JOURNAL OF BEHAVIORAL FINANCE
2020, VOL. 21, NO. 3, 233–247
https://doi.org/10.1080/15427560.2019.1672167

Does Probability Weighting Drive Lottery Preferences?

Benjamin M. Blau, R. Jared DeLisle, and Ryan J. Whitby

Utah State University

ABSTRACT

We propose a test of the theory of skewness preferences. The probability weighting feature that is the basis of their theory relies on investors overweighting the probability of extreme, positive returns. The resulting investor preferences for positive skewness in return distributions will lead to excess demand, contemporaneous price premiums, and negative expected returns. We use the well-documented 52-week high bias as a method to truncate investors' weighted probability of expected right-tail events. We find evidence supporting the theoretical framework of Barberis and Huang as the negative return premiums associated with positive skewness is driven almost entirely by stocks that are farther away from the their 52-week high. No negative premiums related to skewness are detected when stock prices are close to the 52-week high.

KEYWORDS

Lotteries; Skewness; Anchoring; 52-week high; Probability weighting; Cumulative prospect theory

Introduction

Traditional asset pricing theory suggests that, in a mean-variance framework, various types of risk will be correctly priced. However, a number of stock characteristics or anomalies, which are not risk-based, are associated with significant return premiums. For example, empirical tests find lottery-like stocks or stocks with positively skewed return distributions, exhibit significant, negative expected returns (Bali, Cakici, and Whitelaw 2011; Boyer, Mitton, and Vorkink 2010; Conrad, Dittmar, and Ghysels 2013; Kumar 2009; Mitton and Vorkink 2007). While there are several theories why skewness premiums exist, Barberis and Huang (2008) use the concept of probability weighting Tversky and Kahneman (1992) to show that investors tend to overweight the tails of return distributions. The result of investors subjectively assigning higher probabilities to events with objectively lower probabilities is excess demand, contemporaneous price premiums, and negative future returns for stocks that exhibit positive skewness. In other words, the return premiums associated with positive skewness are likely to be explained by behavioral preferences for lottery-like stocks.

In this study, we attempt to provide tests of Barberis and Huang's (2008) theory by focusing on the role that probability weighting plays in explaining the skewness premiums. We use a well-documented behavioral bias, anchoring, to do so. Kahneman, Slovic, and Tversky (1982) define an anchor as "an initial value that is adjusted to yield the final answer." Prior research suggests that anchors often play an important role in the decision-making process of individuals. Tversky and Kahneman (1974) use experimental results to illustrate that the assessed subjective probability distributions of individuals suffering from anchoring bias are too tight. The anchoring bias can be so strong that even arbitrary numbers can be influential. For example, Ariely, Loewenstein, and Prelec (2003) find that when participants are asked to write down the last two digits of their social security number prior to answering a question, those numbers, even though arbitrary, have an anchoring effect on their responses. While the effects of anchors are well documented (see Kristensen and Gärling 1997), anchors are often just common reference points used as benchmarks or rules of thumb.

In the finance literature, the 52-week high has been used as one example of a common reference point that might act as an anchor. This reference point has the potential to create an anchor that could influence investor decision making. For example, if a stock is close to the 52-week high, then an investor might anchor on the 52-week high and therefore assess the subjective probability of the returns of that stock too tightly. This common benchmark for stock prices has

CONTACT R. Jared DeLisle jared.delisle@usu.edu Department of Economics and Finance, Jon M. Huntsman School of Business, Utah State University, 3500 Old Man Hill, Logan, UT 84322.

the potential to influence the purchase or sale of shares, and if systematic, could influence the prices of stocks that are either closer to or further away from those anchors. George and Hwang (2004) find that anchoring to the 52-week high explains a large portion of the momentum premium. Simlarly, Baker, Pan, and Wurgler (2012) find that prior stock-price peaks act as reference points and affect several aspects of mergers and acquisitions. In particular, Baker et al. find that M&A offer prices are biased towards recent price peaks and that the probability of a targets' acceptance of an acquirers' offer is higher if the offer price is above the price peak. Thus, anchoring to the 52-week high could influence an investors assessment of the expected return distributions. In the context of our study, the probability weighting that leads to preferences for positively skewed stocks might be inhibited the closer the stock is to the 52-week high. More generally, anchoring may truncate the upside potential of a particular security and result in less demand for those positively skewed stocks that are closest to their 52-week high. For example, when prices are near the 52-week high, demand by investors with lottery preferences will be muted because of the perception that prices cannot meaningfully move beyond the 52-week high. Thus, the tail probabilities computed by investors' weighting functions will be reduced as well as the perceived skewness. To the extent that this is true, the negative return premiums associated with positive skewness should be driven by stocks that are further from their 52-week high.

More formally, our analysis attempts to answer the following research question: Does the tightening of subjective probabilities associated with anchoring negate the overweighting of the tails of the return distributions associated with preferences for lotteries? If the 52-week high truncates the investors' perception of possible outcomes by removing the possibility of extreme, right-tail events, then risk premiums might vary with the distance from that anchor. Using a number of traditional asset pricing tests, our empirical results show that the 52-week high indeed acts as an anchor and meaningfully impacts the return premium associated with lottery-like securities. In a series of Fama and MacBeth (1973) regressions, we use several proxies for lottery-like characteristics and find that the negative return premiums associated with these characteristics are driven primarily by stocks that are further away from their 52-week high. In fact, we do not find a reliable return premium in the quintile of stocks closest to the 52-week high. Additionally, our portfolio analyses allow us to draw similar conclusions as negative return premiums are not observed in portfolios of stocks closest to their 52-week high.

The results presented in our study have important implications and provide evidence that is consistent with the notion that anchoring on the 52-week high may truncate the extreme, right-tail of the expected probability distribution and therefore weaken the skewness return premiums discussed in the empirical literature. These findings provide support for the probability weighting feature of cumulative prospect theory by investors making portfolio decisions (Barberis and Huang 2008). Our findings generally hold for each of our proxies for lottery-like characteristics, which include Kumar's (2009) lottery-stock classification and Bali et al.'s (2011) maximum daily return during a month. While we cannot rule out additional explanations for the presence of return premiums associated with positive skewness, probability weighting does seem to appear to play a major role in determining premiums.

