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February 12, 2025

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1 Introduction

The comparison between financial markets and casinos, both as places to express our natural urge for gambling, has a long tradition in popular and academic circles (Keynes, 1936, Chapter 12). Yet, the formalization of the idea that gambling plays a role in understanding the price of financial assets has been challenging.

Early works have introduced a preference for skewness in otherwise standard expected utility models (EUT models, henceforth) of portfolio selection (Arditti, 1967; Rubinstein, 1973; Kraus and Litzenberger, 1976; Scott and Horvath, 1980). This literature shows that *systematic* skewness is priced and that the resulting skewness risk premium cannot be fully explained by known risk factors (Chang et al., 2013). Related works have shown that downside risk is priced, thus revealing the role of negative skewness at the market level as a critical risk factor driving the market risk premium (Kelly and Jiang, 2014; Lu and Murray, 2019).

At the individual stock level, however, positive rather than negative skewness is often observed (Albuquerque, 2012; Bessembinder, 2018; Oh and Wachter, 2022), spurring a new wave of models that depart from the standard EUT framework to explain how positive skewness can impact individual stock returns.

These models emphasize the key role of probability distortions (Brunnermeier et al., 2007; Barberis and Huang, 2008; Driessen et al., 2021), thereby generating novel predictions that do not consistently arise under EUT, while also explaining existing financial puzzles, such as the low average return on IPOs and private equity, as well as the lack of diversification in household portfolios. In particular, these models predict that an asset's future skewness, even if *idiosyncratic*, will impact asset pricing. More specifically, a positively skewed asset can earn a negative average excess return even if it is in small supply and independent of other risks (Barberis and Huang, 2008). This is precisely the prediction we want to test. Doing so, we will also directly test the mechanism underlying most of these behavioral models, namely probability weighting. As originally proposed by Barberis and Huang (2008), lottery assets, characterized by positive skewness and typically a small chance of obtaining a large reward, will trigger risk-seeking behaviors because people tend to overweight small probabilities (Quiggin, 1982; Tversky and Kahneman, 1992; Prelec, 1998; Gonzalez and Wu, 1999; Abdellaoui, 2000; Bruhin et al., 2010; l'Haridon and Vieider, 2019).

Empirical studies to date have primarily examined the reduced-form predictions of these behavioral theories, rather than directly testing their underlying mechanisms. Studies have shown that people who invest in the stock market resemble those who purchase state lotteries (Kumar, 2009; Doran et al., 2012) and that punctual increases in lottery prizes lead to reduced investments in stocks with lottery features (Dorn et al., 2015; Gao and Lin, 2015).

Furthermore, an abnormally high proportion of stock market investors are diagnosed as compulsive gamblers (Cox et al., 2020). The evidence also shows a general appeal for stocks exhibiting positive skewness. In particular, using archival data, a series of papers have shown that positive skewness is associated with lower returns, thus reflecting a preference for skewness (Boyer et al., 2010; Bali et al., 2011; Conrad et al., 2013, 2014; Lin and Liu, 2018).

One notable exception in the empirical literature is the work of Barberis et al. (2016) who propose a test of the underlying mechanism of skewness preferences based on probability weighting (Barberis and Huang, 2008). To that end, the authors assume that the representative investor maximizes a prospect theory (PT, henceforth) value function using the parameter values estimated by Tversky and Kahneman (1992). Using archival data, they calculate the estimated value of a stock according to PT from its monthly return distribution over the last five years. They show that stocks with a higher PT value produce lower returns. In line with previous empirical studies, they also report that positive expected skewness is the main driver of lower returns.

Despite the contribution of Barberis et al. (2016), current empirical research largely favors reduced-form evidence over direct tests of the models of skewness preferences. This might be one reason why no behavioral asset pricing model has yet been widely accepted. As emphasized in Hirshleifer (2015), there is a critical need to test behavioral models by studying the proposed causal pathways. Testing the causal links between skewness, probability weighting, and asset pricing using archival data is a daunting task because researchers can neither exogenously manipulate the skewness of a stock nor precisely assess investors' probability weighting. Archival evidence reveals a negative relationship between a stock's expected skewness and its subsequent return. However, stocks with high expected skewness might also differ from other stocks in terms of unknown risk factors. As is often the case, this joint hypothesis problem makes it difficult to provide causal estimates (Fama, 1970). Moreover, the pricing of idiosyncratic skewness can also be rationalized by EUT preferences when agents are heterogeneous (Mitton and Vorkink, 2007), making it difficult to distinguish between standard and behavioral models without evidence on the underlying mechanisms.

To alleviate the previous issues, we use an experimental approach that allows us to manipulate asset skewness exogenously and elicit precise individual estimates of probability weighting. Our protocol enables us to test the causal impact of probability weighting on asset pricing thus providing a direct test of the model of Barberis and Huang (2008). Our asset markets build on CAPM experiments (Bossaerts and Plott, 2004; Bossaerts et al., 2007) in which participants trade two risky assets and a risk-free asset in a continuous double auction. We consider a 2x2 design in which we varied the skewness of one of the risky assets across two levels (zero and positive). We focus on the case of positive skewness rather than negative skewness due to its empirical relevance at the level of individual assets (Albuquerque, 2012), and because it enables us to test the prediction made by Barberis and Huang (2008) that positive skewness can lead to excess negative returns. We also varied the supply of the skewed asset across two levels (low and high) to test the specific prediction of Barberis and Huang (2008) that a positively skewed asset can earn a negative return even when its supply is low and thus its impact on the market portfolio is minimal. As we show in our theory section, the comparative statics across supply treatments are critical for teasing apart the predictions of behavioral models from those of standard EUT models.

Our first result, based on the high-supply treatments confirms a basic prediction of early models incorporating systematic skewness as a risk factor (Arditti, 1967; Rubinstein, 1973; Kraus and Litzenberger, 1976; Scott and Horvath, 1980) by showing that systematic positive skewness produces negative expected returns.[1] Furthermore, we show that idiosyncratic skewness is priced in the low-supply treatments in line with non-EUT models (e.g., Barberis and Huang, 2008; Driessen et al., 2021), but contrary to the predictions of EUT-based models. Finally, we provide a direct test of the model proposed by Barberis and Huang (2008) and show that, consistent with predictions, the negative return is most pronounced when traders in a market distort probabilities by assigning greater weight to low-probability positive payoffs.

Going beyond consistency checks, ours is the first study to provide causal tests of competing models that incorporate skewness pricing. Our approach paves the way for new research offering granular tests of both behavioral and classical asset pricing models. The remainder of the paper is organized as follows. In Section 2 we present our experimental design, including the asset market, the treatments, the risk-preference elicitation protocol and other details. In Section 3 we discuss the asset pricing implications of different theories in our setting and derive hypotheses. We contrast standard theories such as CAPM and the mean-variance-skewness model to behavioral theories that incorporate probability-weighting. Section 4 analyzes the results and tests the hypotheses and Section 5 concludes.

2 Design

The experiment involves three parts: an asset market, a series of multiple-price lists, and a questionnaire aimed at measuring cognitive ability, financial literacy, and demographics.

[1] Previous experimental evidence is limited to single-asset markets, e.g. Huber et al. (2014).

The design along with our hypotheses were preregistered at AsPredicted #148757.[2]

2.1 The Asset Market

We employ a standard CAPM experimental asset market (Bossaerts and Plott, 2004; Bossaerts et al., 2007) involving the trading of two risky assets and a risk-free asset. The asset market consists of 13 periods (including an initial practice period), with each period lasting 5 minutes. During each period, there are 10 market participants who can buy and sell two risky assets, called X and Y, and a safe asset, called Z. Each unit of an asset yields a payoff if held until the end of the period. Participants know the probability distribution of the asset payoffs, which varies from period to period. Participants start each period with new endowments of the three assets and cash. The assets and cash accumulated in the previous period are not carried over to the next period.

During the market period, participants trade assets for cash. Participants can enter limit orders (called bids and asks), which are displayed in electronic order books, with one book for each asset. Each limit order is for one unit of an asset. If a limit order bid (ask) surpasses an existing limit order ask (bid), a unit of the asset is exchanged at the prevailing limit order ask (bid) price. Alternatively, a transaction can be instantly executed by selecting any existing bids or asks in the order books (i.e. through a market order). Assets X and Y cannot be sold short, while short sales of asset Z (the risk-free asset) are allowed up to 5 units.[3] Participants are also endowed with a cash reserve that cannot be used to purchase assets (unlike the cash endowment) and is used to buffer potential negative earnings from short sales.

At the end of each market period, the computer randomly determines the final payoffs of the assets using the given probabilities. The participant's score for the period is equal to the final payoffs of each asset multiplied by the number of units of each asset owned by the participant, plus the cash available at the end of the period and the cash reserve. To calculate the participant's final payment for the market experiment, the computer randomly selects one of the 12 periods. For the randomly selected period, the participant receives their score as payment in cents of euros.

[2]Our main hypothesis was in line with our PT model à la Barberis and Huang (2008) (see Section 3.2) captured in Hypothesis 3, and was stated as follows: "The main hypothesis is that positive skewness will lead to a higher asset price and even negative expected returns, when the skewed asset supply is lower and probability weighting is larger."

[3]We allow for short sales of the risk-free asset following Bossaerts and Plott (2004) as it can be an equilibrium strategy depending on the risk-aversion of the individual. As shown in Bossaerts and Plott (2004), forbidding the short-selling of risky assets does not alter the standard theoretical predictions much.

2.2 Treatments

We consider a 2x2 design in which we vary the skewness of one of the risky assets across two levels (Skew and NoSkew) along with the supply of the skewed asset (High and Low). We thus have four treatments: Skew-H, Skew-L, NoSkew-H and NoSkew-L. We adopt a within-subject design, repeating each treatment for 3 periods in a random sequence of 12 market periods (the first practice period is always a NoSkew-L treatment). Information on periods, treatments and sessions is summarized in Table 1 for convenience.

Practice period	Periods	Periods per treatment	Sessions	Participants per session
1	12	3	13	10

Table 1: Information on market periods and sessions

2.2.1 Payoffs and skewness

The risk-free asset Z has a sure payoff of 100. Each risky asset $j \in \{X, Y\}$ yields either a high payoff $\overline{d}_j$ or a low payoff $\underline{d}_j < \overline{d}_j$. The payoff values and the respective probabilities are summarized in Table 2. The payoff distribution of asset Y is varied across treatments. In Skew treatments, asset Y has skewed payoffs and in NoSkew treatments it has a symmetric (non-skewed) payoff distribution. These two types of asset Y are thus never traded in the same market. The non-skewed version of asset Y has the same marginal payoff distribution as asset X. Importantly, the payoffs of X and Y are independent. This simplifying assumption is not critical to our main prediction and is used in Barberis and Huang (2008) (Assumption 13). We thus have four states, $\{(\overline{d}_X, \overline{d}_Y), (\overline{d}_X, \underline{d}_Y), (\underline{d}_X, \overline{d}_Y), (\underline{d}_X, \underline{d}_Y)\}$, with probabilities $\{0.25, 0.25, 0.25, 0.25\}$ in the NoSkew treatments and $\{0.025, 0.475, 0.025, 0.475\}$ in the Skew treatments. Another simplifying feature of our market is that the two risky assets have the same mean ($\mu_X = \mu_Y = \mu$) and variance ($\sigma_X^2 = \sigma_Y^2 = \sigma^2$). The payoff distribution of X is symmetric, with zero skewness, and the same holds for the non-skewed version of asset Y (used in NoSkew treatments). However, the skewed version of asset Y (used in Skew treatments) has a positive skewness, measured in Table 2 as:

$$skew_j \equiv E\left[\left(\frac{d_j - \mu_j}{\sigma_j}\right)^3\right]$$

.

Asset	Payoff distribution	Mean	SD	Skewness
X	(156,84;0.5,0.5)	120	36	0
Y: non-skewed	(156,84;0.5,0.5)	120	36	0
Y: skewed	(277,112;0.05,0.95)	120	36	4
Z	(100;1)	100	0	0

Table 2: Asset payoffs

2.2.2 Supply of skewed assets

The experiment varies not only the distribution of payoffs, but also the endowments, as shown in Table 3. In high-supply treatments (Skew-H and NoSkew-H), the aggregate supply of Y (N_Y) is as large as that of X (N_X), where: $N_X = N_Y = 55$. In low-supply treatments (Skew-L and NoSkew-L), asset Y is in short supply relatively to asset X: $N_X = 100, N_Y = 10$, and amounts to only 9.1% of the total supply of risky assets compared to 50% in the high-supply treatments. The relative supply of the skewed asset was chosen to be low enough so that the prediction in Barberis and Huang (2008) regarding the excess negative return of the skewed asset holds (see Section 3.2).

