



Delft University of Technology

Aspirational utility and investment behavior

Aristidou, Andreas; Giga, Aleksandar; Lee, Suk; Zapatero, Fernando

DOI

[10.1016/j.jfineco.2024.103970](https://doi.org/10.1016/j.jfineco.2024.103970)

Publication date

2025

Document Version

Final published version

Published in

Journal of Financial Economics

Citation (APA)

Aristidou, A., Giga, A., Lee, S., & Zapatero, F. (2025). Aspirational utility and investment behavior. *Journal of Financial Economics*, 163, Article 103970. <https://doi.org/10.1016/j.jfineco.2024.103970>

Important note

To cite this publication, please use the final published version (if applicable).
Please check the document version above.

Copyright

Other than for strictly personal use, it is not permitted to download, forward or distribute the text or part of it, without the consent of the author(s) and/or copyright holder(s), unless the work is under an open content license such as Creative Commons.

Takedown policy

Please contact us and provide details if you believe this document breaches copyrights.
We will remove access to the work immediately and investigate your claim.

Green Open Access added to TU Delft Institutional Repository

'You share, we take care!' - Taverne project

<https://www.openaccess.nl/en/you-share-we-take-care>

Otherwise as indicated in the copyright section: the publisher is the copyright holder of this work and the author uses the Dutch legislation to make this work public.



Aspirational utility and investment behavior^{☆,☆☆}

Andreas Aristidou^{a,1}, Aleksandar Giga^b, Suk Lee^c, Fernando Zapatero^{d,*}

^a Netflix, 121 Albright Way, 95032, Los Gatos, CA, USA

^b Faculty of Technology, Policy and Management, TU Delft, Jaffalaan 5, 2628 BX, Delft, The Netherlands

^c UNSW Business School, UNSW Sydney, NSW 2052, Australia

^d Questrom School of Business, Boston University, 595 Commonwealth Ave, 02215, Boston, MA, USA

ARTICLE INFO

JEL classification:

D9

G0

G4

Keywords:

Aspirational utility

Social status

Investment behavior

Laboratory experiment

ABSTRACT

We explore the extent to which aspirations – such as those forged in the course of social interactions – explain ‘puzzling’ behavioral patterns in investment decisions. We motivate an aspirational utility, reminiscent of Friedman and Savage (1948), where social considerations (e.g., status concerns) provide an economic foundation for aspirations. We show this utility can explain a range of observed investor behaviors, such as the demand for both right- and left-skewed assets; aspects of the disposition effect; and patterns in stock-market participation consistent with empirical observations. We corroborate our theoretical findings with two novel laboratory experimental studies, where we observed participants’ preference for skewness in risky lotteries shift as lab-induced aspirations shifted.

1. Introduction

It is well-known that standard utilities, such as CRRA utility, have certain limitations in their ability to address the large number of empirically observed patterns on investment behavior. In this regard, a growing literature focuses on the fact that social interactions often influence our decision-making, and explores how such considerations can aptly be modeled to explain financial (investment) decisions (e.g., Hirshleifer (2015)). One key aspect of social interaction is that it can often sow the seed of an *aspiration*, the setting of a forward-looking goal that provides a burst of utility if realized. As a prominent example, frequent social interactions can reinforce an aspiration for a higher *social status* than one’s own, either because of a status competition with a peer, or because one learns – during the course of social interactions – that high status can reward that person with favorable social outcomes (e.g., respect).² The literature has looked at such social aspects in the context of asset pricing and investment behavior, for

example, status concerns (Roussanov, 2010) or internal and external habit formation (Sundaresan, 1989; Constantinides, 1990; Campbell and Cochrane, 1999). Rayo and Becker (2007) argue that this type of utility provides an evolutionary edge. While the vast majority of these analyses underscore the importance of the *relative position* of wealth, our focus is also on the fact that socializing often has *aspirational* consequences. For example, the realization that the majority of one’s peers are homeowners can fuel an aspiration for the status of homeownership. And because such an aspiration is typically attained through the acquisition of a non-divisible, and prohibitively expensive good, it remains an aspiration until it is fulfilled, and generates a surge of utility once it is obtained. We solidify this intuition and motivate a representation of aspirational utility by paraphrasing (Ng, 1965). This motivational exercise illustrates why aspirational utility is likely to be a highly realistic feature that arises commonly in economic activities, attributable to well-established concepts in the literature such as status-seeking, external habits, peer pressure, and in general,

[☆] Nikolai Roussanov was the editor for this article. We thank the editor and an anonymous referee for their insightful and constructive comments. We also benefited from comments from Odilon Camara, Kevin Murphy, and Francesco Stradi, as well as seminar participants at USC Marshall School of Business, Toulouse Business School, ITAM Mexico, University of Palma de Mallorca, ICADE (Madrid) and the Spanish Finance Forum. All remaining errors are ours.

^{☆☆} A previous version of this paper was circulated under the title: “Rolling the Skewed Die: Economic Foundations for the Demand for Skewness and Experimental Evidence”.

^{*} Corresponding author.

E-mail addresses: aristidouandreas13@gmail.com (A. Aristidou), a.giga@tudelft.nl (A. Giga), suk.lee@unsw.edu.au (S. Lee), fzapa@bu.edu (F. Zapatero).

¹ Disclaimer: Dr. Aristidou contributed to this article as part of his doctoral dissertation at the University of Southern California. The views expressed are his own and do not necessarily represent the views of Netflix.

² Clearly, status is not the sole source of aspiration. Ng (1965) shows how indivisible consumption in general – e.g. university education – creates aspirations. Genicot and Ray (2017) motivate aspiration as “the inspiration of higher goals and the potential frustrations that can result”. Our experiment stipulates that a charitable donation be made on behalf of the participant if their lottery gains exceeds a threshold: This threshold serves as an aspiration.

whenever consumption goods are not perfectly divisible. In this paper, we aim to explore the extent to which this aspirational utility can account for puzzles in individual investment behavior. Overall, we find that it has the potential to explain many aspects of investment behavior, to a degree comparable to leading theories such as Prospect Theory.

To start our analysis, we explore the capacity of aspirational utility to explain the *preference for skewness*. Skewness-seeking plays an important part in people's investment decisions (Kumar, 2009), and investors have been observed to sacrifice some diversification and high(er) returns for positive skewness (Mitton and Vorkink, 2007). In fact, it has been argued that the demand for skewness has the potential to explain some of the most challenging empirical puzzles contemplated in the literature such as the *value premium puzzle* (Zhang, 2013). While these are predominantly discussed in the context of right-skewness, the demand for left-skewness is also present in many economic decisions, as we will later argue, exemplify and present experimental evidence for. Nevertheless, the motives for such demand for skewness remain unexplained to a large extent. We find that aspiration has a natural potential to generate a preference for skewness in both directions. As an example (for positive skewness), consider a salaried “middle class worker” who yet aspires to the glamour of upper class lifestyle; the Rolls-Royce, mansion, and a yacht. Devoid of any practical maneuver to climb the status ladder, one “realistic” option to address this aspiration is to buy a lottery ticket; *i.e.* demand positive skewness. To formalize this intuition, we build upon the aspirational utility framework by Diecidue and van de Ven (2008) using the *concavification* principle, and show how a demand for skewness can arise endogenously. The utility function is similar in shape to a CRRA function but incorporates socially-driven elements such as status-seeking and external habits, by specifying an aspiration (R) that induces a positive jump in utility if the spending exceeds R . We then introduce a parsimonious set of securities (called ‘binomial martingales’) that contain different levels of skewness allowing investors to choose the exact level of skewness – right or left – optimal for their position in the utility function. From this setting, we derive the demand for skewness as the optimal choice of security, the result we succinctly express in the “*four seasons of gambling*” diagram.

In particular, we show analytically that the relative position of the aspiration R (*i.e.*, how far away the aspiration is), with respect to the agent's current wealth/consumption level (C_0) is a critical factor in determining the demand for skewness. If the agents' aspiration is only marginally higher than the current endowment, they choose to sell skewness. In other words, when the next aspiration point is within the reach of hand, in close proximity to their current endowment, the agent selects a security that lands on that aspiration level with relatively high probability. Such a security – high chance of a small gain – is negatively skewed. On the other hand, by exactly symmetric arguments, as the aspiration level moves further away from the current position, the agent reaches for a long shot and chooses to buy right-skewed securities, *i.e.* lotteries. This is in sharp contrast to the standard mean–variance analysis – with reasonable parameter values – where agents avoid risk-taking when the expected return is zero or negative. We also explore how endogenous demand for skewness changes with respect to the parameters of the utility function. Predictably, the size of the jump is a main factor. Perhaps surprisingly though, if attaining the aspiration leads to a big jump in utility, agents choose *less* positively skewed securities. Intuitively, this is because a big jump implies greater importance of aspiration: the agent is then forced to demand securities that can help get to the aspiration level with higher probability, albeit at the expense of a lower level of consumption if the gamble fails. Such securities contain low or even negative skewness. Analogous results are presented for the level of risk aversion and initial wealth of the agent.

Leading theories on investment behavior – most notably Prospect Theory (Kahneman and Tversky, 1979) – attempt to provide a unified explanation for individual risk-taking behaviors such as skewness-seeking and the *disposition effect* (Shefrin and Statman, 1985). In this regard, we also explore the extent to which aspirations can produce

the disposition effect. In summary, we find that the aspirational setup makes substantial progress towards generating the disposition effect, although not to its full entirety. The part that we *can* address is the general tendency of the (aspiration-driven) investor to “sell when winning, and hold when losing”, which we call the ‘*temporal component*’ of the disposition effect. Intuitively, an aspiration can generate this temporal component because it functions as a clear milestone in the investor's mindset, for example, the desire to purchase a “luxury handbag” once the investment surpasses the price of the bag. Consequently, such an aspiration would promote a premature selling of the investment, namely, as soon as the invested amount surpasses the price tag of the “luxury handbag”, generating the behavior of “selling when winning”. (A similar, symmetric argument can be applied to explain why aspirational investors tend to “hold on to losses”.) However, the aspirational setup also has a clear limitation in its capacity to explain the disposition effect: While an aspiration can make an investor sell the portfolio when winning (and hold on when losing), it is unable to make the investor choose the particular winning (losing) stock to sell (retain), within the cross-section of stocks in the portfolio. In this sense, it is unable to explain (what we call) the ‘*cross-sectional component*’ of the disposition effect. This limitation arises because our model is too “rational” (other than the notion of aspiration) to fully explain the disposition effect. In our model, agents optimize over the wealth's position in relation to their aspirations. Meanwhile, to generate the disposition effect up to the cross-section, the aspiration must be placed on each individual asset *within* the wealth portfolio, for example, an investment target for every stock with separate mental accounts. Our model is less inviting to the application of asset-specific target, as it is rather challenging to put forward a “rational” reason for such asset-specific, psychological attachment.

Such limitation notwithstanding, the aspirational setup also has a clear advantage over Prospect Theory, which stands as the leading explanation for the disposition effect. As Heimer (2016) points out, the capacity of Prospect Theory to explain the disposition effect is challenged by the fact that those who are predicted to be under the disposition effect (by Prospect Theory) are, in fact, those who are least likely to participate in (*i.e.*, are the most pessimistic about) the stock market in the first place. For this reason, Heimer (2016) argues that a proposed explanation for the disposition effect must simultaneously generate strong stock-market participation. Our aspiration utility meets this requirement, as it offers a natural reason for agents to take risk — the drive to attain the aspiration. In our aspirational setup, this compulsion is represented by a convex segment in utility, where the agents are clearly risk-seeking. This increased appetite for risk raises the portion of stocks in an investor's portfolio, encouraging the aspiration-driven investor to simultaneously display the disposition effect *and* participate in the stock market. The presence of convex segment is a common feature shared by the utility proposed by Friedman and Savage (1948), Levy (1969), as well as Prospect Theory. Our model adds to this strand of literature by focusing on what we believe is a plausible, *social* underpinning for such convexity.

In addition to addressing stock-market participation behavior in conjunction with the disposition effect, our theory also has the capacity to explain some of the well-known puzzles in household finance regarding the stock-market participation of low income households. Specifically, it has been considered puzzling that the stock market participation among the low income households is lower than optimal, and those that do invest in stocks tend to be hardly diversified, which is clearly sub-optimal according to mainstream theories. While the conventional response to this has been to seek a behavioral alternative based on bias or ignorance, our aspirational narrative provides a unique perspective based on the optimal choice of skewness. That is, given that our theory predicts a demand for positive skewness for the low income households, the seemingly sub-optimally low stock-market participation should be understood as an optimal substitution away from stocks to more positively skewed gambles, such as the lottery.

In similar vein, the reluctance to diversify is hardly puzzling in the aspiration model, as it is understood as the pursuit of positive skewness in individual stocks, in lieu of negative (or neutral) skewness in more diversified portfolios. We gather pieces of evidence from the literature that collectively support this narrative. Moreover, given that aspirations are not exclusively for the low income investors, we conjecture that there are multiple aspirations across the wealth distribution, where some may be representative enough to be priced in the aggregate. For example, many low income investors may aspire to “rise from the economic challenges”, whereas the wealthier may aim for “upper class lifestyle”. This allows us to explore stock-market investment behavior across a wider spectrum of investors than just those in the lower end of the wealth distribution. We show how recent empirical findings from [Bali et al. \(2023\)](#) support this notion of (two) generic aspirations, where the wealthy actively take on risks in the stock market to address their aspirations. This aspiration-based narrative is, in fact, consistent with the idea that the wealthy seek idiosyncratic volatility to address status concerns (e.g., [Roussanov \(2010\)](#)).

Showing how aspirations may affect investment choices in the real world is challenging as it is very rare that the researcher directly observes the decision maker’s financial investments, their aspirations, or how far they are from achieving them. Therefore, we proceed to test our model’s key implications (on skewness) with an exploratory lab experiment.³ University students were given a choice of simple securities with varying degrees of skewness, holding mean and variance constant. The subjects in the experiment were induced with an aspiration point in the form of a (to them) non-monetary but heartwarming award — by stipulating that a donation to a charity of their choice will be made on their behalf, *if* the monetary gains from their experiment result exceeded a pre-specified “Donation threshold”.⁴ Both within- and between-subject studies were conducted in which we controlled how far the donation thresholds were from their current positions and examined how that affected their choice of securities. The results are in line with our predictions. When the aspiration point is close by, the overall demand for a negatively skewed asset increases. When reaching the aspirational jump is possible but distant, the demand for positively skewed asset increases. Our results also showed that there is substantial heterogeneity in the demand for skewness generated by the aspiration, which may have been due to differences in the degree to which donation generated aspirations, or simply due to “intrinsic” differences in their utility functions.

Our aspirational setup with a status-seeking motive is reminiscent of the framework first established by [Friedman and Savage \(1948\)](#), which is motivated by the ‘puzzling’ observation that some investors simultaneously buy insurance and lotteries. They interpret this puzzle as a shortcoming of standard utility models, and respond to it by suggesting an ‘aspirational’ alternative. It is elucidating to note that the puzzle they observe is valid only when looked through the lens of “volatility”, and not through “skewness”, an aspect that they overlook. In fact, focusing on the net demand for right (positive) skewness provides a rather simple resolution of the puzzle: Buying a lottery ticket amounts to taking a long position in right skewness, and buying insurance implies a short position in left skewness, *both* revealing a preference for net right skewness. While this amply demonstrates the merits of extending the scope of analysis to beyond what is habitually explored, the second part of [Friedman and Savage \(1948\)](#)’s message — namely, the shortcomings of standard utility models — remains just as

relevant because standard utility models fall far too short of explaining many known patterns in investment behavior. As an example, consider again the demand for skewness. Although CRRA utility in principle implies a preference for right skewness, the optimal policy of a CRRA investor with reasonable parameter values is to *sell* short a lottery because its negative expected return and high variance dominate the effect of positive skewness.⁵ Efforts have been made to enrich the utility function to account for the observed skewness preference. [Kraus and Litzenberger \(1976\)](#) add weight to the positive third moment of wealth in the standard utility function. [Barberis and Huang \(2008\)](#) explain the demand for lottery-like securities through probability weighting of the Cumulative Prospect Theory ([Tversky and Kahneman, 1992](#)). In [Brunnermeier et al. \(2007\)](#)’s model, over-optimism generates the under-diversified and lottery-seeking portfolios. Despite these efforts, the demand for *negative* skewness is almost entirely rejected by these theories — unless when presented with a sufficiently large and positive expected payoff — and yet we show both conceptual and experimental evidence for such choices. Similar shortcomings abound regarding other ‘puzzling investment behavior’ beyond the demand for skewness, and these observations altogether justify our search for economic motives whose utility representation opens an avenue to address them. We believe that aspiration, in the context of social interactions, is one such motive worth exploring.

The paper is organized as follows. In Section 2 we motivate our setup and derive our utility function. In Section 3 we study the optimal demand for skewness for an agent with this utility. In Sections 4 and 5 we discuss how our aspirational model compares against leading theories on investment behavior regarding some behavioral “puzzles” such as the disposition effect and known patterns in stock-market participation. Section 6 discusses how our aspirational model complements existing theories on how social interactions affect investments. In Section 7 we present our laboratory study and results. We close the paper with some conclusions.

2. An aspirational utility: A motivation and representation

In this section, we motivate and discuss ‘aspirational utility’: a standard utility function augmented by elements of “goal and its attainment”. We are not the first to discuss aspiration in the context of risk-taking choices. [Lopes \(1987\)](#) establishes a theory (“SP/A theory”) where the “hope” (or “fear”) of attaining (or missing) and aspiration (“A”, for Aspiration) determines the choice of the decision-maker. [Shefrin and Statman \(2000\)](#) develops this idea into a theory of portfolio choice (“Behavioral Portfolio Theory”). Operationally, these theories embed the notion of aspiration into the model by over- or under-weighting probabilities in line with the psychological response of the agent vis-a-vis the aspiration. (This is reminiscent of the “Weighting Function” in Cumulative Prospect Theory.) Our approach shares the focus on aspiration of these works, but is more akin to — and builds upon — the work of [Diecidue and van de Ven \(2008\)](#) who microfound a discontinuity in utility function as a representation of aspiration.

2.1. A motivation: Local, bulky status goods

To illustrate how aspirational utility may arise from natural microeconomic foundations, we consider [Roussanov \(2010\)](#) who analyzes status-seeking in the context of investment choices. Under his setup, agents care not only about standard consumption (C) but also about status; their wealth *relative* to the (global) average in the economy. We

³ For some of the other predictions, we provide numerical simulations; for example, a simulation based on [Odean \(1998\)](#) for the disposition effect.

⁴ In the literature, the idea that donation directly enters the utility function is referred to as “warm-glow giving” (See, for example, [Andreoni \(1989\)](#) and [Andreoni \(1990\)](#)). Also, while the act of donation can be a source of utility in its own right, charity donations have also been identified as a social status symbol ([Glazer and Konrad, 1996](#)), which, as we argue in section 2, can be a separate source of aspiration.

⁵ To see how CRRA implies some preference for skewness, consider the third-order term in the Taylor expansion of a standard CRRA utility function, which yields a small but positive coefficient. Meanwhile, the selling of lottery — as is predicted by CRRA — is clearly in stark contrast to the observed large and positive aggregate demand for lottery tickets.

