Lottery Preferences and AI Stock Exuberance

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In Partial Fulfillment of the Requirements
for the Degree of Bachelor of Science
in Applied Mathematics

December 2, 2025

1 Introduction

Classical economic theory assumes that agents maximize the expected value of their utility. This "expected utility" framework predicts that, when faced with a menu of risky investments, agents construct a portfolio that maximizes expected return for their chosen level of risk. Many undergraduate courses go a step further, introducing a local approximation called "mean-variance" utility, that is explicitly increasing in expected value and decreasing in variance. These traditional models, however, are unable to capture some commonly observed behavior—for example, the simultaneous demand for insurance and lotteries.[1] Such observations inspired the introduction of nonexpected utility models, among the most successful of which is known as "cumulative prospect theory," introduced by Tversky and Kahneman [1992] to provide a closer fit to experimental evidence. In this paper, we study the asset-pricing implications of cumulative prospect theory, evaluating its predictions in the context of present-day stock market data.

When considering a risky prospect, an agent with cumulative prospect theory preferences assigns the prospect a single numerical value using two functions: the "value function" and the "probability transformation." The value function is defined over gains and losses; steeper in losses than in gains; and concave over gains while convex over losses. When evaluating the prospect, the agent applies the value function to each possible outcome and then sums these values, weighting each term by its transformed, rather than objective, probability. The primary effect of the probability transformation (often called "probability weighting") is to overweight the tails of the distribution, placing undue emphasis on low-probability outcomes. This behavior holds significance for asset pricing and may be especially relevant to present-day (2025) equities markets.

Artifical intelligence (AI) associated firms have buoyed markets. Since 2023, the stock market darlings have been the Magnificent 7, a group of seven U.S. technology companies that have grown to be some of the largest firms worldwide by market cap. Among them is Nvidia—a graphics card manufacturer with a near monopoly on the chips that power AI models—which has grown by a factor of 10× since 2023, becoming the most valuable firm in the world. The CEOs of other prominent firms, however, have expressed concerns about exuberance in financial markets. Sam Altman is the CEO of OpenAI, maker of ChatGPT and the most valuable privately-held company in history. In late August 2025, he told a group of reporters that "we [are] in a phase where investors as a whole are overexcited about AI," [Butts, 2025]. In October 2025, Jeff Bezos, founder of Magnificent 7 member Amazon, is quoted as saying at a conference that "this is kind of an industrial bubble," and at that same conference, David Solomon, CEO of Goldman Sachs, proclaimed that "there will be a lot of capital that was deployed that didn't deliver returns. It's not different this time," [Bradshaw, 2025]. So why are valuations still sky-high?

These same CEOs may offer a clue in their follow-ups to these bearish remarks, in which they gesture toward massive returns to AI firms at some unknown point in the future. In his next sentence, Altman reassured investors that "AI [is] the most important thing to happen in a very long time."

[1] When survey participants are asked to choose between a certain loss of \$5 and a loss of \$5000 with probability 0.001, the majority choose to lose \$5. When choosing between a certain gain of \$5 or a gain of \$5000 with probability 0.001, most elect the chance to win \$5000. In either choice, both options offer the same \$5 expected value. A standard concave expected utility function cannot accommodate the demonstrated preferences. The demand for lotteries would require convexity over some region.

Bezos promised that "the benefits to society from AI are going to be gigantic." And Solomon still believes that eventually, the "business of work will be transformed by AI globally." Each statement references a massive payout from AI at some uncertain future date. If the probability of such a payout is small, then cumulative prospect theory investors, who overweight low-probability events, may be especially enthusiastic about these stocks. This is the possibility we explore. While episodes in which investors chase assets with remote, high-magnitude payoffs are not new, contemporary AI-associated equities offer a timely and vivid example.

One well-known implication of cumulative prospect theory is so-called "lottery preferences," which the expected utility framework is incapable of predicting. Intuitively, an agent with lottery preferences can become excited about an asset with a small probability of a large payout and be willing to pay more than a rational benchmark price for exposure to its payoffs. In an economy where agents have cumulative prospect theory preferences, this can lead to an overvaluation of that lottery-like asset.

In the original paper discussing lottery preferences, Barberis and Huang [2008] present a model in which investors evaluate risk according to cumulative prospect theory. The representative investor faces a one-period economy consisting of many multivariate normal securities and a single small, independent, and positively skewed security. In equilibrium, the expected return on the skewed security can be lower than the risk-free rate, a result primarily driven by the probability weighting feature of cumulative prospect theory. Investors take a large, undiversified position in the skewed security because doing so makes the distribution of their overall wealth more lottery-like—an outcome they find desirable since they overweight the tails. As a numerical example, Barberis and Huang [2008] model the skewed asset as a simple binomial lottery.

While this is analytically convenient, it bears little resemblance to the continuous, heavy-tailed return distributions observed in actual equities markets. In this paper, we extend the framework of Barberis and Huang [2008] by replacing the binomially distributed lottery asset with a generalized hyperbolic skewed t distribution calibrated to match empirical features of AI-associated securities. The generalized hyperbolic skewed t distribution allows us to capture both fat tails and significant skewness in a single parametric family, bringing the model into closer alignment with the data while preserving tractability.

Our goal is to ask a simple question: given empirically plausible preferences and a realistic specification of returns, can lottery preferences meaningfully contribute to the current valuations of AI-related stocks? To answer this, we first revisit the model of Barberis and Huang [2008] under their binomial specification, and then extend it to a setting in which the skewed asset return is drawn from a generalized hyperbolic skewed t distribution. We calibrate the parameters of the generalized hyperbolic skewed t distribution to match cross-sectional and forward-looking measures of AI-stock return skewness, determine the equilibrium expected return of the skewed asset, and analyze its overvaluation relative to a standard expected-utility benchmark.

In Section 2, we review prospect theory and lottery preferences. In Section 3, we present a model that incorporates these concepts and discuss its equilibrium structure. In Section 4, we calibrate the model to data on AI-associated securities and discuss its predictions. Section 5 concludes.

2 Background

In this section, we review prospect theory and the existing literature on lottery preferences.

2.1 Prospect Theory

Prospect theory was first introduced by Kahneman and Tversky [1979]. In the theory, a prospect (gamble) is defined

$$(x_1, p_1; \ldots;\ x_n, p_n), \tag{1}$$

which is read as "receive x_i with probability p_i" for i from 1 to n. Kahneman and Tversky surveyed students and university faculty on their preferences over gambles, asking participants to choose option A or B in scenarios like the below:

A: 50% chance to win 1,000,
50% chance to win nothing;

B: 450 for sure.

Finding that the responses of students and university faculty to these hypothetical choice problems regularly violated the expected utility framework, Kahneman and Tversky introduced a value function $v(\cdot)$ and a probability weighting function $w(\cdot)$. In their specification, utility over some gamble $(x, p; y, q)$—receive x with probability p, y with probability q, and nothing with probability $1 - p - q$, where $p + q \leq 1$—is evaluated as

$$V\big(x, p; y, q\big) = w(p) \cdot v(x) + w(q) \cdot v(y), \tag{2}$$

where $v(0) = 0$, $w(0) = 0$, $w(1) = 1$. Based on the responses to their survey questions, they find that $v(\cdot)$ is defined over gains and losses relative to a fixed reference level, concave over gains (risk aversion), convex over losses, and has a kink at the origin that makes it steeper in losses than in gains (dubbed loss aversion). The probability weighting function $w(\cdot)$ satisfies $w(0) = 0$ and $w(1) = 1$, is increasing, and generally overweights low probabilities.

Though impactful, this original version has its limitations. Perhaps most significant among them, it is defined only for gambles with two or fewer nonzero outcomes. In this analysis, we adopt an extension of the theory called *cumulative* prospect theory, provided in Tversky and Kahneman [1992].