Within each treatment, there are also individual differences in endowments, which are introduced to provide incentives to trade. In each market period, half of the participants (5 out of 10) have a type-1 endowment and the remaining have a type-2 endowment. Endowment types are randomly assigned in each period. As shown in Table 3, a type-1 participant has a larger endowment of asset X and a lower endowment of asset Y relative to a type-2 participant. In all treatments, participants have a zero endowment of the risk-free asset Z and have a cash endowment of 200. As mentioned before, in each period participants also receive a cash reserve, which cannot be used for transactions. The cash reserve is set to 500 in order to absorb the highest potential payment incurred by a participant selling asset Z short (up to the short-selling limit of 5 units).

Supply of Y asset	
High	Low
Aggregate supply	
$N_X = 55$	$N_X = 100$
$N_Y = 55$	$N_Y = 10$
$N_Z = 0$	$N_Z = 0$
Individual endowments	
Type 1:	
$n_X = 9$	$n_X = 11$
$n_Y = 2$	$n_Y = 0$
Type 2:	
$n_X = 2$	$n_X = 9$
$n_Y = 9$	$n_Y = 2$
All types:	
$n_Z = 0$	$n_Z = 0$
Cash=200	Cash=200

Note: In a market there are 5 type-1 participants and 5 type-2 participants.

Table 3: Aggregate supply and endowments

2.3 Risk Preferences Elicitation

The risk preference elicitation consists of collecting certainty equivalents of binary lotteries $L = (x, y; q, 1 - q)$, with x being the outcome that occurs with probability q, and y being the outcome that occurs with probability $1 - q$. We use a multiple-price list technique in which the certainty equivalent of a lottery is inferred through binary decisions between two options. The first option is the lottery, and the second one is a list of equally spaced certain outcomes, ranging from $\max\{x, y\}$ to $\min\{x, y\}$. The elicitation involves the 12 binary lotteries reproduced in Table 4, obtained by combining four probabilities $q \in Q = \{0.025, 0.05, 0.25, 0.5\}$ and three different (x, y) pairs. These probabilities and outcomes are chosen to allow for both the parametric estimation of the probability weighting function (Tversky and Kahneman, 1992) and the semi-parametric elicitation of probability weights (Abdellaoui et al., 2008; Kpegli et al., 2023; Corgnet et al., 2023). The semi-parametric estimation procedure allows us to estimate the individual weights traders assigned to each of the probabilities that are relevant to our asset payoffs.[4] Appendix B provides additional details on our elicitation procedure.

Table 4: Lotteries used in the risk elicitation procedure

$N°$ Lottery	x	y	q
1	100	0	0.025
2	100	50	0.025
3	50	0	0.025
4	100	0	0.05
5	100	50	0.05
6	50	0	0.05
7	100	0	0.25
8	100	50	0.25
9	50	0	0.25
10	100	0	0.50
11	100	50	0.50
12	50	0	0.50

2.4 Protocol

We recruited 130 participants from the GATE platform in Lyon (France), which had an active pool of participants of around 1,500 at the time of the experiment (November 2023). We conducted 13 independent sessions with 10 participants each leaving us with 169 market observations.[5] Two sessions were conducted at a time except for the first session. Most of the participants in the pool belong to the business school or the engineering school.

Participants were recruited for 90 minutes and sessions were completed on average in 75 minutes for an average payment of 16 euros. When entering the lab, participants were invited to pick a card from an opaque bag indicating their exact cubicle location. Participants read the instructions for an average of 20 minutes before answering a 5-item incentivized quiz giving them 25 cents per correct answer. The full set of instructions is available at `https://osf.io/z82bj/?view_only=e00a334ccda3486dafa2ee2d8f34cc5e`.

[4] Indeed, the set of probabilities Q used in the elicitation procedure includes 0.025 and 0.25, which are associated with the highest payoffs for assets X and Y: $\overline{d}_X$ and $\overline{d}_Y$.

[5] Using previous CAPM experiments as a benchmark (Bossaerts and Plott, 2004), we calculated that we needed about 150 market-level observations to detect significant differences in returns for asset Y across treatments at the 5% level. We thus conducted 12 sessions, resulting in 156 market observations, to which we added the pilot session data (13 observations). Our sample size was preregistered at AsPredicted #148757.

At the end of the market experiment, participants completed a questionnaire lasting 10 minutes on average. They first completed the risk preference elicitation described in Section 2.3. We then asked participants to complete a financial literacy test using the big-five questionnaire (Angrisani et al., 2020) and a 4-item version of the Cognitive Reflection Test (CRT, henceforth) (Frederick, 2005; Toplak et al., 2014) to assess cognitive ability (Corgnet et al., 2018; Bosch-Rosa and Corgnet, 2022). Finally, we collected basic demographics: age, gender, and field of study. In Appendix C, we report descriptive statistics for our individual measurements. The experiment was developed in oTree (Chen et al., 2016).[6]

3 Theory and Hypotheses

3.1 Expected Utility Theory

In this section, we discuss the predictions of different theoretical frameworks with regard to the pricing of skewness in our experimental market.[7] We begin with the standard theory of asset pricing, i.e. the CAPM, which is based on the assumption that investors have mean-variance utility. In turn, such preferences can be derived as a second-order approximation of expected utility (which is exact for a quadratic Bernoulli utility). Thus, we assume that the utility of a representative investor is given by:

$$E(W) - \frac{1}{2}\gamma \times var(W)$$

where W is final wealth.[8] Then, in our market with two independent risky assets, the price of asset $j \in \{X, Y\}$ is given by:

$$P_j(1 + r_f) = \mu_j - \gamma N_j \sigma_j^2$$

where r_f is the return on the risk-free asset Z, μ_j is the expected payoff of asset j, N_j is the aggregate supply of asset j, σ_j^2 is the variance of asset j payoffs. Assuming investors are variance-averse ($\gamma > 0$) and prices are positive, risky assets X and Y will have positive expected returns in any treatment:

$$E(r_j) = \frac{\mu_j r_f + \gamma N_j \sigma_j^2}{\mu_j - \gamma N_j \sigma_j^2} > 0$$

[6]For another experiment using the same oTree asset market platform, see Duffy et al. (2024).

[7]The main mathematical expressions used in this section are derived in Appendix A.

[8]Although our market is incomplete, a representative agent exists if investors have linear risk tolerance with common cautiousness parameters, see Rubinstein (1974).

where $r_j = \frac{d_j - P_j}{P_j}$ is the return on asset j.[9] Risk premia will be affected by aggregate supplies so that a smaller supply will result in a higher price and thus a lower, yet positive, expected return. But, payoff skewness, unlike variance, will not be priced. Thus, while asset prices will be different in treatments with different supply levels, prices will not be affected by whether the payoffs of Y are skewed or not.

Going beyond the simple quadratic utility case, it is well-known that EUT can generate a preference for positive skewness in final wealth, which in turn can affect asset prices. To analyze this effect, we consider a mean-variance-skewness model, which can be obtained as a third-order approximation of expected utility:

$$E(W) - \frac{1}{2}\phi_v var(W) + \frac{1}{3}\phi_s S(W) \tag{1}$$

where $\phi_v > 0$ and $\phi_s > 0$ capture variance aversion and skewness seeking, and $S(W) \equiv E[(W - E(W))^3]$ denotes the third central moment of final wealth.[10] As shown by Kraus and Litzenberger (1976), under such preferences, an asset coskewness with the market portfolio (i.e. its contribution to market skewness) will be priced. This is often taken to imply that the idiosyncratic skewness of an asset will not be priced since the share of any individual stock in the market portfolio is negligible.[11] This is not the case in our experimental markets because even in the low-supply treatments the aggregate expected payoff of asset Y is around 9% of the market expected payoff. Thus, the skewness of asset Y will affect asset prices if the traders in our experiment have mean-variance-skewness preferences. Assuming investors prefer positive skewness ($\phi_s > 0$), asset Y will trade at higher price (earning lower expected returns) in the skewed treatment.

Nonetheless, even in our experiment, the mean-variance-skewness model cannot rationalize negative returns when the aggregate supply of asset Y is small. To illustrate this point, we solve for the expected return of asset Y in equilibrium:

$$E(r_Y) = \frac{r_f \mu_Y + \phi_v \sigma_Y^2 N_Y - \phi_s S_Y N_Y^2}{\mu_Y - \phi_v \sigma_Y^2 N_Y + \phi_s S_Y N_Y^2} \tag{2}$$

where $S_Y \equiv E[(d_Y - E(d_Y))^3]$ is the the third central moment of Y's payoffs. We plot the

[9] Throughout the paper we refer to net returns simply as returns. All our theoretical results can also be expressed in terms of excess returns. In our data, excess returns are close to net returns on average, because the risk-free rate is close to 0 since there is no scope for time discounting by design, but excess returns are noisier.

[10] The third central moment $S(X)$ and the skewness of a random variable $skew(X)$ are related by the following formula: $skew(X) = \frac{S(X)}{SD(X)^3}$, where $SD(X)$ is the standard deviation.

[11] However, see Mitton and Vorkink (2007) for a model of mean-variance-skewness preferences where idiosyncratic skewness is priced when investors have heterogeneous preferences for skewness.

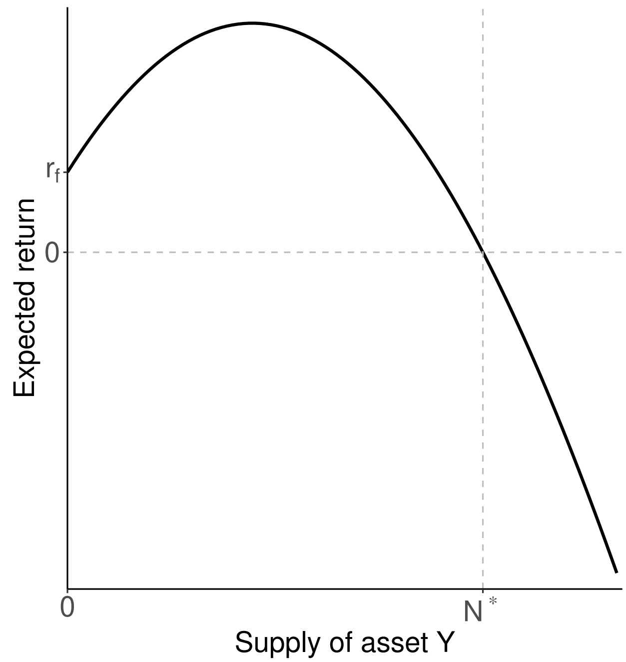


Figure 1: Effect of supply on returns of the skewed asset

expected return of asset Y as a function of asset Y supply in Figure 1. For high supply values, skewness seeking dominates variance aversion, resulting in negative returns. For low supply values, below a given threshold N^*, variance aversion dominates, resulting in positive returns.[12] This is a consequence of the fact that the size of the investment has a higher-order effect on portfolio skewness than on portfolio variance, and thus portfolio skewness vanishes more rapidly as asset holdings decrease.[13] While we do not know the value of N^* in our experiment as it depends on preferences, the mean-variance-skewness model makes a clear comparative static prediction: if skewed asset Y earns positive returns when its supply is large, then it cannot earn negative returns when its supply is small.[14] A formal proof of this statement is provided in Appendix A.2.

[12]In the same vein, Corgnet et al. (2023) show that for a small positively skewed productivity shock affecting wages, below a given threshold, variance aversion dominates skewness seeking for a decision-maker under mean-variance-skewness. Conversely, skewness seeking dominates variance aversion only when the positively skewed productivity shock affecting wages is large.

[13]Ebert and Karehnke (2021) demonstrate that skewness seeking has a third-order effect while risk-aversion has a second-order effect under mean-variance-skewness utility and under EUT more generally.

[14]The analysis so far has assumed a representative investor. However, the main conclusion is likely to hold even when investors have heterogeneous preferences, as in the model of Mitton and Vorkink (2007). In this model a group of investors ends up holding a portfolio that is heavily tilted towards the skewed asset. If a decrease in the aggregate supply of the skewed asset results in a decrease in the holding of that asset by skewness seeking investors, then our main conclusion continues to hold in this model.

3.2 Prospect Theory

PT provides distinct implications for the pricing of skewed assets. As shown in Barberis and Huang (2008), not only an asset's own skewness level will affect prices, but a positively skewed asset will earn negative expected excess returns when its supply is small and even infinitesimal. To show this, we adapt the model of Barberis and Huang (2008) to our setting. The investor's preferences are defined over the gain or loss relative to the final wealth that could have been obtained investing only in the risk-free asset:

$$\hat{W} \equiv W - (1 + r_f)W^0$$

where we denote by W^0 and W initial and final wealth respectively. In our setting, $\hat{W}$ is a random variable that can be represented with the following lottery:

$$(\hat{W}_{-m}, q_{-m}; ...; \hat{W}_{-1}, q_{-1}; \hat{W}_0, q_0; \hat{W}_1, q_1; ...\hat{W}_n, q_n)$$

where $\hat{W}_k < \hat{W}_l$ for $k < l$, $\hat{W}_0 = 0$ and q_k is the probability of occurrence of an outcome of rank k. The preferences of the investor are represented by:

$$V(\hat{W}) = \sum_{k=-m}^{n} \pi_k v(\hat{W}_k)$$

where $v(\cdot)$ is the value function and the π_k terms are decision weights, defined as:

$$\pi_k = \begin{cases} w(q_k + ... + q_n) - w(q_{k+1} + ... + q_n), & \text{if } 0 \leq k \leq n \\ w(q_{-m} + ... + q_k) - w(q_{-m} + ... + q_{k-1}), & \text{if } -m \leq k < 0 \end{cases}$$

where $w(\cdot)$ is the probability weighting function. We follow Barberis and Huang (2008) and specify the functions $v(\cdot)$ and $w(\cdot)$ as follows:

$$v(x) = \begin{cases} x^\alpha, & \text{if } x \geq 0 \\ -\lambda(-x)^\alpha, & \text{if } x < 0 \end{cases}$$

$$w(q) = \frac{q^\delta}{[q^\delta + (1-q)^\delta]^{1/\delta}}$$

The parameters α, δ and λ are set equal to the values estimated by Tversky and Kahneman (1992): $\alpha = 0.88$, $\delta = 0.65$ and $\lambda = 2.25$.