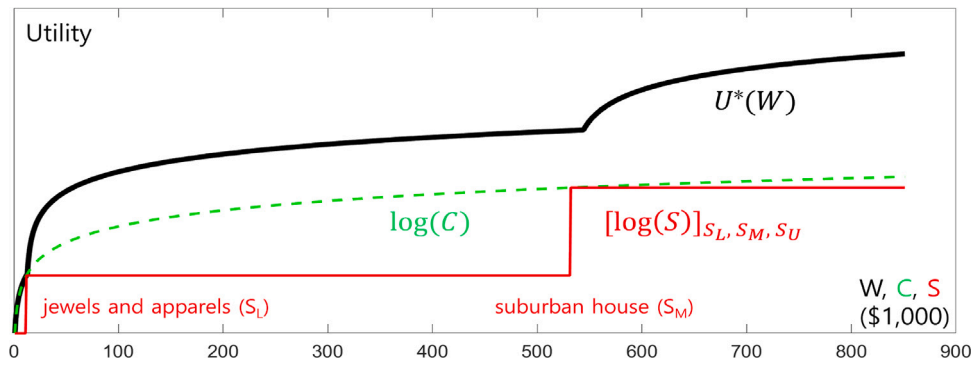


Fig. 1. Utilities from C , S and optimized utility over wealth, $U^*(W)$. The status good for the upper class (S_U) is omitted here (because, being disproportionately expensive, it cannot be aptly drawn to scale), but the shape of the aspirational ‘jump’ around S_U closely resembles the first two.

Table 1

The share of population (Column 2) by “class identifications” comes directly from a survey done in the United States (Pew Research Center, 2024). The (net) household wealth intervals (Column 3) were found by matching Column 2 with data from the Federal Reserve’s Survey of Consumer Finances (2023), after (piecewise linear) interpolation. Column 4 is a notional value of the signature status good in each class, which we simply assume to be the arithmetic mean of each wealth interval.

	Share of Population	Household Wealth (Net, US Dollars)	“S-good Value” (US Dollars)	“Signature” S-Good
Lower class	28%	–\$36,000 ~ \$61,000	$S_L = \$12,000$	“Jewels and Apparels”
Middle class	52%	\$61,000 ~ \$1,002,000	$S_M = \$532,000$	“Suburban House”
Upper class	19%	\$1,002,000 ~ \$4,856,000	$S_U = \$2,929,000$	“Boat in Marina”

make two observations that further enhance the realism of this setup: (i) Realistically, status is conferred by status goods (denoted ‘ S ’) that are typically expensive and *indivisible*. (ii) The competition for status is likely to be *local*, rather than global; the task is to “keep up with the Joneses”, not the Rockefellers.⁶

Table 1 describes a survey of social class in the United States, along with the wealth levels they represent. In line with the two observations above, suppose the status competition is *local*; there are class-specific status benchmarks (e.g., the average wealth level of each class), that can only be beaten by acquiring the respective status goods (S_{Lower} , S_{Middle} , S_{Upper}).⁷ For example, the lower class could compete with “jewels and apparels” ($S_{Lower} = \$12\text{ k} \approx \frac{-\$36\text{k} + \$61\text{k}}{2}$); the symbol of a robust-income middle class may be “home-ownership” ($S_{Middle} = \$532\text{ k} \approx \frac{\$61\text{k} + \$1,002\text{k}}{2}$); an exclusive upper class society may require a “yacht” ($S_{Upper} = \$2,929\text{ k} \approx \frac{\$1,002\text{k} + \$4,856\text{k}}{2}$) to be acknowledged as a competent peer. Because these status goods are effectively local signals of wealth, they are unavoidably bulky and indivisible. Using log-utility and assuming (for simplicity) that utility from status (S) is on par with $\log(C)$, the described setup can be represented as:

$$U(C, S) = \log(C) + [\log(S)]_{S_L, S_M, S_U}, \quad C + S \leq W. \quad (1)$$

The second term is the utility from status, depicted as a ‘log-inscribing step function’ in Fig. 1 (steps occurring at S_L , S_M , S_U) to represent the innate indivisibility of S .

⁶ The notion that status can be “bought” (conferred by status goods) is common in the status literature; see for example, Becker et al. (2005) or Heffetz and Frank (2011). Also, the local nature of status goods is akin to the analyses of Charles et al. (2009) who explore the economic consequences of viewing race as a localized status group. Lastly, the notion of indivisibility and its impact on economic choice have been explored in various other contexts as well, for example, on timing options (Henderson and Hobson, 2013) and monetary policy (McKay and Wieland, 2021).

⁷ This is clearly a simplification. However, the aspirational shape of utility – which is the goal of this motivational exercise – is invariant to the specific assumptions we make on how the status good is priced within each wealth class.

Solving the optimization problem on (1) yields $U^*(W)$ in Fig. 1. The utility is notably ‘aspirational’, surging when W modestly exceeds the status benchmark. This represents the status jump that occurs when the individual has enough wealth to acquire the status symbol, on top of the ‘bread and butter’ (C) needed to sustain herself. Finally, $U^*(W)$ is very similar to Ng (1965), who motivates a nearly identical aspirational utility based on the notion of indivisibility alone. This similarity implies that aspirational utility is likely to be common, occurring whenever there is some element of indivisibility. One prominent source of such bulkiness, as we argue, is status-seeking.

2.2. A functional representation of aspirational utility

For the sake of our focus – the interaction between aspiration and risk-taking behavior – we simplify $U^*(W)$ using a well-known *concavification* principle: Any two utility functions that share the same convex hull yields the same optimizing solution using martingale gambles (investments). Operationally, this simply means that the utility functions in Panels I and II in Fig. 2 are “the same” as long as we use martingale gambles for analysis (which we generally do). Going forward, we use the representation in Panel II, which is easier to handle analytically, and has a clearer aspiration point (‘ R ’ in Panel II), a useful feature for the experiment section that follows.

The following is a formal representation of the utility in Panel II. Going forward, we dispense with the motivational distinction between C and S , and abbreviate all wealth denominations into C . Consider an expected utility (EU) maximizing agent with initial endowment C_0 . The utility of consuming C is conventional ($u' > 0$, $u'' < 0$), except that the agent has an aspiration to reach R , ($R > C_0$) so that the agent effectively discounts payoffs that fall below R ;

$$U(C) = \begin{cases} \delta u(C), & \text{if } C < R \quad (\text{where } 0 < \delta < 1) \\ u(C), & \text{if } C \geq R. \end{cases} \quad (2)$$

Here, δ is a multiplicative constant ($0 < \delta < 1$) that applies a *discount* to utility that fall below the location of aspiration, R . Hence, a value of δ close to 1 (0) indicates that the aspiration is mild (strong).

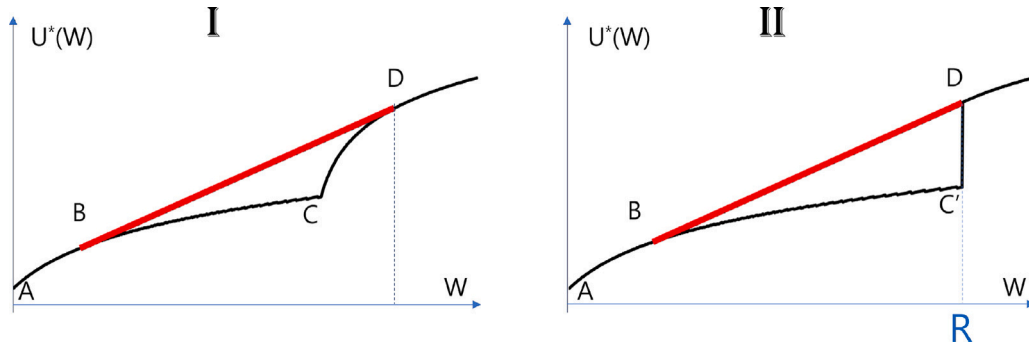


Fig. 2. An illustration of concavification. Panel I is (essentially part of) the original $U^*(W)$ in Fig. 1. Via concavification, the utilities in Panels I and II yield the same optimization solutions using martingales, because they share the same convex hull, i.e., the same ‘bridge’ (BD) above C and C’.

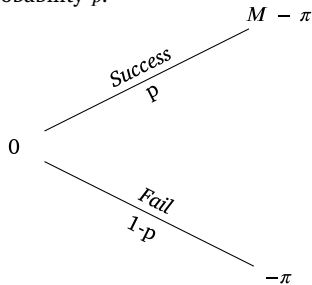
3. The optimal demand for skewness

For many, skewness-seeking is an important element in their investment decisions (e.g. Kumar (2009)). And there is substantial evidence that skewness is demanded and priced in the market for financial securities, in equities (Kraus and Litzenberger (1976), Harvey and Siddique (2000), Boyer et al. (2010), Bali et al. (2011), Conrad et al. (2013)), options (Boyer and Vorkink, 2014), and IPOs (Green and Hwang, 2012). In this Section, we explore how the optimal choice of skewness arises endogenously given the aspirational utility we derived in Section 2. To this end, we first define the set of “skewed die” that the aspirational agent can roll (‘binomial martingales’). We then observe the optimal choice (“the four seasons of gambling”), and subsequently, how these optimal choices may vary with respect to the underlying parameters (comparative statics).

3.1. The aspirational agent’s choice set: The “skewed die”

Since the goal in this Section is to understand how preference for skewness can endogenously arise from aspirations, we introduce an expected utility (EU) maximization setting that allows agents to make their optimal choice of skewness. To this end, we introduce the following set of securities that defines the choice set of the EU-maximizing agents. The idea is to first focus parsimoniously on the level of skewness embedded in these set of securities, and add in other features if needed.

Let $L(p)$ be a *binomial martingale* (i.e., fair game with two outcomes) with $p \in (0, 1)$. That is, $L(p)$ is a fair gamble which costs π to purchase, and pays M with probability p .



To ensure that $L(p)$ is a martingale, we require: $0 = p(M - \pi) + (1 - p)(-\pi)$. This pins down M as a function of price of lottery π and p : $M(\pi, p) = \frac{\pi}{p}$.

Similarly, let $L^*(p)$ be an *extended binomial martingale* with $p \in (-\infty, 1)$. That is, it is a gamble which pays C_S with “probability” p and C_F with “probability” $1 - p$, such that:

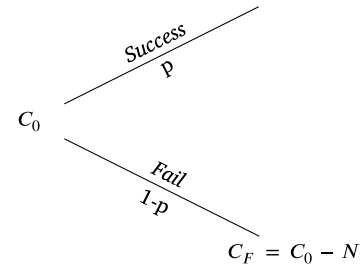
$$0 = p(M - \pi) + (1 - p)(-\pi), \quad p \in (-\infty, 1) \quad (3)$$

Note that the only difference is the domain of p . That we allow $p < 0$ means that at this stage, p and $1 - p$ should be interpreted as ‘weights’,

rather than probabilities. The reason for extending the domain is to keep the structure consistent and tidy throughout the analysis; for those who prefer to focus on ‘real-world intuition’, it would not do much harm to ignore the term ‘extended’ for now. The real-world interpretation of $p < 0$ will be provided in Theorem 2.

Using the set of securities $L^*(p)$, the agent can construct a *consumption scheme* by exercising freedom over two dimensions: (i) which security ($L^*(p)$, choice is over p) to purchase and (ii) how much of that security she wishes to purchase. Let N be the number of security she purchases. Let C_S be the consumption she enjoys if each unit of her security pays $M - \pi$. Let C_F be the consumption she gets if each unit of her security pays $-\pi$. Without loss of generality,⁸ we fix the unit cost of investment (π) at 1, going forward.

$$C_S = C_0 + N(M - 1)$$



Note here that because $L^*(p)$ is a martingale, the structure of his consumption scheme is also a martingale (can easily be verified algebraically by eliminating N in Eqs. (6), (7) and adding in (8) below), namely:

$$C_0 = pC_S + (1 - p)C_F. \quad (4)$$

To summarize, we have created a set of securities that abstracts away from variations in the first moment (expected returns) by imposing the martingale assumption. We also simplify the distributional structure of these fair games by assuming a binomial payoff. All this is to ensure a particular focus on the *third* moment: skewness, a particularity we relax in the internet appendix. Using binomial martingales, the agent can set up her consumption scheme by choosing (p, N) . Under this setup, we now move on to the utility maximization problem of the agent.

3.2. Utility maximization: “Rolling the Skewed Die”

Consider an agent with aspirational utility represented by (2), with aspiration point R and current wealth C_0 ($C_0 < R$). The *EU – maximization problem*, with the *extended* $L^*(p)$ is:

⁸ Under the martingale restriction, $M(\pi, p) = \frac{\pi}{p}$, hence $M - \pi = \pi(\frac{1}{p} - 1)$. This means that any change in π simply amounts to adjusting the scale of bet, N . Since N is already a choice variable, we can fix ‘ $\pi = 1$ ’ without loss of generality.

$$\max_{\substack{p \in (-\infty, 1) \\ N \in [0, \infty)}} (1-p)U(C_F) + pU(C_S) \quad (5)$$

subject to:

$$C_F = C_0 - N, \quad (6)$$

$$C_S = C_0 + N(M-1), \quad (7)$$

$$0 = p(M-1) + (1-p)(-1). \quad (8)$$

This problem requires optimization over two dimensions, N and p . The following Lemma allows us to reduce a dimension.

Lemma 1. Consider the EU-maximization problem above for (2). Assume the following holds:

$$U'(\bar{C}_F) = U' \left(\frac{C_0 - pR}{1-p} \right) > U'(R^+). \quad (9)$$

Then any solution to the EU-maximization problem, (p^*, N^*) , satisfies $C_S^* = R$.

Assumption (9) of Lemma 1 is not automatically satisfied unless $\delta = 1$ (in which case it is automatic since it can be easily verified that $\bar{C}_F < R$ and CRRA marginal utility decreases in C), yet is still innocuous. It only requires that the marginal utility at $\bar{C}_F$ is higher than the marginal utility at R . This is intuitive: Once the agent attains the aspiration, the hankering dissipates and marginal utility goes down, almost by definition.

This Lemma is useful because for any proposedly optimal p , the corresponding N is automatically adjusted so that $C_S = R$ holds. Hence, using Lemma 1, we can reduce the EU-maximization problem (Eqs. (5)–(8)) to the following ‘reduced form’ setup:

$$\max_{p \in (-\infty, 1)} (1-p)U(C_F) + pU(R) \quad \text{subject to} \quad C_0 = pR + (1-p)C_F. \quad (10)$$

The constraint here inherits from (4) with C_S fixed at R , as per Lemma 1. From now on, we adhere to this reduced form setup, which means we will only look at the parameter space $(\delta, R, C_0) \subset \mathbb{R}^3$ where Assumption (9) applies.

Before laying down a set of results that characterize the behavior of solutions to the problem, we introduce an ancillary Lemma that relates p with the level of skewness embodied in $L(p)$. The definition of skewness we use is ‘Pearson’s moment coefficient of skewness’: $S(p) = \mathbb{E} \left[\left(\frac{X-\mu}{\sigma} \right)^3 \right]$.

Lemma 2. Let $S : p(0,1) \mapsto \mathbb{R}$ denote ‘Pearson’s moment coefficient of skewness’ of the consumption scheme induced by $L(p)$. Then:

- (i) $S(p)$ is monotonically decreasing in p
- (ii) $S(p) \uparrow \infty$ as $p \downarrow 0$ (iii) $S(\frac{1}{2}) = 0$
- (iv) $S(p) \downarrow -\infty$ as $p \uparrow 1$

This Lemma describes the relationship between p and skewness implied by p . In particular, it shows that skewness is monotone in p and hence, the p^* chosen as the solution to the EU-maximization problem (10) uniquely determines the level of skewness that the agent’s choice implies. If $p^* = \frac{1}{2}$, the agent is demanding a symmetric security. If $p^* < \frac{1}{2}$, the agent is demanding a positively-skewed security; a security that has ‘lottery-like’ features. If $p^* > \frac{1}{2}$, the agent is demanding a negatively-skewed security; e.g., a security that delivers modestly positive returns most of the time, but very negative returns in rare, but unfortunate states. Note that when $p^* > \frac{1}{2}$, the returns during the bad state have to be ‘very negative’ in order to honor the martingale assumption, since it has to compensate for the high ($> \frac{1}{2}$) likelihood of reaching a good state. This is increasingly so as p^* approaches 1.

3.3. The optimal choice of skewness: “The Four Seasons of Gambling”

We now return to the EU-maximization problem. We specialize $u(\cdot)$ to be the power (CRRA) utility with coefficient of relative risk aversion γ ($\gamma > 1$). For technical comfort (and realism), we assume $1 \leq C_0 < R$. Namely, first, it is natural to assume that C_0 is lower than R . We also require $1 \leq C_0$ to ensure that utility is always positive at C_0 , so that multiplying by δ at R ($> C_0$) is indeed a discount. This does not harm generality, since we can always translate the utility function to be positive. Also, to make the problem non-trivial, we assume $0 < \delta < 1$. Theorems 1 and 2 characterize the solution to the EU-maximization problem, p^* .

Theorem 1 below describes how p^* – the optimal security demanded by the agent with aspirational utility – changes with the position of his aspiration (R) relative to current wealth level (C_0).

Theorem 1. Let $u(C)$ be the power utility function and let $L^*(p)$ be an extended binomial martingale with p : }probability of success ($p \in (-\infty, 1)$). Fix C_0 : initial wealth, and consider the reduced EU-maximization problem (10) with R : aspiration ($C_0 < R$). Let p^* be the }probability that maximizes the expected utility. Then:

- (i) $\frac{\partial p^*}{\partial (\frac{C_0}{R})} > 0$
- (ii) as $(\frac{C_0}{R}) \uparrow 1$ (i.e., as $C_0 \uparrow R$), $p^* \uparrow 1$
- (iii) $\exists (\frac{C_0}{R})^* \in (0, 1)$ such that $p^* \leq 0$.

Theorem 1-(i) asserts that as R moves further out, away from C_0 , the agent demands more positively skewed security. In everyday parlance, this means that as her aspiration becomes ‘unrealistically high’, the agent starts to demand more and more ‘lottery-like’ securities to meet the aspiration. When C_0 is far away from R , attempting such a big jump in consumption ($R - C_0$) with high chance comes at the cost of disastrously low consumption if the attempt fails. (Recall that all securities in the choice set are fair gambles.) Thus, the agent rationally avoids the abysmally low utility levels in bad states, through the purchase of positively skewed security (with low p^*). Moreover, the positive sign on the derivative asserts that this relationship is monotonic. That is, as agents’ aspirations move far from (close to) C_0 , the optimal choice of skewness will increase (decrease) monotonically.

Theorem 1-(ii) describes the opposite situation. As R moves closer to C_0 , the agent prefers increasingly negatively-skewed security: that which takes her to the aspiration (R) with high chance at the expense of a low-chance event of a disaster. While it is true that the martingale assumption requires that C_F be low (because p^* is close to 1), the proximity of C_0 to R ensures that the associated C_F is not unacceptably low. In other words, the proximity of the aspiration ensures that the agent can avoid exposing herself to the risk of “ruin” (destitute poverty), even while taking negatively skewed bets.

Theorem 1-(iii) describes what happens when the aspiration is too far, or equivalently, when the agent is “too poor”. Theorem 1-(iii) asserts that at some point, the aspiration will be so remote that it is optimal to choose $p^* \leq 0$. At this point, however, we are interpreting p^* as “optimal weights”, because p^* has no real world analogue. The full meaning of Theorem 1-(iii) will be revealed in Theorem 2.

Taken together, Theorem 1-(i), -(ii), and -(iii) show that as R gets pushed away from C_0 , the agent’s demand runs through the entire gamut of securities, starting from the most negatively skewed to the most positively skewed. This happens for any fixed $\delta \in (0, 1)$, which determines the ‘size of jump.’

Theorem 2. Assume (as is in the real world) that only $L(p)$ with $p \in (0, 1)$ is available. When $p^* \leq 0$, the agent chooses C_0 over any $L(p)$ with $p \in (0, 1)$.