Related literature and motivation

Consistent with the theoretical predictions in Barberis and Huang (2008), Mitton and Vorkink (2007), and Goetzmann and Kumar (2008) use datasets of investor trading accounts and find individual investors hold undiversified portfolios containing stocks with high levels of idiosyncratic skewness. These findings seem to suggest that investors sacrifice mean-variance efficiency, a characteristic fundamental to asset pricing, in order to obtain portfolios with higher probabilities of extreme, right-tail events. Kumar (2009) finds individual investors prefer stock with lottery-like characteristics, such as positive skewness, and these stocks typically underperform non-lottery stocks.[1] Realizing historical idiosyncratic skewness is unstable, Boyer, Mitton, and Vorkink (2010) create a measure of expected idiosyncratic skewness and find that this measure is negatively related to future abnormal returns. In addition, their measure partially explains the negative relation between future returns and idiosyncratic volatility documented by Ang et al. (2006). Bali, Cakici, and Whitelaw (2011) use the maximum daily return during a month (MAX) as a proxy for positive skewness given that skewness is not very persistent. They find that MAX also has a negative relation with future returns. Using the risk-neutral distribution of returns constructed from options data, Conrad, Dittmar, and Ghysels (2013) observe that stocks with high option-implied skewness earn low future abnormal returns relative to stocks with low option-implied skewness. Consistent with Barberis and Huang's conjecture, Mitton and Vorkink (2010) and Green and Hwang (2012) demonstrate skewness plays a significant role in the diversification discount and the IPO returns puzzle, respectively. Additionally, Schneider and Spalt (2017), DeLisle and Walcott (2016), and Schneider and Spalt (2016) show skewness impacts acquisitions in various dimensions, such as target selection, acquisitions premiums, method of payment, and post-acquisition returns. Taken together, there is substantial evidence that skewness is negatively priced in the cross-section of returns and is related to several documented anomalies.

Our study is related to two areas of the asset pricing literature: the preferences for lottery-like characteristics, such as skewness or maximum daily returns, and the 52-week high anchoring bias. The literature regarding lottery preferences focuses on how or why investors price stocks that resemble lotteries. The most common lottery-like characteristic is skewness. In general, this literature demonstrates that investors are positive skewness-seeking and that skewness carries a negative price of risk (i.e., investors are willing to pay a premium for positively skewed stocks, which leads to low future returns). Thus, it deviates from the traditional mean-variance optimization framework that is rooted deeply in the finance literature (e.g., Markowitz 1952, 1959; Sharpe 1964). For example, Brunnermeier and Parker (2005) and Brunnermeier, Gollier, and Parker (2007) create theoretical models based in rational optimal expectations, where investors must evaluate the tradeoff between favorable beliefs and the costs of holding those beliefs, which predict skewness preferences in investors. Mitton and Vorkink (2007) construct a model with investors that hold heterogeneous beliefs; a portion of the investors are mean-variance optimizers while the remainder are skewness-preferring. Their model shows that, in equilibrium, some investors hold positively skewed, undiversified portfolios.

In another important theoretical study, Barberis and Huang (2008) produce an asset allocation model using a unique feature of cumulative prospect theory (CPT)—probability weighting. Tversky and Kahneman (1992) introduce a modification to their original prospect theory (Kahneman and Tversky 1979) where agents apply a weighting function to real probabilities to obtain a weighted probability used to evaluate expected outcomes. Under this revised model, the CPT, Tversky and Kahneman show individuals overweight small probabilities which result in extremely risk-seeking behavior when faced with improbable gains. Barberis and Huang (2008) find that the probability weighting feature of CPT results in some investors holding undiversified portfolios with assets that have positively skewed return distributions. The lottery-like characteristics of these assets (large gains with very low probabilities) make them desirable to the investors who overweight the tails of the probability distribution. Thus, these investors contemporaneously bid up the price of the positively skewed securities and lower the expected returns. Given their results, Barberis and Huang suggest that incorporating probability weighting into models can assist in explaining asset pricing anomalies such as option implied volatility skews, the diversification discount, IPO returns, private equity premiums, and momentum returns. To this end, De Giorgi and Legg (2012) include probability weighting in their asset pricing model and demonstrate it generates smaller (larger) equity premiums for positively (negatively) skewed assets. In experimental studies, Kunreuther, Novemsky, and Kahneman (2001) find that their subjects treat a probability of 1/100,000 the same as the probability of 1/10,000,000, which is empirically consistent with the predictions of CPT. Further supporting the use probability weighting functions, Teigen (1974a, 1974b, 1983) finds that individuals' sum of construed probabilities of a set of outcomes exceeds one. Additionally, Grossman and Eckel (2015) demonstrate their subjects are skewness-seeking and exhibit decision-making consistent with probability weighting.

In a different stream of psychological literature, studies have examined the psychological concept of anchoring. Anchoring refers to the process of making adjustments away from an anchor, but the adjustments are biased towards the anchor and do not sufficiently move away from it. An anchor may come from the formulation of the problem to be solved, a computation made along the process of solving the problem, or a random value that has nothing to do with the problem. Kahneman et al. (1982) give several examples of anchoring documented in previous studies. Two of them highlight the insufficient adjustment associated with anchoring. One study examines the framing of the question, where the anchor is embedded in the problem: two groups of students are given the same multiplication problem and asked to estimate the product in five seconds. The difference between the two groups is that the problem's factors are arranged in different orders, one ascending and the other descending ($1 \times 2 \times 3 \times 4 \times 5 \times 6 \times 7 \times 8$ versus $8 \times 7 \times 6 \times 5 \times 4 \times 3 \times 2 \times 1$). The anchoring hypothesis suggests that the subjects will read the problem from left to right and anchor on the relative size of the first few numbers. Consistent with that hypothesis, the group with ascending (descending) numbers had a median estimate of 512 (2,250).

Another study Kahneman et al. (1982) describe uses completely random numbers as an anchor. Subjects spin a wheel to determine a number between 1 and 100 and asked to estimate certain quantities as a percentage. The random number generated by the wheel systematically biases the subjects estimate towards that number. Similarly, Ariely et al. (2003) find their subjects, after having them write down the last two digits of their social security number, anchor to that random number when estimating the price of a bottle of wine. It is this tendency for individuals to anchor that inspires George and Hwang (2004) to investigate distance from the 52-week high stock prices and the relation to the momentum phenomenon (Jegadeesh and Titman 1993).