When $\delta < 1$, the probability weighting function features overweighting of small probabilities, which in turn leads to a preference for positive skewness. Since investors value positive skewness, a positively skewed asset will have a higher price and lower expected returns than a non-skewed asset, ceteris paribus. However, as in Barberis and Huang (2008), the utility investors obtain from holding the skewed asset is non-monotonic in the fraction of wealth allocated to asset Y relative to the fraction of wealth allocated to asset X, denoted s (see Figure 2). Beginning with a portfolio containing only the risk-free asset and the non-skewed asset, a small investment in the skewed asset initially diminishes utility due to its negative average return. As s increases, the skewed asset contributes more significantly to the skewness of the portfolio's returns. Consequently, utility rises. However, as the investment in the skewed asset further increases, the increased skewness fails to offset the heightened risk, resulting in a decline in utility. This has two important consequences. First, there are two optima in the investor's portfolio problem ($s = 0$ and $s = s^*$), leading to heterogeneous portfolios in equilibrium even when investors have the same preferences. Second, the equilibrium can be sustained only when the aggregate supply of the skewed asset is small enough that it is possible to clear the market at the optimal holding s^*. Next, we examine whether our treatments admit a heterogeneous equilibrium à la Barberis and Huang (2008).

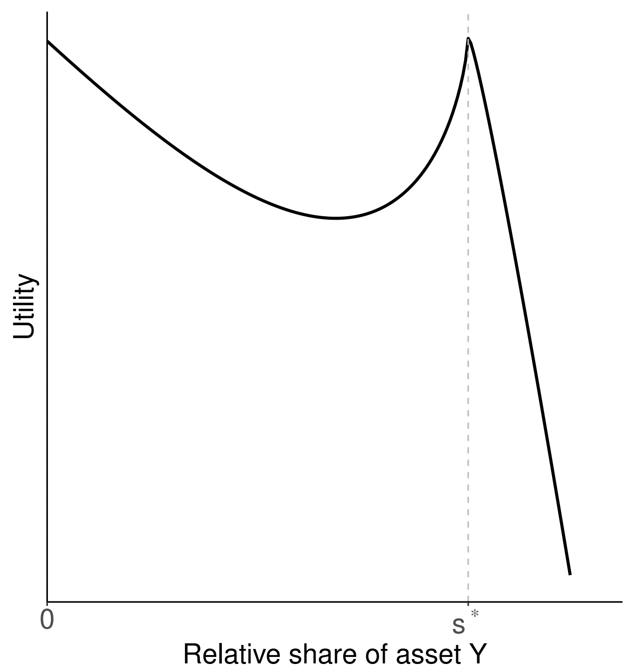


Figure 2: Prospect theory utility and portfolio share in the skewed asset

In a heterogeneous equilibrium, each investor will hold one of two possible portfolios. The first portfolio combines the risk-free asset Z and asset X but takes no position at all in asset Y. The second portfolio combines all three assets. The conditions for a heterogeneous equilibrium are the following:

$$V(\hat{r}_X) = 0 \tag{3}$$

$$V(\hat{r}_X + s^*\hat{r}_Y) = 0 \tag{4}$$

$$V(\hat{r}_X + s\hat{r}_Y) < 0 \text{ for } s \neq s^* \tag{5}$$

$$V(\hat{r}_Y) < 0 \tag{6}$$

where $\hat{r}_j \equiv r_j - r_f$ is the excess return on asset j. As shown in Appendix A.4, these conditions correspond to those derived in Barberis and Huang (2008) when applied to our setting. Condition (3) requires that the PT value of investing one dollar in asset X must be zero, otherwise, investors who hold the first portfolio will prefer to change their holdings of asset X. Condition (4) similarly requires that the PT value of investing one dollar in asset X and s^* dollars in asset Y must be zero, otherwise, investors who hold the second portfolio will prefer to change their holdings of assets X and Y. Condition (5) requires that s^* is the optimal fraction of wealth allocated to asset Y relative to the fraction of wealth allocated to asset X in the second equilibrium portfolio. Condition (6) requires that investing only in asset Y is a dominated option. Importantly, a heterogeneous equilibrium exists only if the aggregate supply of asset Y is below a threshold determined by s^* and asset prices. The reason is that if the aggregate supply is too large relative to the optimal fraction of wealth allocated to asset Y, it is not possible to clear the market at the optimal portfolio choices of the investors.

Following Barberis and Huang (2008) and using their preference parameters, we solve conditions (3), (4), (5) and (6) numerically for the case of our experiment parameters.[15] We find that only our treatments with a low supply of asset Y (NoSkew-L and Skew-L) admit a heterogeneous equilibrium.[16] In the NoSkew-L treatment, the heterogeneous equilibrium involves $r_X = 0.15$, $r_Y = 0.03$ and $s^* = 0.58$. Thus, in this treatment asset X earns positive expected returns and so does asset Y. This is not surprising because asset Y does not have a skewed payoff distribution. In the Skew-L treatment, the heterogeneous equilibrium involves $r_X = 0.15$, $r_Y = -0.04$ and $s^* = 0.16$. In this treatment, the skewness of asset Y results in a negative expected return.

Negative returns are a robust prediction of PT for a skewed asset in small supply. To

[15]The four conditions determine the expected excess returns of the risky assets in equilibrium. To back out the model's predictions about returns and prices we need to make an assumption about the return on the risk-free asset Z. We assume that $r_f = 0$ because there is no time-value of money in our experiment, as all monetary payoffs are realized at the same moment.

[16]Different types of equilibria may exist in the other treatments. For instance, in the NoSkew-H treatment, we find a homogeneous equilibrium where $r_X = r_Y = 0.1$. Using the parameters of the Skew-H treatment, we fail to find either a homogeneous or heterogeneous equilibrium.

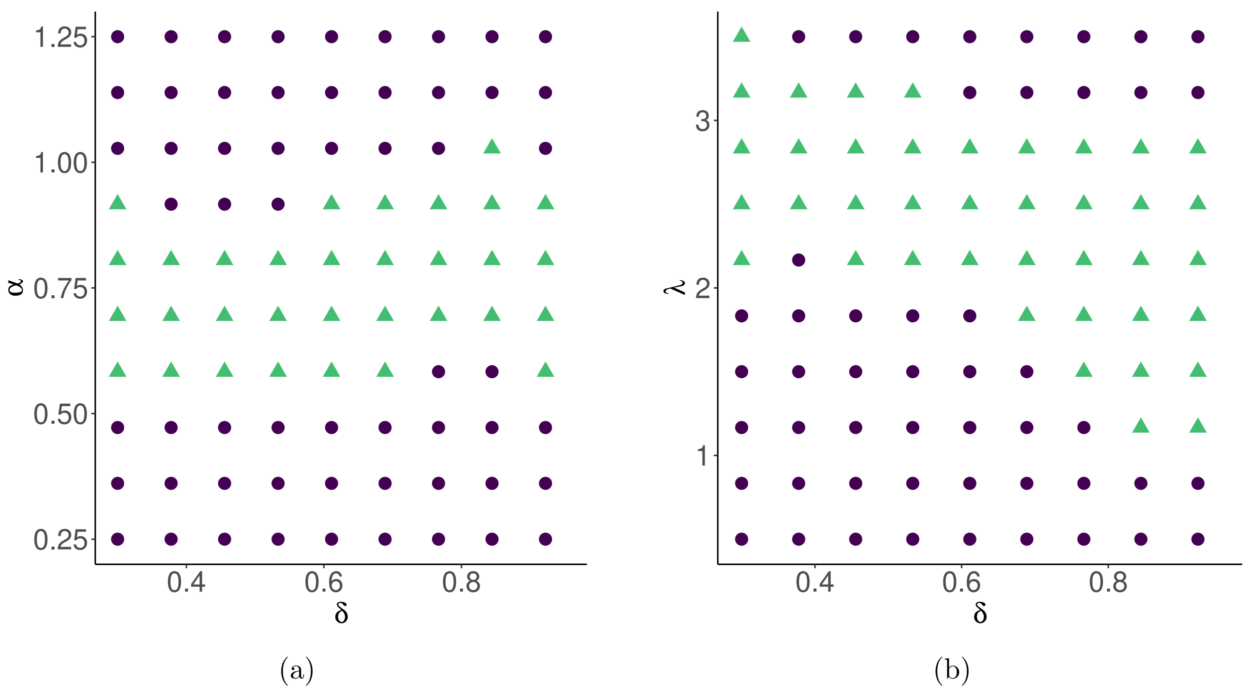


Figure 3: Prospect theory parameters and negative returns

Note: This figure shows whether an equilibrium with $E(r_Y) < 0$ exists in the low-supply treatment using the model of Barberis and Huang (2008). A triangle denotes that the equilibrium exists, a circle denotes that the equilibrium does not exist. We fix $\lambda = 2.25$ in panel (a) and $\alpha = 0.88$ in panel (b), which are the values used in Barberis and Huang (2008) and taken from Tversky and Kahneman (1992).

show this, we solve the model numerically for a broad range of combinations of preference parameters α, δ and λ that cover standard estimates found in the literature (Abdellaoui et al., 2008; Harrison and Rutström, 2009; Bruhin et al., 2010). Figure 3 shows the results. Under probability weighting ($\delta < 1$), an equilibrium where the skewed asset Y earns negative expected returns can be sustained in the low-supply treatment as long as diminishing sensitivity (α) and loss aversion (λ) take intermediate values. Importantly, none of these parameter combinations can sustain a heterogeneous equilibrium in the high-supply treatment.

PT also predicts that a stronger degree of probability weighting will result in a lower expected return of asset Y in the heterogeneous equilibrium of the Skewed-L treatment. To illustrate this prediction, we solve the model for different values of the parameter δ and plot the equilibrium $E(r_Y)$ in Figure 4. A lower δ, which implies a greater overweighting of small probabilities, results in a higher P_Y and thus lower (more negative) expected returns earned by asset Y.

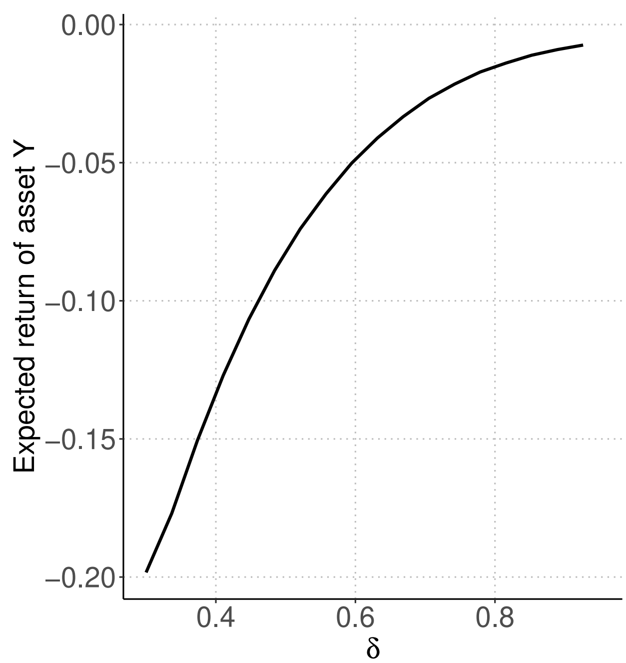


Figure 4: Probability weighting and expected returns

Note: This figure shows the effect of the probability weighting parameter δ on the expected return of asset Y in the treatment Skew-L using the model of Barberis and Huang (2008). We fix $\lambda = 2.25$ and $\alpha = 0.88$, which are the values used in Barberis and Huang (2008) and taken from Tversky and Kahneman (1992).

3.3 Other models of probability weighting

We have thus far focused on the PT model of Barberis and Huang (2008). However, other models incorporating probability weighting can produce similar predictions.