Theorems 1 and 2 together tell us what happens as R increases relative to C_0 . At first, as C_0 stands close to R , the agents demand negatively skewed securities for the reasons explained above. As R increases, the

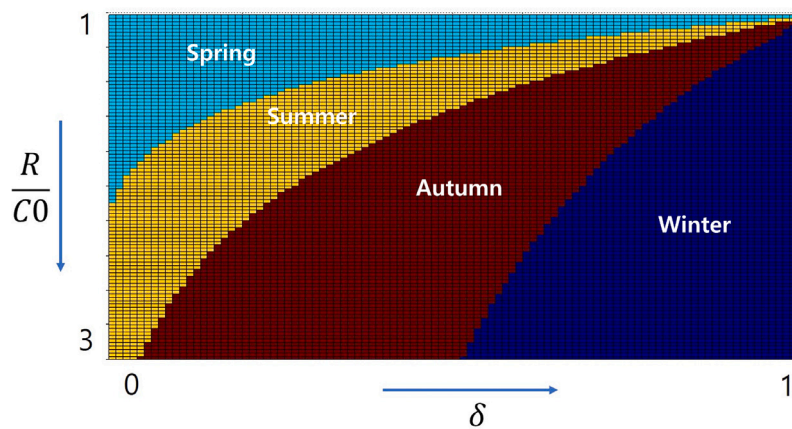


Fig. 3. “The Four Seasons of Gambling” (Thm 1 and 2). Fix any point of δ . As $\frac{R}{C_0}$ increases (moving downward, i.e. as the aspiration moves farther away), the “four seasons” always appear in the order of “Spring” (light blue, negative skewness); “Summer” (yellow, symmetric); “Autumn” (brown, positive skewness); “Winter” (navy, no gamble). This was diagram was drawn with a CRRA utility function with coefficient of relative risk aversion of 2 ($\gamma = 2$) and initial wealth of 1 ($C_0 = 1$). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

agents start demanding more symmetric securities (e.g., stocks), then positively skewed ‘lottery-like’ securities. As we move the R away from C_0 further, agents eventually reach a certain threshold where they stay with C_0 , thereby stop demanding risky securities altogether. We may call this the “four seasons of gambling” as depicted in Fig. 3.

The horizontal axis represents the $\delta \in [0, 1]$, and the vertical axis represents $\frac{R}{C_0} \in [1, 3]$. Fix any δ , and start from $\frac{R}{C_0} = 1$. Theorems 1 and 2 says that when $\frac{R}{C_0} \approx 1$, agents start fresh by buying negative skewness (Spring, light blue). Then, as $\frac{R}{C_0}$ increases, they start to buy symmetric securities (Summer, yellow), then positively skewed securities (Autumn, brown), and ultimately, they stop (Winter, navy). Although the picture is truncated at $\frac{R}{C_0} = 3$, if we were to elongate the picture, we would indeed see that winter hits agents for any given δ .

3.4. Negative skewness: Some real-world examples

As mentioned, a distinguishing feature our framework is that it also predicts the demand for *negative* skewness, as well as positive skewness. Negative skewness-seeking is a situation where decision-makers seek bets that provide modest gains most of the time but disastrous losses on rare occasions, a proverbial “picking up pennies in front of a steamroller”. While seemingly less encountered than positive skewness – which has a salient presence in the real world in the form of lotteries – we provide examples to illustrate the fact that negative skewness is present in many facets of our economic life, and quite possibly, even beyond.

In the financial derivative markets, the practice of selling (writing) an “out-of-the-money” option allows an investor to pocket the modest premium in the likely event that the option expires unexercised, at the expense of incurring a ‘tail event’ of an unlimited downside when the option is exercised. This strategy is popularized using books and media exposure for general public explaining easy-to-follow steps to implement the strategy.⁹ In another example, popular exchange traded products (ETPs) allow retail investors to short (bet inversely on) the movement of the volatility index (VIX). Since the VIX moderately

declines during “normal” times and spikes during “abnormal times” of high volatility, shorting it allows investor to often profit, but also to lose significantly when the VIX spikes.¹⁰ In the context of institutional investing, such preference for negative skewness may be reinforced by a payment structure where the fund manager is rewarded by fees dependent on frequent gains while protected with limited personal liability in the case of extreme losses.

Negatively skewed bets are found beyond the world of finance: consider for example the various cases of fraud. While a moderate-scale tax delinquency provides some extra income, it entails a small but positive chance of detection by the tax authorities leading to serious consequences. Yet, tax evasion is a widespread phenomenon (Slemrod, 2019) and likely across the entire wealth distribution (Artavanis et al., 2016). Some types of fraud are associated with aspirations or goals. Managers may be prone to commit white-collar crime (e.g. financial misconduct) under pressure to achieve company performance targets (Soltes, 2016). Chen et al. (2024) present a theory which argues that white-collar crime can be viewed as negatively-skewed bets to attain (or maintain) a managerial aspiration (milestone). Also not so uncommon (Ntoumanis et al., 2014) and scandalous when uncovered, cheating in sports (e.g. doping) is likely to go undetected and leave the perpetrator with gains — such as a win, a record or a medal that endows the player with superiority status.¹¹ This goal-oriented attitude has been linked to cheating in sports (Ring and Kavussanu, 2018).

3.5. Comparative statics

We are now ready to harvest a few comparative statics results that illustrate the choice of skewness by aspirational agents. We continue specializing $u(C)$ to be CRRA utility with risk aversion γ .

⁹ For example, *The Complete Guide to Option Selling: How Selling Options Can Lead to Stellar Returns in Bull and Bear Markets*, by Cordier and Gross (2014). Cordier gained a reputation as a successful investor selling options, by collecting option premium that “expires worthless” during normal times. This strategy proved reasonably lucrative until the fund was unable to respond to margin calls during a high volatility event, and subsequently liquidated, leading to Cordier’s public apology.

¹⁰ Indeed, this is precisely what happened during a “Volmageddon” event in 2018 when the VIX soared 115% overnight and a number of such short-VIX funds were closed down after record losses. (“Four years after ‘Volmageddon’, new volatility ETFs to hit market”, Reuters)

¹¹ The following Wall Street Journal article covers an example of such in the professional game of chess; on how it is likely to be common, difficult to detect, and how an ambitious player may have succumbed to the temptation to cheat his way to beat the incumbent champion. (“Chess Probe Finds U.S. Grandmaster Cheated—Just Not Against Magnus Carlsen”, *The Wall Street Journal*)

3.5.1. Size of jump

Theorem 3. $\frac{dp^*}{d\delta} < 0$

Theorem 3 explains what happens as δ increases. Recall that δ is how much the agent *keeps* when the consumption falls short of the reference point R , hence $(1 - \delta)$ determines the ‘size of jump’. As δ increases, agents take the aspirations *less* seriously, and can hence afford to attain it with lower probability (like lottery). In other words, when δ is high, it is less imperative to attain R , and agents demand securities with higher skewness which limits the downward risk (i.e., low C_F) at the expense of lower chance of attaining R . However, as δ decreases, agents must take the kink more seriously, forcing them to give up more of their C_F in bad state to ensure that they reach R with higher probability. The agents thus demand increasingly negative-skewed securities. Fig. 3 also illustrates this.

3.5.2. Initial endowment

Theorem 4. Fix δ, γ , and $\xi = \frac{C_0}{R}$. Then, $\frac{\partial p^*}{\partial C_0} \big|_{\delta, \gamma, \xi} > 0$

Theorem 4 is also very intuitive. As agents become wealthier, they need to worry less and less about the disastrous states where marginal utility is extremely high. Hence, they can afford to take more and more downside risk, thereby demanding less skewed securities. This coincides with the empirical findings (e.g., Kumar (2009)) that report more active engagement in lottery-like bets among consumers with lower income.

Note that **Theorem 4** is saying a little more than **Theorem 1**-(ii), which is effectively saying that

$$\frac{\partial p^*}{\partial C_0} \big|_{\delta, \gamma, R} > 0.$$

The difference here in **Theorem 4** is that we are fixing $\xi = \frac{C_0}{R}$ instead of R . Thus, here we are not decreasing the distance between C_0 and R as we increase C_0 . The point here is that p^* increases even when R increases along with C_0 , and that the increase of p^* is purely an endowment effect, rather than effect of C_0 approaching R as in **Theorem 1**-(ii).

3.5.3. Risk aversion

Theorem 5. Fix C_0 and δ . Suppose R is ‘big enough’ to satisfy:

$$\left(\frac{R}{C_0}\right)^{-\gamma} \left[\frac{\left(\frac{R}{C_0}\right) \log \frac{R}{C_0}}{\left(\frac{R}{C_0}\right) - 1} \right] + \mathcal{O}\left(\frac{1}{R}\right) < \delta,$$

where $\mathcal{O}\left(\frac{1}{R}\right)$ is a positive term which vanishes at the rate of $\frac{1}{R}$. Then,

$$\frac{\partial p^*}{\partial \gamma} \big|_{\delta, C_0, R} < 0.$$

We first give some numerical examples to get a feel for how stringent the assumption is. For reasonable parameters values such as $\delta = 0.8$, $\gamma = 2$, $C_0 = 2$, $\frac{\partial p^*}{\partial \gamma} < 0$ will hold whenever $R > 3.491$. For $\delta = 0.8$, $\gamma = 2$, $C_0 = 1.5$, $\frac{\partial p^*}{\partial \gamma} < 0$ will hold whenever $R > 2.227$. For $\delta = 0.8$, $\gamma = 2$, $C_0 = 1$, $\frac{\partial p^*}{\partial \gamma} < 0$ will hold whenever $R > 1.159$. The role of this R -threshold (higher than which will allow full monotonicity) can be interpreted as follows. Suppose the agent has C_0 in his hands. Higher γ implies that his utility function is more concave. In the power utility setting, this extra concavity is achieved by pulling down the utility of the agent both on positive outcomes ($C > 1$) and negative outcomes ($C < 1$) with $C = 1$ as the anchoring case. (See Fig. 4 below.) In our setting, the agent with higher γ discounts both $u(C_S)$ and $u(C_F)$ more heavily than in the log-utility case. This has consequences on p^* . The depressed $u(C_S)$ affects p^* unequivocally; it acts to lower p^* . Intuitively, this is because the reduced upside discourages the agent from taking much downside risk (in the form of lower C_F) in return, and the agent consequently decreases p^* to ensure that C_F does not

fall too low. (Recall that we are envisioning a martingale situation.) Hence, the agent with higher γ chooses lower p^* . Meanwhile, the effect of the depressed $u(C_F)$ on p^* can go both ways. When γ is higher and the downside is even lower, the agent faces a predicament: on the one hand, she wishes to avert the painful depth of the downside by choosing to increase C_F . However, this can only be done at the cost of lowered p^* , again, because of the martingale assumption. The lowered p^* means that she is undermining her very chance of avoiding the downside, albeit perhaps a less painful one. Since the agent faces this inevitable trade-off, the effect of depressed $u(C_F)$ is ambivalent. Nevertheless, we still can say this with absolute certainty: as $C_S = R$ grows, so does the magnitude by which $u(C_S)$ gets depressed. (See Fig. 4.) This means that the unequivocal effect of the depressed upside (i.e., lower p^*) will grow bigger and bigger, until at some point it dominates the (ambivalent and hence limited) effect of the depressed downside. This is precisely our assumption in **Theorem 5**: as R exceeds a certain threshold, the effect of γ on p^* becomes monotonic. Modulo the assumption, the broad-strokes conclusion of **Theorem 5** is intuitive: agents with higher risk-aversion will choose lower p^* securities to minimize their perceived downside.

4. Aspiration and the disposition effect

As an attempt to explain “puzzling” investment behavior, our aspirational setup is certainly not alone; for example, prospect theory is a prominent alternative. While not always successful (see Barberis and Xiong (2009)), versions of Prospect Theory – e.g., *dynamic* versions of Cumulative Prospect Theory (Tversky and Kahneman, 1992; Barberis, 2012; Ebert and Strack, 2015) – do deliver unified explanations for risk-taking behaviors such as the preference for skewness, and simultaneously, the disposition effect (Heimer et al., 2023). In this section, we discuss how the aspirational model can also generate aspects of the disposition effect, but also be clear about its limitations in its ability to do so.

4.1. The disposition effect: A decomposition

The disposition effect (DE), as introduced by Shefrin and Statman (1985), is:

[Full DE] The disposition to sell winners too early and ride losers too long.

This definition has both a cross-sectional and a temporal component. Cross-sectionally, the investor tends to keep the losers and sell the winners, *within* the cross-section of her portfolio of stocks. Over time (temporally), this would manifest itself as the investor’s overall tendency to sell the portfolio of stock investments when it is winning, and retain it when it is losing.¹² We introduce a “weak disposition effect” that pertains to the second (temporal) component, but not the first (cross-sectional):

[Weak DE] The disposition to sell too early when winning and ride too long when losing.

The second definition is weak in the sense that the “Full DE” would imply the “Weak DE”, but not the other way around. What we show in the following (sub)section is that the aspirational utility generates “Weak DE”, but not the “Full DE”.

The reason that the aspirational model falls short of the “Full DE” is as follows: Apart from the notion of an aspiration, our model is based on optimization *i.e.*, is “rational”. Because only the return on the *portfolio*

¹² That is, given that winning portfolios are more likely to contain more winners than losers, the investor’s cross-sectional inclination to sell the winners and hold on to the losers would – averaged over time – result in a tendency to sell winning portfolios and hold on to losing portfolios.

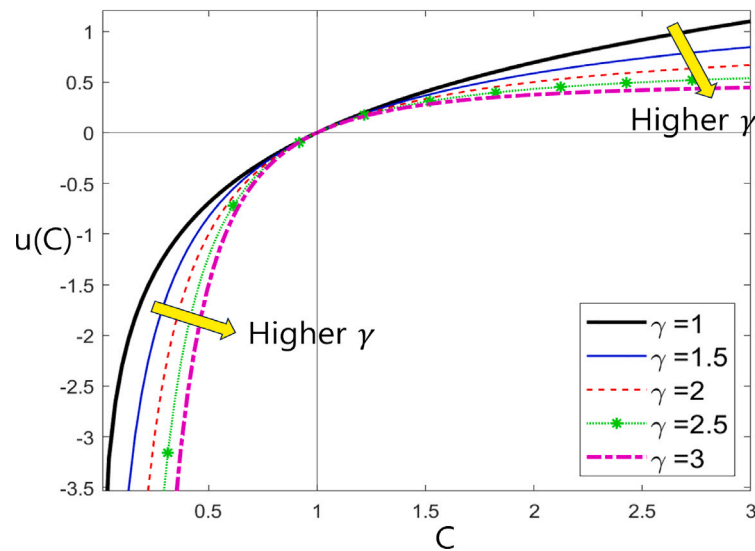


Fig. 4. Various power utility functions (CRRA utility functions) with different coefficients of relative risk aversion (γ). The case of $\gamma = 1$ represents log utility. All utility functions pass through the point $(C, u(C)) = (1, 0)$.

of stocks is relevant for optimization, rationality reduces the cross-section of returns to a single return on the portfolio, thereby making it impossible to deliver predictions in the cross-section. The disposition effect, on the other hand, requires that agents behave as if they have a psychological attachment to the particular stock that incurred losses. For example, after a fall in stock price, they should refuse to realize this loss to switch to a different stock with an identical return distribution, even when one can obtain tax benefits by doing so (Constantinides (1983, 1984)). It is for this reason that explanations of the disposition effect – including prospect theory – typically involve cognitive biases (e.g., “mental accounting”) applied to each asset *individually*. While this may not be inappropriate for models like prospect theory that already carry a heavily psychological flavor, it may be less compatible with a model that aims to be more microfounded, as does ours. Since the “Weak” DE does not require cross-sectional predictions, this is the extent to which our model generates the disposition effect, at least under our current simple setup.¹³

4.2. Aspirational utility and the (weak) disposition effect

We first illustrate intuitively, through an example, how an aspiration can generate the “weaker” version of the disposition effect, which we subsequently supplement with a formal test: Consider an investor holding a wealth (W_0) worth \$57,000, with an aspiration to reach $R = \$65,000$ within the next 12 months to buy a “dream-car”. (We change the previous notation, ‘ C_0 ’, to W_0 in line with our current focus on investments.) To this end, she invests 46% of W into a portfolio

of stocks, the rest in a risk-less bond. Suppose she is lucky during the first 6 months; her stocks perform well, her wealth increases to $W = \$65,000$, hence realizes her aspiration precociously. Given that ‘ $W = R$ ’, volatility is an enemy during the remaining 6 months, potentially jeopardizing the aspiration that is already held in her hand. Hence, the investor optimally chooses to “realize the gain early (6 months)”. Now conversely, consider a situation where the investor experiences a loss in the first 6 months. In this case, volatility is a (perhaps the only) friend during the remaining months; maintaining a high stake in stocks is the only way to fill the enlarged gap between the reality and her aspiration. Hence, the aspirational investor chooses to “hold on to losses”. These behaviors are consistent with the (weak) disposition effect, and is essentially illustrated, respectively, by the green and red arrows of sub-tree ‘A’ in Fig. 5.¹⁴

The aforementioned logic only works when the aspiration is neither too close, nor too far. If the aspiration is “too close”, it can essentially be reached by investing in bonds alone, hence little reason to condition the investment behavior on stock performance as they should if under the disposition effect. If the aspiration is “too far”, even a small drop in stock price can render the aspiration irrelevant, whence the aspirant reverts to CRRA. In “Theorem 2-talk”, the agent passes from “Autumn” to “Winter”, effectively forcing her to relinquish the aspiration and cut losses ($w_S = 63\% \rightarrow w_S = 16\%$), as is shown in sub-tree B of Fig. 5. These behaviors are inconsistent with the disposition effect, and shows that aspirations must be in a “Goldilocks zone” to work. This qualification, however, is sensible, since the very definition of an aspiration carries the premise that it is neither too close (in which case, nothing to aspire to) nor too far (in which case, merely a remote fantasy).

We validate the logic outlined above in a more standard test of the disposition effect, following the method in Barberis and Xiong (2009) who report the $\frac{PGR}{PLR}$ ratio (Odean, 1998), $\frac{\text{Proportion of Gains Realized}}{\text{Proportion of Losses Realized}}$, over a simulated stream of stock price realizations. As the disposition effect is the relative fondness to realize gains (than losses), ‘ $\frac{PGR}{PLR} > 1$ ’

¹³ We conjecture, however, that it may be possible to push the aspirational model to target the “Full DE” by adding additional structure, for instance, by assuming a negative relationship between volatility and expected returns. As we explain in the next subsection, aspiration generates the tendency to “sell when winning and hold on when losing” because the distance to the aspiration increases (decreases) with loss (gain), calling for the addition of volatility into the portfolio when it is losing. Assuming a negative relationship between volatility and returns could deliver a cross-sectional disposition effect (“Full” DE) because the aspirational investor would seek to keep the more volatile (losing) stock when the portfolio is losing, in order to bridge the widening gap between her current position and the aspiration. In short, the cross-sectional disposition would arise under the said assumption because volatility would be more valued in the losing states, whence they would keep the losers (more volatile stocks). A formal argument would call for a model, which we leave for future research.

¹⁴ The change in optimal weights in sub-tree A is rather exaggerated (e.g., $w_s = 46\% \rightarrow w_s = 1\%$ or $w_s = 46\% \rightarrow w_s = 97\%$) due to the fact that this is the penultimate node, which we focus on for expositional purposes. These movements are modulated when further away from the final nodes, for example, as can be seen in the first node with $T = 0$ m. Clearly, this realism will eventually dominate as the number of T -intervals increases (i.e., with a finer grid).