Even in a weak-form efficient market, the past 52-week high should not carry any information about the future prospects of the stock. Yet, George and Hwang (2004) find that an investing strategy based on the distance to the 52-week high explains most of the returns from the traditional momentum strategy. Their findings imply investors anchor to a stock's 52-week high when valuing the stock, and do not sufficiently adjust above the 52-week high. This downward bias in the valuation leads to the stock price drifting up over time instead of a relatively quick adjustment. Lee and Piqueira (2017) suggest short sellers are aware of this phenomenon, as short selling is negatively related to the nearness to the 52-week high. Using stock indices instead of individual stocks, Du (2008) and Li and Yu (2012) find similar effectiveness in 52-week high strategies. Sapp (2010) shows an analogous strategy applied to mutual funds is also successful in predicting future returns. There is evidence of anchoring in the options market as well, as Driessen, Lin, and Van Hemert (2013) find option-implied volatility decreases when the underlying stock price approaches the 52-week high and increases if a new 52-week high is reached (i.e., the stock price breaks through the historical 52-week high). Additionally, Heath, Huddart, and Lang (1999) demonstrate how employees use their firm stock's 52-week high as a reference point to exercise their stock options.

The extensive literature in these two areas motivates us to investigate if the negative return premium associated with skewness is robust to anchoring to the 52-week high price. If investors perceive the 52-week high price as an anchor that is difficult to break through (e.g., investors bias a stock's valuation downward toward this anchor), then the 52-week high phenomenon may interfere with investors' probability weighting function by truncating the right-hand side of the perceived return distribution.[2] This truncation would, in turn, reduce the skewness premium. In other words, a stock with a highly positively skewed return distribution would not be a candidate to receive a skewness premium if it were close to the 52-week high because the weight the investor puts on the probability the stock will cross the 52-week high anchor is severely diminished. Conversely, if the current stock price is far from the 52-week high, there is a lot of "room" for the stock price to jump up. Thus, the skewness premium effect should be strong far from the 52-week high and weak close to the 52-week high. This is the focus of our study.

In a related study, An et al. (2019) examine lottery stock returns' relation to mental accounting and reference-dependent preferences by using stocks' capital gains overhang (CGO). The CGO measures current stock price relative to a reference price. This is important to loss aversion as the theory predicts different behavior by investors when CGO is positive than when it is negative. They find the negatively priced skewness is more pronounced in stocks with capital losses than in those with capital gains. Our study differs because our hypothesis relies solely on anchoring behavior interacting with probability weighting, and not on loss aversion or mental accounting. Thus, our investigation does not require any estimation of purchase prices to establish reference prices.

Data and sample

The data used throughout the study is obtained from a variety of sources. From the Center for Research on Security Prices (CRSP), we gather daily and monthly returns, prices, trading volumes, shares outstanding, etc. From Compustat, we obtain annual balance sheet data in order to obtain the book-value of equity. The sample period spans from 1980 to 2012.

Following the existing literature, we use two simple, yet strong proxies for the skewness of stock return distributions. We follow Kumar (2009) by creating an indicator variable to classify stocks that are most likely to resemble lotteries. *Lottery* is equal to one if, during a particular month, a stock has idiosyncratic skewness above the median, idiosyncratic volatility above the median, and a closing share price below the median. We note that idiosyncratic measures of skewness and volatility are obtained from the residuals of a daily four-factor model. Stated differently, we estimate a four-factor model, where the factors are described in Fama and French (1993) and Carhart (1997). From these regressions, we obtain residual returns to estimate the idiosyncratic moments of the return distribution. Given the need to have a sufficiently large number of observations when accurately estimating the higher moments of the return distribution, we use a rolling six-month window from a particular month. For the second proxy, we follow Bali et al. (2011) by calculating *MaxRet,* defined as the maximum daily return for stock *i* during month *t*.

As in George and Hwang (2004), 52-Week is the 52-week high price while *Anchor* is the ratio of the current (end-of-month) price scaled by the 52-week high. *Beta* is the CAPM beta obtained from estimating a standard daily CAPM data using a six-month rolling window. *Size* is the end-of-month market capitalization (in $Billions). *B/M* is the natural log of the book-to-market ratio for each stock in each month. *Illiquidity* is the Amihud (2002) measure of illiquidity, which is the ratio of the absolute value of the daily return scaled by dollar volume (in $Millions).

Table 1. Summary statistics.

	Mean [1]	Std. deviation [2]	25th percentile [3]	Median [4]	75th percentile [5]
Lottery	0.2020	0.4015	0.0000	0.0000	0.0000
Maxret	0.0732	0.0794	0.0325	0.0531	0.0888
52-week	37.32	1,020.31	9.06	19.00	34.52
Anchor	0.7508	0.2931	0.5617	0.7838	0.9221
Beta	0.8697	0.8593	0.3745	0.8492	1.3174
Size	1.8020	10.2350	0.0371	0.1470	0.6859
B/M	0.4365	12.2196	0.0376	0.0652	0.1057
Illiquidity	3.8441	45.4465	0.0065	0.0813	0.9152

The table reports statistics that describe our data. Lottery is an indicator variable that captures Lottery Stocks. Following Kumar (2009), Lottery is equal to unity if, during a particular month, a stock has idiosyncratic skewness above the median, idiosyncratic volatility above the median, and a closing share price below the median. We note that idiosyncratic measures of skewness and volatility are obtained from the residuals of a daily four-factor model. We use a rolling six-month window from a particular month. Maxret is the maximum daily return for stock i during month t. 52-Week is the 52-week high price while Anchor is the ratio between the current monthly price and the 52-week high. Beta is the CAPM beta obtained from estimating a standard daily CAPM data using a six-month rolling window. Size is the end-of-month market capitalization (in $Billions). B/M is the book-to-market ratio for each stock in each month. Illiquidity is the Amihud (2002) measure of illiquidity, which is the ratio of the absolute value of the daily return scaled by dollar volume (in $Millions).

Table 1 reports statistics that summarize the data used throughout the analysis. From the table, we find that approximately 20.2% of stocks are classified as *Lottery* stocks. Furthermore, the average stock in our sample has a maximum daily return of 7.32%, a 52-week high price of $37.32, a ratio of current price to the 52-week high (*Anchor*) of 0.7508, a beta of 0.8697, market capitalization of $1.80 billion, a book-to-market ratio of 0.4365, and Amihud's (2002) measure of illiquidity of 3.8441. Additional summary statistics are also reported in the table.

Empirical results

Portfolio tests—raw returns

To start our analysis, we examine the performance of portfolios sorted by both anchoring and lottery preferences. Table 2 reports next-month raw returns by double-sorted portfolios. Stocks are first sorted into quintiles based on their proximity to the 52-week high, which is our anchoring variable. Within each quintile, stocks are then sorted into lottery and non-lottery portfolios, based on the classification in Kumar (2009). Differences between lottery and non-lottery and high and low anchor portfolios are then calculated and reported with corresponding t-statistics.

Table 2. Portfolio analysis—the return premium of lottery stocks.