To extend the theory to an arbitrary number of nonzero outcomes, the probability transformation is applied to the entire cumulative distribution function rather than individual probabilities. The full specification of the model allows for different weighting functions to apply over gains and losses, however the present analysis ignores this feature.[2]

For demonstration, consider the gamble

$$(x_{-m}, p_{-m}; \ldots; x_0, p_0; \ldots; x_n, p_n), \tag{3}$$

[2]For the functional forms in Equations (7) and (8), when Tversky and Kahneman [1992] separately calibrate the probability weighting function over gains and over losses, they find that the two parameterizations are nearly identical. They also allow for the curvature of $v(\cdot)$ to be different in gains and losses, but their calibration finds that this is not the case—both are found to have the same value for α, the curvature parameter.

where $\sum_i p_i = 1$, $x_i < x_{i+1}$ for all i, and $x_0 = 0$ so that $x_{-m}, \ldots, x_{-1}$ are losses and $x_1, \ldots, x_n$ are gains. An agent with cumulative prospect theory preferences would assign the given gamble the value

$$\sum_{i=-m}^{n} \pi_i v(x_i), \tag{4}$$

where

$$\pi_i = \begin{cases} w(p_i + \cdots + p_n) - w(p_{i+1} + \cdots + p_n) & 0 \le i \le n, \\ w(p_{-m} + \cdots + p_i) - w(p_{-m} + \cdots + p_{i-1}) & -m \le i < 0, \end{cases} \tag{5}$$

and $w(\cdot)$ is the original probability weighting function. Compare this to the expected utility formulation, which assigns the gamble the value

$$\sum_{i=-m}^{n} p_i U(W + x_i), \tag{6}$$

for starting wealth W.

There are two key differences between the preferences in Equations (4) and (6). First, in cumulative prospect theory, value is determined by gains and losses—starting wealth W does not enter $v(\cdot)$. Second, the cumulative prospect theory agent uses transformed probabilities in evaluating the gamble, which are determined by applying the transformation $w(\cdot)$ to the objective probabilities used in the expected utility evaluation.

Note that by Equation (5), p_{-m} and p_n map to $w(p_{-m})$ and $w(p_n)$, respectively. If we assume both p_{-m} and p_n are small, then $w(p_{-m}) > p_{-m}$ and $w(p_n) > p_n$ since, as noted above, $w(\cdot)$ tends to overweight small probabilities. Therefore the primary effect of Equation (5) is to overweight the tails of the distribution. As a result, investors with cumulative prospect theory preferences like gambles with low-probability large payouts, much like a lottery ticket. This fact is key to the model and analysis we present.

Tversky and Kahneman [1992] propose the functional forms below:

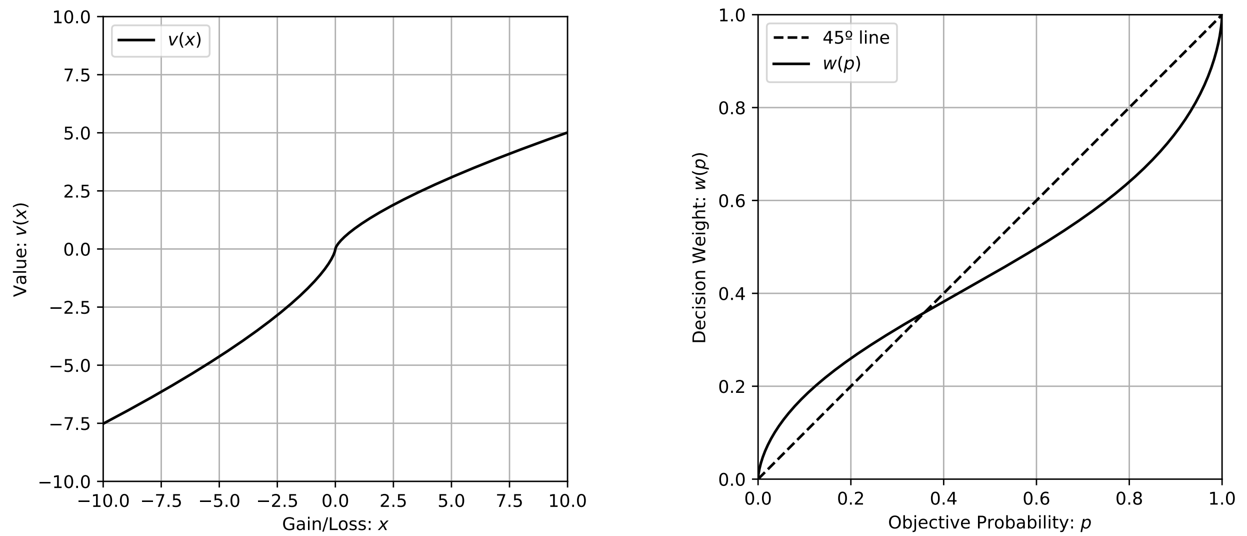
$$v(x) \triangleq \begin{cases} x^{\alpha} & x \ge 0 \\ -\lambda(-x)^{\alpha} & x < 0 \end{cases} \tag{7}$$

where $\alpha \in (0,1)$, $\lambda > 1$, and

$$w(p) \triangleq \frac{p^{\delta}}{(p^{\delta} - (1-p)^{\delta})^{1/\delta}} \tag{8}$$

for $\delta \in (0,1)$. We adopt the functional forms from Equations (7) and (8) in the analysis that follows. Figure 1 plots them. We discuss how we chose the numerical values of the preference parameters α, δ, and λ in Section 4.

The prospect theory parameters α, δ, and λ in the Tversky and Kahneman [1992] functional forms have appealing intuitive interpretations. First consider the value function, which is governed by α and λ. The degree of curvature in $v(\cdot)$ is controlled by α, and low α leads to significant risk aversion (risk seeking) over gains (losses). We can see in Figure 1a that the value function is indeed



(a) Value function using the functional form of Equation (7) with $(\alpha, \lambda) = (0.7, 1.5)$.

(b) Probability weighting function using the functional form of Equation (8) with $\delta = 0.65$.

Figure 1: Prospect theory functions suggested by Tversky and Kahneman [1992].

convex in the region of losses and concave over gains, though only moderately so for our choice of α. The degree of loss aversion is λ, with the interpretation that losses are felt λ times more intensely than gains. In Figure 1a, $v(x)$ is kinked at the origin and steeper in losses than in gains, as expected.

The probability weighting function has a single parameter, δ, which determines the degree of probability weighting. A value of δ near 0 implies significant overweighting of the tails of the probability distribution, while $\delta = 1$ returns to objective probabilities (doing away with probability weighting entirely). In Figure 1b, the solid line corresponds to a typical level of probability weighting, and the dashed 45° line reflects the objective (unweighted) probabilities. Observe how $\pi(\cdot)$ overweights small probabilities.

2.2 Lottery Preferences

Cumulative prospect theory generates rich predictions for asset pricing. Of the most relevance to this analysis, Barberis and Huang [2008] show that an investor with cumulative prospect theory preferences can be skewness-loving and will price the idiosyncratic skewness of a security, in some cases causing it to have a negative expected excess return in equilibrium. This result relies on the probability weighting aspects of cumulative prospect theory and contradicts the prediction of the standard expected utility model that idiosyncratic skewness is not priced.

Barberis and Huang [2008] propose a model of a representative agent economy in which the agent has cumulative prospect theory preferences and must allocate his wealth among a riskless asset, J multivariate normal securities, and a single skewed security in small supply. The tangency portfolio consisting of only the riskless asset and the J multivariate normal securities is dubbed the J-market portfolio, terminology we adopt herein. Under this regime, they find that if the skewed security has sufficient skewness, there exists a *heterogeneous holdings equilibrium*. In one group, all investors hold a portfolio combining only the risk-free asset and J-market portfolio, and in the other, all investors hold a portfolio combining the risk-free asset, the J-market portfolio, and a long position in the skewed security. In such an equilibrium, the expected return of the skewed asset is low. They dub this result *lottery preferences*, as the low return on the positively skewed asset implies that investors are willing to pay a relatively high price for it (much like a lottery ticket). The concept of lottery preferences has intuitive appeal: a small chance of a large payout is exciting.

This framework is able to explain a number of real-world stock market phenomena. Barberis and Huang [2008] provide some examples. Among them is the observation in Ritter [1991] that IPO securities have a low average return empirically. Likely due to the fact that firms that IPO tend to be young and thus have much of their value in future growth potential, the distribution of a security's returns in the three years after its IPO is highly positively skewed. Lottery preferences would predict this low return on IPO securities. The pricing of idiosyncratic skewness may also play a role in option pricing (deep out-of-the-money options have positively skewed returns), equity stub valuations (subsidiaries are more likely to work in new technologies and therefore have more return skewness), and even under-diversification (under-diversified investors tend to hold more skewed stocks).