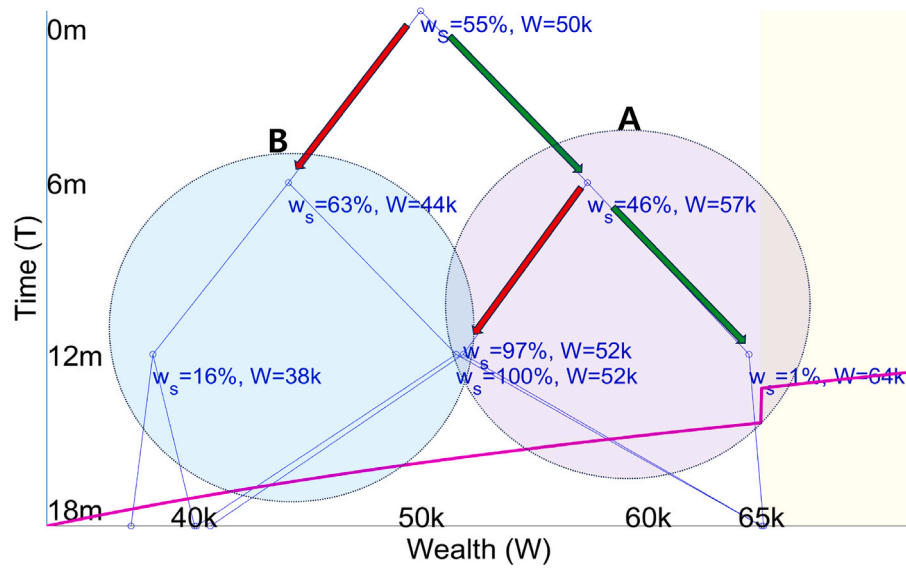


Fig. 5. Dynamic ‘stock-vs-bond’ portfolio optimization tree under aspirational utility. The horizontal axis is the portfolio value of wealth (W , in units of \$). The vertical axis represents time (T , in units of 6 months). The top node at $T = 0$ m denotes the original node. Nodes at $T = 18$ m are the final nodes where the outcomes are realized with aspirational utility (pink graph). Nodes at $T = 6$ m and $T = 12$ m represent interim optimization results. w_s represent the percentage of (optimal) allocation into the stock. Parameter values are “standard”: $W_0 = 50$ k, $R = 65$ k, $\mu_S = 1.06$; $\sigma_S^2 = 0.2$, $R_f = 1.01$ (annualized); $\gamma = 1.1$ (risk-aversion), $\delta = 0.9$ (discount). Green arrows denote “selling the winner”, red arrows “riding the loser”; both consistent with the disposition effect. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 2

This reports the $\frac{PGR}{PLR}$ ratio across two dimensions: the location of the aspiration point, R (in units of \$1,000); and N_T , the number of sub-periods within the investment period ($N_T = 3, 4, 5$ from top to bottom row). W_0 is fixed at $W_0 = 50$ k, while R is varied 50 k ~ 80 k. All other parameters (e.g., bond and stock returns, discount rate, etc.) are recycled from Fig. 5. The highlighted cells indicate ‘ $\frac{PGR}{PLR} > 1$ ’, where the disposition effect is observed.

$N_T \backslash R$	50	52.5	55	57.5	60	62.5	65	67.5	70	72.5	75	77.5	80
3	0.00	2.00	1.00	2.00	2.00	2.00	2.00	1.00	2.00	0.67	0.67	0.67	0.67
4	0.40	0.75	5.00	4.50	4.50	3.00	1.00	1.33	0.60	0.44	0.53	0.75	0.75
5	1.00	∞	9.33	5.35	2.63	1.46	1.13	1.43	1.93	1.14	1.17	0.89	0.80

signals the disposition effect. The only material difference (to Barberis and Xiong (2009)), other than the utility being tested (aspirational vs prospect theory), is that we only track the temporal investment behavior, and not the cross-section, for the aforementioned reasons. We report the results in Table 2. Modulo some aberrations due to discretization, the presence of the disposition effect is evident within the “Goldilocks” range of R , around 55 k ~ 70 k. See Appendix C for details of the methodology and some additional results.

5. Aspiration and stock-market participation

The aspirational utility delivers some predictions on stock-market predictions. This feature is particularly important as an explanation for the disposition effect. We also discuss how the discontinuity generated by the aspiration may shed a novel, skewness-based perspective on some well-known puzzles in household finance.

5.1. The simultaneous generation of risk-taking and the disposition effect

As noted above, there are versions of prospect theory that can generate the disposition effect. One shortcoming of prospect theory in this regard, however, is that this explanation relates most to those who are *least* likely to participate in the stock market at the first place — namely, those that are most pessimistic about future expected returns (Barberis and Xiong, 2009). For this reason, it has been argued that a suitable explanation for the disposition effect must also generate strong stock market participation simultaneously (Heimer, 2016). Our aspirational utility meets this standard. Aspiration provides a natural reason to take risk and participate in the stock market: the pressure

to attain the aspiration. This can also be deduced from the fact that aspirational utility — just like the Friedman and Savage (1948) utility — exhibits both a concave and a convex segment where risk is sought, presumably leading to higher participation in the stock market. As an example, Fig. 6 compares the optimal stock allocations of a CRRA against an agent with aspiration R — who are otherwise equal, — showing an increase (24% → 59%) when aspiration is introduced. This exemplifies a general fact that is easy to show: Under a standard bond-stock optimization problem with aspirational utility, the allocation on stock (w_s) increases monotonically in $R - C_0$, up to a threshold after which the agent reverts back to CRRA.

The above analysis illustrates that aspiration can act as a “common factor” which, on the one hand, promotes risk-taking such as in the stock market, while on the other, the same factor also generates the (weak) disposition effect. Thus, an aspiration-based explanation of the disposition effect is well-targeted — i.e., it pertains to a group of people who have a clear reason to take risks in the stock market at the first place — a potential advantage over the explanation based on prospect theory. Lastly, we note that the above analysis assumes — as it is in conjunction with the disposition effect — that agents are reasonably wealthy, in the sense that they are in the “Goldilocks” proximity to the aspiration (R). In the next subsection, we focus on a different wealth segment; the investment behavior of those with relatively low wealth.

5.2. The puzzling investment behavior of the low-income households

A long-standing puzzle in household finance is that stock-market participation is significantly lower than what is anticipated by theory,

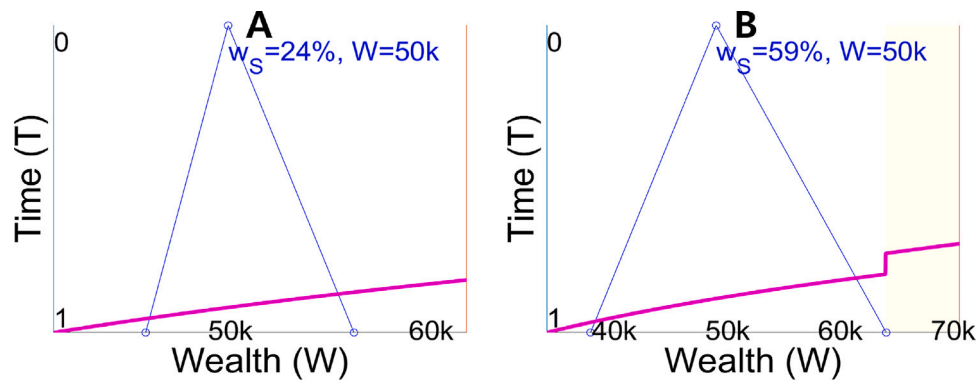


Fig. 6. This single-period simplification of Fig. 5 compares the optimal bond-stock portfolio allocations in a standard CRRA utility (Panel A; $\delta = 1$) against that of an agent with an aspirational utility (Panel B). Other than the presence of a reference point $R = 65$ k in B, the parameters in A and B are identical, and are generated from the setup in Fig. 5.

especially for the lower segment of the wealth distribution (henceforth *low-income households*). For example, Campbell (2006) reports that only about 20% of the population in the lower quartile of the wealth distribution participate in the stock market, whereas standard portfolio optimization dictates that all investors should allocate at least a portion of their asset into stocks (*i.e.*, 100% participation). A separate, but important finding in this literature is that low-income investors hardly diversify their portfolios (*e.g.*, Goetzmann and Kumar (2008)), which is puzzling because they can presumably do better by reducing idiosyncratic risk. Given the difficulty to find a rational explanation for these phenomena, they are often attributed to cognitive factors, such as ignorance, bias, herding, and over-confidence.¹⁵

Our aspirational model offers an alternative, yet unified interpretation for these puzzles. First, the lack of stock-market participation among the low-income households is well in accord with our skewness perspective. Our model predicts that the low-wealthed would choose positively skewed gambles over (the relatively symmetrically distributed) stocks, alluding to the possibility that the low-income households are optimally diverting their investments towards assets with more skewed payoffs, in lieu of stocks.¹⁶ Operationally, this could take the form of participation in the lottery market; investing in call options (or fractions of options, especially for those with low resources); or more recently, cryptocurrency (whose returns have been documented to be positively skewed; for example, Iyer and Popescu (2023)) and “meme-stocks”. While these clearly cannot substitute for a direct empirical validation, it is nonetheless corroborated by the abundance of evidence that those with lower income tend to invest higher portions of their income into lotteries (*e.g.*, Clotfelter and Cook (1991), Clotfelter (2000), Rubenstein and Scafidi (2002)). These findings are consistent with our proposed narrative that the low-income households are redirecting their investment away from stocks, and into positively skewed assets.

Second, the lack of diversification in the portfolios held by the low-income households may also be an *optimally* skewed response, rather than a “failure to diversify”. Since individual stock returns are generally positively skewed whereas the return on the market is negatively skewed (Albuquerque, 2012), an under-diversified investment implies higher exposure to positive skewness in their portfolio.

¹⁵ A notable exception to this, at least as an explanation for the low participation rate in the stock market, is the introduction of a fixed (or on-going) participation cost.

¹⁶ One may argue that it is possible to dynamically generate positive skewness, even with a relatively symmetric payoff (as stocks), by committing to sell upon a modest loss and hold on until high gains are achieved, as in Barberis (2012). However, as Barberis (2012) shows, this strategy is vulnerable to a dynamic inconsistency problem, making it unlikely to be used as a widespread instrument to target positive skewness.

Again, this is in line with the prediction of the aspirational model, namely that those with lower wealth (C_0) will seek more positively skewed gambles. As C_0 increases, the empirical finding is that investors incrementally tend to choose more diversified portfolio (*e.g.* mutual funds), which would reduce the skewness profile as it more closely mirrors the market portfolio. In the context of our model, this simply represents a migration from “Autumn” to “Summer”. Again, while these are admittedly anecdotal, it is also corroborated by the finding that those who engage in skewed gambles (lotteries) also tend to be holders of undiversified, lottery-like stocks (Kumar, 2009), indicating that the lack of diversification is indeed likely to be a manifestation of a preference for positive skewness.

5.3. Stock-market investment behavior across the wealth distribution

Given that aspirations are not exclusively for the low-income households, there is a possibility that our aspirational model can deliver predictions on the stock-market investment behavior across a wider spectrum of the wealth distribution than just the lower end. However, the obvious challenge here is that aspirations are personal and unobservable. Moreover, any aspiration that supposedly impacts the prices of publicly traded assets – such as stocks – must be commonly shared by many, otherwise they would be washed away in the aggregate. We nevertheless conjecture that there are at least two aspirations common enough to be priced macroeconomically: (1) the aspiration to “escape poverty” (Shefrin and Statman, 2000), and (2) the aspiration for “upper-class lifestyle”. This bifurcation is analogous to the observation made in the SP/A theory of Lopes (1987) – and later re-introduced in Shefrin and Statman (2000)’s BPT theory – that farmers plant two distinct crops; “food crops” and “cash crops” where the former is used to ensure subsistence, and the latter to gamble on “hope”. A similar preference appears in investment strategy, for example, the “barbell” combination of extremely safe and risky assets.¹⁷ A recent paper by Bali et al. (2023) lends support to this possibility of double aspiration. In a nutshell, they find that, interestingly, the wealthy gamble in the stock market in a fashion much similar to the low-income households. Roughly speaking, this similarity alludes to a common feature that drives investment behavior *across class* – aspiration.

To see how Bali et al. (2023) supports our aspirational narrative, we first outline their finding: (i) The low-income households demand stocks with higher idiosyncratic volatility (IVOL), and this demand decreases with wealth. This is in line with Kumar (2009)’s finding that the low-income investors seek high-IVOL and positively-skewed stocks. [$W \uparrow \Rightarrow$ IVOL demand $\downarrow$ & Skewness demand $\downarrow$] (ii) Importantly, this trend is

¹⁷ N. N. Taleb named this a “barbell strategy” (Taleb, 2007) – investing a large part of the portfolio in a safe asset (*e.g.*, T-bills) and a small portion in a high-risk asset.

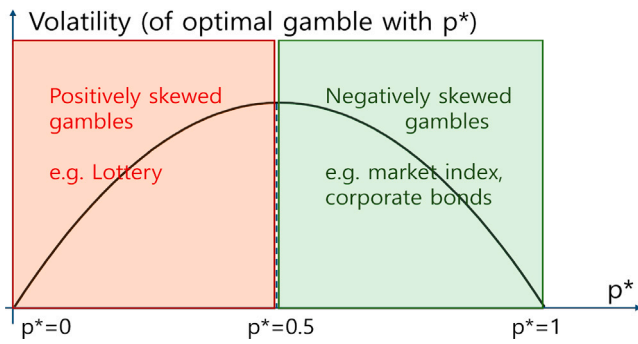


Fig. 7. This figure provides a pictorial example of Lemma 3 (Appendix) which roughly states that the optimal binomial martingale gamble with p^* (i.e., the consumption scheme that arises as an optimal response to the EU-maximization problem) has the highest volatility when $p^* = \frac{1}{2}$.

subverted in the upper (top 10%) part of the distribution where the wealthier seek higher IVOL in stocks. $[W_{[90\%,100\%]} \uparrow \Rightarrow \text{IVOL demand } \uparrow]$. They interpret this non-linearity as arising from an increased awareness for social status among the rich; namely, status is a luxury. (iii) To support this interpretation, they offer the finding that *conditioning* on the subsample of the rich (top 10%) who *also* engage in positively skewed investment behavior – which is often associated with status-seeking in the literature – tends to reinforce the finding in (ii). $[W_{[90\%,100\%]} \uparrow \Rightarrow \text{IVOL demand } \uparrow, \text{ conditional on positive skewness-seeking}]$.

Since the above findings are centered on IVOL, we briefly pause to note that in our model, volatility is highest when the optimal choice of skewness is $p^* = \frac{1}{2}$ (symmetric bet). That is, as seen in Fig. 7 below, volatility is lowest in the most skewed bets (left or right) and peaks when skewness is zero (Lemma 3, Appendix). In fact, this is intuitive given that skewness is understood in the literature as a tool to seek “prudence” (Menezes et al., 1980; Kimball, 1990) – for example, the use of positive skewness allows one to “prudently” aim for an ambitious upside (albeit remotely) without incurring a large downside risk, hence, minimizing volatility. Insofar as skewness can be used as a tool to “prudently” target aspirations, volatility is *maximized* when skewness is absent ($p^* = \frac{1}{2}$).

With these, the following outlines how Bali et al. (2023)’s findings support the presence of two separate aspirations in the macroeconomy. The fact that the low-income households seek highly volatile and lottery-like stocks (‘finding (i)’) is suggestive that some of them may be gambling in the stock market to attain their first aspiration, the desire to escape the pain of poverty. As W increases further beyond that of the low-income households, Bali et al. (2023)’s finding that increments in wealth (W) reduce positive skewness-seeking and IVOL-seeking (i.e., ‘finding (i)’) is also in line with the aspirational prediction that p^* increases (i.e., lower skewness demanded) with W (Theorem 4) and that volatility decreases with p^* in that segment of wealth (represented as the ‘green zone’ in Fig. 7). Intuitively, this means that as the agents become richer, they no longer need to “gamble in the stock market” to attain their aspirations, hence perhaps would migrate to skew-neutral or mildly negatively-skewed investments by holding the market portfolio or corporate bonds. Meanwhile, the subversion of the aforementioned trend at the top of the wealth distribution (i.e., ‘finding (ii)’) – where the demand for volatility seems to be rekindled among the top 10% wealthy – is indicative of an emergence of a new aspiration as people move up into the top 10% of the wealth bracket. This may quite plausibly be interpreted as the aspiration to join the ‘upper class’. ‘Finding (iii)’ – that the demand for volatility increases with W , conditional on revealed preference for positive skewness – reinforces this narrative, because this is precisely what our model predicts should be the behavior of an aspirational agent when the aspiration is an ambitious goal to attain, as is depicted in the ‘red zone’ in Fig. 7 where

positive skewness is sought and the choice of volatility increases with (p^* , and hence) W . Intuitively, this is the wealth segment where the fierce aspiration for ‘upper class status’ forces the agents to gamble – much in the way the low-income households gamble to shoot out of poverty – taking on increasingly more risk as their wealth increase. As such, ‘finding (iii)’ has a natural interpretation in our model: The wealthy are treating status as an “ambitious” aspiration that would best be addressed by positively skewed gambles ($p^* < \frac{1}{2}$).

6. Discussion: Existing theories based on social interactions

Thus far, we (mostly) compared the predictions of our aspirational model against those of prospect theory. A separate, but burgeoning strand of literature emphasizes the role of *social interaction* on investment behavior, in the spirit of Hirshleifer (2015)’s call that “the time has come to move beyond behavioral finance to *social finance*” and Becker (1974)’s notion of “social utility”. The idea is that investments do not happen in vacuum, and social interactions can shape the way people invest. For example, it may increase stock market participation (Hong et al., 2004), make investors more reluctant to admit their losses (Shefrin and Statman, 1985) and more enthusiastic to advertise their gains (Han et al., 2022; Heimer and Simon, 2015). Heimer (2016) suggests that these forces generated by social interactions can lead to the disposition effect, a conjecture he confirms using data on social interaction in online investment forums.

Is it a coincidence that these predictions made by the social-interaction-based theories – for example, the increased propensity to take risk, and the generation of the disposition effect – are similar to those made under our aspirational setup? We think not. Aspirations and social interactions are inherently connected. For example, consider two groups; the first group consisting of socially active individuals, and the second with comparatively more isolated individuals. The presence of aspiration would be more common in the former group, because the frequent social interactions would likely exert pressure to purchase the conspicuous and indivisible goods that motivate our aspirational setup. Relatedly, frequent social interactions can open up opportunities to “brag”, the satisfaction of which generates another source of aspiration. For example, a socially active individual may aspire to the pomp of a “successful investor” she could enjoy – presumably more than would a reclusive individual – by bragging about the proceeds of her investment that is now proudly sitting in her bank account. Insofar as anything “brag-worthy” would be a significant distance away from the investor’s current standing, the desire to brag is a source of aspiration.¹⁸ In short, social interactions and aspirations are intricately connected, in the sense that the former will almost invariably generate the latter.

Given this connection, the predictions from the social interaction-based theories have a natural interpretation in our aspirational model. Consider for example, the disposition effect. In the social interaction-based theory, this is motivated by the need to “manage impressions” when investors engage actively in social interactions (Heimer, 2016). In the aspirational setup, there is a related, but distinct focus. Here, social interactions first foster an aspiration, for example, an aspiration to “brag” with a luxury car. An aspiration-driven investor would feel an urge to realize the profits from her investments prematurely, as soon as it arrives at a “brag-worthy” car, providing a reason to sell the gain too soon.¹⁹ Similarly, consider the relationship between social interaction and the increase in stock market participation. Theories based on social

¹⁸ The idea that one can derive utility from “bragging” upon the realization of a successful investment is in line with the notion of “realization utility”, also known to be a potential source of the disposition effect (Barberis and Xiong, 2012).

¹⁹ Clearly, the ability of an aspiration to generate the disposition effect depends on the location of R , relative to C_0 . For example, there are cases where the aspiration is too remote ($C_0 \ll R$), hence the agent would dynamically seek *positive* skewness (cut losses quickly, ride the gains long) as in Barberis

interactions typically motivate this through the possible reduction in participation cost (e.g., Hong et al. (2004)). Our model primarily focuses on the aspiration that social interactions can produce, and the subsequent increase in risk appetite to attain it, resulting in increased stock market participation when the circumstances are right (i.e., for those “wealthy” enough). The parallel is clear: Our model supplements the literature on social interaction-based explanations of investment behavior, by focusing on the investment consequences (skewness) of what we believe is an essential element of social interaction; the aspiration it engenders.