	(Far) QI [1]	Q II [2]	Q III [3]	Q IV [4]	(Close) QV [5]	Q V—Q I [6]
Panel A. Equal weighted portfolios						
Non-Lottery	0.0121	0.0091	0.0103	0.0118	0.0135	
Lottery	0.0054	0.0055	0.0098	0.0141	0.0196	
Lot—Non-Lot	−0.0067***	−0.0036**	−0.0005	0.0023	0.0062***	0.0128***
	(−4.09)	(−2.25)	(−0.27)	(1.15)	(2.96)	(6.84)
Panel B. Value weighted portfolios						
Non-Lottery	0.0112	0.0081	0.0096	0.0107	0.0103	
Lottery	−0.0025	0.0040	0.0090	0.0128	0.0181	
Lot—Non-Lot	−0.0137***	−0.0041	−0.0006	0.0021	0.0078**	0.0215***
	(−4.51)	(−1.63)	(−0.21)	(0.70)	(2.53)	(7.13)

The table reports two-way portfolio sorts. We first sort stocks into quintiles by Anchor. Within each Anchor portfolio, we sort by Lottery and Non-Lottery stocks. We then report next-month raw returns for each of the portfolios. The horizontal sorts (first-stage) are based on Anchor while the vertical sorts (second-stage) are based on Lottery. Panel A reports the results for equal-weighted portfolios while Panel B shows the results for value-weighted portfolios. Column [6] reports the differences between extreme Anchor portfolios while the bottom row in each panel consists of the difference between Lottery and Non-Lottery portfolios. The sample is sorted in quintiles based on Anchor, where quintile 1 (5) contains firms with the lowest (highest) ratio of current monthly price scaled by the 52-week high. T-statistics are reported below each difference. At the bottom of column [6], we provide the difference-in-differences along with a corresponding t-statistic. *,**, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

Table 3. Portfolio analysis—the max return premium.

	(Far) QI [1]	Q II [2]	Q III [3]	Q IV [4]	(Close) QV [5]	Q V—Q I [6]
Panel A. Equal weighted portfolios						
Q I (Low Max)	0.0165	0.0153	0.0124	0.0082	−0.0015	
Q II	0.0128	0.0119	0.0098	0.0072	0.0005	
Q III	0.0120	0.0125	0.0113	0.0099	0.0049	
Q IV	0.0119	0.0130	0.0125	0.0128	0.0100	
Q V (High Max)	0.0116	0.0129	0.0143	0.0161	0.0179	
Q V—Q I	−0.0049*	−0.0025	0.0018	0.0079**	0.0194***	0.0243***
	(−1.74)	(−0.75)	(0.50)	(2.15)	(5.39)	(10.29)
Panel B. Value weighted portfolios						
Q I (Low Max)	0.0142	0.0111	0.0087	0.0030	−0.0075	
Q II	0.0113	0.0098	0.0074	0.0055	0.0005	
Q III	0.0122	0.0112	0.0087	0.0048	0.0020	
Q IV	0.0111	0.0106	0.0109	0.0108	0.0073	
Q V (High Max)	0.0095	0.0110	0.0109	0.0130	0.0155	
Q V—Q I	−0.0047*	−0.0001	0.0022	0.0100**	0.0230***	0.0277***
	(−1.88)	(−0.02)	(0.59)	(2.44)	(4.87)	(6.71)

The table reports two-way portfolio sorts. We first sort stocks into quintiles by Anchor. Within each Anchor portfolio, we again sort stocks into quintiles based on Maxret. We then report next-month raw returns for each of the portfolios. The horizontal sorts (first-stage) are based on Anchor while the vertical sorts (second-stage) are based on Maxret. Panel A reports the results for equal-weighted portfolios while Panel B shows the results for value-weighted portfolios. Column [6] reports the differences between extreme Anchor portfolios while the bottom row in each panel consists of the difference between extreme Maxret portfolios. T-statistics are reported below each difference. At the bottom of column [6], we provide the difference-in-differences along with a corresponding t-statistic. *,**, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

Panel A of Table 2 reports results for equally-weighted portfolios while Panel B reports results for value-weighted portfolios. Although there are some significant differences between portfolios in Table 2 Panel A, the relation between anchoring and the lottery return premium is not as clear. A few results are noteworthy. First, the difference between returns for lottery compared to non-lottery stocks in Panel A is positive and significant in stocks that are closest (high anchor) to their 52-week high. We also note that while the Lottery minus Non-Lottery differences are not increasing monotonically across anchoring quintiles, the difference between the differences (in Column [6]) is positive and reliably different from zero (diff-in-diff = 0.0128, t-statistic = 6.84). When examining the value-weighted portfolios in Panel B, we find that the difference between next-month returns for Lottery stocks and Non-Lottery stocks are increasing monotonically across anchoring portfolios. For instance, in Column [1], the difference is −0.0137 (t-statistic = −4.51). Interestingly, the difference in Column [5] is positive and significant (difference = 0.0078, t-statistic = 2.53). Again, the difference between the differences (in Column [6]) is positive and reliably different from zero (diff-in-diff = 0.0215, t-statistic = 7.13). The results in Table 2 provide evidence supporting the idea that the negative return premium associated with lottery stocks does not exist in stocks that are closest to their 52-week high. If anything, Table 2 suggests that the return premium for lottery stocks is positive in these stocks.

Table 3 is similar to Table 2, but instead of a binary choice between lottery and non-lottery stocks we sort stocks into quintiles based on MaxRet during the second sort. The horizontal sort is based on the nearness to the 52-week high while the vertical sort is based on increasing maximum returns. Similar to the previous table, Panel A reports results for equally-weighted portfolios while Panel B reports results for value-weighted portfolios. Panel A shows that the negative return premium associated with MaxRet is greatest in Column [1], which identifies the stocks that have the lowest price/52-week high ratio (stocks that are farthest away from the 52-week high). In fact, we find that differences at the bottom of Panel A are generally increasing—though not monotonically. The difference between the differences (in Column [6]) is 0.0243 with a t-statistic of 10.29. This difference is both economically and statistically significant. The return premium associated with MaxRet is approximately 10% higher in stocks that closer, vis-à-vis further away from their 52-week high. This finding highlights the fact that the negative return premium associated with preferences for lotteries is mitigated by the stock's nearness to the 52-week high. We interpret these findings as evidence that anchoring to the 52-week high appears to offset the behavior associated with lottery preferences.

Panel B shows the results from the value-weighted portfolios. Here, we find even stronger results as the negative return premium associated with MaxRet is only found in Column [1]. Differences between high

Table 4. Portfolio analysis—the return premium of lottery stocks: Multifactor regressions.