This model has not been applied to current market data. There is, however, evidence that investors perceive AI-associated securities as having significant positive skewness. Amodei [2024], the CEO of artificial intelligence firm Anthropic (maker of Claude), presents an extremely bullish case for AI, claiming that all human disease will be cured within 5-10 years of the advent of so-called superintelligence. The return to investors in the firm controlling this technology would necessarily be immense. This belief in a low-probability high-magnitude return implies a perception of positively skewed return distribution. In what follows, we explore the predictions of the framework presented in Barberis and Huang [2008], applying it to modern AI-associated securities.

3 Model

In this section, except where indicated, we follow the framework set forth in Barberis and Huang [2008].

3.1 Model Setup

We consider a two-period ($t = 0, 1$) representative agent economy with a single risk-free asset R_f, J normally distributed securities $\widetilde{R}_j$, and a single skewed security $\widetilde{R}_n$. The focus is on investor decision making in the first period, when the investor has cumulative prospect theory preferences.

Suppose that the investor has wealth W_0 in period 0 and wealth $\widetilde{W} = W_0 \widetilde{R}$ in period 1, where $\widetilde{R}$ is the return on the investor's portfolio in period 1. To apply cumulative prospect theory requires some reference wealth level. Assuming that the investor sets his reference wealth level in period 1 according to the time-value of his initial wealth, we can define the gain or loss in wealth $\widehat{W}$ by

$$\widehat{W} \triangleq \widetilde{W} - W_0 R_f. \tag{9}$$

This definition uses $W_0 R_f$ as the future value of present wealth instead of $W_0(1 + R_f)$ since R_f is the gross risk-free rate.

Under the assumption that the representative investor has cumulative prospect theory preferences where $v(\cdot)$ and $w(\cdot)$ take the functional forms given in Equations (7) and (8), the investor's goal function is

$$V\left(\widehat{W}\right) \triangleq V\left(\widehat{W}^{+}\right) + V\left(\widehat{W}^{-}\right), \tag{10}$$

where $\widehat{W}^{+} = \max\left\{\widehat{W}, 0\right\}$ and $\widehat{W}^{-} = \min\left\{\widehat{W}, 0\right\}$. Here, $V(\cdot)$ is defined by

$$V\left(\widehat{W}^{+}\right) = \int_{0}^{\infty} w(1 - P(x))\, dv(x), \tag{11}$$

$$V\left(\widehat{W}^{-}\right) = -\int_{-\infty}^{0} w(P(x))\, dv(x), \tag{12}$$

where $P(\cdot)$ is the cumulative distribution function of $\widehat{W}$, x is the variable of integration, and $dv(\cdot)$ is the (discontinuous) derivative of $v(\cdot)$. The specification of $V(\cdot)$ given in Equations (11) and (12) is derived by Barberis and Huang [2008] from a continuous version of Equation (4). We assume these integrals are well-defined, which requires only technical assumptions.[3] Note that there is no security-level narrow framing here—$V(\cdot)$ is defined over the final wealth level, not any security-specific characteristics, so it is not obvious that the skewness of an individual security should be priced in equilibrium.

Finally, we assume that the joint distribution of the normally distributed assets $\widetilde{R}_j$, $1 \leq j \leq J$, at time 1 is multivariate normal; all investors have a positive net endowment and identical preferences and beliefs; the return on the skewed security $\widetilde{R}_n$ is independent of the J normally distributed securities; and the payoff of the skewed security is infinitesimal relative to the total payoff of the J normal securities. With these assumptions, Barberis and Huang [2008] show that we can replace the J normal securities with a single security $\widetilde{R}_M$ (the tangency portfolio considering only R_f and $\widetilde{R}_j$, $1 \leq j \leq J$) without affecting the optimal allocations due to the independence and infinitesimal supply of the skewed security.

With these assumptions, defining $\widehat{R}_M \triangleq \widetilde{R}_M - R_f$ and $\widehat{R}_n \triangleq \widetilde{R}_n - R_f$, we have the following equilibrium conditions:

$$V\left(\widehat{R}_M\right) = V\left(\widehat{R}_M + x^{*}\widehat{R}_n\right) = 0, \tag{13}$$

$$V\left(\widehat{R}_M + x\widehat{R}_n\right) < 0 \quad \text{for} \quad 0 < x \neq x^{*}, \tag{14}$$

$$V\left(\widehat{R}_n\right) < 0, \tag{15}$$

where

$$V\left(\widehat{R}_M + x\widehat{R}_n\right) = -\int_{-\infty}^{0} w(\mathrm{P}_x(R))\, dv(R) + \int_{0}^{\infty} w(1 - \mathrm{P}_x(R))\, dv(R), \tag{16}$$

[3]Namely, that (1) $V\left(\widehat{W}\right)$ has finite expectation and variance, (2) $\delta \geq 0.28$, and (3) $\alpha < 2\delta$; where α and δ are the preference parameters.

having R as its variable of integration, and

$$\mathrm{P}_x(R) = \mathrm{P}\left(\widehat{R}_M + \widehat{R}_n \leq R\right). \tag{17}$$

Note that x^* is the fraction of wealth allocated to the skewed security relative to the fraction allocated to $\widetilde{R}_M$, that is, the fraction of wealth in $\widetilde{R}_M$ is normalized to 1. Equation (13) ensures finite and positive holdings in equilibrium. Equation (14) ensures that only one portfolio that holds the skewed security is optimal. Equation (15) guarantees that it is not optimal to hold any combination of just the skewed security and risk-free asset. Together, these conditions result in exactly two optimal portfolios—the tangency portfolio holding only riskless asset and the normally distributed securities, and a portfolio holding a combination of all available securities with a long position in the skewed security.

3.2 Pricing Skewness

To illustrate, Barberis and Huang [2008] apply their framework to a security with a binomial return distribution, much like a literal lottery ticket. To build an understanding of how skewness is priced, we maintain the binomial return distribution in this section, though a substantially different return distribution is used for the skewed asset thereafter.

Recall that for some μ and σ,

$$\widetilde{R}_M \sim \mathcal{N}(\mu, \sigma^2) \implies \widehat{R}_M \sim \mathcal{N}(\mu - R_f, \sigma^2), \tag{18}$$

so if we define $\mu_M \triangleq \mu - R_f$ and $\sigma_M \triangleq \sigma$, we have

$$\widehat{R}_M \sim \mathcal{N}(\mu_M, \sigma_M^2). \tag{19}$$

We set $\sigma_M = 0.15$ and let μ_M be determined in equilibrium by Equation (13). Now, suppose the skewed asset is lottery-like. That is, it has some small probability q of paying out a large jackpot of size L, and otherwise it pays nothing. Then, borrowing from the notation introduced in Section 2.1, we can model the skewed asset as a gamble

$$(L, q;\ 0, 1-q). \tag{20}$$

If the price level of the skewed asset is some constant p_n, then its return distribution is given by

$$\widetilde{R}_n \sim \left(\frac{L}{p_n}, q;\ 0, 1-q\right), \tag{21}$$

$$\widehat{R}_n \sim \left(\frac{L}{p_n} - R_f, q;\ -R_f, 1-q\right). \tag{22}$$

We set $L = 10$, $R_f = 1.02$, and $q = 0.09$. These imply substantial skewness in the return distribution of $\widehat{R}_n$, giving

$$\mathrm{Skew}\left(\widehat{R}_n\right) \approx 2.865. \tag{23}$$

As a point of reference, the skew-normal distribution cannot accommodate skewness levels higher than approximately 1. With $\widehat{R}_n$ distributed as above, Equation (17) becomes

$$\begin{aligned}
\mathrm{P}_x(R) &= \mathrm{P}\left(\widehat{R}_M + x\widehat{R}_n \le R\right) \\
&= \mathrm{P}\left(\widehat{R}_M + x\widehat{R}_n \le R \,\middle|\, \widehat{R}_n = \frac{L}{p_n} - R_f\right) q + \mathrm{P}\left(\widehat{R}_M + x\widehat{R}_n \le R \,\middle|\, \widehat{R}_n = -R_f\right)(1-q) \\
&= \Phi\left(\widehat{R}_M + x\left(\frac{L}{p_n} - R_f\right) \le R\right) q + \Phi\left(\widehat{R}_M + x(-R_f) \le R\right)(1-q) \\
&= \Phi\left(\frac{R - x\left(\frac{L}{p_n} - R_f\right) - \mu_M}{\sigma_M}\right) q + \Phi\left(\frac{R + xR_f - \mu_M}{\sigma_M}\right)(1-q)
\end{aligned} \tag{24}$$

To examine the equilibrium, we must now set the prospect theory parameters $(\alpha, \delta, \lambda)$. Here, we depart from Barberis and Huang [2008], who used the values estimated by Tversky and Kahneman [1992]: $(\alpha, \delta, \lambda) = (0.88, 0.65, 2.25)$. Though it is not important for this part of the analysis, for the sake of consistency throughout this paper, we use $(\alpha, \delta, \lambda) = (0.7, 0.65, 1.5)$ that were estimated by Barberis et al. [2021]. The choice of this parameterization is discussed in more detail in Section 4.