7. Experimental evidence

We have thus far discussed a theory that suggests a reason why an economic agent may seek skewness in their investments (aspiration), either positive or negative, depending on the circumstances. Meanwhile, finding empirical evidence for a causal relationship between aspirations and skewness-seeking in the real world is complicated by the fact that researchers rarely observe a financial decision maker's intrinsic motivations (e.g. one's aspirations). Moreover, their decisions and associated payoffs are highly endogenous, rendering identification even harder. For these reasons, we conduct a controlled laboratory experiment to test how the potential aspiration points we induced affect the skewness-seeking behavior of experimental subjects. Specifically, we test the claim of Theorem 1, which predicts that the further (closer) the agent's current position is from their aspiration point, the more likely they are to purchase positively (negatively) skewed assets.

The experiment took place at the Marshall behavioral research laboratory at the University of Southern California. A total of 126 subjects participated in one of 13 equally-run experiment sessions, each consisting of 20 subjects according to lab capacity. In the sessions, subjects submitted their series of choices using pen and paper. This was an individual decision-making experiment, thus there was no strategic interaction between participants. Participants were given written instructions and were guided through a presentation prior to the start of the experiment. To ensure proper understanding, they were encouraged to ask questions both in public and in private and asked to complete a series of comprehension questions which were checked for errors prior to the start of the experiment. Sessions lasted between 50–60 min and subjects earned on average \$20 including a \$5 show-up fee.

The experiment consisted of two separate studies both of which were incorporated in the same experimental session (i.e., all subjects participated in both experimental studies). Each session was split into three parts, sections 1, 2 and 3, which were completed in order. Sections 1 and 3 conducted the first experimental study while Section 2 conducted the second study. Each section consisted of 10 rounds, for a total of 30 rounds. Each round consisted of a menu of (two, three or five) binary lotteries,²⁰ out of which the participant had to select one by circling the appropriate letter (“A”, “B”, “C”, “D”, “E”) representing that lottery. At the end of the experiment one of the 30 rounds was selected at random for payment and the choice for that round was executed for each participant using 3-sided and 10-sided dice. An example round is shown in Fig. 8 (Appendix D lists all rounds in detail.)

(2012), quite the contrary to the disposition effect. As reasoned above, in our model, this constitutes the upper boundary of the “Goldilocks zone”, where the aspiration is too remote to generate the disposition effect. In general, however, when R resides within the Goldilocks zone, the aspirational agent perceives the gain as “getting closer” to her aspiration, and hence, *reduces* the exposure to the winning stock, generating a behavior that is consistent with the disposition effect. (See Appendix C for further details on how skewness can be generated dynamically in the aspirational setup.)

²⁰ This corresponds to “binomial martingale” in the theory part. We used the term “binary lottery” to our subjects instead because (1) it makes more colloquial sense and (2) we generalize the gambles to have non-zero means.

Each binary lottery clearly indicated two possible monetary rewards in \$ amounts each with a corresponding % chance of happening. Since lottery outcome was determined using a 10-sided die, the die number which corresponded to each monetary outcome was also stated for additional clarity - e.g. 10-sided die numbers 0–4 will correspond to \$10 (50% chance), and numbers 5–9 will correspond to \$20 (50% chance). A potential aspiration point was induced through what we called a “Donation threshold” \$ amount. This referred to the minimum monetary amount that if a participant reached in the randomly chosen round then we (the experimenters) would donate a \$25 amount to a charity organization chosen by the participant (out of a list that we provided at the start of the experiment). Note that the “Donation threshold” was round-specific while the \$25 donation amount was constant. Whether a participant achieved the donation or not had no impact on her monetary earnings from her choices. Finally, only the round chosen for payment was relevant for the potential donation. Thus the aspiration point (the location) varied between rounds while the donation amount was kept constant.

7.1. Study 1: Within-subject test of preference reversals

Study 1 was conducted in sections 1 and 3 of our experimental sessions. It followed a within-subject design, meaning that all subjects faced the same questions in the first and last section of the experiment. Since the study involved checking for preference reversals (i.e., a subject faced the same lottery twice) we split the study into two sections – before and after Study 2 – to ensure that the purpose of the study was not obvious to the participants.

7.1.1. Experimental design

All 20 rounds involved choices between two binary lotteries, “A” and “B”. The two lotteries within each round always had the same mean and standard deviation. Since binary lotteries are uniquely defined by their first three moments, the only difference between the two lotteries was the level of skewness, with lottery “A” always having zero skewness (i.e. a 50% chance of each outcome) and option “B” being either positively (1.5 or 2.7) or negatively (–1.5 or –2.7) skewed. Both section 1 and section 3 consisted of 10 rounds. Each round (pair of lotteries) in section 1 had its exact same counterpart in section 3. In other words, a round was presented twice, once in section 1 and once in section 3, but with different donation thresholds — that was the “treatment” in this study. Always, in one of the two rounds with the same lotteries, the donation threshold was not attainable by any of the potential earnings in the two lotteries. Therefore, in this control scenario, the choice is unaffected by the potential aspiration point of the donation. In the other case, the counterpart round, the donation threshold was attainable by either lottery B (for lottery pairs with a zero and a positively skewed lottery) or both choices A and B (for lottery pairs with a zero and a negatively skewed lottery), with choice B potentially maximizing the chance of attaining the threshold. This part served as the treatment choice — the choice impacted by the potential aspiration point of the donation. Within the total of 10 unique combinations of binary lotteries we varied the expected value and standard deviation to test whether the first two moments played a role in the decision to switch skewness preference in the presence of the aspiration. Appendix D details the moments of each round.

The motivation here is to see whether we can identify (and whether they exist) circumstances under which a participant may prefer the less skewed option (lottery “A”) when not affected by a potential donation aspiration but may then opt to seek more skewness - positive or negative - (lottery “B”) when the aspiration is attainable - as our theory suggests. In our design that would be reflected as the revealed preference choices “AB”, where the first letter indicates the choice under no induced aspiration and the second letter would indicate the choice under the induced aspiration. Note that our design does not preclude the presence of other intrinsic aspiration points (e.g. a

Round 3: Donation threshold = \$9

A	\$8 with 50% chance (Die # 1,2,3,4,5)	OR	\$14 with 50% chance (Die # 6,7,8,9,10)
B	\$2 with 10% chance (Die # 1)	OR	\$12 with 90% chance (Die # 2,3,4,5,6,7,8,9,10)

Fig. 8. Round 3 of Section 1. By choosing lottery “A”, the subject will have the chance to earn \$8 with 50% probability (if the 10-sided die rolls 1,2,3,4,5) or \$14 with 50% probability (if the 10-sided die rolls 6,7,8,9,10). Since only the \$14 reward is at least as much the “Donation threshold” of \$9, the subject has a 50% chance of achieving the \$25 donation to her chosen charity. Conversely, by choosing lottery “B”, the subject will have the chance to earn \$2 with 10% probability or \$12 with 90% probability depending on the 10-sided die roll. The subject now has a 90% chance of achieving the donation since the \$12 is above the “Donation threshold”. Notice that both lotteries have the same expected value (\$11) and standard deviation (\$3) but differ in the skewness (0 versus -2.7).

Table 3

The first [second] letter indicates the lottery choice in the control [treatment] part of each pair of lotteries. *i.e.* The “AB” row indicates the % of times that participants chose the zero skewed option in the control part (lottery “A”) and the skewed option in the treatment part (lottery “B”).

Revealed preference	All lottery pairs	Pairs with {0, +ve} skewness	Pairs with {0, -ve} skewness
AA	34.68%	27.62%	41.75%
AB	20.71%	23.02%	18.41%
BA	13.73%	15.04%	12.06%
BB	30.87%	33.97%	27.78%
Total	100%	100%	100%
N = 1260 (2,520 “A” or “B” paired choices.)			

participant may aspire to leave the experiment with ‘\$10’ or more), nor does it always guarantee that our induced aspiration points are relevant to all participants (*e.g.* some may not care for any of the charities that we presented or in an extreme case may receive disutility from charitable donation). We did not design the experiment to answer these questions for individual subjects and so we rely on averages to test our hypotheses.

7.1.2. Results

A total of 126 subjects generated 2520 choices (20 choices each across two sections). Option A (the zero skewed option) was chosen 52% of the time while option B (the skewed option) 48% of the time. Breaking down these numbers by the rounds that involve (zero-skewed, positively skewed) pairs vs. (zero-skewed, negatively skewed) pairs, option A was chosen 47% and 57% of the time while option B 53% and 43% of the times respectively. Turning to our object of interest – preferences over pairs in the control and treatment – Table 3 shows the % of times that each pair {AA, AB, BA, BB} was chosen by all participants for all rounds. Choice pairs “AA” or “BB” indicate that the participant did not exhibit a preference reversal (*i.e.* they revealed a stable choice of skewness) in the presence of a potential aspiration. The distinction between the two cases is that while in “AA” the participants intrinsically preferred the less skewed option, “BB” indicates an intrinsic preference for the more skewed option (regardless of the presence of aspiration). Participants choosing “AB” would showcase a preference reversal in the direction that our hypothesis predicts, *i.e.* preference for the less skewed option in the absence of the potential aspiration coupled with a preference reversal (demand for the more skewed option) when the possibility of achieving an aspiration point is present. Finally “BA” choices indicate the opposite, *i.e.* a participant seeking less skewness even when donation was achievable by seeking more.

The majority of the choices (65.55%) were stable (“AA”, “BB”), *i.e.* unaffected by the presence of the potential donation. This tells us that participants understood the experiment and were clearly not randomizing. This stability is natural in light of the strong intrinsic heterogeneity we observe across the participants in their preference for skewness. (See the paragraph below.) That is, some participants are intrinsically drawn to skewed options whereas others prefer to be less skewed, regardless of the presence of aspiration. Hence, we refer to these stable choices (“AA” and “BB”) as the “baseline of inactivity”. We focus on revealed preference reversals (“AB” and “BA”) that occur over

and above this “baseline of inactivity”. To recall, our theory predicts a reversal of “AB”, and not “BA”. Our results match these predictions. Of these choices that do exhibit preference reversals (34.44%), the majority ($\frac{20.71\%}{20.71\%+13.73\%} = 60.13\%$) are preference reversals in the direction predicted by our hypothesis. This finding is qualitatively stable if we split the choices across pairs with zero-positive or zero-negative skewed pairs remains. We also find qualitatively similar results if we further split the sample into choices involving pairs with skewness of {(0, 1.5), (0, 2.7), (0, -1.5), (0, -2.7)} and further if we examine each lottery pair combination. (See Appendix D.) There does not seem to be any systematic pattern regarding the preference reversals with the means and variances of the lotteries. Thus, we conclude that our induced potential aspiration points, on average, seem to cause participants to exhibit additional demand for skewness.

We further report a more detailed analysis of the preference reversal. Fig. 9 (left panel) shows the histogram of the number of “AB” preference reversals observed per participant. The histogram seemingly shows that each participant can be reliably expected to exhibit a preference reversal between zero to four times. However, this statistic overlooks the wide range of intrinsic preference for skewness of each participant. Fig. 9 (right panel) shows the histogram of the ratio of preference reversals (*i.e.* “AB”) to choosing “A” in the control choice (*i.e.* “AA” + “AB”), $\frac{\#AB}{\#AA+\#AB}$, per participant. This is a sharper statistic because it shows, in percentage terms, the distribution of preference reversals (in face of a potential aspiration), *conditional* on such a reversal being feasible (*i.e.* the less skewed option chosen in the control).²¹ Interestingly, we observe that while most participants exhibit a preference reversal between zero to four times (left panel), this does not take into account the intrinsic preferences for skewness of each participant. If we exclude all the choices where option “B” was chosen in the control part, we find substantial heterogeneity across the participants: some participants never demand additional skewness, while others always demand more skewness under the presence of the aspiration. Thus, the induced aspiration of a potential charitable donation has very differential effects on the skewness-seeking of our participants. We interpret this as arising from the differences in the intrinsic strength of skewness preferences of each participant.²²

A drawback of Study 1 is that participants often chose option “B” (the skewed option) in the control part, meaning that there was no

²¹ Note that if the participant revealed preference for the skewed option in the control part (*i.e.* “B”), then we have no way of checking whether he or

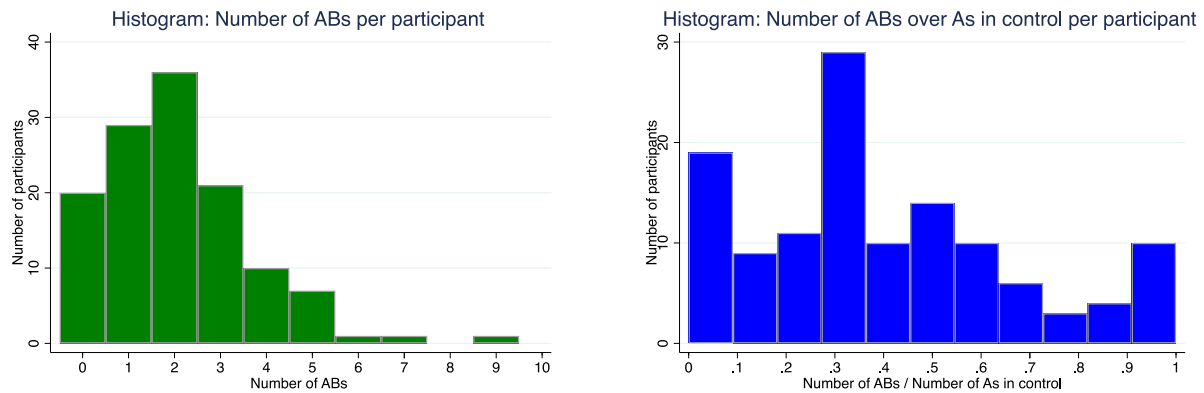


Fig. 9. Left: Histogram of number of preference reversals “AB” per participant. Right: Ratio of “AB” over all such possible choices (“AB” + “AA”) - Choices of “B” in the control part are excluded since for those we cannot examine a potential preference reversal for additional skewness seeking.

more skewed option for them to choose in the treatment part where the aspiration point is achievable. This led to the disposal of a sizable number of observations. Study 2 complements Study 1 by overcoming this problem, as well as adding an additional dimension to the analysis.

7.2. Study 2: Between-subject test of skewness preferences with aspiration shifts

7.2.1. Experimental design

Study 2 was designed as an alternative framework to ‘Study 1’, to overcome some of the aforementioned limits and to function as a robustness check that facilitates more in-depth analysis. Study 2 was conducted in section 2 of our experimental sessions and in contrast to Study 1, it varied between subjects in three treatments (that were varied over the donation threshold). Subjects were faced with 10 rounds. Each round involved a number of lotteries (either 3 or 5) out of which the subject was asked to select one. Thus, from the subjects’ perspective, the task was similar to Study 1 (sections 1 and 3), apart from the number of lotteries available in each round. From the researcher’s perspective however, the higher number of binary lottery choices (same mean and variance) allowed us to qualitatively test for movements along the skewness dimension that is predicted by our model. In addition, by utilizing a between-subject design and since each subject was made to encounter the same lottery only once, we overcome any potential issues related to experimenter demand effects that Study 1 may be subject to.

Across participants, the 10 rounds differed only in the donation threshold (location of the potential utility jump), *i.e.* all participants faced the same lottery choices in each round, but with possibly different donation thresholds. Each lottery within a round was marked with a letter (“A”, “B”, “C”, “D”, “E”) in order of the magnitude of skewness, with “A” being the most negatively skewed lottery and “C” (in the 3-choice rounds) or “E” (in the 5-choice rounds) being the most positive skewed lottery. The middle option (“B” or “C” respectively) was the zero-skewness lottery. All lottery choices are depicted in [Appendix D](#).

What we are testing in Study 2 is whether manipulations in the location of the potential utility jump (donation threshold) cause qualitative changes to the types of lotteries chosen. More specifically, will participants choose more positively [negatively] skewed lotteries as the donation threshold increases [decreases]? While we are not able to make quantitative predictions due to the absence of other measures

like the risk aversion parameter, or the size/location of the utility jump due to the \$25 donation, this is a useful exercise that qualitatively showcases the mechanics of our model: the potential presence of a non-monetary aspiration point (representing a discontinuous utility jump) can affect the direction and magnitude of skewness that is sought in financial decision making. Thus what we expect to observe is that an increase [decrease] in the donation threshold will cause, on average in our sample, a more positive [negative] skewness seeking, or equivalently, lean towards the lottery that “maximizes the probability of donation”.²³

The example in [Fig. 10](#) provides an illustration of the three treatments and our hypotheses: The binary lotteries “A”, “B”, “C”, have the same first two moments (mean = 11, standard deviation = 3). Thus, from the property of binary lotteries, the skewness (third moment) of each uniquely determines each lottery (skewness = {−2.7, 0, +2.7} respectively). Participants in all three treatments faced the same lotteries. What varied across treatments is the “donation threshold”. [Fig. 10](#) shows a donation threshold of \$11. In this case, a participant seeking to maximize the probability of reaching the donation threshold should choose lottery “A”. In another treatment, the donation threshold was somewhere in the range (12, 14]. Thus a participant in that treatment, seeking to maximize the probability of reaching that threshold should choose lottery “B”. Finally, the highest threshold would be in the range of (14, 20]. Participants in such treatments should choose “C” if they are to have any chance of reaching the threshold. Of course, other factors affect the lottery choice (intrinsic skewness preferences, size and direction of the utility jump from the donation). However, random assignment to treatments means that, we should expect those factors to average out across treatment groups. Thus, if at least some of our participants receive positive utility from making a donation to their chosen charity, our model predicts that, as the donation threshold increases [decreases], participants will be more likely to choose a lottery with more positive [negative] skewness.

7.2.2. Results

A total of 126 subjects generated 1260 choices (10 choices each) – 1008 from eight rounds of three lottery choices and 252 from two rounds of five lottery choices. For our main analysis, we examine whether the distribution of choices changes across treatments (locations of the donation threshold), and if so, how. To do that, we pool together all rounds with three lottery choices. We can do that because lottery “A” is always negatively skewed, lottery “B” has always zero skewness

she would demand more skewness in the presence of the aspiration since there was no more skewed option to choose from.

²² Alternative explanations may include: variances in the size of the utility jump due to the donation (δ), the possibility of disutility from donating to a charity, or subject confusion about the experiment design.

²³ This equivalence is essentially ‘[Lemma 1](#)’. The reason an aspirational investor avoids payoffs in significant excess of the aspiration in [Lemma 1](#) is, at its core, because doing so detracts from the probability of attaining it. In other words, [Lemma 1](#) asks the investor to cleverly use skewness to “maximize the probability of attaining the aspiration”.

Round 1: Donation threshold = \$11

A	\$2 with 10% chance (Die # 1)	OR	\$12 with 90% chance (Die # 2,3,4,5,6,7,8,9,0)
B	\$8 with 50% chance (Die # 1,2,3,4,5)	OR	\$14 with 50% chance (Die # 6,7,8,9,0)
C	\$10 with 90% chance (Die # 1,2,3,4,5,6,7,8,9)	OR	\$20 with 10% chance (Die # 0)

Fig. 10. Round 1 of section 2 in one of the treatments. Lottery “A” maximizes the probability of donation at the current donation threshold. As the donation threshold moves up in the range of (12, 14] we should expect qualitative movements away from “A” and towards “B” and “C”. As the donation threshold moves further up in the range of (14, 20] we should expect further qualitative movements towards “C”. The three treatments thus involve donation thresholds in the ranges of {(10, 12], (12, 14], (14, 20]}.