3.3.1 Π-CAPM

Driessen et al. (2021) propose an alternative approach for analyzing the effect of skewness on asset prices under probability weighting. In their model, dubbed Π-CAPM, investors have mean-variance preferences but weigh probabilities as in PT when computing the mean and variance of their final wealth. Using the Π-CAPM model of Driessen et al. (2021), it is possible to show that when the supply of asset Y is small, an increase in skewness will lead to a higher price of asset Y and may even lead to negative expected returns (depending on the other parameters of the model). In this respect, their model provides a similar prediction to Barberis and Huang (2008) for our experiment. A major difference from Barberis and Huang (2008) is that the Π-CAPM model yields a homogeneous equilibrium, rather than a heterogeneous equilibrium.

The representative Π-CAPM investor has preferences given by:

$$E^{\Pi}(W) - \gamma var^{\Pi}(W) \tag{7}$$

where $E^{\Pi}(W) \equiv \sum_i \pi_i W_i$ and $var^{\Pi}(W) \equiv \sum_i \pi_i [W_i - E^{\Pi}(W)]^2$. The W_i terms denote different realizations of final wealth and the π_i terms are decision weights. The decision weights are obtained from cumulative probabilities as before, but Driessen et al. (2021) assume the following probability weighting function:

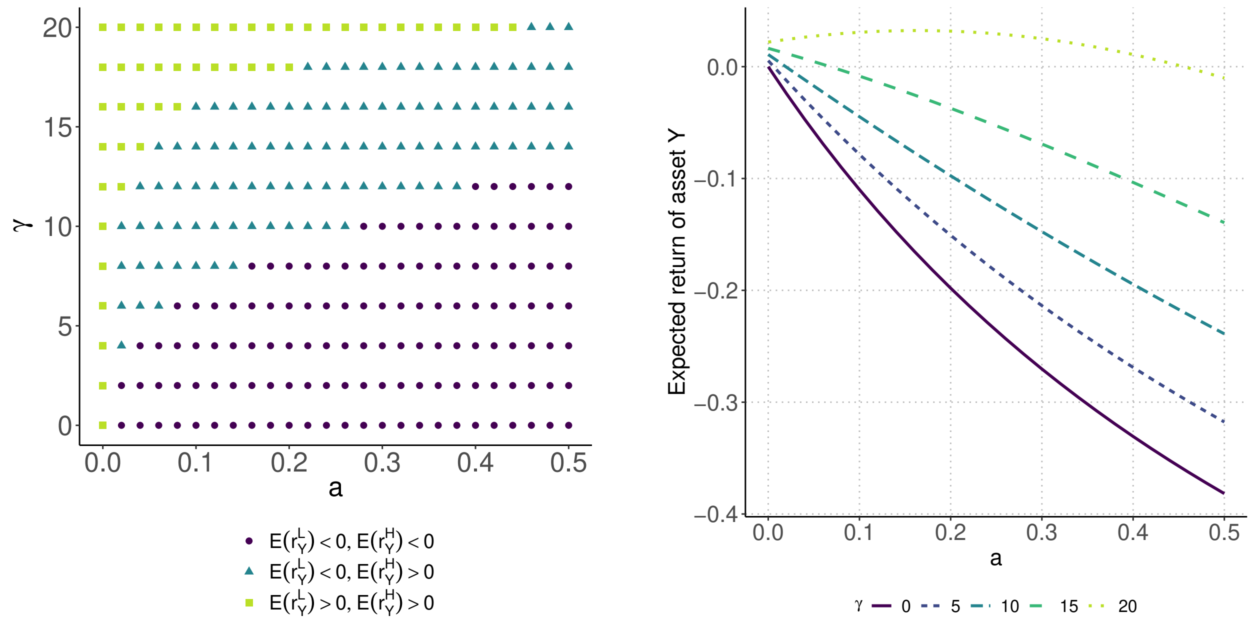
$$w(q) = \begin{cases} 0, & \text{if } q = 0 \\ (1-2a)q + a, & \text{if } 0 < q < 1 \\ 1, & \text{if } q = 1 \end{cases}$$

with $a \in [0, 0.5]$. Note that this probability weighting function also implies overweighting of small probabilities. A higher a parameter implies a larger overweighting of small probabilities, while the case $a = 0$ yields the CAPM. Following Driessen et al. (2021), the equilibrium price of skewed asset Y is given by:

$$P_Y(1+r_f) = \mu_Y + a\frac{S_Y}{\sigma_Y^3} - \gamma N_Y \left[\sigma_Y^2 + a(1-a)\frac{S_Y^2}{\sigma_Y^4}\right] - \gamma N_X a \frac{\sigma_X \sigma_Y}{\sqrt{q_Y(1-q_Y)}} \tag{8}$$

where q_Y is the probability that asset Y pays out the high payoff $d_Y = \overline{d}_Y$ and $S_Y \equiv$

$E[(d_Y - E(d_Y))^3]$.



(a) (b)

Figure 5: Predictions of the Π-CAPM model

Note: This figure illustrates the predictions of the model of Driessen et al. (2021) for our experiment. Panel (a) shows under which parameter combinations the skewed asset Y earns negative expected returns in markets with high or low supply: r_Y^L denotes the returns earned by asset Y in the treatment Skew-L, while r_Y^H denotes the returns earned by asset Y in the treatment Skew-H. Panel (b) shows the effect of the model parameters on the expected return of asset Y in treatment Skew-L. In both panels parameter γ is rescaled by multiplying it by 10000.

Using the pricing equation, we can analyze for which combinations of preference parameters γ and a the model predicts the skewed asset Y will earn negative returns in our experimental markets. We show the results in Figure 5a. As before, in the CAPM, i.e. when $a = 0$, asset Y earns positive returns. Under probability weighting, $a > 0$, negative returns can occur if the risk-aversion parameter γ is sufficiently low. Moreover, for intermediate values of γ, the model predicts asset Y will earn negative returns when its supply is small ($E(r_Y^L) < 0$) and positive returns when its supply is large ($E(r_Y^H) > 0$), an outcome that cannot occur under mean-variance-skewness preferences.

Finally, we examine the relationship between probability weighting and the expected returns of skewed asset Y predicted by the Π-CAPM model. We focus on the case where the supply of asset Y is small and compute $E(r_Y)$ for different values of the parameters a and γ. The results are shown in Figure 5b. In general, the effect of probability weighting on $E(r_Y)$ is non-monotonic. However, for low values of the risk-aversion parameter γ, stronger probability weighting leads to a lower expected return. Overall, the Π-CAPM model of

Driessen et al. (2021) provides qualitatively similar predictions as the original PT model of Barberis and Huang (2008) for the purpose of our experiment.

3.3.2 Rank-Dependent Utility

We also examine the pricing of skewed assets within a rank-dependent utility framework (RDU henceforth; Quiggin, 1982). As in PT, RDU incorporates probability weighting to investors' preferences; however, unlike PT, it does not include a reference point.

Under RDU, we show that when the supply of asset Y is small, an increase in skewness will lead to negative expected returns (see Appendix A.3). In this respect, RDU provides a similar prediction to Barberis and Huang (2008) for our experiment. A major difference from Barberis and Huang (2008) is that the RDU model yields a homogeneous equilibrium, rather than a heterogeneous equilibrium. Our results suggest that probability weighting is sufficient to produce negative returns of the skewed asset in low supply in the PT model of Barberis and Huang (2008), while loss aversion is a necessary ingredient for the existence of a heterogeneous equilibrium.

The representative RDU investor has preferences given by:

$$RDU(W) = \sum_{i=1}^{4} \pi_i u(W_i) \tag{9}$$

where W_i terms denote different realizations of final wealth, $u(.)$ is a concave utility function (e.g, x^α with $\alpha \in (0,1)$), and π_i terms are decision weights. The decision weights are obtained from cumulative probabilities as before. For the RDU specification to be well defined over final wealth (see e.g., Driessen et al., 2021), we assume a neo-additive probability weighting function:[17]

$$w(p) = (1-\rho)p + \frac{\rho - \eta}{2} \tag{10}$$

where $\rho \in (0,1)$ and $\eta \in (-\rho, \rho)$.

The parameters ρ and η are the indexes of insensitivity and pessimism (e.g, Abdellaoui et al., 2011). The insensitivity parameter produces an inverse S-shape in the probability weighting function (e.g, Gonzalez and Wu, 1999), and is our main parameter of interest when assessing the effect of probability weighting on the expected return of asset Y.

We solve the model numerically for a broad range of combinations of preference parame-

[17] The weights assigned to the two intermediate states, $(\overline{d}_X, \underline{d}_Y)$ and $(\underline{d}_X, \overline{d}_Y)$, depend on whether the final wealth in state $(\overline{d}_X, \underline{d}_Y)$ is greater or less than the final wealth in state $(\underline{d}_X, \overline{d}_Y)$. However, in our experiment, we do not know which intermediate state corresponds to higher wealth. Neo-additive weighting function has the particularity to provide weights for the two intermediate states that are independent to what state is associated with higher wealth (see e.g., Driessen et al., 2021).

ters α, η and ρ that cover standard estimates found in the literature (Abdellaoui et al., 2008; Harrison and Rutström, 2009; Bruhin et al., 2010). Figure 6 shows the results. In Figure 6a, we vary $\rho \in [0,1]$ and $\eta \in [-1,1]$, while keeping $\alpha = 0.88$ (Tversky and Kahneman, 1992). In figure 6b, we vary $\rho \in [0,1]$ and $\alpha \in [0.2,1]$, while keeping $\eta = 1/6$ (e.g, Gonzalez and Wu, 1999).[18] The values of all the other parameters $(N_X, N_Y, \overline{d}_X, \underline{d}_X, \overline{d}_Y, \underline{d}_Y, q)$ are directly taken from our experimental setup.

In the absence of probability weighting ($\eta = 0$ and $\rho = 0$), asset Y earns positive returns, reflecting the standard CAPM prediction (Figure 6a).

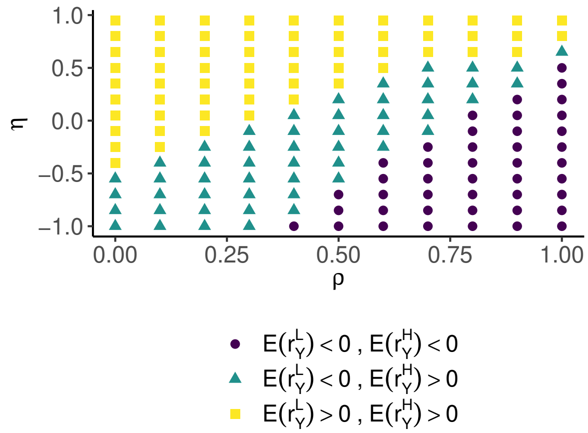
Under probability weighting, $\rho \neq 0$ and $\eta \neq 0$, asset Y can yield negative returns if the likelihood-insensitivity parameter ρ is high and/or the pessimism parameter η is low (Figure 6a). Importantly, for a set of parameter values that have been validated empirically ($\alpha = 0.88, \rho = 1/2, \eta = 1/6$; Tversky and Kahneman, 1992; Gonzalez and Wu, 1999), the model predicts asset Y will earn negative returns when its supply is small ($E(r_Y^L) < 0$) and positive returns when its supply is large ($E(r_Y^H) > 0$) (Figure 6a). Interestingly, we note that in the presence of probability weighting, asset Y can only produce negative returns if the utility function is not too concave (Figure 6b).

RDU also predicts that a stronger degree of probability weighting will result in a lower expected return of asset Y. To illustrate this prediction, we solve the model for different values of the insensitivity parameter ρ and pessimism parameter η, and plot the equilibrium value of $E(r_Y)$ in Figure 7. A higher insensitivity ρ and/or a lower pessimism η, which implies a greater overweighting of small probabilities, results in a higher P_Y and thus lower (more negative) expected returns earned by asset Y.

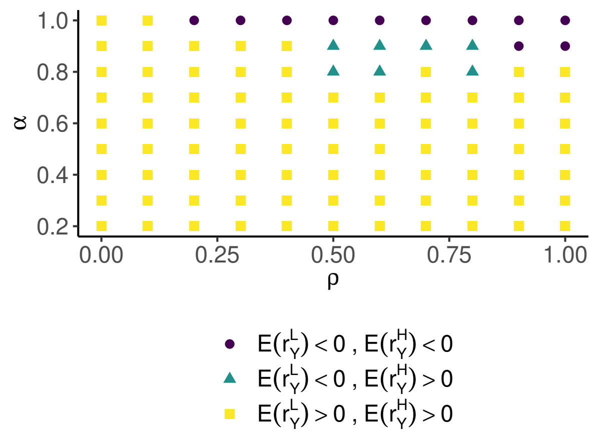
Finally, under RDU, only a homogeneous equilibrium exists in our experimental setup. Due to the absence of loss aversion, an infinitesimal supply of a skewed asset tends to be systematically overpriced, as RDU valuation of final wealth is increasing and concave over small supplies of the skewed asset. This rules out the possibility of an equilibrium with nonunique (heterogeneous) global optima in which some RDU decision-makers do not hold skewed assets.[19]

[18]For the weighting function, a pessimism index of $\eta = \frac{1}{6}$ and an insensitivity index of $\rho = \frac{1}{2}$ yield a crossing-over point at $p = \frac{1}{3} = w\left(\frac{1}{3}\right)$, consistent with the standard findings in the literature (e.g., Gonzalez and Wu, 1999).