Figure 2 shows the investor's utility $V\left(\widehat{R}_M + x\widehat{R}_n\right)$ as a function of x, the relative fraction of the skewed asset in his portfolio, calculated numerically for the chosen parameters. Observe that with this price level $p_n = 0.8957$, the skewed asset has an expected return

$$\mathrm{E}\left(\widehat{R}_n\right) = \frac{qL}{p_n} - R_f = \frac{(0.09)(10)}{0.8957} - 1.02 \approx -0.0152, \tag{25}$$

which is negative. We can clearly see two global optima in Figure 2: one at $x = 0$ and another at $x^* = 0.055$. Since the skewed asset is in infinitesimal supply, we can clear the market by assigning each investor to one or the other of these global optima. Checking that Equations (13) to (15) are satisfied confirms this is a heterogeneous holdings equilibrium.

To interpret Figure 2, consider slowly increasing x from 0 to 0.1. As x increases from 0 to around 0.02, the investor is reducing the expected return of his portfolio without increasing its skewness very much. This reduces utility as his expected return decreases without adequate compensation by way of portfolio skewness. Then as x increases from 0.02 to 0.055, the potential payoff of the position in the skewed security is large enough that the investor becomes excited and is willing to take on the reduction in his portfolio expected return to grow the jackpot. Mathematically, this follows from the fact that the investor overweights the tails of the return distribution. Then for $x > 0.055$, the investor begins to recognize that he is undiversified, and the expected value of his portfolio decreases faster than its increasing skewness can compensate, thereby reducing utility.

4 Applying the Framework to Market Data

In the rest of this analysis, we instead assume that the skewed asset has a generalized hyperbolic skewed t distribution, a continuous and more realistic return distribution. For what follows, it

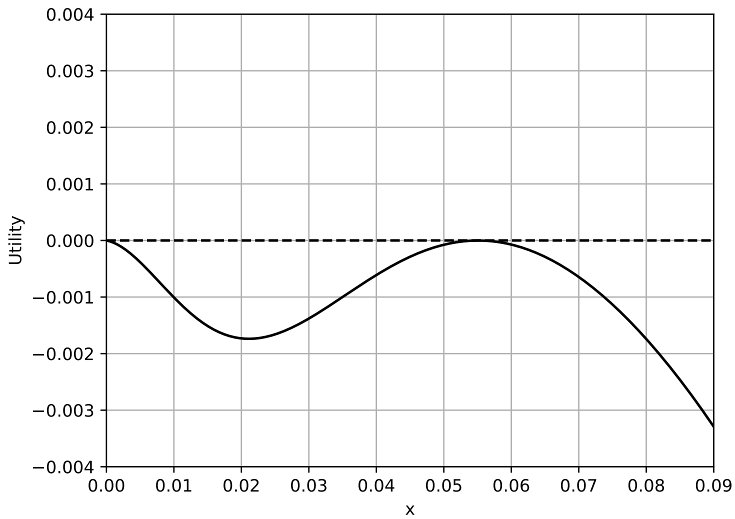


Figure 2: A heterogeneous holdings equilibrium for a binomially distributed skewed asset.

is useful to note that in the case of a skewed asset with a continuous distribution, Equation (17) becomes

$$\begin{aligned} \mathrm{P}\Big(\widehat{R}_M + x\widehat{R}_n \le R\Big) &= \mathrm{P}\Big(\widehat{R}_M + x(\widetilde{R}_n - R_f) \le R\Big) \\ &= \int_{\mathbb{R}} \mathrm{P}\Big(\widehat{R}_M \le R - x(\widetilde{R}_n - R_f) \,\Big|\, \widetilde{R}_n = k\Big) \, f_{\widetilde{R}_n}(k)\, dk \\ &= \int_{\mathbb{R}} \mathrm{P}\Big(\widehat{R}_M \le R - x(k - R_f)\Big) \, f_{\widetilde{R}_n}(k)\, dk \\ &= \int_{\mathbb{R}} \Phi\left(\frac{R - x(k - R_f) - \mu_M}{\sigma_M}\right) f_{\widetilde{R}_n}(k)\, dk, \end{aligned} \tag{26}$$

where $f_{\widetilde{R}_n}(\cdot)$ is the probability density function of the skewed security, and $\widehat{R}_M \sim \mathcal{N}\Big(\mu_M, \sigma_M^2\Big)$.

The generalized hyperbolic skewed t distribution is generally seen as a superior method of modeling skewed and fat-tailed distributions in asset returns as argued by, among others, Aas and Haff [2006], Hu and Kercheval [2010]. Since there is just one skewed asset in this model, we need only the one-dimensional generalized hyperbolic skewed t distribution. Following the specification in Barberis et al. [2021], the skewed asset therefore has probability density function given by

$$f(R) = \frac{2^{1-\frac{\nu+1}{2}}}{\Gamma\left(\frac{\nu}{2}\right)(\pi\nu S)^{1/2}} \cdot \frac{K_{\frac{\nu+1}{2}}\left(\sqrt{\left(\nu + \frac{(R-\mu)^2}{S}\right)\frac{\zeta^2}{S}}\right)\exp\left(\frac{(R-\mu)\zeta}{S}\right)}{\left(\sqrt{\left(\nu + \frac{(R-\mu)^2}{S}\right)\frac{\zeta^2}{S}}\right)^{-\frac{\nu+1}{2}}\left(1 + \frac{(R-\mu)^2}{\nu S}\right)^{\frac{\nu+1}{2}}}, \quad \text{for } \zeta \neq 0, \tag{27}$$

$$f(R) = \frac{\Gamma\left(\frac{\nu+1}{2}\right)}{\Gamma\left(\frac{\nu}{2}\right)(\pi\nu S)^{1/2}}\left(1 + \frac{(R-\mu)^2}{\nu S}\right)^{-\frac{\nu+1}{2}}, \quad \text{for } \zeta = 0,$$

where $\Gamma(\cdot)$ is the Gamma function and K_ℓ is the modified Bessel function of the second kind with order ℓ. The four parameters of the distribution are μ, ζ, S, and ν. The location parameter is μ, which enters into the expectation with a coefficient of 1; ζ is the asymmetry parameter, mainly affecting skewness; S is the scale parameter, governing the spread of the distribution; and ν is a degree of freedom scalar, impacting the heavy-tailedness. The moments of the distribution are given by

$$\mathrm{E}\left(\widetilde{R}\right) = \mu + \frac{\nu}{\nu - 2}\zeta, \tag{28}$$

$$\mathrm{Var}\left(\widetilde{R}\right) = \frac{\nu}{\nu - 2}S + \frac{2\nu^2}{(\nu - 2)^2(\nu - 4)}\zeta^2, \tag{29}$$

$$\mathrm{Skew}\left(\widetilde{R}\right) = \frac{2\zeta\sqrt{\nu(\nu - 4)}}{\sqrt{S}\left(2\nu\zeta^2/S + (\nu - 2)(\nu - 4)\right)^{\frac{3}{2}}}\left[3(\nu - 2) + \frac{8\nu\zeta^2}{S(\nu - 6)}\right]. \tag{30}$$

These equations are key to our empirical calibration. First, we fix $\nu = 7.5$, which gives a reasonably fat-tailed distribution. The exact value of ν, as long as the moments are well-defined, is not particularly impactful. We are left with three equations (the moments) and three unknowns (the remaining parameters). A numerical solver can easily find the values of μ, ζ, and S that satisfy the system. This produces a generalized hyperbolic skewed t distribution that fits our data.