	(Far) QI [1]	Q II [2]	Q III [3]	Q IV [4]	(Close) QV [5]	Q V—Q I [6]
Panel A. Equal weighted portfolios						
Non-Lottery	0.0042***	−0.0006	−0.0002	0.0009	0.0019**	
	(2.97)	(−0.82)	(−0.22)	(1.26)	(2.41)	
Lottery	−0.0023	−0.0049***	−0.0017	0.0016	0.0069***	
	(−0.89)	(−2.63)	(−0.99)	(0.85)	(3.68)	
Lot—Non-Lot	−0.0065***	−0.0042***	−0.0015	0.0007	0.0050***	0.0115***
	(−3.79)	(−2.82)	(−1.01)	(0.40)	(2.86)	(5.77)
Panel B. Value Weighted Portfolios						
Non-Lottery	0.0028*	−0.0011	−0.0001	0.0003	−0.0009	
	(1.85)	(−1.03)	(−0.13)	(0.50)	(−1.25)	
Lottery	−0.0108***	−0.0078***	−0.0038*	−0.0010	0.0040*	
	(−4.17)	(−3.81)	(−1.94)	(−0.40)	(1.79)	
Difference	−0.0136***	−0.0067***	−0.0037*	−0.0013	0.0049**	0.0185***
	(−4.73)	(−3.05)	(−1.78)	(−0.53)	(2.23)	(5.54)

The table reports the results from estimating the following equation for two-way sorted portfolios.

$$Return_{p,t} - R_{f,t} = \alpha + \beta_{MRP}(MRP_t) + \beta_{SMB}(SMB_t) + \beta_{HML}(HML_t) + \beta_{UMD}(UMD_t) + \varepsilon_{p,t}.$$

The dependent variable is the excess return (or the return in excess of the risk-free rate) for each portfolio. Following Fama and French (1993) and Carhart (1997), the independent variable includes MRP, which is the market risk premium, or the excess return of the market less the risk-free rate. SMB is the small-minus-big return factor while HML is the high-minus-low return factor. UMD is the up-minus-down factor. Portfolios are obtained from two-way sorts. We first sort stocks into quintiles by Anchor. Within each Anchor portfolio, we sort by Lottery and Non-Lottery stocks. We then report the alphas from estimating the four-factor model for each of the portfolios. The horizontal sorts (first-stage) are based on Anchor while the vertical sorts (second-stage) are based on Lottery. Panel A reports the results for equal-weighted portfolios while Panel B shows the results for value-weighted portfolios. Column [6] reports the differences between extreme Anchor portfolios while the bottom row in each panel consists of the difference between Lottery and Non-Lottery portfolios. T-statistics, which are robust to conditional heteroscedasticity (White 1980) are reported below each difference. At the bottom of column [6], we provide the difference-in-differences along with a corresponding t-statistic. *,**, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

and low MaxRet are increasing monotonically across quintiles and the difference between the differences (Column [6]) is again positive and both statistically and economically significant (diff-in-diff = 0.0277, t-statistic = 6.71). The disappearance of the skewness premium as the stock price approaches the 52-week high is consistent with probability weighting influencing skewness preferences.

Portfolio tests—multifactor analysis

Since a variety of risk factors have been shown to influence the expected return of stock returns it is important to try and control for some of these factors in a multivariate setting. Tables 4 and 5 present our findings for the following regression:

$$Return_{p,t} - R_{f,t} = \alpha + \beta_{MRP}(MRP_t) + \beta_{SMB}(SMB_t) + \beta_{HML}(HML_t) + \beta_{UMD}(UMD_t) + \varepsilon_{p,t} \quad (1)$$

The dependent variable is the excess return (or the return in excess of the risk-free rate, which is approximated by the yield on one-month U.S. Government Treasury Bills) for each portfolio. Following Fama and French (1993) and Carhart (1997), the independent variables include *MRP*, which is the market risk premium, or the return of the market less the risk-free rate. *SMB* is the small-minus-big or size return factor while *HML* is the high-minus-low or value return factor. *UMD* is the up-minus-down or momentum factor. We report the alphas from estimating the four-factor model for each of the double-sorted portfolios—first by our measure of Anchor and then by one of our two proxies for lottery-like characteristics. The next two tables take the same format as those in Tables 2 and 3. In essence, Table 4 controls for various risk factors and, therefore, provides robustness for Table 2, and Table 5 provides robustness for Table 3.

Table 4 shows the four-factor alphas across double-sorted portfolios—first by Anchor, then by Kumar's (2009) classification for lottery stocks. Results in Table 4 are qualitatively similar to the corresponding results in Table 2. In particular, Panel B of the table shows that in the stocks that are farthest away from their 52-week high, the negative return premium is the most significant. For example, in Column [1], the negative difference in four-factor alphas between lottery and non-lottery stocks is 127 basis points per month. Column [5] reports that a positive difference of 49 basis points. These results support our findings in Table 2 and provide strong evidence of our hypothesis. We note that the results in Panel A are weaker. However, we still find that the lottery stocks carry a positive return premium instead of a negative premium in Column [5]. These results suggest that any negative return premium associated with lottery preferences is not driven by stocks that closest to their 52-week high.

Table 5. Portfolio analysis—the max return premium: Multifactor regressions.

	(Far) QI [1]	Q II [2]	Q III [3]	Q IV [4]	(Close) QV [5]	Q V—Q I [6]
Panel A. Equal weighted portfolios						
Q I (Low Max)	0.0090***	0.0075***	0.0051***	0.0003	−0.0093***	
	(5.38)	(4.21)	(2.61)	(0.13)	(−3.58)	
Q II	0.0034***	0.0023**	−0.0002	−0.0030**	−0.0098***	
	(2.91)	(2.08)	(−0.23)	(−2.47)	(−6.17)	
Q III	0.0026***	0.0024***	0.0006	−0.0013	−0.0064***	
	(2.62)	(2.67)	(0.63)	(−1.57)	(−5.15)	
Q IV	0.0025**	0.0025***	0.0013	0.0010	−0.0021**	
	(2.48)	(2.88)	(1.50)	(1.16)	(−2.06)	
Q V (High Max)	0.0019*	0.0018**	0.0021**	0.0030***	0.0049***	
	(1.84)	(1.98)	(2.10)	(2.64)	(3.10)	
Q V—Q I	−0.0071***	−0.0057***	−0.0031	0.0028	0.0142***	0.0213***
	(−4.17)	(−2.66)	(−1.27)	(1.11)	(5.12)	(10.09)
Panel B. Value weighted portfolios						
Q I (Low Max)	0.0063***	0.0030	0.0004	−0.0058**	−0.0171***	
	(3.96)	(1.33)	(0.15)	(−2.29)	(−5.20)	
Q II	0.0020	0.0011	−0.0023	−0.0052***	−0.0105***	
	(1.49)	(0.68)	(−1.40)	(−2.72)	(−4.72)	
Q III	0.0033**	0.0016	−0.0013	−0.0070***	−0.0096***	
	(2.54)	(1.37)	(−1.05)	(−5.60)	(−5.06)	
Q IV	0.0016	0.0003	−0.0001	−0.0011	−0.0051***	
	(1.46)	(0.33)	(−0.09)	(−0.92)	(−3.40)	
Q V (High Max)	−0.0007	−0.0003	−0.0007	0.0001	0.0021	
	(−0.67)	(−0.31)	(−0.53)	(0.08)	(0.97)	
Q V—Q I	−0.0071***	−0.0033	−0.0010	0.0060*	0.0191***	0.0262***
	(−3.52)	(−1.25)	(−0.36)	(1.96)	(5.23)	(6.54)

