95. Distributions with the same absolute value of the skewness coefficient also have the same kurtosis. Only one distribution is shown at a time, and it can be changed by moving the horizontal slider placed below the picture.

Multiple-partial task (Round 5): same decision environment of the *Multiple-base* task, but one measure of risk/return shown. Depending on the assigned treatment, there are three possible measures that can be shown: the probability of a loss, the probability of a loss larger than 20%, and the probability of a gain larger than 40%. The treatment is randomly assigned at the subject level.

Multiple-full task (Round 6): same decision environment of the *Multiple-base* and *Multiple-partial* task, but all the three measures of risk/return potentially provided in the *Multiple-partial* task are now shown.

Skew-risk task (Round 7): multiple choice among fifteen distributions with the same expected return, but differing in skewness and standard deviation. The levels of standard deviations are 0.16, 0.20, 0.24, while the levels of skewness are − 0.95, − 0.85, − 0.75, − 0.50, − 0.30 for the subjects assigned to the negative skewness treatment, and + 0.30, + 0.50, + 0.75, + 0.85, + 0.95 for those assigned to the positive skewness treatment. Treatment is assigned randomly at the subject level. Only one distribution is shown at a time, and it can be changed by moving a horizontal slider to change the skewness, or by moving a vertical slider to change standard deviation.

Skew-risk-reference task (Round 8): same decision environment of the *Skew-risk* task, but the skewness treatment assigned is now the opposite. Moreover, the current return accumulated is shown. Subjects are told that the final payment for the first part of the experiment will be equal to the current return (shown in this task) compounded with the return obtained in this task.

Sample generation process of the Binary-base task

In the *Binary-base* task (Round 1) subjects could generate samples from the two displayed distributions. The generation process of the samples worked in this way: ten random observations were drawn from a standard uniform distribution, they were ranked from the largest to the smallest, and then for each $u_{(10)}$, $u_{(9)}, \ldots,$ $u_{(2)}$, $u_{(1)}$, $F^{-1}(u_{(j)})$ and $G^{-1}(u_{(j)})$ were shown to the subjects (where F and G are the cumulative distribution functions of the two displayed investment opportunities and $u_{(j)}$ is the j^{th} order statistics). Subjects could generate as many samples as they wished.

Questionnaires

The subjects were asked to express their level of agreement with the statements reported in Fig. 8. Investment-related questions should be answered hypothetically in case the subject does not have enough money to invest.

The upside score is computed based on answers to questions 1, 6, 7, and 9, and it indicates how much a subject focuses on the upside.

The downside score is computed based on answers to questions 3, 5, 10, and 12, and it indicates how much a subject focuses on the downside.

Statements	Disagree				Agree
When I invest, I care more about the possibility to obtain large gains than to suffer large losses	1	2	3	4	5
I think a 7% average annual return for stocks in the long term is a very good result	1	2	3	4	5
Avoiding large losses is my first target when I invest	1	2	3	4	5
I consider my investment strategy prudent with respect to downside risks	1	2	3	4	5
When I invest, I care more about avoiding losses than obtaining very large returns	1	2	3	4	5
If I believe an asset is in a bubble, I buy that asset to make a profit before the bubble pops	1	2	3	4	5
I think buying a lottery ticket is a good idea because I might become rich	1	2	3	4	5
I am a gambler	1	2	3	4	5
Cryptocurrencies represent more than 10% of my ideal portfolio	1	2	3	4	5
I believe the ideal amount of cryptocurrencies to hold is less than 1% or even 0% of a portfolio	1	2	3	4	5
I am willing to invest in a bond with a return lower than 1% or to hold a lot of cash to avoid investing too much in riskier assets, like stocks.	1	2	3	4	5
I do not want to invest in the stock market because it is too risky	1	2	3	4	5
In general, I believe a positively skewed distribution is riskier than a negatively skewed distribution	1	2	3	4	5
In the first part of the experiment, I based my decisions more on the probability of gains and losses than on the pictures of the distributions	1	2	3	4	5

Fig. 8 Questionnaire

The soundness score is computed based on answers to questions 2, 4, 8 (reversed), and 11, and it indicates how reasonable a subject is about her approach to the financial markets.

The questionnaire above was followed by a demographic questionnaire asking about gender, age, race, profession, education level, education field, and nationality.

Sample descriptive statistics

In Table 4 we summarize some of the characteristics of the subjects in our sample.