Now we must set the prospect theory parameters α, δ, and λ. Barberis et al. [2021] break with the traditional Tversky and Kahneman [1992] parameterization, opting for values that are a better fit to recent empirical calibrations of preferences in financial markets. To set α and δ, they consider the list of experimental estimates from Booij et al. [2010], who report estimates of α in the range 0.5 to 0.95. So we set $\alpha = 0.7$, near the midpoint of the range in Booij et al. [2010] and below the value of 0.88 reported in Tversky and Kahneman [1992]. For probability weighting δ, the median value of the list of estimates in Booij et al. [2010] is around 0.65. Since this matches the commonly-used value of 0.65 from Tversky and Kahneman [1992], we set $\delta = 0.65$. This leaves loss aversion λ.

In a meta-analysis of experimental estimates of loss aversion, Walasek et al. [2024] report a median value of $\lambda = 1.31$, nearly a halving of the classic Tversky and Kahneman [1992] estimate of 2.25. Subsequent experiments estimate λ even lower. Since a high degree of loss aversion makes negative returns more painful, it attenuates our findings (the lower estimates of λ would increase the overvaluation of skewed securities). To remain conservative while responding to recent estimates, we set $\lambda = 1.5$, which is within the 95% confidence interval reported by Walasek et al. [2024] and in line with the value of 1.6 found by Booij et al. [2010]. Our prospect theory parameters are thus

$$(\alpha, \delta, \lambda) = (0.7, 0.65, 1.5). \tag{31}$$

Figure 3 plots $v(x)$ with the Barberis et al. [2021] parameterization that we opt for alongside its classic Tversky and Kahneman [1992] parameterization. We can see that our parameterization (solid line) has more curvature than the classic one (dash-dot line), owing to the smaller value of $\alpha = 0.7 < 0.88$. The solid line is also flatter in losses than is the dash-dot one, reflecting our choice of a smaller loss aversion $\lambda = 1.5 < 2.25$. The general shape, however, is the same.

4.1 Empirical Approach

We will estimate the overvaluation predicted by the framework set forth in Section 3.1 in three steps. First, we estimate the skewness of the return distribution for a general AI security in the

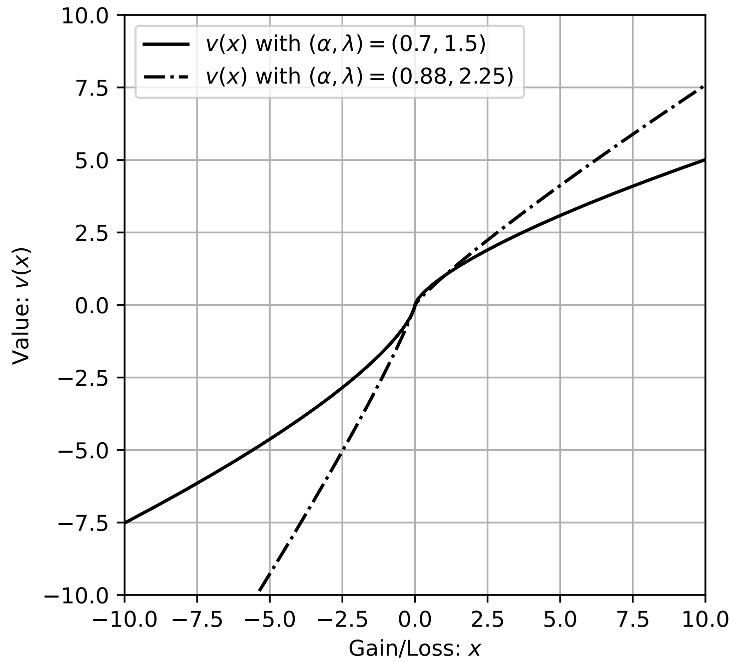


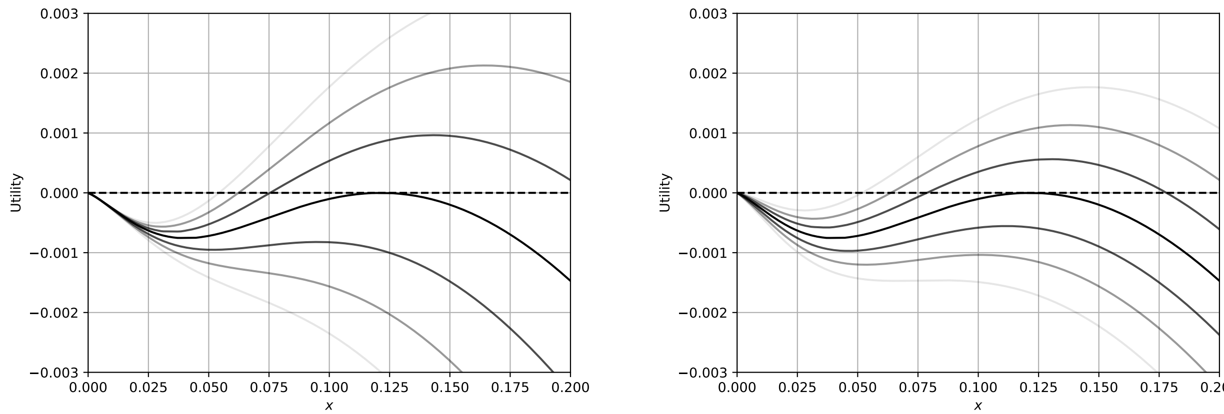
Figure 3: A comparison of the value function with our prospect theory parameters (solid line) and the value function with the classic values (dash-dot line). Our parameterization is flatter in losses and has more curvature than the one proposed by Tversky and Kahneman [1992].

present stock market. Then, we use this skewness to define a generalized hyperbolic skewed t return distribution for the skewed asset and determine its expected return in a heterogeneous holdings equilibrium. Finally, we use this expected return as an input to a valuation model and compare the result to an expected utility benchmark.

Figure 4 demonstrates how investor utility varies with the skewness and expected return of the skewed security. The opacity of each line corresponds to the distance of the parameter being varied from its value in equilibrium.[4] In Figure 4a, it is $\text{Skew}\left(\widetilde{R}_n\right)$ that varies, allowing us to observe how skewness is priced. The bottommost (nearly transparent) line corresponds to the smallest skewness plotted. For that minimally-skewed $\widetilde{R}_n$, utility is nearly linear in x, reflecting the fact that the $\widetilde{R}_n$ is insufficiently skewed for investors to view it as lottery-like. In this case, the primary effect of adding the skewed asset to a portfolio is to reduce expected return, and there is not enough compensation in terms of skewness for utility to be increasing in the portfolio share of the skewed asset at any value of x. As skewness (and opacity) is increased to its value in the heterogeneous holdings equilibrium, the curvature of the utility function increases, and utility near the equilibrium portfolio share x^* increases to 0. Observe, however, that the utility function is almost uniformly decreasing until $x \approx 0.025$, regardless of the skewness of $\widetilde{R}_n$. This reflects the fact that investors find a reduction in expected return painful—it is only when the payoff of a jackpot becomes large

[4]Only the expected return is actually *determined* by equilibrium considerations. Skewness and variance are set exogenously, and agents cannot affect either value. What we mean here is that we perturb the parameters of the generalized hyperbolic skewed t distribution around their values in the heterogeneous holdings equilibrium plotted in the darkest line in Figure 4.

that the skewness of $\widetilde{R}_n$ causes utility to be increasing in x. Otherwise, the effect of the reduction in expected return dominates. The analysis is mirrored if we begin with the uppermost (almost transparent) line—skewness is high enough that investors are *too* excited about the prospect of a jackpot, and an equilibrium with this expected return and variance would require a reduction in $\mathrm{Skew}\left(\widetilde{R}_n\right)$.[5] Mathematically, this "excitement" is due to probability weighting and the resultant overweighting of the tails of the distribution, where the jackpot payout lies.