The table reports the results from estimating the following equation for two-way sorted portfolios.

$$Return_{p,t} - R_{f,t} = \alpha + \beta_{MRP}(MRP_t) + \beta_{SMB}(SMB_t) + \beta_{HML}(HML_t) + \beta_{UMD}(UMD_t) + \varepsilon_{p,t}.$$

The dependent variable is the excess return (or the return in excess of the risk-free rate) for each portfolio. Following Fama and French (1993) and Carhart (1997), the independent variable includes MRP, which is the market risk premium, or the excess return of the market less the risk-free rate. SMB is the small-minus-big return factor while HML is the high-minus-low return factor. UMD is the up-minus-down factor. Portfolios are obtained from two-way sorts. We first sort stocks into quintiles by Anchor. Within each Anchor portfolio, we then sort stocks into quintiles based on Maxret. We then report the alphas from estimating the four-factor model for each of the portfolios. The horizontal sorts (first-stage) are based on Anchor while the vertical sorts (second-stage) are based Maxret. Panel A reports the results for equal-weighted portfolios while Panel B shows the results for value-weighted portfolios. Column [6] reports the differences between extreme Anchor portfolios while the bottom row in each panel consists of the difference between extreme Maxret portfolios. T-statistics, which are robust to conditional heteroscedasticity (White 1980) are reported below each difference. At the bottom of column [6], we provide the difference-in-differences along with a corresponding t-statistic. *,**, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

Table 5 reports the four-factor alphas by double-sorted portfolios, where the second sort is based on MaxRet. The four-factor results in Table 5 also provide consistency for the corresponding results in Table 3. Panel A shows that the differences in alphas between high MaxRet stocks and low MaxRet stocks are generally increasing across anchoring quintiles. We note, however, that the difference between these differences in Column [6] is positive (0.0213) and significant at the 0.01 level. Panel B only the other hand shows that differences in alphas—at the bottom of each column—are monotonically increasing across anchoring quintiles. These findings strongly support the idea that the negative return premium associated with maximum returns is driven by stocks further away from their 52-week high. In the framework of our hypothesis, these results suggest that the 52-week high acts as an anchor and mitigates (to some extent) investor preferences for lottery-like stocks. Again, the results are supportive of Barberis and Huang's (2008) theory of skewness preferences.

Cross-sectional multivariate tests—a Fama and MacBeth (*1973*) approach

To further examine the relation between preferences for lottery stocks and anchoring, we estimate the following equation in a Fama and MacBeth (1973) framework, with standard errors adjusted as described by Newey and West (1987).

$$\begin{aligned} \text{Return}_{i,t+1} = {} & \beta_0 + \beta_1 Lottery_{i,t} + \beta_2 Beta_{i,t} \\ & + \beta_3 Size_{i,t} + \beta_4 B/M_{it} + \beta_5 Momentum_{i,t} \\ & + \beta_6 Illiquidity_{i,t} + \varepsilon_{i,t+1} \end{aligned} \quad (2)$$

The dependent variable in this regression is the monthly return for stock i in month $t+1$. The independent variables include *Beta,* which is the CAPM beta obtained from estimating a standard daily CAPM model using a six-month rolling window. *Size* is the natural log of end-of-month market capitalization in billions of dollars. *B/M* is the natural log of the book-

Table 6. Fama and MacBeth (1973) regressions—the return premium of lottery stocks.

	(Low anchor) Quintile 1 [1]	Quintile 2 [2]	Quintile 3 [3]	Quintile 4 [4]	(High anchor) Quintile 5 [5]
Constant	4.7616***	1.9296***	1.4649***	1.9512***	3.3329***
	(6.09)	(3.45)	(3.18)	(4.10)	(7.15)
Lottery	−0.6423***	−0.2123	0.0774	0.3254*	0.4230**
	(−4.35)	(−1.44)	(0.43)	(1.65)	(2.10)
Beta	−0.0713	−0.0156	−0.0207	−0.0143	−0.0033
	(−0.92)	(−0.19)	(−0.22)	(−0.13)	(−0.03)
Size	−0.0624	0.0779*	0.0697**	−0.0043	−0.1218***
	(−1.21)	(1.95)	(2.03)	(−0.13)	(−3.82)
B/M	1.0264***	0.7249***	0.5310***	0.3243***	0.2607***
	(12.12)	(10.50)	(8.76)	(6.49)	(4.10)
Momentum	0.9063***	1.0924***	0.8980***	0.9888***	0.9025***
	(6.04)	(6.92)	(5.19)	(5.24)	(5.02)
Illiquidity	0.0094**	0.0038	0.0009	−0.0262***	−0.0352*
	(2.14)	(1.07)	(0.10)	(−3.48)	(−1.91)

The table reports the results from estimating variants of the following equation using a Fama and MacBeth (1973) regression.

$$Return_{i,t+1} = \beta_0 + \beta_1 Lottery_{i,t} + \beta_2 Beta_{i,t} + \beta_3 Size_{i,t} + \beta_4 B/M_{it} + \beta_5 Momentum_{i,t} + \beta_6 Illiquidity_{i,t} + \varepsilon_{i,t+1}.$$

The dependent variable is the monthly return for stock i in month t + 1. The independent variables include the following. Beta is the CAPM beta obtained from estimating a standard daily CAPM data using a six-month rolling window. Size is the natural log of end-of-month market capitalization (in $Billions). B/M is the natural log of the book-to-market ratio for each stock in each month. Momentum is the cumulative return from month t − 12 to t − 2. Illiquidity is the Amihud (2002) measure of illiquidity, which is the ratio of the absolute value of the daily return scaled by dollar volume (in $Millions). The independent variable of interest is Lottery, which is the indicator variable capturing lottery-like stocks (Kumar 2009). Anchor is the ratio of the current monthly share price to the 52-week high price. The sample is sorted in quintiles based on Anchor, where quintile 1 (5) contains firms whose stock price is furthest from (closest to) the 52-week high. T-statistics are obtained from Newey and West (1987) standard errors that account for three lags. *,**, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively. There are approximately 360,000 stock-month observations in each quintile.

to-market ratio for each stock in each month. *Momentum* is the cumulative return from month $t-12$ to month $t-2$ for each stock. *Illiquidity* is Amihud's (2002) measure of illiquidity, which is the ratio of the absolute value of the daily return scaled by dollar volume in millions. *Lottery* is the indicator variable capturing lottery-like stocks (Kumar 2009).