Table 4 Descriptive statistics about the subjects in the sample

Gender	
Male	88
Female	91
Other	1
Race	
White	112
Black/brown	47
Latino	11
Other	10
Education level (completed)	
High School	53
Bachelor	69
Master	45
MBA/PhD	6
Other	7
Education field	
STEM	110
Non-STEM	70
Profession	
Student	107
Part-time worker	14
Full-time worker	49
Other	4
Continent	
Europe	110
Africa	49
Americas	14
Asia	6
Oceania	1
Age	
Mean	24.86
Median	24
St. dev	3.68

Appendix B: Comparability of the distributions

In this section, we show some criteria to compare the distributions we employed in the experiment from a theoretical perspective. Consider two distributions such as those we employ in the *Multiple* tasks. We show that the distribution with the higher skewness coefficient third-order stochastically dominates and has less downside risk than the other distribution with a lower skewness coefficient. Moreover, the two distributions are skewness-comparable (Chiu 2010).

Stochastic dominance

In the *Binary-base*, *Multiple-base*, *Multiple-partial*, and *Multiple-full* tasks subjects chose a distribution from a given set of distributions, none of which was first-order (FSD) or second-order stochastically dominated (SSD). However, the distributions with a higher skewness coefficient third order stochastically dominated (TSD) those with a lower skewness coefficient. Considering the EUT framework, if the decision maker's utility function is such that $U'(w) > 0$, $U''(w) < 0$, and $U'''(w) > 0$, then the (third-order) dominant alternative has a higher expected utility (Levy 1992).

The introduction of the bonus and penalty in the *Binary-adjustment* tasks may have altered the situation of stochastic dominance with respect to the *Binary-base* task depending on the size of the adjustment. In the *Skew-risk* and *Skew-risk-reference* tasks, subjects chose among distributions differing in skewness and standard deviation. For both tasks, all distributions such that standard deviation was not minimized were second-order stochastically dominated by the other distributions with the same expected return, the same skewness but lower variance. Considering once again the EUT framework if the decision maker's utility function is such that $U'(w) > 0$, $U''(w) < 0$, then the (second-order) dominant alternative has a higher expected utility (Levy 1992).

Given two random variables A and B, with distribution functions $F_A(x)$ and $F_B(x)$, then

- "A" FSD "B" if $F_B(x) - F_A(x) \geq 0 \forall$x with strict inequality for some x.
- "A" SSD dominates "B" if $\int_{-\infty}^{x} F_B(t) - F_A(t)\mathrm{d}t \geq 0 \forall$x with strict inequality for some x.
- "A" TSD dominates "B" if $\int_{-\infty}^{x} \int_{-\infty}^{\tau} F_B(t) - F_A(t)\mathrm{d}t\mathrm{d}\tau \geq 0 \forall$x with strict inequality for some x.

Figure 9 reports the graphs of the three functions above using the cumulative distributions functions of the positively and negatively skewed distributions employed in the *Binary-base* task. In the first and the second plots, the function lays both above and below the horizontal axis, showing the absence of FSD and SSD. On the contrary, in the third plot, the function lies above the horizontal axis, meaning that the positively skewed distribution TSD is the negatively skewed one. In our experimental framework, for all pairwise comparisons between distributions with the same mean and variance, the distribution with the larger skewness coefficient TSD the other one with a lower skewness coefficient.

Downside risk

Menezes et al. (1980) define of downside risk in the following way: *"g(x) has more downside risk than f(x) if g(x) can be obtained from f(x) by a sequence of MVPTs"*

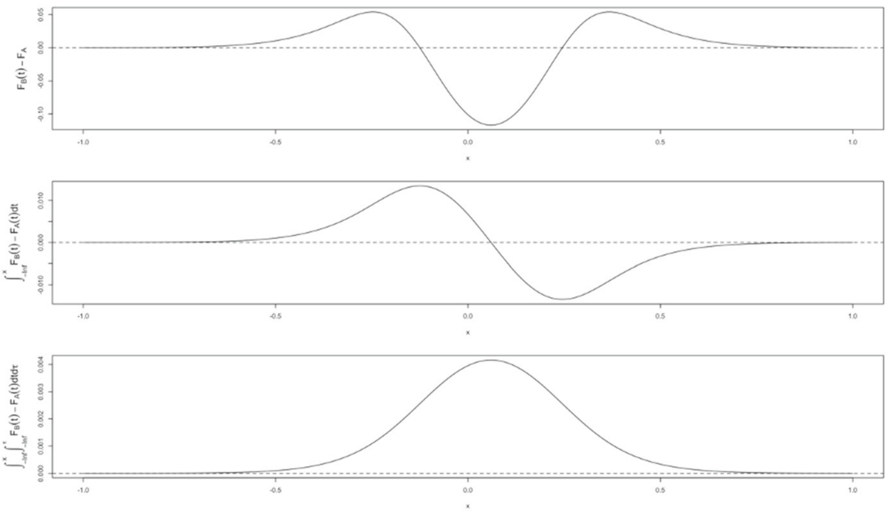

Fig. 9 Stochastic dominance tests for the positively skewed distribution (**A**) and the negatively skewed distribution (**B**) employed in the *Binary-base* task

(mean–variance preserving transformations). Moreover, they posit that if two distributions f and g have the same mean and variance, and f TSD g, then g can be obtained from f with a sequence of mean–variance preserving transformations.