(a) Investor utility as a function of the portfolio weight of the skewed security for varying levels of $\mathrm{Skew}\left(\widetilde{R}_n\right)$, holding $\mathrm{E}\left(\widetilde{R}_n\right)$ and $\mathrm{Var}\left(\widetilde{R}_n\right)$ fixed. Skewness increases linearly from the bottommost line to the topmost.

(b) Investor utility as a function of the portfolio weight of the skewed security for varying levels of $\mathrm{E}\left(\widetilde{R}_n\right)$, holding $\mathrm{Var}\left(\widetilde{R}_n\right)$ and $\mathrm{Skew}\left(\widetilde{R}_n\right)$ fixed. Expected return increases linearly from the bottommost line to the topmost.

Figure 4: A demonstration of how investor utility varies with $\mathrm{Skew}\left(\widetilde{R}_n\right)$ and $\mathrm{E}\left(\widetilde{R}_n\right)$. Opacity increases as the parameter being varied approaches its value in equilibrium.

Figure 4b demonstrates the exact method we use to solve for an equilibrium. Holding variance and skewness constant, Figure 4b plots utility as a function of the portfolio share x of the skewed asset, varying its expected return for each plotted line. Again, opacity corresponds to the distance of expected return from its equilibrium value. Matching intuition, the lowermost (nearly transparent) line corresponds to the lowest $\mathrm{E}\left(\widetilde{R}_n\right)$ plotted, and utility is increasing in expected return all the way up to the topmost (nearly transparent) curve. For fixed variance and skewness, our approach begins with an initial guess of the equilibrium $\mathrm{E}\left(\widetilde{R}_n\right)$. Then we iterate, increasing expected return if the utility lies below 0 for all x and decreasing expected return if utility lies above 0 for any x—in Figure 4b, this process proceeds in the direction of increasing opacity from any starting point. At each step, we check the equilibrium conditions in Equations (13) to (15). If at any iteration they are all satisfied within a reasonable numerical tolerance (no larger than 10^{-6}), we determine that we have found a heterogeneous holdings equilibrium.

Such an equilibrium, as Barberis and Huang [2008] found and as we will find below, is not

[5] In practice, we would hold skewness fixed and reduce expected return, as $\mathrm{E}\left(\widetilde{R}_n\right)$ is the search variable.

guaranteed to exist. If return skewness is too small or probability weighting too weak, the effect of lottery preferences may not be strong enough to overcome the utility loss resulting from the lack of diversification and reduction in expected return that are required to support a heterogeneous holdings equilibrium.

4.2 Cross-Sectional Skewness Estimate

To arrive at a first-order approximation of investors' perceived skewness of the AI security return distribution, we begin with a cross-sectional approach. What follows relies on the assumption that these AI-associated stocks are in some sense similar.

We consider a basket of 31 prominent and publicly-traded AI-associated equities. Taking the trailing twelve month return for each generates 31 observations from some annual return distribution. If one of these stocks posted an excellent return this year, causing the cross-sectional distribution to be highly skewed, then since the securities are similar, it is reasonable to believe that all securities in the basket have the potential to earn a similarly impressive return the following year.[6] Hence, we can think of each security drawing its next-year return from the distribution of realized annual returns over the past year (among all stocks in the basket). So, to estimate the variance and skewness investors perceive for a general AI security, we can calculate the corresponding moments for our basket of 31 AI stocks. Doing so gives

$$\mathrm{Skew}\left(\widetilde{R}_n\right) \approx 2.2, \tag{32}$$

$$\mathrm{Var}\left(\widetilde{R}_n\right) \approx 0.88. \tag{33}$$

Using these moments to calibrate the generalized hyperbolic skewed t distribution as described in Section 4, we produce Figure 5. The expected return of the basket of AI stocks is required to fix the location of the fitted generalized hyperbolic skewed t distribution. However that is just for demonstration. The expected value of the skewed asset is ultimately determined in equilibrium. We can see that in Figure 5, most of the mass, of both the histogram and the distribution, is located between a return of 0 and 1. There are two far right-tail returns reported in the neighborhood of 3.5, matching the long right tail of the generalized hyperbolic skewed t distribution.

Yet the values reported in Equations (32) and (33) do not support a heterogeneous holdings equilibrium with negative expected excess return. Figure 6 shows the investor's goal function for varying portfolio shares x of the skewed security assuming that $\mathrm{E}\left(\widetilde{R}_n\right) = R_f$, so that the expected excess return on the skewed security is 0. For the remainder of this analysis, we assume

$$R_f \triangleq 1.03, \tag{34}$$

approximately the long-term average value of the gross one-year Treasury rate. The curve is nearly linear, characteristic of an economy where the skewed security lacks sufficient skewness to support multiple equilibria (see the bottommost line in Figure 4a). Increasing expected return beyond the level plotted in Figure 6 does not lead to an equilibrium, either.

[6] We consider only the trailing twelve month return so that this assumption is well-founded. If we consider too broad a timeframe, we risk including data that is of no relevance to the asset's return next year—like, say, the return on Microsoft stock in 1994—clouding our estimate of future skewness.

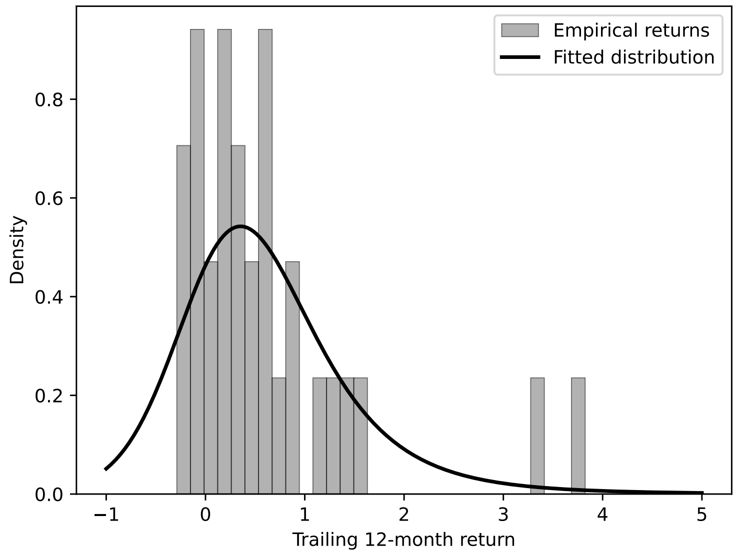


Figure 5: A generalized hyperbolic skewed t distribution plotted atop a histogram of empirical returns. The histogram and the generalized hyperbolic skewed t distribution have the same expected value, variance, and skewness.

There are many possible interpretations of this result. Perhaps lottery preferences do not play a role in AI stock exuberance. Maybe there is no exuberance. Or could it be that this empirical calibration is inaccurate? It is the investor's perceived future skewness that enters the goal function. If investors perceive greater skewness in the AI security return distribution than is visible in realized returns over the past year, then the skewness observed in cross-sectional returns is not the relevant quantity to our analysis. Because the right tail of a positively skewed distribution is composed of low-probability, high-magnitude outcomes, realized cross-sectional returns are likely to understate the amount of right-tail mass that investors perceive. In order to evaluate the role of lottery preferences, we must instead estimate investor *perceptions* of future skewness.

4.3 Forward-Looking Skewness Estimate

Now we argue that investors perceive more skewness in the return distributions than we found in Section 4.2, presenting a stylized analysis that may lead to substantial perceived skewness. Perhaps the strongest justification for this approach is the widespread belief that artificial general intelligence (AGI, or superintelligence) will lead to an explosion on productivity growth. As no firm has yet, to our knowledge, achieved AGI, the skewness that this possibility contributes to investor perceptions of the future return distribution is not captured with backward-looking measures like that of Section 4.2. We emphasize that this is an intentionally optimistic scenario designed to model the far-right tail; less extreme assumptions would lower the implied skewness.