To better understand the relationship between anchoring and lottery stocks, we sort stocks into quintiles based on the ratio of the current stock price scaled by the 52-week high. Stocks farthest away from their 52-week high will have a low price/52 week high ratio and are labeled as low anchor stocks (quintile 1) and stocks near their 52-week high will have a high price/52 week high ratio and are labeled as high anchor stocks (quintile 5). We then estimate Equation 2 for each quintile of stocks based on our anchoring variable. Column [1] of Table 6 reports the estimates from the regression on low anchor stocks. With respect to the control variables, we find a negative return premium associated with Beta and market capitalization and a positive return premium associated with book-to-market ratios and momentum. We also find that illiquidity generates a positive return premium. These results support findings in the prior literature (Amihud 2002; Fama and French 1992, 1996; Frazzini and Pedersen 2014; Jegadeesh and Titman 1993).[3] Furthermore, we find a negative and significant relation between lottery stocks and next-month returns for low anchor stocks. The coefficient on Lottery is −0.6423 and is significant at the 0.01 level and suggests that, after controlling for factors that have been shown to influence the predictability of stock returns, lottery stocks underperform non-lottery stocks by nearly 65 basis points per month. Similar results are found in Column [2], which reports the results from estimating Equation 2 for the second quintile sorted by anchoring. We note, however, that the negative coefficient on Lottery is only marginally significant. In the latter three quintiles, we start to see a difference in the estimated coefficient on Lottery for stocks in the higher anchoring quintiles. For instance, the coefficient on Lottery in Column [3] is 0.0774, but is not significantly different from zero. In fact, we find that the coefficient on Lottery is strictly monotonic across each of the five increasing quintiles. The results for the high anchor stocks, found in the fifth quintile (Column [5]), shows an estimated coefficient on Lottery of 0.4230 with a t-statistic of 2.10. These results suggest that a (slightly) positive return premium exists for stocks closest to their 52-week high. This finding demonstrates the relation between investor preferences for lottery-like stocks and the propensity to anchor on the 52-week high. The well-documented return premium associated with preferences for lotteries is apparently offset by an anchoring effect that is measured by the distance from the stock's 52-week high. In other words, preferences for skewness weaken as stocks approach their 52-week high.

Table 7. Fama and MacBeth (1973) regressions—the max return premium.

	(Low anchor) Quintile 1 [1]	Quintile 2 [2]	Quintile 3 [3]	Quintile 4 [4]	(High anchor) Quintile 5 [5]
Constant	5.3698***	2.8206***	2.0669***	2.3232***	3.7535***
	(6.64)	(4.80)	(4.21)	(4.93)	(7.30)
MaxRet	−9.4185***	−8.0897***	−6.3780***	−3.9234***	−0.9571
	(−9.84)	(−7.02)	(−4.90)	(−2.83)	(−0.97)
Beta	−0.0409	0.0373	0.0143	−0.0172	0.0093
	(−0.50)	(0.47)	(0.16)	(−0.18)	(0.09)
Size	−0.0924*	0.0301	0.0345	−0.0268	−0.1565***
	(−1.71)	(0.73)	(0.94)	(−0.80)	(−4.30)
B/M	0.9513***	0.6747***	0.4905***	0.3058***	0.2448***
	(11.42)	(10.11)	(8.77)	(6.59)	(4.09)
Momentum	0.7660***	1.0854***	0.9494***	1.0696***	0.8905***
	(4.97)	(6.65)	(5.54)	(5.85)	(4.89)
Illiquidity	0.0156***	0.0072**	0.0069	−0.0186**	−0.0331
	(3.56)	(1.99)	(0.76)	(−2.41)	(−1.51)
Reversal	−1.1567***	0.4177	1.1148***	1.4356***	0.8914**
	(−3.22)	(1.07)	(2.69)	(3.30)	(2.26)

The table reports the results from estimating variants of the following equation using a Fama and MacBeth (1973) regression.

$$Return_{i,t+1} = \beta_0 + \beta_1 MaxRet_{i,t} + \beta_2 Beta_{i,t} + \beta_3 Size_{i,t} + \beta_4 B/M_{it} + \beta_5 Momentum_{i,t} + \beta_6 Illiquidity_{i,t} + \beta_7 Reversal_{i,t} + \varepsilon_{i,t+1}.$$

The dependent variable is the monthly return for stock i in month t + 1. The independent variables include the following. Beta is the CAPM beta obtained from estimating a standard daily CAPM data using a six-month rolling window. Size is the natural log of end-of-month market capitalization (in $Billions). B/M is the natural log of the book-to-market ratio for each stock in each month. Momentum is the cumulative return from month t − 12 to t − 2. Illiquidity is the Amihud (2002) measure of illiquidity, which is the ratio of the absolute value of the daily return scaled by dollar volume (in $Millions). Maxret is the maximum daily return for a particular stock during month t (Bali, Cakici, and Whitelaw 2011). We also follow Bali, Cakici, and Whitelaw (2011) and include Reversal to account for the price reversal. Anchor is the difference between the current share price and the 52-week high price. The sample is sorted in quintiles based on Anchor, where quintile 1 (5) contains firms whose stock price is furthest from (closest to) the 52-week high. T-statistics are obtained from Newey and West (1987) standard errors that account for three lags. *,**, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively. There are approximately 360,000 stock-month observations in each quintile.