Table 4

The percentages across columns indicate the relative frequency of choices across treatments. The “Low” [“Mid”/“High”] treatment includes all rounds in which the “Donation threshold” was set such that lottery “A” [“B”/“C”] maximized the probability of the donation.

Chosen Lottery	Donation threshold		
	Low	Mid	High
A (–ve skewness)	24.11%	15.48%	18.45%
B (0 skewness)	32.44%	48.51%	28.87%
C (+ve skewness)	43.45%	36.01%	52.68%
Total	100%	100%	100%
N = 1008	336	336	336

while lottery “C” is always positively skewed. In addition, the donation thresholds always fall in one of three regions: (1) where lottery “A” maximizes the probability of donation (we will refer to those regions as the “Low” donation threshold region), (2) where lottery “B” maximizes the probability of donation (“Mid” donation threshold region) and (3) where lottery “C” maximizes the probability of donation (“High” donation threshold region). As a reminder, higher donation thresholds required more positively skewed lotteries to reach the thresholds while lower donation thresholds that could be reached with several lotteries, required more negatively skewed lotteries to maximize the probability of reaching the threshold.

We find that, in accordance with our model’s predictions, on average, participants chose more positively skewed lotteries (*i.e.* demand more positive skewness) when the donation threshold (aspiration point) is higher and more negatively skewed lotteries (*i.e.* demand more negative skewness) when the donation threshold is lower. **Table 4** shows the distribution of choices across rounds, conditional on the respective donation threshold regions, where all rounds were classified into donation thresholds falling in each of the three regions across treatments. If the possibility of achieving the donation made no impact on participants, we would expect the three distributions “Low”, “Mid”, “High” not to be statistically different from each other, since the lottery choices were identical. However, two-sided Kolmogorov–Smirnov tests of equality of distributions reject the hypothesis that any two of the two distributions are equal. (The Kolmogorov–Smirnov tests of equality were rejected at p -value = 0.002 for the distributions “Low” and “Mid”; at p -value < 0.001 for the distributions “Mid” and “High”.) While the negatively skewed lottery (A) is generally not the preferred choice (chosen less than 20% of the time), it is relatively more popular in the “Low” treatment where it maximizes the probability of attaining the donation threshold. Similarly, lotteries B/C are relatively more popular in treatments “Mid” / “High” which are the respective treatments where those lotteries maximize the probability of donation.

While **Table 4** shows the average results across all rounds with 3 lottery choices, the qualitative results hold across most rounds. **Table 10** in the Appendix shows the breakdown of **Table 4** for each of 8 rounds involving 3 lottery choices. Out of the 24 comparisons (8×3), 18 are qualitatively identical to the comparisons from **Table 4**, *i.e.*, each lottery is chosen relatively more often when the donation threshold is where that lottery maximizes the probability of donation. Qualitatively similar are the results of binary lotteries with five choices (rounds 9 and 10)

but less statistically conclusive due to smaller sample size and more lotteries to choose from. These results can be found in [Appendix](#).

Overall, the findings in Study 2 corroborate and reinforce those of Study 1 and are in line with our model’s prediction, namely that decision makers will, other things being equal, seek skewness in order to increase the chance of achieving their aspiration. Of course, as expected, intrinsic risk and skewness preferences played an important role and thus some participants chose lotteries that did not maximize the probability of achieving the donation. On average, however, there is a clear directional movement towards the lottery with the skewness that maximizes the probability of donation.

7.2.3. Robustness across different “sizes” of lotteries

As noted above, our experiment involved 126 subjects who earned, on average, \$20 each (including a \$ 5 show-up fee). A reasonable concern in such experiments, in general, is whether the conclusions drawn from modest stakes will hold even when the stakes are scaled up. While we are not able to provide a complete answer due to obvious resource constraints, we report trends using data from Study 2 that seem to offer some reassurance that our results are likely to be scale-able to larger stakes.

We show this succinctly in **Tables 5** and **6**, which report the percentage of skewness choices that were made across all 10 rounds in such a way that the choice maximized the subjects’ chances of attaining the donation. In other words, we computed the percentage of choices that conformed to the prediction of our model. The ‘benchmark’, on the other hand, is the choice that would have been made if the subjects did *not* factor in the presence of aspiration, *i.e.* the randomizing choice of skewness. The second columns in **Tables 5** and **6** report the raw percentages of the aforementioned “predicted” choice (the “(donation) maximizing choice”). The third columns in **Tables 5** and **6** report the distance from the hypothetical ‘benchmark’, *i.e.*, the distance from the choice of randomization (“distance to benchmark”). Note that the decisions from three and five lottery choices were aggregated and the probabilities for five lottery choices were re-calibrated to match those of three-lottery choices.

Table 5 reports these numbers across different subgroups of expected lottery payoffs (subgroups of “means”), which varied in the range of \$11 ~ \$22 in our experiment sessions. Within this range of expected payoffs, the percentage of choice that conformed to our model prediction (*i.e.*, the percentage of (donation) “Maximizing Choice”) are maintained stably above the benchmark of randomization. More importantly, we do not observe any systematic pattern across the subgroups of means, and the percentage of choices that conform to the predictions of our model remain stably in the range of 34% ~ 45%.²⁴ **Table 6** reports analogous results from a different exercise where the ‘size’ of lotteries are now measured by the standard deviation of lottery payoffs (instead of mean). Here too, a similar pattern of stability is

²⁴ If anything, we observe that the percentage of donation maximizing choice very slightly increases when the stakes are expanded (both in terms of the lottery mean and standard deviation), although the sample size is small. This would imply that the subjects are (slightly) more responsive to the aspiration as stakes grow, meaning that they align more tightly with the prediction of our model when they confront lotteries with larger stakes.

Table 5

“Maximizing Choice” indicates the proportion of choices that maximizes the probability of attaining the donation. “Distance to Benchmark” indicates the proportion of choices *above* the benchmark choice that would have been made if the agents were randomizing, i.e. the choice of skewness made heedless of the presence of aspirations. The numbers are reported in subgroups of expected lottery payoffs; “mean”. N = 1260.

Mean	Maximizing Choice	Distance to Benchmark
11	0.44	+0.11
13	0.34	+0.01
15	0.39	+0.06
17	0.42	+0.09
18	0.44	+0.11
19	0.41	+0.08
22	0.45	+0.12

Table 6

This table reports the same variables in Table 5 over various subgroups of “standard deviation” in the lotteries offered to subjects. N = 1260.

Standard Deviation	Maximizing Choice	Distance to Benchmark
2	0.44	+0.11
3	0.34	+0.01
4	0.39	+0.06
6	0.42	+0.09
8	0.44	+0.11

observed over subgroups of lotteries that varied in standard deviations within the range of \$2 ~ \$8. Thus, overall, the skewness-optimizing behavior were observed to be stable over substantial variations in the size of lottery – as measured by the mean and standard deviations, which varied from two- to four-fold. We cautiously anticipate that this pattern would extrapolate to lotteries that are larger in scale.

8. Conclusions

In this paper, we investigate how social considerations can help us understand investment behavior. In particular, we study the capacity of aspirational utility to explain behavioral patterns in investment decisions. We motivate and derive a version of aspirational utility by noting that social interactions can often trigger a desire for the purchase of non-divisible goods, such as status goods. The aspirational utility that we arrive at is in the spirit of [Friedman and Savage \(1948\)](#), but we extend our scope of analysis beyond the first two moments into the third moment (skewness) and explore notable behavioral patterns beyond the simultaneous purchase of lotteries and bonds — which was the motivation of their paper. Our analysis yields a rich set of results broadly consistent with empirical observations. In particular, our model is able to deliver an explanation for the demand for skewness in both directions, and makes significant progress in generating the disposition effect. Moreover, our aspirational utility features a convex segment arising from a discontinuity (as in [Diecidue and van de Ven \(2008\)](#)), and this convexity generates patterns of stock-market participation across the cross-section of wealth, modulo the aspirations by class. Our aspirational setup has a natural, tight connection to existing theories on investment behaviors that focus on the role of social interactions. As such, our predictions share a natural overlap with those of the “social utility” based theories. We support some of our theoretical findings with a lab experiment. We chose to pursue a lab-based experiment because aspirations are often personal and unobserved, making a data-based empirical strategy challenging. We conducted two complementary studies (Study 1 and Study 2) where aspirations were potentially induced by the possibility of charitable

donations. Our results imply that the presence of aspiration induces a demand for skewness that were clearly in the direction predicted by our “four seasons of gambling”.

CRedit authorship contribution statement

Andreas Aristidou: Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Aleksandar Giga:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Suk Lee:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Fernando Zapatero:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Lemma 3

Lemma 3. Fix any $R(> 1)$. Consider a collection of EU-maximization problem (5), parameterized by $\xi = \frac{C_0}{R} \in (0, 1)$. Let $\tilde{C}_\xi^*$ denote the optimal consumption scheme used by the aspirational agent to solve (5) for a given ξ within this collection of problems. Within this collection of problems, the variance of $\tilde{C}_\xi^*$ is highest on the EU-maximization problem whose p^* equals $\frac{1}{2}$.

Proof of Lemma 3. Let V denote the variance of $\tilde{C}_\xi^*$. Using Lemma 1, V can be written explicitly as:

$$V = \frac{p^*}{(1-p^*)} (R - C_0)^2 = R^2 \frac{p^*}{1-p^*} (1-\xi)^2.$$

Differentiating, we get

$$\begin{aligned} \frac{1}{R^2} \frac{\partial V}{\partial \xi} &= 2 \left(\frac{1-\xi}{1-p^*} \right) \left(\frac{1}{2} \frac{1-\xi}{1-p^*} \frac{\partial p^*}{\partial \xi} - p^* \right) \\ &= 2 \left(\frac{1-\xi}{1-p^*} \right) \left(\frac{1}{2} - p^* \right), \end{aligned}$$

where the second equality follows from

$$\frac{\partial p^*}{\partial \xi} = \frac{1-p^*}{1-\xi},$$

which can be easily verified by applying the implicit function theorem on the first order condition for (5). Therefore,

$$\begin{aligned} \frac{\partial V}{\partial p^*} &= \frac{\frac{\partial V}{\partial \xi}}{\frac{\partial p^*}{\partial \xi}} \\ &= \frac{2R^2 \left(\frac{1-\xi}{1-p^*} \right) \left(\frac{1}{2} - p^* \right)}{\frac{1-p^*}{1-\xi}} \\ &= \underbrace{2R^2 \left(\frac{1-\xi}{1-p^*} \right)^2}_{>0} \left(\frac{1}{2} - p^* \right). \end{aligned}$$

The Lemma then follows from observing that $\frac{\partial V}{\partial p^*}$ is monotone decreasing in p^* and that it has the unique root at $p^* = \frac{1}{2}$.

Appendix B. Proofs of Lemmas and Theorems

Proof of Lemma 1. (Step 1) Show that any consumption scheme whose C_S exceeds R is dominated by a consumption scheme whose C_S equals R .

Let N_0 be the N such that $C_S = R$ on Eq. (7). (It can easily be shown that) EU is continuously concave in N on $N \geq N_0$. It then suffices to show that $\frac{\partial EU}{\partial N} \Big|_{N_0} < 0$ in the original problem. Namely, if $\frac{\partial EU}{\partial N} \Big|_{N_0} < 0$, then by continuous concavity of EU, $\frac{\partial EU}{\partial N} \Big|_N < 0$ for all $N \geq N_0$, and (again, by continuous concavity of EU) any consumption scheme with $N > N_0$ is dominated by a consumption scheme with N_0 .

To prove this sufficient condition ($\frac{\partial EU}{\partial N} \Big|_{N_0} < 0$), first, write down the EU $\Big|_{N \geq N_0}$ under Eqs. (6)–(8):

$$\begin{aligned} EU \Big|_{N \geq N_0} &= (1-p)U(C_F) + pU(C_S) \\ &= (1-p)U(C_0 - N) + pU(C_0 + N(M-1)) \\ &= (1-p)U(C_0 - N) + pU(C_0 + N \frac{1-p}{p}). \end{aligned}$$

Then differentiate $EU \Big|_{N \geq N_0}$ with respect to N at N_0 , and any $p \in (-\infty, 1)$:

$$\begin{aligned} \frac{\partial EU}{\partial N} \Big|_{N_0, p} &= -(1-p)U'(C_0 - N) + p \frac{1-p}{p} U'(C_0 + N \frac{1-p}{p}) \Big|_{N_0} \\ &= (1-p)(U'(C_S) - U'(C_0 - N)) \Big|_{N_0} \\ &= (1-p)(U'(R^+) - U'(\tilde{C}_F)) \\ &< 0, \end{aligned}$$

where the last inequality follows from the domain of $p \in (-\infty, 1)$, and Assumption (9).

Step2 Show that any consumption scheme whose C_S falls below R is dominated by a consumption scheme whose C_S equals R .

When $C_S < R$, $U(c) = \delta u(c)$. Then by our standard assumptions on $u(c)$ and Jensen's inequality, we know that $p = 0$ (no trade) dominates all other consumption scheme, which is by definition, (weakly) dominated by p^* because $p = 0$ is in the choice set. $\square$

Proof of Lemma 2. Since $p \in (0, 1)$, $C_F = \frac{C_0 - pR}{1-p}$, and $C_F - C_0 = \frac{p(C_0 - R)}{(1-p)}$. Also by Lemma 1, $C_S = R$. Some calculations yield:

$$\sigma^2 = \frac{p}{(1-p)}(R - C_0)^2, \quad (11)$$

and similarly,

$$\mathbb{E}[(C - C_0)^3] = \frac{p(1-2p)}{(1-p)^2}(R - C_0)^3. \quad (12)$$

$$\therefore S(p) = \frac{1-2p}{\sqrt{p(1-p)}} \text{ and } S'(p) = \frac{-1}{2p(1-p)^{3/2}} < 0. \quad \square$$

Proof of Theorem 1. The optimization problem in (10) is specialized to power utility:

$$\max_p \left(\delta(1-p) \frac{C_F^{1-\gamma} - 1}{1-\gamma} + p \frac{R^{1-\gamma} - 1}{1-\gamma} \right), \quad \text{where } C_0 = pR + (1-p)C_F. \quad (13)$$

Substitute in the expression for C_F and let $\xi = \frac{C_0}{R}$. The f.o.c. $\frac{\partial EU}{\partial p}$ gives:

$$F(p; \cdot) = \frac{\delta}{1-\gamma} \left(\frac{\xi - p}{1-p} \right)^{-\gamma} R^{1-\gamma} \frac{\gamma - 1 + p - \xi\gamma}{1-p} + \frac{R^{1-\gamma} + \delta - 1}{1-\gamma} = 0 \quad (14)$$

Checking the s.o.c.,

$$\frac{\partial F(p; \cdot)}{\partial p} = \frac{\delta}{1-\gamma} R^{1-\gamma} \left(\frac{\xi - p}{1-p} \right)^{-\gamma-1} \frac{\gamma^2(1-\xi)^2}{(1-p)^3} < 0 \quad (15)$$

Hence, the EU-optimization problem amounts to finding the p^* which satisfies

$$F(p^*; \cdot) = 0 \quad (16)$$

Proof of part (i): By Implicit Function Theorem, $\frac{\partial p^*}{\partial \xi} = -\frac{\frac{\partial F}{\partial \xi}}{\frac{\partial F}{\partial p^*}}$ holds.

Partial differentiation yields:

$$\frac{\partial F}{\partial \xi} = -\frac{\delta}{(1-\gamma)(1-p)} R^{1-\gamma} \gamma \left(\frac{\xi - p}{1-p} \right)^{-\gamma-1} \frac{(\gamma-1)(1-\xi)}{1-p}$$

and

$$\frac{\partial F}{\partial p^*} = -\frac{\delta}{(1-\gamma)(1-p)} R^{1-\gamma} \gamma \left(\frac{\xi - p}{1-p} \right)^{-\gamma-1} \frac{(1-\gamma)(1-\xi)^2}{(1-p)^2}$$

Hence,

$$\frac{\partial p^*}{\partial \xi} = \frac{1-p^*}{1-\xi} > 0 \quad (17)$$

Proof of part (ii) : Recall that p^* are quantities that depend on ξ , ceteris paribus. Hence, for any sequence $\xi_n \rightarrow 1$, there is a corresponding sequence p_n^* . Consequently, from (14), we can define a sequence $F(p_n^*; \cdot)$ with $\xi_n \rightarrow 1$.

The proof argues by contradiction. Suppose (ii) does not hold, i.e., $\exists \xi_n \uparrow 1$ such that:

$$\lim_{\xi_n \rightarrow 1} p_n^* \neq 1. \quad (18)$$

From examining (14), we note that the expression

$$\lim_{\xi_n \rightarrow 1} F(p_n^*; \cdot)$$

is well defined as long as (18) holds. On such a sequence $\xi_n \rightarrow 1$ where (18) holds, the limit is computed (from (14)) as:

$$\lim_{\xi_n \rightarrow 1} F(p_n^*; \cdot) = -\frac{\delta}{1-\gamma} R^{1-\gamma} + \frac{R^{1-\gamma} + \delta - 1}{1-\gamma}. \quad (19)$$

Since $F(p^*; \cdot) = 0$ ($\because$ first order condition), $F(p_n^*; \cdot)$ is a sequence of 0's that must invariably converge to 0. This implies:

$$-\frac{\delta}{1-\gamma} R^{1-\gamma} + \frac{R^{1-\gamma} + \delta - 1}{1-\gamma} = 0. \quad (20)$$

Rearranging, this becomes: $R^{1-\gamma} = 1$, a contradiction under our assumptions $R > 1$ and $\gamma > 1$.

Proof of part (iii): Let

$$\begin{aligned} g(\xi) &:= F(0; \cdot) \\ &= \frac{\delta}{1-\gamma} \xi^{-\gamma} R^{1-\gamma} (\gamma - 1 - \xi\gamma) + \frac{R^{1-\gamma} + \delta - 1}{1-\gamma}. \end{aligned}$$

Showing $\exists (\frac{C_0}{R})^* \in (0, 1)$ such that $p^* = 0$ requires us to show that $g(\cdot)$ has a root in $(0, 1)$. Note:

$$g(1) = \frac{1-\delta}{1-\gamma} (R^{1-\gamma} - 1) > 0$$

Then, by Intermediate Value Theorem (IVT), it suffices to show that:

$$\exists C_{\delta, R} \in (0, 1), \text{ such that } g(C) < 0. \quad (21)$$

Proof of (21):

Rearranging $g(\xi)$, we get:

$$g(\xi) = -\delta \xi^{-\gamma} R^{1-\gamma} (1 - \xi \frac{\gamma}{\gamma-1}) + \frac{R^{1-\gamma} + \delta - 1}{1-\gamma}$$

However, $\xi^{-\gamma} (1 - \xi \frac{\gamma}{\gamma-1}) > \xi^{-\gamma} \rightarrow \infty$ as $\xi \downarrow 0^+$. Plugging this back into (22), this implies $g(\xi) \rightarrow -\infty$ as $\xi \downarrow 0^+$. Hence, for any $N \in \mathbb{R}$, $\exists C \in (0, 1)$ such that $g(C) < -N$, which proves (21). $\square$

Proof of Theorem 2. Recall that

(i) $\frac{\partial F(p; \cdot)}{\partial p} < 0$ (from s.o.c.), and

(ii) $C_F - C_0 = \frac{p^*}{1-p^*} (C_0 - R)$.