[19]More generally, under RDU, the valuation of final wealth remains concave in the supply of skewed assets, leading to an equilibrium with a unique (homogeneous) global optimum. By contrast, in PT models, the presence of loss aversion implies that the valuation of final wealth, relative to a reference point, can be decreasing and convex when the skewed asset is in small supply thus leading to underpricing. This supports the possibility of an equilibrium with nonunique (heterogeneous) global optima as in Barberis and Huang (2008).



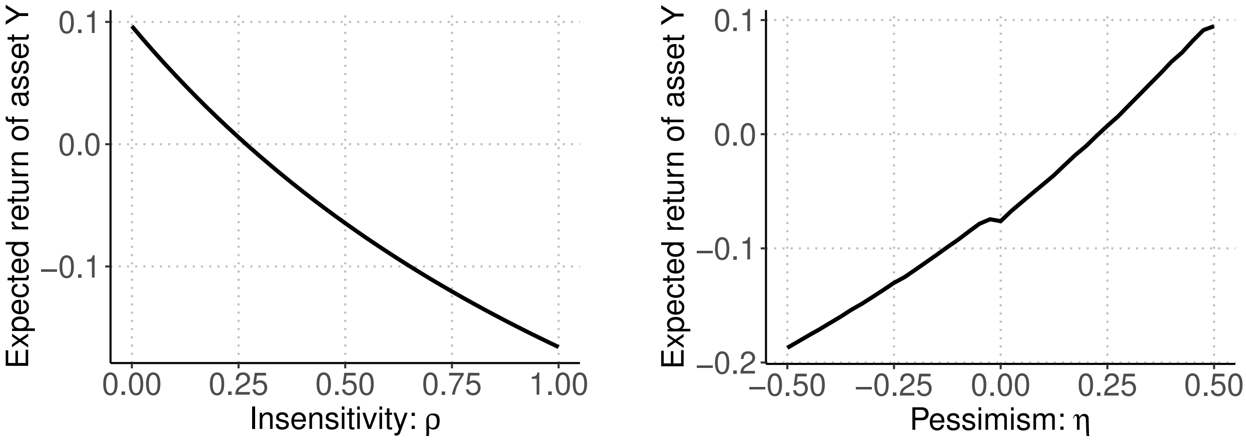
(a)



(b)

Figure 6: Predictions of the RDU

Note: This figure illustrates the predictions of RDU for our experiment. Panel (a) shows, for $\alpha = 0.88$ following Tversky and Kahneman (1992) and Barberis and Huang (2008), the parameter combinations (η, ρ) of the probability weighting function for which the skewed asset Y earns negative expected returns in markets with high or low supply: r_Y^L denotes the returns earned by asset Y in the treatment Skew-L, while r_Y^H denotes the returns earned by asset Y in the treatment Skew-H. Panel (b) shows, for $\eta = 1/6$, the parameter combinations of utility curvature (α) and insensitivity (ρ) for which the skewed asset Y earns negative expected returns. The values of all the other parameters $(N_X, N_Y, \overline{d}_X, \underline{d}_X, \overline{d}_Y, \underline{d}_Y, q)$ are directly taken from our experimental setup.



(a) (b)

Figure 7: Probability weighting and expected returns

Note: This figure shows the effect of the probability weighting parameters (ρ, η) on the expected return of asset Y in the treatment Skew-L under RDU. We fix $\alpha = 0.88$ following Tversky and Kahneman (1992) and Barberis and Huang (2008). In Panel (a), we set pessimism at $\eta = 1/6$ and vary insensitivity ρ. In Panel (b), we set insensitivity at $\rho = 1/2$ and vary pessimism $\eta \in (-\rho, \rho) = (-1/2, 1/2)$. The specific combination $(\rho, \eta) = (1/2, 1/6)$ leads to a crossing-over point at $p = 1/3 = w(1/3)$, which is consistent with standard results in the literature (Gonzalez and Wu, 1999). The values of all the other parameters $(N_X, N_Y, \overline{d}_X, \underline{d}_X, \overline{d}_Y, \underline{d}_Y, q)$ are directly taken from our experimental setup.

3.4 Hypotheses

We summarize the implications of EUT and probability weighting models regarding the pricing of the skewed asset in our experimental design in three hypotheses. In the first hypothesis, we establish a prediction that is common to all models accounting for asset skewness. According to all these models, the positively skewed asset should be priced higher than the non-skewed asset, regardless of the relative supply of the assets.

Hypothesis 1. ***(Skewness & Asset Prices)***
Asset Y will earn lower expected returns in the Skew than in the NoSkew treatments, whether its supply is low or high.

Next, we consider specific predictions of each type of model. In particular, EUT models imply that the return of the skewed asset is expected to be positive when in small supply (see Figure 1). More specifically, as shown in Section 3.1, a third-order approximation of expected utility implies that the return on the skewed asset cannot be negative when in small supply if it is positive when in high supply. If rejected, our hypothesis leads to a falsification of EUT. We state this prediction in Hypothesis 2 below.

Hypothesis 2. ***(EUT & Skewness)***
The expected return on asset Y will not be negative in Skew-L if it is positive in Skew-H.

By contrast with EUT models, in a plausible range of the preference-parameter space, PT predicts that the expected return of the skewed asset will be negative when in small supply (see Figures 3 and 5a). A similar prediction is obtained for the two other models of probability weighting (Π-CAPM and RDU, see Section 3.3). We summarize this prediction in Hypothesis 3*i*. This prediction follows from the PT model of Barberis and Huang (2008) as well as from Π-CAPM and RDU.

In Hypothesis 3*ii*, we go one step beyond establishing the consistency of our data with PT models by directly testing their underlying mechanism. To that end, we test the prediction that the return of the skewed asset, when in small supply, will decrease when market participants exhibit higher degrees of overweighting of small probabilities (see Figures 4, 5b and 7).

Hypothesis 3. ***(Probability Weighting & Skewness)***
i) The expected return on asset Y will be negative in Skew-L, even if it is positive in Skew-H.
ii) The expected return on asset Y will be lower in markets in which the overweighting of small probabilities is more pronounced.

4 Results

4.1 Asset Returns

We begin our empirical analysis by noting some broad patterns in expected returns across securities. We compute asset prices at the market period level, by taking the average of the transaction prices across all trades in a period (each trade is for one unit). We then compute the expected return for asset $i \in \{X, Y, Z\}$ in period n of session s as: $E(r_{isn}) \equiv \frac{E(d_i)}{P_{isn}} - 1$, where P_{isn} is the price of asset i in period n of session s and d_i is the payoff of asset i. Figure 8 shows the means and 95% confidence intervals of the expected returns earned by the three assets for all the treatments. In the NoSkew-H treatment, where assets X and Y have the same non-skewed marginal distribution of payoffs and the same aggregate supply, they earn similar expected returns, equal to 24% on average (p-value = 0.78 using a paired Wilcoxon signed rank test). This is reassuring and consistent with all the models.

In all other treatments, where asset Y has either a more skewed distribution or a lower supply than asset X, Y earns lower returns than X (p-values < 0.001 using paired Wilcoxon signed rank tests for each of these treatments). We also note that the risk-free asset Z

earns small but positive returns in line with previous CAPM experiments (e.g., Bossaerts and Plott, 2004).[20]

In the next section, we directly test our three hypotheses.

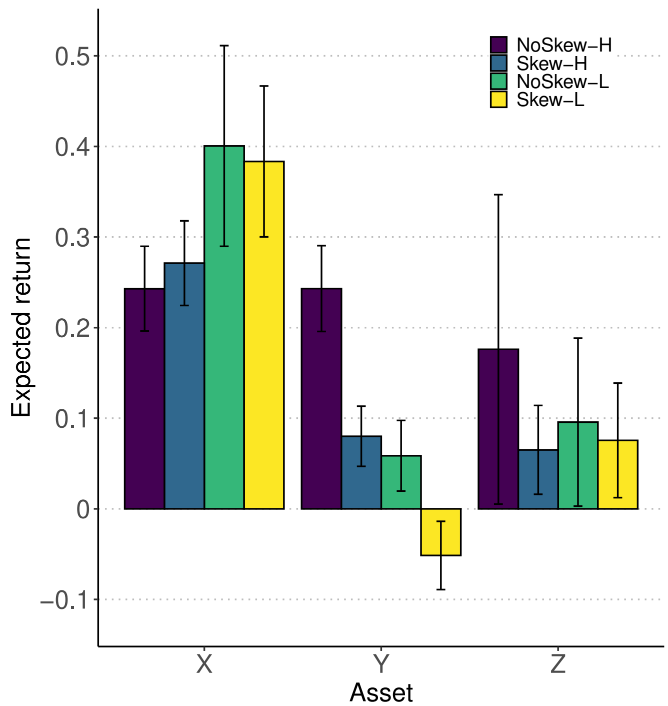


Figure 8: Expected returns (means and 95% CI)

4.2 Tests of the Hypotheses

We proceed by testing our hypotheses using the following regression specification:

$$\boldsymbol{r}_{Ysn} = \beta_0 + \beta_1 \boldsymbol{Skew\_L}_{sn} + \beta_2 \boldsymbol{Skew\_H}_{sn} + \beta_3 \boldsymbol{NoSkew\_L}_{sn} + \eta_s + \epsilon_{sn} \tag{11}$$

where $\boldsymbol{r}_{Ysn}$ is the expected return earned by asset Y in period n of session s. The variables $\boldsymbol{Skew\_L}$, $\boldsymbol{Skew\_H}$, and $\boldsymbol{NoSkew\_L}$ are indicators for the corresponding treatments. We denote by η_s session random effects, and by ϵ_{sn} the error term, which is clustered at the session level. Column (1) of Table 5 shows the estimation results for this regression.

[20] This result likely reflects people's willingness to borrow in order to execute trades in other assets.

Dependent variable	Asset Y return		
	(1)	(2)	(3)
Skew-L	-0.29***	-0.94***	-0.94***
	(0.03)	(0.31)	(0.31)
Skew-H	-0.16***	-0.29	-0.29
	(0.03)	(0.34)	(0.35)
NoSkew-L	-0.18***	-0.54	-0.54
	(0.04)	(0.41)	(0.42)
δ		-0.53	-0.75
		(0.83)	(0.80)
Skew-L $\times$ δ		1.30**	1.30**
		(0.56)	(0.57)
Skew-H $\times$ δ		0.29	0.29
		(0.65)	(0.66)
NoSkew-L $\times$ δ		0.74	0.74
		(0.76)	(0.77)
Period		-0.01	-0.01
		(0.00)	(0.00)
α			0.08
			(0.30)
CRT			-0.01
			(0.03)
Financial literacy			-0.12
			(0.08)
Gender (% women)			0.14
			(0.22)
Constant	0.24***	0.55	0.86
	(0.05)	(0.41)	(0.67)
p-value: Skew-L vs NoSkew-L	<0.001	0.072	0.076
p-value: Skew-H vs NoSkew-H	<0.001	0.743	0.746
p-value: Skew-L + Constant = 0	0.034	0.253	0.857
p-value: Skew-H + Constant = 0	0.001	0.524	0.254
p-value: Skew-L $\times$ δ vs NoSkew-L $\times$ δ		0.197	0.157
p-value: Skew-H $\times$ δ vs NoSkew-H $\times$ δ		0.930	0.931
N	169	169	169

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Asset Y return and probability weighting

Results for Hypothesis 1. Asset Y earns lower returns on average in the Skew treatments than in the NoSkew treatments, whether its supply is low or high. The returns of asset Y decrease significantly from 6% in the NoSkew-L treatment to -5% in the Skew-L treatment (Coefficient test: Skew-L vs NoSkew-L, p-value < 0.001, see bottom of Table 5 for regression

(1)). Similarly, returns for asset Y decrease significantly from 24% in NoSkew-H to 8% in Skew-H (Coefficient test: Skew-H vs NoSkew-H, p-value < 0.001, see regression (1)). Overall, our data support Hypothesis 1 according to which asset Y will earn lower returns in Skew treatments.

Results for Hypotheses 2 and 3*i*. In contrast with our second hypothesis, the return on asset Y is negative and significant in Skew-L (-5%, Coefficient test: Skew-L + Constant = 0, p-value = 0.034, see bottom of Table 5 for regression (1)) while being positive and significant in Skew-H (8%, Coefficient test: Skew-H + Constant = 0, p-value = 0.001).[21]

Our results are inconsistent with the asset pricing predictions derived from a third-order approximation of expected utility, the mean-variance-skewnes model, leading us to reject Hypothesis 2. Instead, this finding is consistent with PT models and other probability weighting models, as summarized in Hypothesis 3*i*.