Consider any pair of distributions we employ in the *Multiple* tasks: they always have the same mean and variance, and the distribution with the higher skewness coefficient TSD the other. Therefore, by Menezes et al.'s definition, the distribution with the lower skewness coefficient has more downside risk than the other. Thus, within our experimental framework, we can order distributions with the same mean and variance according to the downside risk criterion.

Skewness comparability criteria

Following Chiu (2010), we say that two distributions with probability density functions f and g are skewness comparable in the sense of Van Zwet (1964), if $F^{-1}(G(x))$ is either convex or concave. If $F^{-1}(G(x))$ is convex, then F is more positively skewed than G. Oja (1981) provided a weaker version of skewness comparability: two distributions are skewness comparable in the sense of Oja if $F(\sigma_F x + \mu_F)$ and $G(\sigma_G x + \mu_G)$ cross exactly twice. f is more positively skewed than g if G crosses F exactly twice, first from above. Chiu (2010, definition 5) also provides a more general form of skewness comparability, which relates to Menezes et al.'s definition of downside risk: *"distributions F and G are (generalized) skewness comparable if* $[F(\sigma_F x + \mu_F) \rightarrow G(\sigma_G x + \mu_G)]$ *is a downside risk increase or downside risk decrease [...]"*, with the expression in the brackets interpreted as passing from distribution F to distribution G.

Chiu's (2010) second lemma posits that Van Zwet's comparability implies Oja's comparability and Oja's comparability implies generalized skewness comparability. It

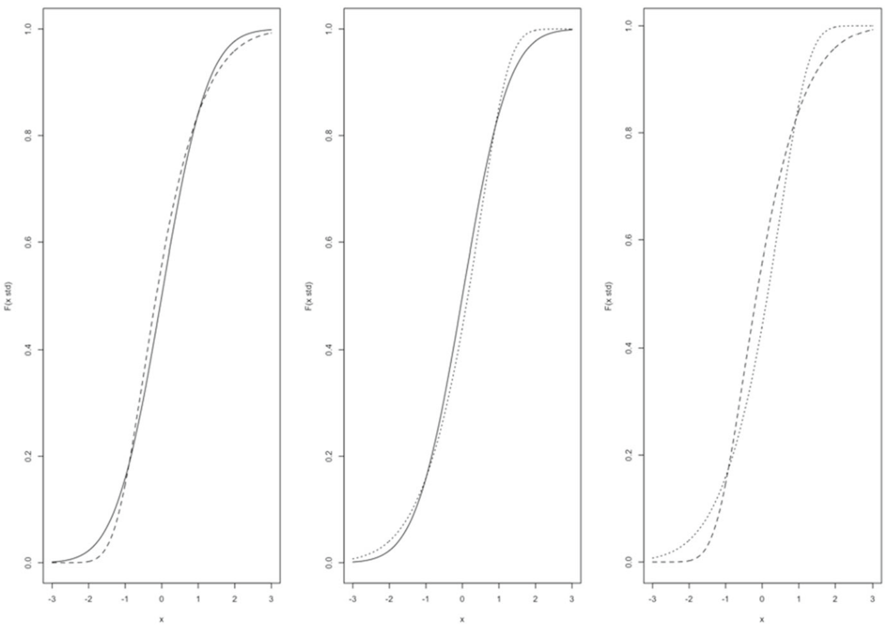

Fig. 10 Verification of Oja's skewness comparability criterion for distributions with skewness coefficient equal to − 0.75, 0, and 0.75. The cdf of the symmetric distribution is reported with the continuous line, the cdf of the positively skewed distribution with the dashed line, and the cdf of the negatively skewed distribution with the dotted line. In all three plots, the cumulative distribution functions cross each other twice, and the cdf of the distribution with the lower skewness coefficient (G) crosses that with a higher coefficient (F) first from above

can be shown graphically that all criteria are satisfied by the distributions we employed. As an example, Fig. 10 shows three pairwise comparisons of the distribution functions of the "standardized distributions" of the three distributions employed in the *Binary-base* task, proving that Oja's skewness comparability criterion is satisfied.