Our argument is inspired by the analysis of potential gains from existing AI, not AGI, from the prominent consultancy firm McKinsey. In McKinsey & Company [2024], McKinsey partners argue that AI could substantially drive innovation in R&D, claiming that

"For industries whose products consist of intellectual property (IP) or whose R&D

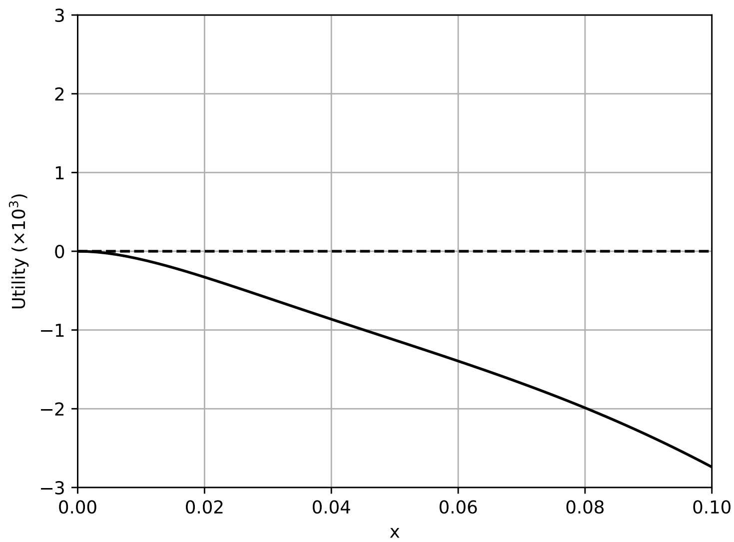


Figure 6: An empirical analysis of a cross-section of AI-associated stock returns over the past year finds insufficient skewness to support a heterogeneous holdings equilibrium. This figure plots utility as a function portfolio share of the skewed asset when the expected excess return is 0. The curve is nearly linear.

> processes are closest to scientific discovery, the rate of innovation could potentially be doubled."

For various industries, they propose potential increases in annual EBIT up to 60%.

Based on more bullish sources Korinek and Suh [2024], Fernald and Jones [2014], AGI could lead to a literal singularity in income, where productivity growth rates increase each year as AI performs R&D, quickly diverging to $+\infty$. The CEO of Anthropic, Amodei [2024], has claimed that once AGI is achieved, "AI-enabled biology and medicine will allow us to compress the progress that human biologists would have achieved over the next 50-100 years into 5-10 years". Given that the returns to such a successful technology would be difficult (and maybe meaningless) to estimate, we take a more conservative approach and apply an exceedingly bullish interpretation of McKinsey & Company [2024]. For concreteness, we use real-world data on Alphabet stock (the parent company of Google).

The historical average annual revenue growth for Alphabet is around 12%, its operating margin is around 30%, and it trades at $\frac{P}{E} \approx 30$. Since the market capitalization is around 3.4T, this implies $E \approx 113.33$B and revenue ≈ 377.77B.[7]

The following back-of-the-envelope calculation will estimate the firm's revenue in 2030, assuming it wins the race for "AI superintelligence" (in a rather conservative sense), find P_{2030} assuming the $\frac{P}{E}$ ratio remains the same, then discount the price back to today using the firm's cost of capital,

[7]These estimates align well with official data of \$100B and \$349.8B in earnings and revenue, respectively, for the 12 month period ending September 30, 2025.

$\mathrm{E}\left(\widetilde{R}\right)$, given its $\beta = 1.08$.

Suppose that as a result of leveraging advanced AI, Google achieves dominance for the next 5 years, increasing its revenue growth rate by 100%, from 12% annually to 24% per annum. This gives a lower bound on revenue in 2030 assuming there are no other contributors to growth:

$$\text{Revenue}_{2030} \geq 377.77B \cdot 1.24^5 \approx 1107.48B. \tag{35}$$

McKinsey & Company [2024] model the returns from AI as it exists today, not the returns of AGI. So the assumption of doubled revenue growth is at worst defensible—a firm that has achieved superintelligence should expect more productive R&D and rapid growth in popularity of AI offerings like agents and chatbots, as well as highly effective AI-powered advertising.

Now, OpenAI has estimated that they will themselves have revenue of around 125B in 2029 according to Reuters [2025], so if Google releases and licenses a superintelligent model that steals market share from OpenAI (and competitors in the AI space), it can expect a boost to annual revenue of, say, 140B by 2030.[8] If we assume this is the only source of growth beyond the increase in the revenue growth rate, then

$$\text{Revenue}_{2030} \approx 1107.48B + 140B = 1247.48B. \tag{36}$$

To translate this into earnings, we optimistically assume that there is a 50% EBIT increase that applies entirely to the firm's existing 30% margin,[9] meaning

$$E_{2030} = (1 + 0.5) \cdot 0.3 \cdot 1247.48B \approx 561.37B. \tag{37}$$

So if the $\frac{P}{E}$ ratio remains near 30,

$$P_{2030} = \frac{P}{E} \cdot 561.37B = 16.841T. \tag{38}$$

Assuming an equity risk premium of 5% and riskless rate of 3%, we find that Alphabet's cost of capital is

$$\mathrm{E}\left(\widetilde{R}\right) = R_f + \beta \cdot 5\% = 3\% + 5.4\% = 8.4\%, \tag{39}$$

and using this to discount to present, we find

$$PV(P_{2030}) = \frac{16.841T}{1.084^5} \approx 11.3T. \tag{40}$$

This implies a return of

$$R = 11.3/3.4 - 1 = 231\%. \tag{41}$$

At the date of writing, before Alphabet's rally in late November 2025 (and any ensuing market movements), the high analyst share price target was \$350, the average was \$312, and the low was

[8] This figure is estimated by calculating the future value of \$125B in 2029 one year forward to 2030 and rounding up to account for growth in excess of the riskless rate.

[9] This does involve some double counting of the McKinsey & Company [2024] estimates; however, this analysis is meant to reflect a far right-tail success in the AI space, so perhaps some optimism is justified.

\$236, with a current price around \$280. If we suppose that there is around a 50% chance that the mean estimate will be correct, equal chance that the low and high will be correct, and assign some probability q to AGI dominance, then we can model the return $\widetilde{R}$ as

$$\mathrm{P}\left(\widetilde{R} = \frac{350-280}{280}\right) = \mathrm{P}\left(\widetilde{R} = \frac{236-280}{280}\right) = (1-q)\frac{1}{4}, \tag{42}$$

$$\mathrm{P}\left(\widetilde{R} = \frac{312-280}{280}\right) = (1-q)\frac{1}{2}, \tag{43}$$

$$\mathrm{P}\left(\widetilde{R} = 2.31\right) = q. \tag{44}$$

If we suppose investors assign a 1% probability to the AGI dominance path for Alphabet, we find

$$\mathrm{Skew}\left(\widetilde{R}\right) \approx 5.51, \tag{45}$$

$$\mathrm{Var}\left(\widetilde{R}\right) \approx 0.071. \tag{46}$$

Does this distribution lead to an overvaluation of the skewed asset? Following the procedure of Section 4.1, we fix the skewness and variance at their levels in Equations (45) and (46) and search for the expected return on the skewed asset that supports a heterogeneous holdings equilibrium.

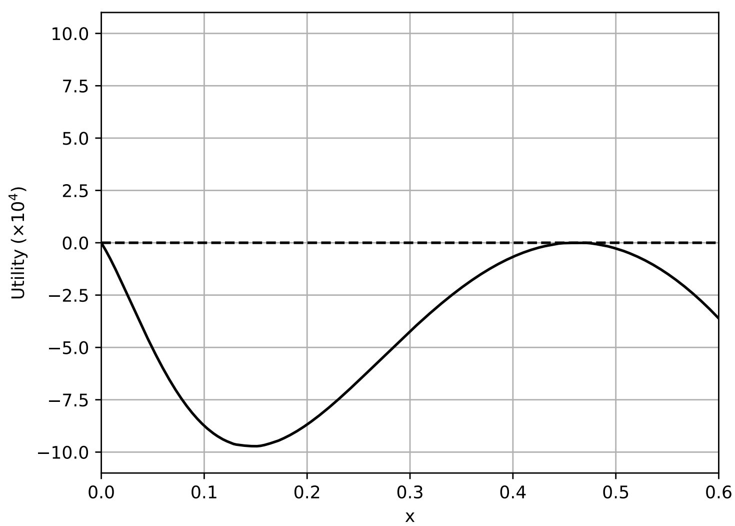


Figure 7: The heterogenous holdings equilibrium in an economy where the skewed asset $\widetilde{R}_n$ has $\mathrm{Skew}\left(\widetilde{R}_n\right) = 5.51$ and $\mathrm{Var}\left(\widetilde{R}_n\right) = 0.071$.