Results for Hypothesis 3*ii* To test for the effect of probability weighting on returns, we first estimate the degree of probability weighting for each participant using data on multiple-price list choices. Our main approach is to estimate the parametric specification of the probability weighting function used in Tversky and Kahneman (1992) and Barberis and Huang (2008):

$$w(q) = \frac{q^\delta}{[q^\delta + (1-q)^\delta]^{1/\delta}}$$

The probability weighting parameter δ is estimated jointly with the diminishing sensitivity parameter α. The estimation procedure is further discussed in Appendix B.

To obtain an index of probability weighting at the market level, we then take the median value of the individual estimates in a given session. We use the median δ because it is largely unaffected by the presence of individual outliers, but our results are qualitatively similar if we adopt alternative measures such as using the average δ of a session. Our session-level measures of probability weighting range between 0.44 and 0.59 (see Table 7 in Appendix B). To illustrate the patterns in probability weighting implied by these estimates, we plot the probability weighting functions for all the thirteen experimental sessions in Figure 9. In line with PT assumptions and previous estimates (Quiggin, 1982; Tversky and Kahneman, 1992; Prelec, 1998; Gonzalez and Wu, 1999; Abdellaoui, 2000; Bruhin et al., 2010; l'Haridon and Vieider, 2019), probabilities under 0.3 are systematically overweighted while larger probabilities are underweighted leading to an inverse S-shaped probability weighting

[21] Furthermore, the proportion of periods in which asset Y earns negative expected returns is significantly higher in the Skew-L treatment (66.7%) compared to the Skew-H treatment (17.9%) (Mann-Whitney test, p-value< 0.001).

function. We also observe heterogeneity in probability weighting across sessions, allowing us to test Hypothesis 3*ii*.

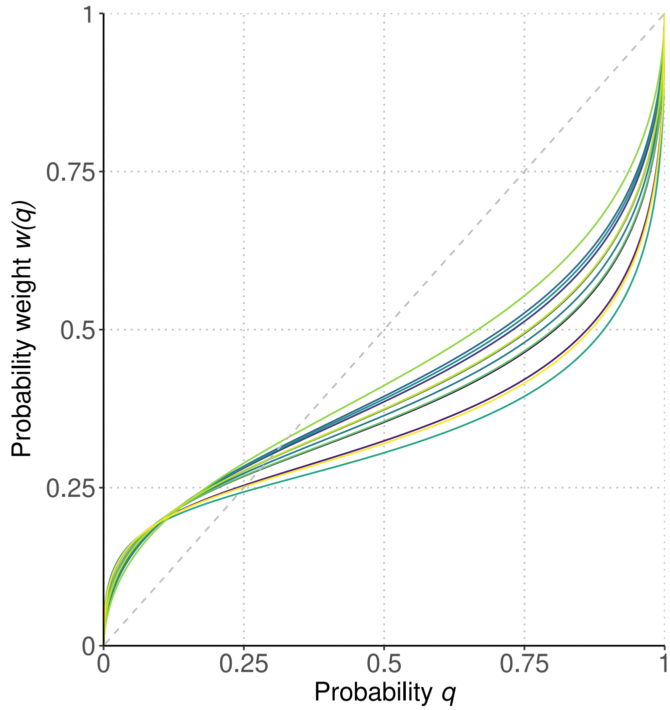
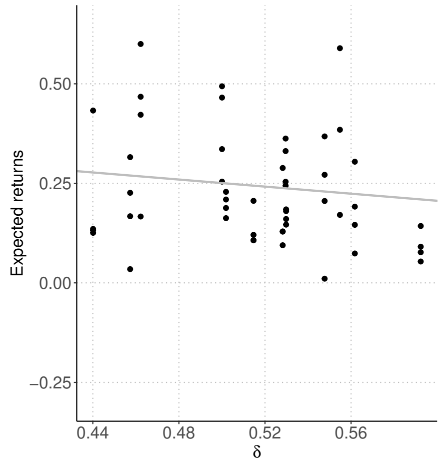
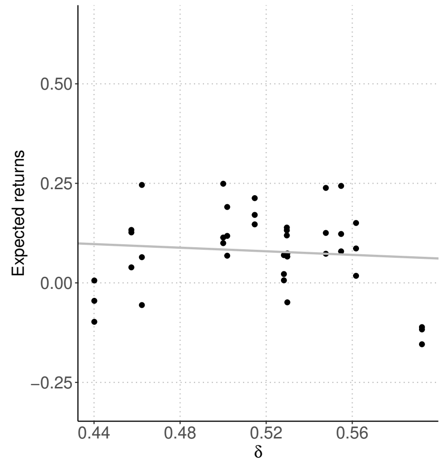


Figure 9: Estimated probability weighting functions

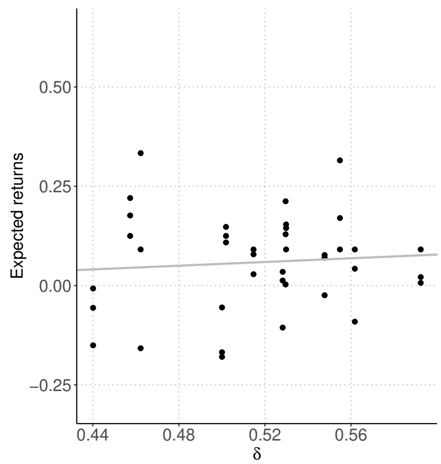
Note: This figure plots the probability weighting functions for all the thirteen experimental sessions. Each curve is the graph of the function $w(q) = \frac{q^\delta}{[q^\delta+(1-q)^\delta]^{1/\delta}}$ where δ is the session-level median of the individual δ estimates.



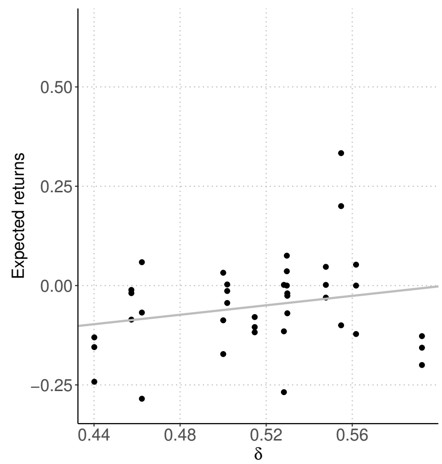
(a) NoSkew-H



(b) Skew-H



(c) NoSkew-L



(d) Skew-L

Figure 10: Returns of asset Y and probability weighting

Note: Each panel of this figure is a scatter plot of the session- and period-level expected return of asset Y against the session-level median probability weighting parameter δ. The grey line is a regression line.

In line with Hypothesis $3ii$, our data show that the more traders overweight small probabilities in a session, that is the lower the session median δ, the more negative is the return of asset Y in treatment Skew-L. This is illustrated in Figure 10, where we plot the expected returns earned by asset Y against the session-level probability weighting index. To formally test Hypothesis $3ii$, we use an augmented version of our previous regression specification in equation (11):

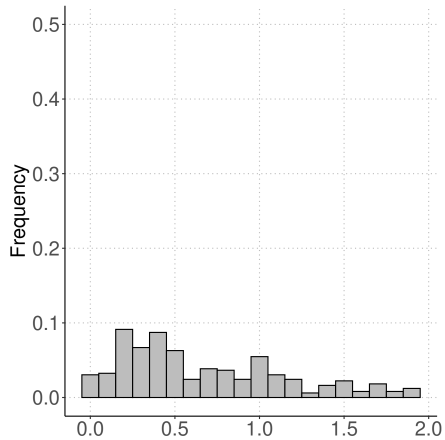
$$
\begin{aligned}
\boldsymbol{r}_{Ysn} = & \beta_0 + \beta_1 \boldsymbol{Skew\_L}_{sn} + \beta_2 \boldsymbol{Skew\_H}_{sn} + \beta_3 \boldsymbol{NoSkew\_L}_{sn} + \beta_4 \boldsymbol{\delta}_{sn} + \\
& \beta_5 \boldsymbol{Skew\_L}_{sn} \times \boldsymbol{\delta}_{sn} + \beta_6 \boldsymbol{Skew\_H}_{sn} \times \boldsymbol{\delta}_{sn} + \beta_7 \boldsymbol{NoSkew\_L}_{sn} \times \boldsymbol{\delta}_{sn} + \\
& \beta_8 \boldsymbol{Period}_{sn} + \beta_9 \boldsymbol{C}_{sn} + \eta_s + \epsilon_{sn}
\end{aligned} \tag{12}
$$

This specification includes the session-level index of probability weighting $\boldsymbol{\delta}$ and its interactions with the treatment indicators. We also control for period number ($\boldsymbol{Period}$), and a vector of session controls ($\boldsymbol{C}$) obtained by aggregating individual characteristics of the participants in a session. We control for the period number to assess any potential effects of learning during the experiment, as experimental markets often show that mispricing tends to decrease with repeated experiments (Smith et al., 1988; Dufwenberg et al., 2005; Haruvy et al., 2007; Palan, 2013). The vector of session controls include risk sensitivity (α), CRT and financial literacy. We include variables that capture traders' cognitive abilities and financial knowledge, as evidence suggests that experimental markets with traders scoring high on these dimensions typically exhibit lower levels of mispricing (see review in Bosch-Rosa and Corgnet, 2022). We also include gender, which has also been shown to impact pricing in previous experimental asset markets (Cueva and Rustichini, 2015; Eckel and Füllbrunn, 2015). All these variables are calculated as the median of individual values in each session. The controls also include the gender composition of the market, defined as the proportion of women in each session.

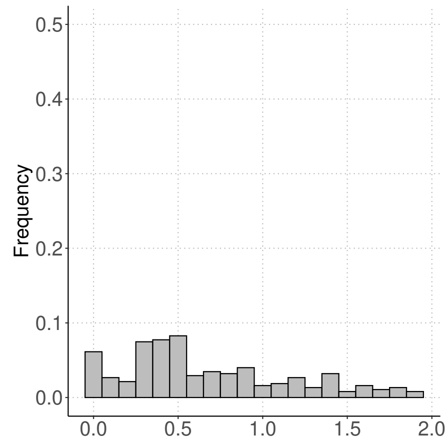
We show the estimation results in columns (2) and (3) of Table 5. The coefficient on $\boldsymbol{Skew\_L} \times \boldsymbol{\delta}$ is positive and significant, implying that more overweighting (lower δ) leads to lower returns. The fact that the interaction term $\boldsymbol{Skew\_H} \times \boldsymbol{\delta}$ is not significant is consistent with our hypothesis, which is derived from the case studied in Barberis and Huang (2008) where the supply of the skewed asset is low. In line with PT, the interaction term is not significant when the Y asset is not skewed ($\boldsymbol{NoSkew\_L} \times \boldsymbol{\delta}$). In Appendix D, we report additional robustness checks using alternative measures of probability weighting at the session level, rather than the median of individual estimates. We also use a semi-parametric estimation of probability weights following the method proposed by Kpegli et al. (2023). These robustness checks confirm our previous results. Overall, our results support PT predictions captured in Hypotheses $3i$ and $3ii$.

4.3 Portfolio holdings

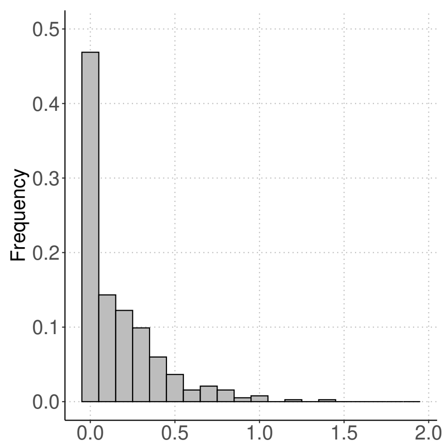
While our main focus is on testing predictions about asset prices, the alternative theories we discussed above also provide distinct implications regarding the composition of individual



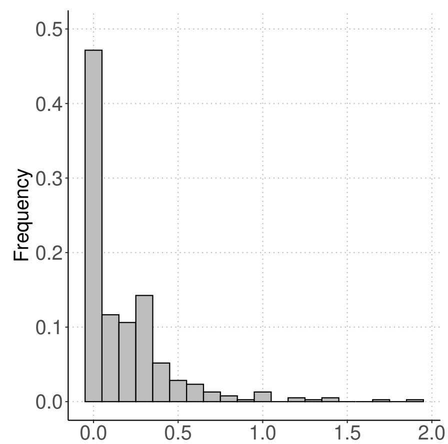
(a) NoSkew-H



(b) Skew-H



(c) NoSKew-L



(d) Skew-L

Figure 11: Histograms of the portfolio share in Y relative to X across treatments

portfolios. Assuming investors have identical preferences, both the CAPM and the mean-variance-skewness model predict all investors will hold the same portfolio of risky assets, i.e. the market portfolio. This prediction is robust to preference heterogeneity in the CAPM, while individual differences in preferences can lead to heterogeneity in portfolio holdings according to the mean-variance-skewness model (see for example Mitton and Vorkink, 2007). A distinct prediction of the prospect theory model of Barberis and Huang (2008) is that, as shown in Section 3.2, investors in the Skew-L and NoSkew-L treatments will hold one of two candidates portfolios: the first one includes both assets X and Y, while the second takes no position at all in asset Y. We refer to an allocation with no holdings of asset Y as a corner portfolio.