Clearly, from (i), the Expected Utility is maximized at $p^* (\leq 0)$. Note that from (ii), choosing $p^* = 0$ is equivalent to choosing C_0 , namely not choosing any gamble. This is certainly an available option for the agent. Hence, we want to show that the agent chooses $p = 0$ over $p \in (0, 1)$. To do this, we need to show

$$EU(p^*) \geq EU(0) > EU(p) \quad (22)$$

where

$$p^* \leq 0 < p \quad (23)$$

By Mean Value Theorem (MVT), $\exists c \in (0, p)$ such that

$$EU(p) - EU(0) = EU'(c)(p - 0) < 0. \quad (24)$$

This follows from the fact that $EU'(c) < 0$, which can be shown by applying MVT again. $\square$

Proof of Theorem 3. Using Implicit Function Theorem, $\frac{dp^*}{d\delta} = -\frac{\frac{\partial F}{\partial \delta}}{\frac{\partial F}{\partial p^*}}$. Note that:

$$\begin{aligned} F(p^*; \cdot) = 0 &\iff \frac{\partial EU}{\partial p} = 0 \\ &\iff \frac{\partial(1-p)\delta \frac{C_F^{1-\gamma}-1}{1-\gamma} + p \frac{R^{1-\gamma}-1}{1-\gamma}}{\partial p} = 0 \\ &\iff \delta \frac{\partial(1-p) \frac{C_F^{1-\gamma}-1}{1-\gamma}}{\partial p} + \frac{R^{1-\gamma}-1}{1-\gamma} = 0 \end{aligned}$$

Hence,

$$\begin{aligned} \frac{\partial F}{\partial \delta} &= \frac{\partial(1-p) \frac{C_F^{1-\gamma}-1}{1-\gamma}}{\partial p} \\ &= -\frac{R^{1-\gamma}-1}{1-\gamma} \frac{1}{\delta} < 0. \end{aligned}$$

Also, from before,

$$\frac{\partial F}{\partial p^*} = -\frac{\delta}{(1-\gamma)(1-p)} R^{1-\gamma} \gamma \left(\frac{\xi-p}{1-p}\right)^{-\gamma-1} \frac{(1-\gamma)(1-\xi)^2}{(1-p)^2} < 0$$

It thus follows that $\frac{dp^*}{d\delta} < 0$. $\square$

Proof of Theorem 4. Using Implicit Function Theorem, $\frac{\partial p^*}{\partial C_0} \big|_{\delta, \gamma, \xi} = -\frac{\frac{\partial F}{\partial C_0}}{\frac{\partial F}{\partial p^*}}$. Note that:

$$\frac{\partial F}{\partial C_0} = \gamma \delta R^{-\gamma} \frac{(1-\xi)}{(1-p)^2} \left(\frac{\xi-p}{1-p}\right)^{-\gamma-1} > 0.$$

Also, from before,

$$\frac{\partial F}{\partial p^*} = -\frac{\delta}{(1-\gamma)(1-p)} R^{1-\gamma} \gamma \left(\frac{\xi-p}{1-p}\right)^{-\gamma-1} \frac{(1-\gamma)(1-\xi)^2}{(1-p)^2} < 0$$

It thus follows that $\frac{\partial p^*}{\partial C_0} \big|_{\delta, \gamma, \xi} > 0$. $\square$

Proof of Theorem 5. A direct algebraic proof is not amenable. We first suggest a sufficient condition (actually, an equivalence condition) and then use this to prove the theorem.

Claim 1. For a given γ (and of course, under the fixed C_0 and δ as assumed in the statement of the theorem), let $R_0^*(\gamma)$ denote the R which leads to $p^* = 0$. (Recall from Theorem 1, we know $\exists R_0^*(\gamma)$.) It suffices to show that $\frac{\partial R_0^*(\gamma)}{\partial \gamma} < 0$

Proof. Let $\gamma_i < \gamma_j$, and denote the optimal solutions pertaining to γ_i and γ_j (as functions of ξ) as $p_{\gamma_i}^*(\xi)$ and $p_{\gamma_j}^*(\xi)$. Note that $p_{\gamma_j}^*(\xi)$ is well-defined as a function of ξ because we have fixed C_0 . In fact, in this setting we can treat $p_{\gamma_j}^*(\xi)$ as a continuously differentiable function, as a direct consequence of the Implicit Function Theorem. Note also that by (17), $p_{\gamma_i}^*(\xi)$ and $p_{\gamma_j}^*(\xi)$ can never intersect. To intersect at, say, point ξ_0 , there must exist a neighborhood of ξ_0 upon which $|\frac{\partial p_{\gamma_i}^*(\xi)}{\partial \xi}|$ always exceeds $|\frac{\partial p_{\gamma_j}^*(\xi)}{\partial \xi}|$. However, (17) prohibits this (i.e. plug in ξ_0 into (17), and for any $\xi > \xi_0$, $|\frac{\partial p_{\gamma_i}^*(\xi)}{\partial \xi}| < |\frac{\partial p_{\gamma_j}^*(\xi)}{\partial \xi}|$ whenever $p_{\gamma_i}^*(\xi) > p_{\gamma_j}^*(\xi)$ and vice versa for $\xi < \xi_0$), asserting our claim that $p_{\gamma_i}^*(\xi)$ and $p_{\gamma_j}^*(\xi)$ can never intersect.

Next, suppose that $\frac{\partial R_0^*(\gamma)}{\partial \gamma} < 0$ holds. Since $\gamma_i < \gamma_j$, this implies $R_0^*(\gamma_i) > R_0^*(\gamma_j)$. Using what we know about $p_{\gamma_j}^*(\xi)$ from Theorem 1, we can deduce that

$$p_{\gamma_i}^* \left(\frac{C_0}{R_0^*(\gamma_j)} \right) > 0 = p_{\gamma_j}^* \left(\frac{C_0}{R_0^*(\gamma_j)} \right),$$

where the inequality follows from combining Theorem 1-(i) (p^* is monotonically increasing in ξ and approaches 1 from the left) and the fact that $0 = p_{\gamma_i}^* \left(\frac{C_0}{R_0^*(\gamma_i)} \right)$, by definition. Similarly, the equality follows from definition of $R_0^*(\gamma)$. But since we established that $p_{\gamma_i}^*(\xi)$ and $p_{\gamma_j}^*(\xi)$ can never intersect, this inequality at $\xi = \frac{C_0}{R_0^*(\gamma_j)}$ must in fact hold uniformly in all ξ , namely, $p_{\gamma_i}^*(\xi) > p_{\gamma_j}^*(\xi)$ whenever $\gamma_i < \gamma_j$. Therefore, $\frac{dp^*}{d\gamma} < 0$, as desired. $\square$

Claim 2. $\frac{\partial R_0^*(\gamma)}{\partial \gamma} < 0$.

Proof. We first specialize (14) by insisting $p^* = 0$, as per the definition of R_0^* :

$$G(\cdot) = F(0; \cdot) = -\delta C_0^{-\gamma} R - \frac{\delta}{1-\gamma} C_0^{1-\gamma} \gamma + \frac{R^{1-\gamma} + \delta - 1}{1-\gamma} = 0$$

By Implicit Function Theorem,

$$\frac{\partial R}{\partial \gamma} = -\frac{\frac{\partial G}{\partial \gamma}}{\frac{\partial G}{\partial R}} = \underbrace{\left(\frac{R}{C_0} \right) - 1}_{A < 0} \cdot \underbrace{\left(\frac{R}{C_0} \right)^{-\gamma} \left[\frac{\left(\frac{R}{C_0} \right)^{\log \frac{R}{C_0}}}{\left(\frac{R}{C_0} \right) - 1} \right] + \mathcal{O}\left(\frac{1}{R}\right) - \delta}_{B > 0} \quad (25)$$

where $\mathcal{O}\left(\frac{1}{R}\right) = \frac{(1-\delta)C_0^{\gamma-1} \log C_0}{\frac{R}{C_0} - 1} > 0$, a positive quantity that converges to 0 at the rate of $\frac{1}{R}$.

Under the current assumptions, $R-1 > C_0-1 > 0$, and $1-\gamma < 0$, thus $A = \frac{\left(\frac{R}{C_0}\right)-1}{\frac{1-\gamma}{C_0}} < 0$. To sign B , note that $\frac{\left(\frac{R}{C_0}\right)^{\log \frac{R}{C_0}}}{\left(\frac{R}{C_0}\right)-1} > 1$ for all $\frac{R}{C_0} > 1$, and $\mathcal{O}\left(\frac{1}{R}\right) > 0$, so if $\left(\frac{R}{C_0}\right)^{-\gamma} \left[\frac{\left(\frac{R}{C_0}\right)^{\log \frac{R}{C_0}}}{\left(\frac{R}{C_0}\right)-1} \right] + \mathcal{O}\left(\frac{1}{R}\right) < \delta$, this implies $\left(\frac{R}{C_0}\right)^{-\gamma} < \delta$, and $B > 0$. Therefore, under the given assumption, $\frac{\partial R}{\partial \gamma} < 0$. $\square$

Combining Claims 1 and 2, we arrive at the desired conclusion. $\square$

Appendix C. Further details on Section 4

Portfolio Simulation Methodology for the Disposition Effect: We provide additional detail on the method we use to generate Table 2. Single stock price movements are simulated with a (recombining) binomial tree that match pre-specified μ_S and σ_S^2 . On the final nodes, aspirational utility realizations are computed using the pre-specified utility parameters. By backward induction, we compute the optimal portfolio weights on all nodes of the binomial tree.

Using the above results, all nodes are classified into one of the four categories along the following criteria, as per Odean (1998): A node represents a ‘Gain’ (‘Loss’) if the stock price at the node is higher (lower) than the average stock price purchased up to that node. A node represents a ‘Realized’ (‘Paper’) gain/loss if the holdings of the stock was reduced (not reduced) at that node. This allows all nodes to be classified into one of the four categories (1) paper gain (2) paper loss (3) realized gain (4) realized loss. Then, the Proportion of Gains Realized (PGR) is computed as:

$$PGR = \frac{\text{realized gain}}{\text{realized gain} + \text{paper gain}},$$

and the Proportion of Loss Realized (PLR) is computed as:

$$PGR = \frac{\text{realized loss}}{\text{realized loss} + \text{paper loss}}.$$

For a full detail of the method, see Barberis and Xiong (2009) or Odean (1998).

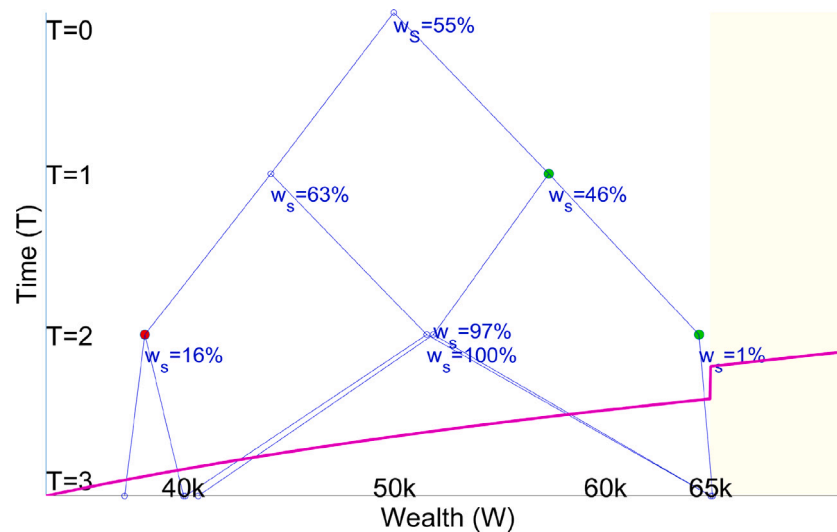


Fig. 11. Dynamic portfolio optimization with 3 sub-periods. Parameters are identical to those in Fig. 5, in particular, the aspiration level is at $R = 65$ k. The green dots denote nodes that display the disposition effect. The red dots denote nodes that do not display the disposition effect. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 7

Revealed preferences for skewness when we break down by the four distinct skewness combinations that our experiment involved. Note that in all pairs the mean and variance is the same across the two options.

Revealed preference	Pairs with skewness of			
	{0, +1.5}	{0, +2.7}	{0, -1.5}	{0, -2.7}
AA	30.16%	25.93%	45.24%	39.42%
AB	21.83%	23.81%	17.06%	19.31%
BA	12.30%	17.46%	13.49%	11.11%
BB	35.71%	32.80%	24.21%	30.16%
	100%	100%	100%	100%

Dynamic Optimization and the Disposition Effect: In Fig. 11 below, we provide additional explanation on how dynamic optimization leads to results as seen on Table 2. The underlying parameters are identical to those in Fig. 5. The vertical location of the nodes denote the (sub)-period, the horizontal location of the nodes denote the size of the portfolio. The colored interim nodes ($T = 1, T = 2$) denote nodes where the investor *realizes* – that is, *reduces* w_S – the (interim) investment outcomes. Those colored in green (red) are those that conform (do not conform) to the notion of the disposition effect: nodes where stocks are realized – i.e., sold off – following a *gain* (loss) in stock price. For example, in the first sub-period ($T = 1$), the node with $w_S = 46\%$ represents a realization of stock investment outcome ($w_S = 55\% \rightarrow w_S = 46\%$) following a gain, hence marked in green. The intuition for this realization is that – conditional on the gain in stock price – agents can afford, and is willing to reduce the exposure to stocks, since the gap between the portfolio value and the aspiration has been reduced due to the gain in stock price: in other words, the aspiration is now more accessible, and too much volatility may undo the gain that they have made. The actions described thus far are in line with the disposition effect. However, in the second sub-period ($T = 2$), the node with $w_S = 16\%$ represents a realization of stock investment outcome ($w_S = 63\% \rightarrow w_S = 16\%$) following a loss. Here, the reduction of w_S owes to the fact that the agent’s aspiration – after two consecutive drops in stock prices – has turned unattainable, and the agent has effectively “given up”, and reduces stock holdings to the default, CRRA level. This does not conform to the disposition effect, and is marked in red. Roughly speaking, that there are more green nodes than red nodes translates to $\frac{PGR}{PLR} > 1$, the measure used by Odean (1998) to document

the disposition effect. The actions seen here are quite typical for the range $R \in (55k, 70k)$, even more so as we increase T to 4 and 5 (where we hit a computational barrier).

Dynamic Optimization Process Outside of the “Goldilocks” Zone:

We describe the optimization process when R is either too far, or too close. Fig. 12 below describes the situation where the aspiration is “too far” ($C_0 = 50$ k, $R = 80$ k). Here, a single drop in stock price is enough to render the aspiration unreachable, hence agents realize their losses (“give up”) as soon as they observe a drop in stock price. As such, there are more “red nodes” than “green nodes” and the aspirational utility fails to generate the disposition effect. As for the other extreme, Fig. 13 below describes a situation where the aspiration is “too close” ($C_0 = 50$ k, $R = 50$ k). Here, the aspiration is attainable simply by burying most of their wealth in the risk-free assets: low w_S ($w_S = 9\%$). Upon a gain in stock, they revert back to the CRRA utility investment scheme ($w_S \approx 16\%$), as they are already a safe distance from R . This translates to increasing their stock exposure following a gain in stock price; again, the opposite of the disposition effect.

Connection with the Dynamic Generation of Skewness in Barberis

(2012): Our model, as it was set up in Section 2 (single period model), suppresses the role of dynamics, and generates skewness “statically”. However, the analysis in Section 4 reassures us that it can be extended to incorporate the core insight of Barberis (2012): that skewed payoffs can be generated dynamically, – even as a continuation of relatively symmetric bets – for example, by committing to exit the gambling scene whenever the cumulative loss exceeds a certain threshold (thereby, in this case, generating positive skewness). To see that our setup is amenable to such dynamically generated skewness, it is useful to compare Fig. 12 against Fig. 13. The payoffs, while generated by symmetric bets (stock movements) are clearly skewed: positively skewed in Fig. 12 and (essentially) negatively skewed in Fig. 13. Moreover, the optimality of the dynamically generated skewness also conforms to the predictions of Theorem 1 – namely, positive skewness is optimal when aspiration is far, and vice versa – indicating that Theorem 1 could likely be easily extended into a setup where skewness is generated dynamically, as opposed to statically in our current setup.

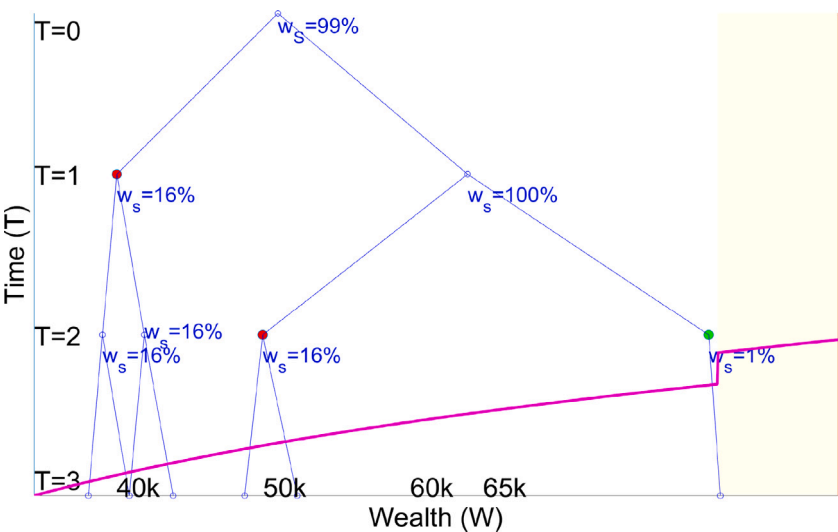


Fig. 12. Aspiration is “too far”. This figure is drawn under an identical setup as in Fig. 11 except for an aspiration that is set to be at $R = 80\text{ k}$ ($> 65\text{ k}$). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

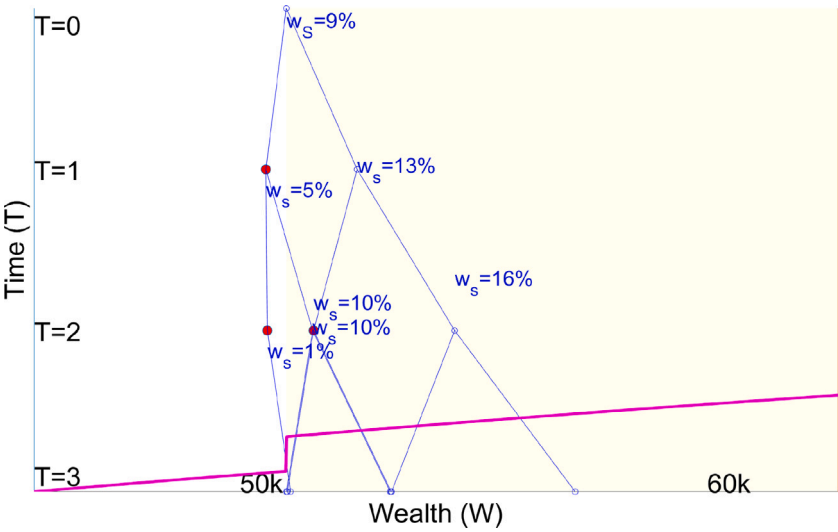


Fig. 13. Aspiration is “too close”. This figure is drawn under an identical setup as in Fig. 11 except for an aspiration that is set to be at $R = 50\text{ k}$ ($< 65\text{ k}$).

Table 8
Further breaking down lottery pairs for all the pairs where the skewed option was positively skewed. The third row shows the mean and standard deviation of the lottery pair.

Revealed preference	Skewness: (μ, σ) :	Pairs with				
		{0, +1.5}		{0, +2.7}		
		(7, 2)	(19, 8)	(11, 3)	(13, 3)	(17, 3)
AA		28.57%	31.75%	26.19%	30.16%	21.43%
AB		20.63%	23.02%	28.57%	19.05%	23.81%
BA		14.29%	10.32%	19.05%	13.49%	19.84%
BB		36.51%	34.92%	26.19%	37.30%	34.92%
		100%	100%	100%	100%	100%

Table 9

All the pairs where the skewed option was negatively skewed.