Appendix C: Additional analyses

Skewness and risk-taking

We have argued that the main reason for subjects assigned to the negative treatment to take more risk than those assigned to the positive treatment is to improve their upside. However, they should in theory first maximize skewness to improve their upside, and only later increase variance. Therefore, we should expect a positive and significant correlation between skewness and variance also in the *Skew-risk* task, at least in the negative treatment. While a simple statistical test on choices suggests the correlation is positive but insignificant, a deeper analysis shows a situation more in line with our expectations: for each of the two treatments, we split the subjects into two groups based on the selected skewness level: the subjects who chose a distribution with a

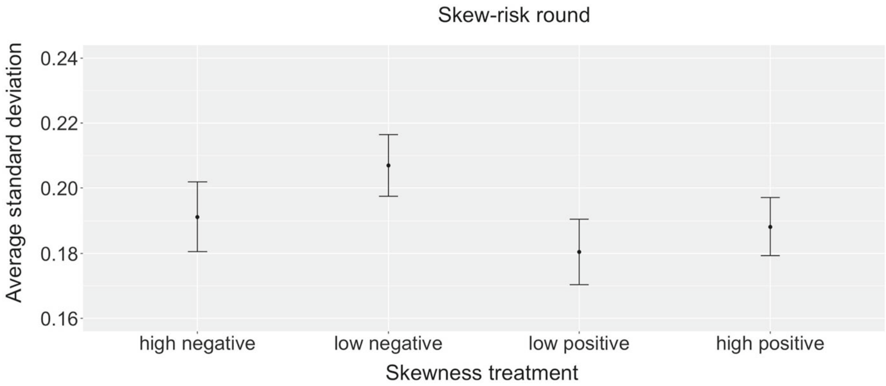

Fig. 11 Choices in the *Skew-risk* task with split based on treatment and skewness level chosen. The subjects who chose distributions with a longer right tail took more risk. This is especially true for the negative treatment

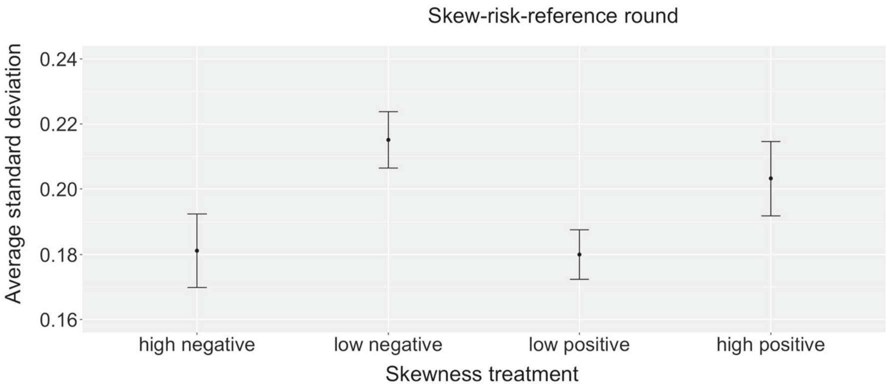

Fig. 12 Choices in the *Skew-risk-reference* task with split based on treatment and skewness level chosen. The subjects who chose distributions with a longer right tail took more risk. This is true for both treatments, and the effect is more pronounced than in the *Skew-risk* task

skewness coefficient lower or equal to 0.5 (in absolute value) are classified in the low skewness group, and the others in the high skewness group. We find that both the subjects in the low negative skewness, and in the high positive skewness took more risk than the subjects assigned to the same treatment, but in the opposite "skewness group" (Fig. 11). In the *Skew-risk* task, this difference is significant only in the negative treatment, while in the *Skew-risk-reference* task, it is significant for both treatments and at a 1% level (Fig. 12).

Skewness and prudence

In Table 5 we report the proportions of subjects exhibiting prudent behavior in the

Table 5 Results of the Chi-squared test on proportions, Ho: proportion of skewness-seeker/prudent decision-makers is equal to 50%

Task	Proportion of skewness-seeking/prudent choices (%)	p-value
Binary-base (pooled)	44.44	0.16
Treatment pos and symm	36.84	0.06
Treatment neg and symm	47.83	0.81
Treatment pos and neg	48.15	0.89
Multiple-base	68.39	< 0.001

Binary-base task (for each treatment), and skewness-seeking behavior in the *Multiple-base* task. In theory, this task could be also used to test for prudence: a prudent decision-maker should have selected the distribution with the highest skewness coefficient. About 17% of the subjects selected this distribution, significantly more than what would be implied by random choice ($p < 0.001$). While the task was not designed with the purpose of testing for prudence, this result confirms the finding that the direction of skewness matters more than its absolute value (Brünner et al. 2011; Ebert 2015). Indeed, both skewness-seekers and skewness-avoiders did not cluster on the most positively skewed or the most negatively skewed distribution, but they selected several distributions, both with high and low absolute skewness.