We analyze data on portfolio composition by computing the final portfolio share in asset Y relative to asset X attained by each trader i at the end of each market period (i.e. $s_i \equiv \frac{P_Y n_{Yi}}{P_X n_{Xi}}$). In computing these portfolio shares we evaluate asset holdings at the average prices in the period. Figure 11 plots the distribution of the relative portfolio share in Y across our four treatments. We observe large differences in the frequency of corner portfolios across treatments. Corner portfolios represent only 3% and 6% of the portfolios in NoSkew-H and Skew-H while representing 47% of final portfolios in each of the low-supply treatments. We test whether these differences are statistically significant using Mann-Whitney tests. We treat the period-level proportions of corner portfolios as observations. For each skewness level, the difference between the low-supply and high-supply treatments is statistically significant (all p-values < 0.001). This finding is qualitatively consistent with the prospect theory model of Barberis and Huang (2008).

Restricting attention to portfolios that invest a positive share in both risky assets, Figure 11 shows that there is a large heterogeneity in final asset holdings in every treatment. Such variability is consistent with previous market experiments and reflects unobserved heterogeneity in preferences or decision-making noise (see Bossaerts et al., 2007). Our experiment allows us test how such variability in asset positions varies with skewness in asset payoffs. We find that the standard deviation in the relative share of asset Y is 2.4 in Skew-H, 2.1 in NoSkew-H, 0.352 in Skew-L and 0.229 in NoSkew-L. For each supply level, the difference between the Skew and NoSkew treatments is statistically significant, using Mann-Whitney tests on period-level standard deviations (p-value < 0.001 for the high supply treatments and p-value$= 0.005$ for the low supply treatments). Thus, skewness in asset payoffs increases portfolio heterogeneity.

5 Conclusion

A new wave of asset pricing models has emerged in recent years featuring probability weighting to account for numerous financial anomalies. These models extend both the standard CAPM and its variant based on mean-variance-skewness preferences. In line with both EUT and probability weighting models featuring skewness pricing, we find that skewed assets systematically earn lower returns.

By taking advantage of our experimental setup, which varies both the level of skewness of risky assets and their relative supply, we proceed to test the distinct predictions of the competing models. In particular, we show that the negative return of skewed assets in low supply is incompatible with EUT models, while it is consistent with PT models and, more generally, with models incorporating probability weighting.

Furthermore, we directly show that probability weighting plays a critical role in explaining the negative returns of skewed assets. Direct evidence on the underlying mechanisms helps rule out potential alternative explanations, such as those suggesting that skewness is priced because it changes the likelihood of incurring a loss (Holzmeister et al., 2020). These results are important because a necessary condition for the widespread adoption of an alternative model to CAPM is evidence of their underlying behavioral mechanism (Hirshleifer, 2015). Absent this evidence, it would be difficult to discriminate between potentially countless alternative models.

Prospect theory not only explains asset prices across our treatments, but it is also qualitatively consistent with the incidence of corner solutions in the traders' portfolio choices. However, data on portfolio holdings reveal a degree of individual heterogeneity that is difficult to reconcile with homogeneous preferences. This fact suggests that it will be critical to develop models with heterogeneous prospect theory preferences. One promising approach could be to adapt the noisy demand approach of Bossaerts et al. (2007) to prospect theory.

We hope our study will stimulate a new wave of empirical research that tests the precise and distinct implications of behavioral models.

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Appendix

A Proofs

A.1 CAPM

Assume the representative investor has utility:

$$U(W) = E(W) - \frac{1}{2}\gamma var(W)$$

Denoting by n_j the demand of asset $j \in \{X, Y\}$, final wealth is:

$$W = R_f \times (W^0 - n_X P_X - n_Y P_Y) + n_X d_X + n_Y d_Y$$

where $R_f = 1 + r_f$.

Using the fact that the two assets are independent, utility can be rewritten as:

$$U(W) = W^0 R_f + n_X(\mu_X - P_X R_f) + n_Y(\mu_Y - P_Y R_f) - \frac{1}{2}\gamma n_X^2 \sigma_X^2 - \frac{1}{2}\gamma n_Y^2 \sigma_Y^2$$

The first-order condition for n_j is:

$$\mu_j - P_j R_f - \gamma n_j \sigma_j^2 = 0$$

Denoting by N_j the aggregate supply of asset j, the equilibrium price of asset j is:

$$P_j = \frac{\mu_j - \gamma N_j \sigma_j^2}{R_f}$$

Finally, the expected return on asset j is:

$$E(r_j) \equiv \frac{\mu_j - P_j}{P_j} = \frac{\mu_j r_f + \gamma N_j \sigma_j^2}{\mu_j - \gamma N_j \sigma_j^2}$$

A.2 Mean-Variance-Skewness model

Assume the representative investor has utility:

$$U(W) = E(W) - \frac{1}{2}\phi_v var(W) + \frac{1}{3}\phi_s S(W)$$

where $\phi_v > 0$ and $\phi_s > 0$ capture variance aversion and skewness seeking, and $S(W) \equiv E[(W - E(W))^3]$.

Denoting by n_j the demand of asset $j \in \{X, Y\}$, final wealth is:

$$W = R_f \times (W^0 - n_X P_X - n_Y P_Y) + n_X d_X + n_Y d_Y$$

Using the facts that the two assets are independent and the skewness of asset X is zero, utility can be rewritten as:

$$U(W) = W^0 R_f + n_X(\mu_X - P_X R_f) + n_Y(\mu_Y - P_Y R_f) - \frac{1}{2}\phi_v n_X^2 \sigma_X^2 - \frac{1}{2}\phi_v n_Y^2 \sigma_Y^2 + \frac{1}{3}\phi_s S_Y n_Y^3$$

where $S_Y \equiv E[(d_Y - E(d_Y))^3$.

The first-order condition for n_Y is:

$$\mu_Y - P_Y R_f - \phi_v n_Y \sigma_Y^2 + \phi_s S_Y n_Y^2 = 0$$

Denoting by N_Y the aggregate supply of asset Y, the equilibrium price of asset Y is:

$$P_Y = \frac{\mu_Y - \phi_v N_Y \sigma_Y^2 + \phi_s S_Y N_Y^2}{R_f}$$

Finally, the expected return on asset Y is:

$$E(r_Y) = \frac{r_f \mu_Y + \phi_v \sigma_Y^2 N_Y - \phi_s S_Y N_Y^2}{\mu_Y - \phi_v \sigma_Y^2 N_Y + \phi_s S_Y N_Y^2}$$

Using these expressions we can prove the following theorem.

Theorem 1. *If skewed asset Y earns positive returns when its supply is large, then it cannot earn negative returns when its supply is small*

Proof. Denote by $\rho(n)$ the expected return on asset Y as a function of the asset's aggregate supply:

$$\rho(n) \equiv \frac{r_f \mu_Y + \phi_v \sigma_Y^2 n - \phi_s S_Y n^2}{\mu_Y - \phi_v \sigma_Y^2 n + \phi_s S_Y n^2}$$

From this expression it is easy to see that:

$$\rho(0) = r_f \geq 0 \tag{13}$$

Moreover, the first derivative of $\rho(n)$ is:

$$\frac{d\rho(n)}{dn} = \frac{\mu_Y(r_f+1)\left(\phi_v\sigma_Y^2 - 2\phi_s S_Y n\right)}{\left[\mu_Y - \phi_v\sigma_Y^2 n + \phi_s S_Y n^2\right]^2}$$

Then we have:

$$\frac{d\rho(n)}{dn} \geq 0 \Leftrightarrow n \leq \frac{\phi_v\sigma_Y^2}{2\phi_s S_Y} \equiv \hat{n} \tag{14}$$

Now consider two supply levels $n^H > n^L$ and $\rho(n^H) > 0$.

Consider the case where $n^L < \hat{n}$. Because of (13) and (14), $\rho(n) > 0 \forall n \in [0, \hat{n}]$. So $\rho(n^L) > 0$.

Next consider the case where $\hat{n} < n^L < n^H$. Because of (14), function $\rho(n)$ is decreasing in this interval. So, $\rho(n^L) > \rho(n^H)$. Since $\rho(n^H) > 0$, it must also be $\rho(n^L) > 0$. □

A.3 RDU model

The no-skewed and skewed assets X and Y are given by: $Y = (\overline{d}_Y, \underline{d}_Y; q, 1-q)$ and $X = (\overline{d}_X, \underline{d}_X; 0.5, 0.5)$. The final wealth W is given by

$$W = (W_1, 0.5(1-q); W_2, 0.5(1-q); W_3, 0.5q; W_4, 0.5q)$$

with

$$W_1 = (W^0 - n_X P_X - n_Y P_Y)(1+r_f) + n_X \underline{d}_X + n_y \underline{d}_Y$$

$$W_2 = (W^0 - n_X P_X - n_Y P_Y)(1+r_f) + n_X \overline{d}_X + n_y \underline{d}_Y$$

$$W_3 = (W^0 - n_X P_X - n_Y P_Y)(1+r_f) + n_X \underline{d}_X + n_y \overline{d}_Y$$

$$W_4 = (W^0 - n_X P_X - n_Y P_Y)(1+r_f) + n_X \overline{d}_X + n_y \overline{d}_Y$$

RDU investor evaluates the final wealth as follows:

$$RDU(W) = \sum_{i=1}^{4} \pi_i u(W_i)$$

with $\pi_1 = 1 - 0.5(1-\rho)(1+q) - \frac{\rho-\eta}{2}$, $\pi_2 = 0.5(1-\rho)(1-q)$, $\pi_3 = 0.5(1-\rho)q$, and $\pi_4 = 0.5(1-\rho)q + \frac{\rho-\eta}{2}$.

Theorem 2. *Assume RDU investor exhibits $w(q) > q$, $w(0.5) \leq 0.5$, and concave utility function. Hence, when the supply of asset Y is small, an increase in skewness (small q) will lead to negative expected returns.*

Proof. The first-order conditions for n_X and n_Y are:

$$\frac{\partial RDU}{\partial n_X} = (\overline{d}_X - P_X(1+r_f))\left[\pi_4 u'(W_4) + \pi_2 u'(W_2)\right] + (\underline{d}_X - P_X R_f)\left[\pi_3 u'(W_3) + \pi_1 u'(W_1)\right] = 0$$

$$\frac{\partial RDU}{\partial n_Y} = (\overline{d}_Y - P_Y(1+r_f))\left[\pi_4 u'(W_4) + \pi_3 u'(W_3)\right] + (\underline{d}_Y - P_Y R_f)\left[\pi_2 u'(W_2) + \pi_1 u'(W_1)\right] = 0$$

At the equilibrium where $n_X = N_X$ and $n_Y = N_Y$, from first-order conditions, the prices of assets X and Y satisfied the equations:

$$P_X(1+r_f) = \frac{\overline{d}_X\left[\pi_4 u'(W_4) + \pi_2 u'(W_2)\right] + \underline{d}_X\left[\pi_3 u'(W_3) + \pi_1 u'(W_1)\right]}{\pi_1 u'(W_1) + \pi_2 u'(W_2) + \pi_3 u'(W_3) + \pi_4 u'(W_4)} \tag{15}$$

$$P_Y(1+r_f) = \frac{\overline{d}_Y\left[\pi_4 u'(W_4) + \pi_3 u'(W_3)\right] + \underline{d}_Y\left[\pi_2 u'(W_2) + \pi_1 u'(W_1)\right]}{\pi_1 u'(W_1) + \pi_2 u'(W_2) + \pi_3 u'(W_3) + \pi_4 u'(W_4)} \tag{16}$$

Note that the outcomes of the assets can be reformulated in terms of their means (μ_X and μ_Y) and standard deviations (σ_X and σ_Y).

$$\overline{d}_Y = \mu_Y + \sigma_Y\sqrt{\frac{1-q}{q}}$$

$$\underline{d}_Y = \mu_Y - \sigma_Y\sqrt{\frac{q}{1-q}}$$

$$\overline{d}_X = \mu_X + \sigma_X$$

$$\underline{d}_X = \mu_X - \sigma_X$$

Hence, the prices of assets X and Y satisfied the equations:

$$P_X(1+r_f) = \mu_X + \sigma_X\frac{\left[\pi_4 u'(W_4) + \pi_2 u'(W_2)\right] - \left[\pi_3 u'(W_3) + \pi_1 u'(W_1)\right]}{\pi_1 u'(W_1) + \pi_2 u'(W_2) + \pi_3 u'(W_3) + \pi_4 u'(W_4)}$$

$$P_Y(1+r_f) = \mu_Y + \sigma_Y\frac{\sqrt{\frac{1-q}{q}}\left[\pi_4 u'(W_4) + \pi_3 u'(W_3)\right] - \sqrt{\frac{q}{1-q}}\left[\pi_2 u'(W_2) + \pi_1 u'(W_1)\right]}{\pi_1 u'(W_1) + \pi_2 u'(W_2) + \pi_3 u'(W_3) + \pi_4 u'(W_4)}$$