Figure 7 shows the our result. We find that our forward-looking estimates of the skewness and variance support a heterogeneous holdings equilibrium. In this economy,

$$\mathrm{E}\left(\widetilde{R}_n\right) = 1.024725, \tag{47}$$

$$\mathrm{E}\left(\widehat{R}_n\right) = -0.005275. \tag{48}$$

So the skewed security earns a negative excess return and is therefore overvalued. We will explore the notion of overvaluation in the next section. Here, it is important to note that the equilibrium portfolio share of the skewed asset is

$$x^* \approx 0.47, \tag{49}$$

meaning that investors hold a significant portion of their wealth in the skewed asset. This may be true, but it is a strong prediction. It is interesting to note, however, that the Magnificent 7 (which are leaders in AI) make up around 35% of the market capitalization of the S&P 500. So this x^* may be within reason, though still a rather high fraction.

Now, it is evident that this method provides a low estimate of the variance. From Equation (46), $\mathrm{Var}\left(\widetilde{R}\right) = 0.071$ implies a volatility of 27%, while the volatility of the S&P 500 is between 10-20%. Though this is a weakness of the model, it is not of first-order significance to our results. If we triple the variance to 0.213—giving a volatility of 46.2%—the economy still supports a heterogeneous holdings equilibrium.[10]

4.4 Predicted Overvaluation

To conclude, we translate the equilibrium expected return into a measure of the degree of overpricing in financial markets. To do so simply, we consider a dividend discount model. Overpricing will be the result of investors applying a low discount rate to the skewed asset.

Assume that dividends grow at a constant rate g. From Section 4.3, we have a CAPM benchmark discount rate of $\mathrm{E}\left(\widetilde{R}_{\mathrm{CAPM}}\right) = 8.4\%$. So,

$$P_{\mathrm{CAPM}} = \sum_{t=1}^{\infty} \frac{D_0(1+g)^t}{\left(1 + \mathrm{E}\left(\widetilde{R}_{\mathrm{CAPM}}\right)\right)^t}. \tag{50}$$

An estimate of the price under the framework of Section 4 requires an additional assumption on the path of investor discount rates. After all, return skewness is the result of the firm's growth options. At some point in the future, it will almost certainly become a mature business without opportunity for extreme growth. So at some future time, the skewness and resultant overpricing should subside. Say this occurs over the course of T periods. The exact timing of this process is almost impossible to model accurately, and we make a highly stylized assumption: the perceived skewness will completely subside over the next T years, and as it does so, the discount rate investors apply will increase linearly to the CAPM benchmark.

In Section 4.3, we found a heterogeneous holdings equilibrium with

$$\mathrm{E}\left(\widehat{R}_n\right) = \mathrm{E}\left(\widetilde{R}_n\right) - R_f = 1.024725 - 1.03 = -0.005275. \tag{51}$$

At $t = 1$, the required return is $\mathrm{E}\left(\widetilde{R}_n\right)$. By assumption, at $t = T + 1$ the discount rate is $\mathrm{E}\left(\widetilde{R}_{\mathrm{CAPM}}\right)$.

[10] For comparison, the volatility of Alphabet stock is around 30%.

The price is therefore given by

$$P_{\text{CPT}} = \sum_{t=1}^{T+1} \frac{D_0(1+g)^t}{\left(1 + \mathrm{E}\left(\widetilde{R}_n\right) + \Delta \cdot (t-1)\right)^t} + \sum_{t=T+2}^{\infty} \frac{D_0(1+g)^t}{\left(1 + \mathrm{E}\left(\widetilde{R}_{\text{CAPM}}\right)\right)^t}, \tag{52}$$

where $\Delta = \frac{\mathrm{E}\left(\widetilde{R}_{\text{CAPM}}\right) - \mathrm{E}\left(\widetilde{R}_n\right)}{T}$.

Now we will compute a numerical example. First, suppose $T = 10$ so that the perception of skewness persists for ten years. Since D_0 is a constant multiplier, it will drop out of Equation (53). So we only need to set g. As this is the growth rate infinitely far into the future, we conservatively let $g = 2\%$. With these assumptions, the degree of overpricing relative to the CAPM benchmark is

$$\frac{P_{\text{CPT}} - P_{\text{CAPM}}}{P_{\text{CAPM}}} \approx 5.07\%. \tag{53}$$

This is a modest, yet meaningful degree of overvaluation. Markets do tend to have daily movements of around 3% a handful of times per year. However, in this model, the 5.07% overpricing figure is a persistent distortion driven only by cumulative prospect theory preferences—namely probability weighting. Moreover, this does not imply that AI securities are 5% overvalued. Rather, this is solely the contribution from lottery preferences. Other forces could make their own contributions to overvaluation, leading to an even more dramatic figure.

The key numerical values of this simplified model of overpricing are g and T. The order of magnitude of the overpricing is relatively insensitive to the exact value of g. Keeping $T = 10$ and increasing g to 2.5% gives an overpricing of about 4.76%; reducing g to 1.5% results in a 5.36% overpricing estimate. Intuitively, increasing (decreasing) dividend growth loads more (less) of the value in later periods, where the CPT discount rate equals the CAPM benchmark. Still, in either case, the magnitude of the overvaluation estimate is nearly the same. However, the estimate is rather sensitive to T. Doubling T to 20 gives an overpricing of 15.5%, and halving T to 5 predicts only a 1.6% overvaluation. So the timing assumption does have a meaningful impact on results. Finally, we return to our discussion of the importance of the variance estimate from Section 4.3. Tripling the variance to $\mathrm{Var}\left(\widetilde{R}_n\right) = 0.213$ predicts an overvaluation of 5.6% rather than the 5.07% overvaluation predicted using $\mathrm{Var}\left(\widetilde{R}_n\right) = 0.071$ from Equation (53).[11] So, the estimate of overvaluation is relatively insensitive to our measure of the variance of the skewed security.

5 Conclusion

This paper examines the implications of cumulative prospect theory, namely its probability weighting component, for the valuation of highly skewed assets. Motivated by recent enthusiasm surrounding

[11] The fact that overvaluation is increasing in variance, all else equal, is the result of probability weighting and the tail behavior of the generalized hyperbolic skewed t distribution. When the distribution has positive skew, its left tail decays far more quickly than its right tail. For the distribution parameterized by Equations (45) and (46), the left tail becomes numerically indistinguishable from 0 at a return of -50%. The right tail, on the other hand, is negligible beyond a 2079% return. The tail mass beyond these two bounds is on the order of 10^{-7}. For the generalized hyperbolic skewed t distribution with triple the variance, the left tail (right tail) is negligible beyond -12.98% (3526%) return, with a similar tail mass beyond those bounds. Even though these distributions have the same skewness, the long right tail of the higher variance distribution makes it more valuable as a lottery-like investment.

AI-associated equities, we extend the framework of Barberis and Huang [2008] by replacing their stylized binomial "lottery ticket" with a generalized hyperbolic skewed t return distribution. This richer specification allows us to model continuous, fat-tailed, and empirically realistic return dynamics. We calibrate the distribution to recent data on a cross section of AI-associated securities and find that, when the return on the skewed security draws from the calibrated distribution, the economy does not support an equilibrium in which the skewed security earns a negative expected excess return. Under forward-looking estimates of skewness motivated by public commentary and firm fundamentals, however, our calibration suggests that lottery preferences can generate a nontrivial overpricing of such assets.

Several extensions would strengthen and broaden these results. First, we can devise more precise methods of estimating the perception of future skewness in financial markets. Second, we can integrate a more realistic model of the time evolution of return skewness into our overvaluation framework, improving the accuracy of our overvaluation estimate. Finally, we could extend our analysis to consider an economy with multiple skewed assets, each calibrated to different real-world securities, and examine the overpricing and portfolio choice implications.

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