Robustness checks on determinants of skewness preferences

In Table 3 we modeled the skewness levels chosen by the subjects in the three *Multiple* tasks. We identified the risk perception and the speculative channels as the main drives of skewness choices. In some specifications, we identified the speculative channel through a division of the sample using the call/put preference. Furthermore, we divided the downside-focused subjects based on the maximum loss threshold. While the first criterion about the call/put preferences did not require any additional assumption, the second criterion required the specification of a loss threshold. The choice of 5% and 10%, although motivated by previous literature and by our design, was somewhat arbitrary. If we changed the threshold for classification, choosing a larger value (up to 15%), the coefficient of risk perception would not change in magnitude and still be highly significant, and the coefficient of the "Call group" would not change in magnitude and be still significant, either at 1% or 5% level, depending on the set threshold. Hence, the two channels we identified are robust to the threshold chosen for the maximum loss.

However, as we increase the threshold from 5 to 15%, the coefficient of the "Put-risk" group would reduce (still remaining positive in all ten alternative specifications) and lose its significance at a 5% level. This is due to the fact that as we increase the threshold for losses, the group "Put-safe" starts to include subjects who have relatively higher thresholds for losses.

Table 6 Correlation of the residuals of the SUR. Significance levels are 5% (*), 1% (**) and 0.10% (***)

	Bin-base	Mult-base	Mult-part	Mult-full	SR	SRR
Bin-base	1	0.24**	0.21**	0.12	0.13	0.07
Mult-base		1	0.40***	0.24**	0.24**	0.28***
Mult-part			1	0.26***	0.27***	0.27***
Mult-full				1	0.51***	0.30***
SR					1	0.33***
SRR						1

Consistency in choices

We show that subjects were consistent in their choices with two approaches. First, we estimated SUR using the choices of all rounds except from the two *Binary-adjustment* tasks (because the expected return was different for the alternative distributions). Here we report the correlation coefficients of the residuals of the six regressions and the levels of significance of the statistical tests on them. All residuals are positively correlated, and this correlation is statistically significant in most cases (Table 6).

Secondly, we use a simulation approach. We compare the standard deviation of the skewness coefficients of the choices in the six rounds indicated above with the standard deviation if these choices had been random. If the subjects had been consistent over the rounds, then the standard deviation of the actual skewness coefficients would have been lower than if the decisions had been made randomly. The simulation shows that the median actual standard deviation is significantly lower than the simulated randomized standard deviation (p-value of Wilcoxon rank sum test is < 0.001), confirming consistency in the choices. Figure 13 shows that the distribution of the real choices has more density located in the low standard deviation area than the distribution of simulated choices.

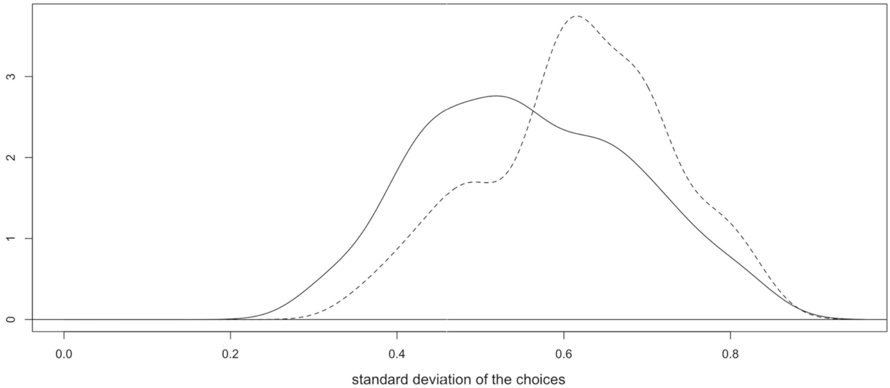

Fig. 13 Estimated density of the standard deviation of the skewness coefficients of the *Binary-base*, *Multiple-base*, *Multiple-partial*, *Multiple-full*, *Skew-risk*, and *Skew-risk-reference* tasks (solid line), and simulation of the same density if choices in those tasks had been made randomly (dashed line). Lower levels of standard deviation indicate consistency in the choices

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