Denote by $s = 1 - \rho$ and $c = \frac{\rho - \eta}{2}$. We then have the following limits:

$$\lim_{N_Y \longrightarrow 0} P_X(1+r_f) = \mu_X + \sigma_X \frac{w(0.5)u'\left((W_0 - N_X P_X)(1+r_f) + N_X \overline{d}_X\right) - (1-w(0.5))u'(((W_0 - N_X P_X)(1+r_f) + N_X \underline{d}_X))}{w(0.5)u'\left((W_0 - N_X P_X)(1+r_f) + N_X \overline{d}_X\right) + (1-w(0.5))u'(((W_0 - N_X P_X)(1+r_f) + N_X \underline{d}_X))}$$

$$\lim_{N_Y \longrightarrow 0} P_Y(1+r_f) = \mu_Y + \sigma_Y \frac{c\sqrt{\frac{1-q}{q}}u'\left((W_0 - N_X P_X)(1+r_f) + N_X \overline{d}_X\right) - (1-s-c)\sqrt{\frac{q}{1-q}}u'\left((W_0 - N_X P_X)(1+r_f) + N_X \underline{d}_X\right)}{w(0.5)u'\left((W_0 - N_X P_X)(1+r_f) + N_X \overline{d}_X\right) + (1-w(0.5))u'(((W_0 - N_X P_X)(1+r_f) + N_X \underline{d}_X))}$$

As $w(0.5) = 0.5s + c \leq 0.5$ and $u(.)$ concave implies $u'\left((W_0 - N_X P_X)(1+r_f) + N_X \underline{d}_X\right) > u'\left((W_0 - N_X P_X)(1+r_f) + N_X \overline{d}_X\right)$, it turns out that

$$\lim_{N_Y \longrightarrow 0} P_X(1+r_f) < 0.5\overline{d}_X + 0.5\underline{d}_X \equiv \mu_X$$

$$\lim_{(N_Y, q) \longrightarrow (0,0)} P_Y(1+r_f) > q\overline{d}_Y + (1-q)\underline{d}_Y \equiv \mu_Y$$

As result, when the supply of asset Y is small (N_Y small), an increase in skewness (small q) will lead to negative expected returns. $\square$

A.4 Heterogeneous equilibrium in prospect theory

The investor's preferences are defined over the gain or loss relative to the final wealth that could have been obtained investing only in the risk-free asset:

$$\hat{W} \equiv W - (1+r_f)W^0$$

where we denote by W^0 and W initial and final wealth respectively.

The preferences of the investor are represented by:

$$V(\hat{W}) = \sum_{k=-m}^{n} \pi_k v(\hat{W}_k)$$

The function $v(\cdot)$ is the value function and the π_k terms are decision weights. The value function is:

$$v(x) = \begin{cases} x^\alpha, & \text{if } x \geq 0 \\ -\lambda(-x)^\alpha, & \text{if } x < 0 \end{cases}$$

In a heterogeneous equilibrium, each investor will hold one of two possible portfolios.

Portfolio A combines the risk-free asset Z and asset X but takes no position at all in asset Y. Denote by θ the share of this portfolio invested in asset X. Portfolio B combines all three assets and we denote by τ_X and τ_Y the shares of this portfolio in assets X and Y respectively.

We derive the equilibrium conditions of Barberis and Huang (2008) in our setting (the main difference is that asset X replaces the market portfolio of their model).

Consider first an investor with portfolio A. For such an investor, final wealth is $W = W_0[(1-\theta)R_f + \theta R_X]$ and so $\hat{W} = W_0\theta\hat{r}_X$, where $\hat{r}_j \equiv r_j - r_f$ is the excess return on asset j. Portfolio A investors will choose a finite a positive θ only if $V(\hat{W}) = 0$, that is $V(W_0\theta\hat{r}_X) = 0$. This implies that $W_0^\alpha\theta^\alpha V(\hat{r}_X) = 0 \Leftrightarrow V(\hat{r}_X) = 0$, that is condition (3).

Next, consider an investor who holds portfolio B. For such an investor, final wealth is $W = W_0[(1-\tau_X-\tau_Y)R_f + \tau_X R_X + \tau_Y R_Y]$. So $\hat{W} = W_0(\tau_X\hat{r}_X + \tau_Y\hat{r}_Y) = W_0\tau_X(\hat{r}_X + s\hat{r}_Y)$, where $s \equiv \frac{\tau_Y}{\tau_X}$. We denote by s^* the investor's optimal choice. Portfolio B investors will choose a finite a positive τ_X only if $V(\hat{W}) = 0$, that is $V(W_0\tau_X(\hat{r}_X + s^*\hat{r}_Y)) = 0$. This implies that $W_0^\alpha\tau_X^\alpha V(\hat{r}_X + s^*\hat{r}_Y) = 0 \Leftrightarrow V(\hat{r}_X + s^*\hat{r}_Y) = 0$, that is condition (4). To ensure that s^* is really the optimal choice, it must be $V(\hat{r}_X + s\hat{r}_Y) < 0$ for $s \neq s^*$, that is condition (5). Finally, holding a portfolio combining only the risk-free asset and asset Y must also be sub-optimal, leading to $V(\hat{r}_Y) < 0$, i.e. condition (6).

B Probability weighting estimation

Denote by $\boldsymbol{ce}, \boldsymbol{x}$, $\boldsymbol{y}$, and $\boldsymbol{q}$ respectively the values of certainty equivalent, the high outcome x, the small outcome y, and the probability. We use the certainty equivalent data to estimate power utility and one-parameter probability weighting:

$$\boldsymbol{ce}_l = \left((\boldsymbol{x}_l^\alpha - \boldsymbol{y}_l^\alpha) \frac{\boldsymbol{q}_l^\delta}{\left(\boldsymbol{q}_l^\delta + (1-\boldsymbol{q}_l)^\delta\right)^{\frac{1}{\delta}}} + \boldsymbol{y}_l^\alpha \right)^{\frac{1}{\alpha}} + \boldsymbol{e}_l \tag{17}$$

where $\boldsymbol{e}$ is the error term, l is the lth line in $\boldsymbol{ce}, \boldsymbol{x}, \boldsymbol{y}$ and $\boldsymbol{e}$; α the utility parameter and δ the probability weighting parameter. We assume that the error term is normally distributed with mean 0 and heteroscedastic variance $\sigma_l = \sigma|\boldsymbol{x}_l - \boldsymbol{y}_l|$. We then estimate α, δ and σ by maximum likelihood method.

Alternatively to (17), we estimate the probability weight $\delta_q = w(q)$ associated to each probability $q \in Q = \{0.025, 0.05, 0.25, 0.5\}$ following the specification of Abdellaoui et al. (2008) and Kpegli et al. (2023):

$$ce_l = \left((x_l^\alpha - y_l^\alpha) \sum_{q \in Q} \delta_k I_l^k + y_l^\alpha \right)^{\frac{1}{\alpha}} + e_l \quad (18)$$

with I^k the dummy variable for the probability p_k.

	Parametric		Semi-parametric				
Session	α	δ	α	$w(0.025)$	$w(0.05)$	$w(0.25)$	$w(0.50)$
1	1.19	0.50	0.85	0.20	0.22	0.32	0.45
2	1.10	0.46	0.96	0.18	0.16	0.29	0.41
3	1.13	0.55	1.00	0.11	0.10	0.32	0.42
4	1.48	0.53	1.08	0.24	0.26	0.31	0.36
5	1.20	0.56	0.73	0.18	0.22	0.37	0.54
6	1.03	0.47	0.94	0.19	0.18	0.29	0.45
7	1.39	0.55	0.88	0.18	0.22	0.36	0.53
8	1.08	0.44	0.74	0.29	0.24	0.31	0.41
9	1.12	0.53	0.93	0.19	0.21	0.32	0.45
10	1.08	0.50	0.80	0.16	0.15	0.36	0.38
11	1.10	0.59	0.84	0.22	0.24	0.40	0.49
12	1.14	0.53	0.55	0.30	0.32	0.43	0.55
13	1.26	0.46	0.85	0.29	0.31	0.41	0.47

Table 6: Median of individual estimates of risk preference at the session level

C Descriptive statistics

	δ	α	CRT	Financial literacy	Gender (% women in the session)
Mean	0.52	1.18	1.77	2.85	0.44
Min	0.44	1.03	1	2	0.1
max	0.59	1.48	3	3	0.6
Standard deviation	0.04	0.12	0.67	0.30	0.14
Median	0.53	1.13	1.5	3	.5

Table 7: Descriptive statistics

Table 8: Correlation matrix (using session level medians)

	δ	α	CRT	Financial literacy	Gender (% women)
δ	1.000				
α	0.269	1.000			
CRT	-0.339	-0.161	1.000		
Financial literacy	-0.041	-0.523*	0.205	1.000	
Gender (% women)	0.131	-0.474	-0.107	-0.305	1.000

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9: Correlation matrix (individual level)

	δ	α	CRT	Financial literacy	Gender (Dummy woman)
δ	1.000				
α	0.042*	1.000			
CRT	0.106***	-0.171***	1.000		
Financial literacy	0.077***	-0.122***	0.227***	1.000	
Gender (dummy women)	-0.032	0.139***	-0.204***	-0.074***	1.000

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

D Additional robustness checks for Hypothesis 3*ii*

This section demonstrates the robustness of the results in Table 5 with respect to the aggregation method of probability weighting at the session level and the specification of the probability weighting function.

Robustness to various probability weighting aggregation methods. Table 10 provides regression estimates in which we used minimum, maximum, and mean of individual probability weighting parameters (δ) instead of the median (as reported in Table 5. The interaction between $\boldsymbol{Skew\_L}$ and $\boldsymbol{\delta}$ continues to be positive and significant across all aggregation methods.

	Returns (Min δ)	Returns (Max δ)	Returns (Mean δ)
Skew-L	-0.51***	-0.30***	-0.39***
	(0.07)	(0.05)	(0.08)
Skew-H	-0.30***	-0.17***	-0.22***
	(0.08)	(0.04)	(0.07)
NoSkew-L	-0.47***	-0.17***	-0.21*
	(0.10)	(0.06)	(0.11)
δ	-0.56***	-0.01	-0.13
	(0.21)	(0.01)	(0.12)
Skew-L $\times$ δ	0.81***	0.02**	0.21**
	(0.18)	(0.01)	(0.10)
Skew-H $\times$ δ	0.51*	0.02**	0.13**
	(0.26)	(0.01)	(0.07)
NoSkew-L $\times$ δ	1.01***	(0.01)	0.09
	(0.28)	0.01	(0.13)
Period	-0.01	-0.01	-0.01
	(0.00)	(0.01)	(0.01)
α	0.01	0.02	0.04
	(0.22)	(0.20)	(0.19)
CRT	-0.00	-0.00	-0.01
	(0.03)	(0.03)	(0.04)
Financial literacy	-0.14**	-0.14**	-0.14**
	(0.06)	(0.07)	(0.07)
Gender (% women)	0.08	0.07	0.08
	(0.18)	(0.21)	(0.19)
Constant	0.81	0.65	0.67
	(0.55)	(0.51)	(0.50)
N	169	169	169

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 10: Robustness to various probability weighting aggregation methods

Robustness to probability weighting specification. Table 11 presents regression estimates that are based on a semi-parametric measurement of probability weights (Kpegli et al., 2023) associated with the high state in our experiment, that is $w(0.025)$ for the Skewed treatments, and $w(0.25)$ for non-skewed treatments. The interaction term between $\boldsymbol{Skew\_L}$ and $w(0.025)$ is negative and significant, indicating that the overweighting of the small probability 0.025 leads to lower returns for asset Y in the Skew-L treatment, consistent with our previous results.

	Return
Skew-L	-0.67***
	(0.22)
Skew-H	-0.24
	(0.22)
NoSkew-L	-0.73***
	(0.22)
$w(0.025)$	-0.81
	(0.51)
Skew-L $\times$ $w(0.025)$	-0.55*
	(0.29)
Skew-H $\times$ $w(0.025)$	-0.24
	(0.51)
NoSkew-L $\times$ $w(0.025)$	0.08
	(0.41)
$w(0.25)$	-0.90*
	(0.52)
Skew-L $\times$ $w(0.25)$	1.49***
	(0.57)
Skew-H $\times$ $w(0.25)$	0.42
	(0.66)
NoSkew-L $\times$ $w(0.25)$	1.62**
	(0.65)
Period	-0.01
	(0.01)
α	-0.15
	(0.15)
CRT	0.03
	(0.02)
Financial literacy	-0.19***
	(0.04)
Gender (women)	-0.07
	(0.10)
Constant	1.41***
	(0.37)
N	169

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 11: Robustness to probability weighting specification