Revealed preference	Skewness: (μ , σ):	Pairs with				
		{0, −1.5}		{0, −2.7}		
		(7, 2)	(19, 8)	(11, 3)	(13, 3)	(17, 3)
AA		43.65%	46.83%	41.27%	34.13%	42.86%
AB		19.84%	14.29%	23.81%	13.49%	20.63
BA		15.08%	11.90%	6.35%	21.43%	5.56%
BB		21.43%	26.98%	30.95%	30.95%	30.95%
		100%	100%	100%	100%	100%

Table 10

The percentages across columns indicate the histogram of choices across treatments. The “Low” [“Mid”/“High”] treatment includes all rounds in which the “Donation threshold” was set such that lottery “A” [“B”/“C”] maximized the probability of the donation. Bolded percentages indicate the largest percentage of the row.

Round	Chosen Lottery	Donation threshold			N
		Low	Mid	High	
1	A (−ve skewness)	26.19%	14.29%	16.67%	126
	B (0 skewness)	33.33%	57.14%	33.33%	
	C (+ve skewness)	40.48%	28.57%	50.00%	
2	A (−ve skewness)	7.14%	19.05%	26.19%	126
	B (0 skewness)	42.86%	54.76%	33.33%	
	C (+ve skewness)	50.00%	26.19%	40.48%	
3	A (−ve skewness)	9.52%	9.52%	14.29%	126
	B (0 skewness)	30.95%	57.14%	35.71%	
	C (+ve skewness)	59.52%	33.33%	50.00%	
4	A (−ve skewness)	38.10%	14.29%	16.67%	126
	B (0 skewness)	21.43%	40.48%	35.71%	
	C (+ve skewness)	40.48%	45.27%	47.62%	
5	A (−ve skewness)	28.57%	16.67%	14.29%	126
	B (0 skewness)	30.95%	38.10%	21.43%	
	C (+ve skewness)	40.48%	45.24%	64.29%	
6	A (−ve skewness)	35.71%	16.67%	16.67%	126
	B (0 skewness)	45.24%	45.24%	26.19%	
	C (+ve skewness)	19.05%	38.10%	57.14%	
7	A (−ve skewness)	11.90%	11.90%	28.57%	126
	B (0 skewness)	28.57%	52.38%	21.43%	
	C (+ve skewness)	59.52%	35.71%	50.00%	
8	A (−ve skewness)	35.71%	21.43%	14.29%	126
	B (0 skewness)	26.19%	42.86%	23.81%	
	C (+ve skewness)	38.10%	35.71%	61.90%	

Appendix D. Further details on Section 7**Lotteries used in Study 1 (Sections 1 & 3):****Table 11**

The percentages across columns indicate the histogram of choices across treatments. The highlighted cells indicate the donation probability maximizing choice for each region (“Low”, “Mid”, and “High”) Note that for “High”, Choice D maximized the donation probability in Question 9, and Choice E maximized the donation probability in Question 10.

Chosen Lottery	Donation threshold		
	Low	Mid	High
A (highly -ve skewness)	10.71%	7.14%	10.71%
B (mildly -ve skewness)	8.33%	10.71%	8.33%
C (0 skewness)	17.86%	36.90%	20.24%
D (mildly +ve skewness)	20.24%	10.71%	29.76%
E (highly +ve skewness)	42.86%	34.52%	30.95%
Total	100%	100%	100%
N = 252	84	84	84

Round	Option	Mean	SD	Skewness	Outcomes	Pr.
1 (5*)	A	7	2	0	{5, 9}	(0.5, 0.5)
1 (5*)	B	7	2	1.5	{6, 11}	(0.8, 0.2)
2* (7)	A	13	3	0	{10, 16}	(0.5, 0.5)
2* (7)	B	13	3	−2.7	{4, 14}	(0.1, 0.9)
3 (2*)	A	11	3	0	{8, 14}	(0.5, 0.5)
3 (2*)	B	11	3	−2.7	{2, 12}	(0.1, 0.9)
4 (9*)	A	11	3	0	{8, 14}	(0.5, 0.5)
4 (9*)	B	11	3	2.7	{10, 20}	(0.9, 0.1)
5* (1)	A	7	2	0	{5, 9}	(0.5, 0.5)
5* (1)	B	7	2	−1.5	{3, 8}	(0.2, 0.8)
6* (10)	A	19	8	0	{11, 27}	(0.5, 0.5)
6* (10)	B	19	8	1.5	{15, 35}	(0.8, 0.2)
7* (4)	A	13	3	0	{10, 16}	(0.5, 0.5)
7* (4)	B	13	3	2.7	{12, 22}	(0.9, 0.1)
8* (3)	A	19	8	0	{11, 27}	(0.5, 0.5)
8* (3)	B	19	8	−1.5	{3, 23}	(0.2, 0.8)
9 (6*)	A	17	3	0	{14, 20}	(0.5, 0.5)
9 (6*)	B	17	3	2.7	{16, 26}	(0.9, 0.1)
10 (8*)	A	17	3	0	{14, 20}	(0.5, 0.5)
10 (8*)	B	17	3	−2.7	{8, 18}	(0.1, 0.9)

Notes:

(a) The rounds in brackets indicate the corresponding round in the experiment section 3. The non-bracketed number indicates the round in section 1.

(b) The starred rounds indicate which section involved the control pair (i.e. when the donation threshold was impossible to reach).

(c) Option A was always the non-skewed option, Option B was always the skewed option.

(d) Participants did not see the moments of the lotteries.

Lotteries used in Study 2 (section 2):

Round	Option	Mean	SD	Skewness	Outcomes	Pr.
1	A	11	3	-2.7	{2, 12}	(0.1, 0.9)
1	B	11	3	0	{8, 14}	(0.5, 0.5)
1	C	11	3	2.7	{10, 20}	(0.9, 0.1)
2	A	13	3	-2.7	{4, 14}	(0.1, 0.9)
2	B	13	3	0	{10, 16}	(0.5, 0.5)
2	C	13	3	2.7	{12, 22}	(0.9, 0.1)
3	A	15	3	-2.7	{6, 16}	(0.1, 0.9)
3	B	15	3	0	{12, 18}	(0.5, 0.5)
3	C	15	3	2.7	{14, 24}	(0.9, 0.1)
4	A	17	3	-2.7	{8, 18}	(0.1, 0.9)
4	B	17	3	0	{14, 20}	(0.5, 0.5)
4	C	17	3	2.7	{16, 26}	(0.9, 0.1)
5	A	18	2	-1.5	{14, 19}	(0.2, 0.8)
5	B	18	2	0	{16, 20}	(0.5, 0.5)
5	C	18	2	1.5	{17, 22}	(0.8, 0.2)
6	A	18	4	-1.5	{10, 20}	(0.2, 0.8)
6	B	18	4	0	{14, 22}	(0.5, 0.5)
6	C	18	4	1.5	{16, 26}	(0.8, 0.2)
7	A	18	6	-1.5	{6, 21}	(0.2, 0.8)
7	B	18	6	0	{12, 24}	(0.5, 0.5)
7	C	18	6	1.5	{15, 30}	(0.8, 0.2)
8	A	18	8	-1.5	{2, 22}	(0.2, 0.8)
8	B	18	8	0	{10, 26}	(0.5, 0.5)
8	C	18	8	1.5	{14, 34}	(0.8, 0.2)
9	A	19	6	-2.7	{1, 21}	(0.1, 0.9)
9	B	19	6	-1.5	{7, 22}	(0.2, 0.8)
9	C	19	6	0	{13, 25}	(0.5, 0.5)
9	D	19	6	1.5	{16, 31}	(0.8, 0.2)
9	E	19	6	2.7	{17, 37}	(0.9, 0.1)
10	A	22	6	-2.7	{4, 24}	(0.1, 0.9)
10	B	22	6	-1.5	{10, 25}	(0.2, 0.8)
10	C	22	6	0	{16, 28}	(0.5, 0.5)
10	D	22	6	1.5	{16, 31}	(0.8, 0.2)
10	E	22	6	2.7	{17, 37}	(0.9, 0.1)

Charity organization options used in the experiment:**1. MAKE-A-WISH Foundation**

The MAKE-A-WISH is a non-profit organization that creates life-changing wishes for children with a critical illness who are between the ages of 2.5 and 18. Children who may be eligible to receive a wish can be referred by either a medical professional treating the child, a parent/guardian or the potential wish child.

2. AMERICAN CIVIL LIBERTIES UNION (ACLU)

The American Civil Liberties Union (ACLU) works in the courts, legislatures and communities to defend and preserve the individual rights and liberties guaranteed to all people in this country by the Constitution and laws of the United States.

3. AMNESTY INTERNATIONAL

Amnesty international is a global movement of more than 7 million people in over 150 countries and territories who campaign to end abuses of human rights.

4. World Wide Fund for Nature (WWF)

The World Wide Fund for Nature (WWF) is an international non-governmental organization founded in 1961, working in the field of the wilderness preservation, and the reduction of human impact on the environment.

5. GREENPEACE

Greenpeace is an independent, campaigning organization which uses non-violent, creative confrontation to expose global environmental problems, and to force solutions for a green and peaceful future.

6. The Salvation Army

The Salvation Army, an international movement, is an evangelical part of the universal Christian Church. Its message is based on the Bible. Its ministry is motivated by the love of God. Its mission is to preach the gospel of Jesus Christ and to meet human needs in His name without discrimination.

Additional Tables for Section 7 - Study 1

See [Tables 7–9](#).

Additional Tables for Section 7 - Study 2

See [Tables 10 and 11](#).

References

- Albuquerque, R., 2012. Skewness in stock returns: Reconciling the evidence on firm versus aggregate returns. *Rev. Financ. Stud.* 25 (5), 1630–1673.
- Andreoni, J., 1989. Giving with impure altruism: Applications to charity and Ricardian equivalence. *J. Polit. Econ.* 97 (6), 1447–1458.
- Andreoni, J., 1990. Impure altruism and donations to public goods: A theory of warm-glow giving. *Econ. J.* 100 (401), 464–477.
- Artavanis, N., Morse, A., Tsoutsoura, M., 2016. Measuring income tax evasion using bank credit: Evidence from Greece. *Q. J. Econ.* 131 (2), 739–798.
- Bali, T.G., Cakici, N., Whitelaw, R.F., 2011. Maxing out: Stocks as lotteries and the cross-section of expected returns. *J. Financ. Econ.* 99 (2), 427–446.
- Bali, T.G., Gunaydin, A.D., Jansson, T., Karabulut, Y., 2023. Do the rich gamble in the stock market? Low risk anomalies and wealthy households. *J. Financ. Econ.* 150 (2), 103715.
- Barberis, N., 2012. A model of casino gambling. *Manage. Sci.* 58 (1), 35–51.
- Barberis, N., Huang, M., 2008. Stocks as lotteries: The implications of probability weighting for security prices. *Amer. Econ. Rev.* 98 (5), 2066–2100.
- Barberis, N., Xiong, W., 2009. What drives the disposition effect? An analysis of a long-standing preference-based explanation. *J. Finance* 64 (2), 751–784.
- Barberis, N., Xiong, W., 2012. Realization utility. *J. Financ. Econ.* 104 (2), 251–271, Special Issue on Investor Sentiment.
- Becker, G.S., 1974. A theory of social interactions. *J. Polit. Econ.* 82 (6), 1063–1093.
- Becker, G., Murphy, K.M., Werning, I., 2005. The equilibrium distribution of income and the market for status. *J. Polit. Econ.* 113 (2), 282–310.
- Boyer, B., Mitton, T., Vorkink, K., 2010. Expected idiosyncratic skewness. *Rev. Financ. Stud.* 23 (1), 169–202.
- Boyer, B.H., Vorkink, K., 2014. Stock options as lotteries. *J. Finance* 69 (4), 1485–1527.
- Brunnermeier, M., Parker, J., Gollier, C., 2007. Optimal beliefs, asset prices, and the preference for skewed returns. *Amer. Econ. Rev.* 97 (2), 159–165.
- Campbell, J., 2006. Household finance. *J. Finance* 61 (4), 1553–1604.
- Campbell, J.Y., Cochrane, J.H., 1999. By force of habit: A consumption-based explanation of aggregate stock market behavior. *J. Polit. Econ.* 107 (2), 205–251.
- Charles, K.K., Hurst, E., Roussanov, N., 2009. Conspicuous consumption and race. *Q. J. Econ.* 124 (2), 425–467.
- Chen, A., Lee, S., Zapatero, F., 2024. Clinging onto the cliff: a model of financial misconduct. Working paper.
- Clotfelter, C.T., 2000. Do lotteries hurt the poor? Well, yes and no. A Summary of Testimony Given to the House Select Committee on a State Lottery (April 28).
- Clotfelter, C., Cook, P., 1991. Selling hope: State lotteries in America. In: National Bureau of Economic Research book, Harvard University Press.
- Conrad, J., Dittmar, R.F., Ghysels, E., 2013. Ex ante skewness and expected stock returns. *J. Finance* 68 (1), 85–124.
- Constantinides, G., 1983. Capital market equilibrium with personal tax. *Econometrica* 51 (3), 611–636.

- Constantinides, G., 1984. Optimal stock trading with personal taxes: Implications for prices and the abnormal January returns. *J. Financ. Econ.* 13 (1), 65–89.
- Constantinides, G., 1990. Habit formation: A resolution of the equity premium puzzle. *J. Polit. Econ.* 98 (3), 519–543.
- Cordier, J., Gross, M., 2014. The complete guide to option selling: How selling options can lead to stellar returns in bull and bear markets, third ed. McGraw-Hill.
- Diecidue, E., van de Ven, J., 2008. Aspiration level, probability of success and failure, and expected utility. *Internat. Econom. Rev.* 49 (2), 683–700.
- Ebert, S., Strack, P., 2015. Until the bitter end: On prospect theory in a dynamic context. *Amer. Econ. Rev.* 105 (4), 1618–1633.
- Friedman, M., Savage, L.J., 1948. The utility analysis of choices involving risk. *J. Polit. Econ.* 56 (4).
- Genicot, G., Ray, D., 2017. Aspirations and inequality. *Econometrica* 85, 489–519.
- Glazer, A., Konrad, K., 1996. A signaling explanation for charity. *Amer. Econ. Rev.* 86 (4), 1019–1028.
- Goetzmann, W., Kumar, A., 2008. Equity portfolio diversification. *Rev. Finance* 12 (3), 433–463.
- Green, T.C., Hwang, B.-H., 2012. Initial public offerings as lotteries: Skewness preference and first-day returns. *Manage. Sci.* 58 (2), 432–444.
- Han, B., Hirshleifer, D., Walden, J., 2022. Social transmission bias and investor behavior. *J. Financ. Quant. Anal.* 57 (1), 390–412.
- Harvey, C., Siddique, A., 2000. Conditional skewness in asset pricing tests. *J. Finance* 55 (3), 1263–1295.
- Heffetz, O., Frank, R.H., 2011. Chapter 3 - preferences for status: Evidence and economic implications. In: Benhabib, J., Bisin, A., Jackson, M.O. (Eds.), *Handbook of Social Economics*, Vol. 1. North-Holland, pp. 69–91.
- Heimer, R.Z., 2016. Peer pressure: Social interaction and the disposition effect. *Rev. Financ. Stud.* 29 (11), 3177–3209.
- Heimer, R., Iliewa, Z., Imas, A., Weber, M., 2023. Dynamic Inconsistency in Risky Choice: Evidence from the Lab and Field. NBER Working Papers 30910, National Bureau of Economic Research, Inc.
- Heimer, R., Simon, D., 2015. Facebook Finance: How Social Interaction Propagates Active Investing. Working Papers (Old Series) 1522, Federal Reserve Bank of Cleveland.
- Henderson, V., Hobson, D., 2013. Risk aversion, indivisible timing options, and gambling. *Oper. Res.* 61 (1), 126–137.
- Hirshleifer, D., 2015. Behavioral finance. *Annu. Rev. Finan. Econ.* 7 (Volume 7, 2015), 133–159.
- Hong, H., Kubik, J.D., Stein, J.C., 2004. Social interaction and stock-market participation. *J. Finance* 59 (1), 137–163.
- Iyer, R., Popescu, A., 2023. New Evidence on Spillovers Between Crypto Assets and Financial Markets, Vol. 2023, No. 213. International Monetary Fund, USA.
- Kahneman, D., Tversky, A., 1979. Prospect theory: An analysis of decision under risk. *Econometrica* 47 (2), 263–291.
- Kimball, M., 1990. Precautionary saving in the small and in the large. *Econometrica* 58 (1), 53–73.
- Kraus, A., Litzenberger, R.H., 1976. Skewness preference and the valuation of risk assets. *J. Finance* 31 (4), 1085–1100.
- Kumar, A., 2009. Who gambles in the stock market? *J. Finance* 64 (4), 1889–1933.
- Levy, H., 1969. A utility function depending on the first three moments. *J. Finance* 24 (4), 715–719.
- Lopes, L.L., 1987. Between hope and fear: The psychology of risk. In: Berkowitz, L. (Ed.), *Advances in Experimental Social Psychology*, Vol. 20. Academic Press, pp. 255–295.
- McKay, A., Wieland, J.F., 2021. Lumpy durable consumption demand and the limited ammunition of monetary policy. *Econometrica* 89 (6), 2717–2749.
- Menezes, C., Geiss, C., Tressler, J., 1980. Increasing downside risk. *Amer. Econ. Rev.* 70 (5), 921–932.
- Mitton, T., Vorkink, K., 2007. Equilibrium underdiversification and the preference for skewness. *Rev. Financ. Stud.* 20 (4), 1255–1288.
- Ng, Y.-K., 1965. Why do people buy lottery tickets? Choices involving risk and the indivisibility of expenditure. *J. Polit. Econ.* 73 (5).
- Ntoumanis, N., Ng, J.Y.Y., Barkoukis, V., Backhouse, S., 2014. Personal and psychosocial predictors of doping use in physical activity settings: a meta-analysis. *Sports Med.* 44 (11), 1603–1624.
- Odean, T., 1998. Are investors reluctant to realize their losses? *J. Finance* 53 (5), 1775–1798.
- Pew Research Center, 2024. Are you in the American middle class? Find out with our income calculator.
- Rayo, L., Becker, G., 2007. Evolutionary efficiency and happiness. *J. Polit. Econ.* 115 (2), 302–337.
- Ring, C., Kavussanu, M., 2018. The impact of achievement goals on cheating in sport. *Psychol. Sport Exerc.* 35, 98–103.
- Roussanov, N., 2010. Diversification and its discontents: Idiosyncratic and entrepreneurial risk in the quest for social status. *J. Finance* 65 (5), 1755–1788.
- Rubenstein, R., Scafidi, B., 2002. Who pays and who benefits? Examining the distributional consequences of the Georgia lottery for education. *Natl. Tax J.* 55 (2), 223–238.
- Shefrin, H., Statman, M., 1985. The disposition to sell winners too early and ride losers too long: Theory and evidence. *J. Finance* 40 (3), 777–790.
- Shefrin, H., Statman, M., 2000. Behavioral portfolio theory. *J. Financ. Quant. Anal.* 35 (2), 127–151.
- Slemrod, J., 2019. Tax compliance and enforcement. *J. Econ. Lit.* 57 (4), 904–954.
- Soltes, E., 2016. *Why They Do It: Inside the Mind of the White-Collar Criminal*. PublicAffairs, New York.
- Sundaresan, S.M., 1989. Intertemporally dependent preferences and the volatility of consumption and wealth. *Rev. Financ. Stud.* 2 (1), 73–89.
- Taleb, N.N., 2007. *The Black Swan: The Impact of the Highly Improbable*. Random House, New York.
- Tversky, A., Kahneman, D., 1992. Advances in prospect theory: Cumulative representation of uncertainty. *J. Risk Uncertain.* 5 (4), 297–323.
- Zhang, X.-J., 2013. Book-to-market ratio and skewness of stock returns. *Account. Rev.* 88 (6), 2213–2240.