Next, we continue our analysis of lottery preferences and anchoring by estimating the following equation. In particular, we estimate the following equation using pooled stock-month data.

$$\begin{aligned} Return_{i,t+1} = \ & \beta_0 + \beta_1 MaxRet_{i,t} + \beta_2 Beta_{i,t} \\ & + \beta_3 Size_{i,t} + \beta_4 B/M_{it} + \beta_5 Momentum_{i,t} \\ & + \beta_6 Illiquidity_{i,t} + \beta_7 Reversal_{i,t} + \varepsilon_{i,t+1} \end{aligned} \quad (3)$$

In Equation 3, we follow Bali et al. (2011) and approximate lottery stocks by including MaxRet. In addition to the control variables included in Equation 2, Equation 3 also includes return reversals to account for the inherent mean reversion associated with stock returns (Bali et al. 2011). The results from estimating Equation 3 are reported in Table 7. As before, Column [1] reports the results for the low anchor quintile and Column [5] reports the results for the high anchor quintile. Once again, the coefficients on the control variables produce estimates that are similar in sign to those in previous research. More importantly, we see that in low anchor stocks exhibit a large and significant negative return premium associated with lottery-like preferences. MaxRet has an estimated coefficient of −9.4185 that is significant at the 0.01 level with a t-statistic of −9.84. In economic terms, the magnitude of this coefficient suggests that a one standard deviation increase in MaxRet is associated with a 75 basis point reduction in next-month returns. In contrast, the coefficient on MaxRet in the high anchor quintile is only −0.9571 and indistinguishable from zero. While the coefficients on MaxRet are not monotonically increasing across anchoring quintiles, the findings in Table 7 indicate that the negative return premium associated with MaxRet does not exist in stocks closest to their 52-week high. More generally, the results thus far seem to suggest that the negative return premium associated with preferences for lotteries are offset by the nearness to the 52-week high.

As additional robustness, we replicate the analysis thus far but include the entire sample. In particular, we estimate the following equation using all of the pooled stock-month observations.

$$\begin{aligned} Return_{i,t+1} = \ & \beta_0 + \beta_1 AnchorQ5_{i,t} + \beta_2 Lottery_{i,t} \\ & + \beta_3 AnchorQ5_{i,t} \times Lottery_{i,t} \\ & + \beta_4 Beta_{i,t} + \beta_5 Size_{i,t} + \beta_6 B/M_{it} \\ & + \beta_7 Momentum_{i,t} + \beta_8 Illiquidity_{i,t} \\ & + \beta_9 Reversal_{i,t} + \beta_{10} Idiovolt_{i,t} \varepsilon_{i,t+1} \end{aligned} \quad (4)$$

As before, the dependent variable is the monthly return for stock *i* in month *t + 1*. The control variables have been discussed previously, with the exception of *Idiovolt*. *Idiovolt* proxies for the stocks' idiosyncratic risk. It is calculated following Ang et al.

Table 8. Fama and MacBeth (1973) regressions—the return premium of lottery stocks.

	[1]	[2]	[3]	[4]
Constant	1.0201***	1.1333***	1.0777***	2.6464***
AnchorQ5	(3.02)	(3.93)	(3.49)	(4.88)
	0.4355***		0.2682*	0.1893*
Lottery			(1.70)	(1.66)
	(2.61)	−0.2783	−0.3577*	−0.2781*
AnchorQ5 × Lotter y		(−1.30)	(−1.75)	(−1.79)
			0.9750***	0.9150***
			(6.44)	(6.22)
Beta				−0.0128
				(−0.15)
Size				−0.0110
				(−0.31)
B/M				0.5834***
				(9.86)
Momentum				0.7880***
				(5.84)
Illiquidity				0.0029
				(1.31)

The table reports the results from estimating variants of the following equation using a Fama and MacBeth (1973) regression.

$$\text{Return}_{i,t+1} = \beta_0 + \beta_1 AnchorQ5_{i,t} + \beta_2 Lottery_{i,t} + \beta_3 AnchorQ5_{i,t} \times Lottery_{i,t} + \beta_4 Beta_{i,t} + \beta_5 Size_{i,t} + \beta_6 B/M_{it} + \beta_7 Momentum_{i,t} + \beta_8 Illiquidity_{i,t} + \varepsilon_{i,t+1}.$$

The dependent variable is the monthly return for stock i in month t + 1. The independent variables include the following. Beta is the CAPM beta obtained from estimating a standard daily CAPM data using a six-month rolling window. Size is the natural log of end-of-month market capitalization (in $Billions). B/M is the natural log of the book-to-market ratio for each stock in each month. Momentum is the cumulative return from month t − 12 to t − 2. Illiquidity is the Amihud (2002) measure of illiquidity, which is the ratio of the absolute value of the daily return scaled by dollar volume (in $Millions). The independent variables of interest include AnchorQ5, Lottery, and the interaction between the two. AnchorQ5 is an indicator that equals one if the ratio of the current monthly share price to the 52-week high price is in the highest quintile. Said differently, this indicator variable captures stocks with prices closest to their 52-week high. Lottery is the indicator variable capturing lottery-like stocks (Kumar 2009). T-statistics are obtained from Newey and West (1987) standard errors that account for three lags. *,**, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively. There are nearly 1.8 million stock-month observations in the pooled sample.

(2006), where idiosyncratic volatility (risk) is the standard deviation of the residuals from the Fama and French (1993) and Carhart (1997) four-factor risk model. We include the idiosyncratic volatility since volatility and skewness are highly related and it may be the *Idiovolt* that is driving future returns rather than the lottery characteristics. The independent variables of interest include *AnchorQ5*, *Lottery*, and the interaction between the two. *AnchorQ5* is an indicator that equals one if the ratio of the current monthly share price to the 52-week high price is in the highest quintile.[4]

If the 52-week high indeed acts as an anchor and offsets the preferences for lottery-like characteristics, then the interaction estimate, β_3, is expected to be positive. Table 8 reports the results from the analysis. Columns [1] through [4] report different specifications of Equation 4. For brevity, we only discuss the findings in the full specification (Column [5]). As before, the coefficients on the control variables produce signs that are similar to the corresponding coefficients in previous tables. The AnchorQ5 variable has a positive and significant parameter estimate (coefficient = 0.1893, t-statistic = 1.66). This is consistent with George and Hwang's (2004) finding of positive momentum in stocks near their 52-week high. Consistent with Kumar's (2009) findings, the Lottery variable has a negative coefficient (−0.2781) that is statistically significant at the 1% level (t-statistic = −1.79). Focusing on the interaction estimate, we find that the AnchorQ5 × Lottery produces a positive and significant coefficient that is both economically and statistically meaningful (coefficient = 0.9150, t-statistic = 6.22). The results indicate that stocks with the highest price/52-week high ratio generally have a return premium that is 92 basis points higher than the stocks in the first four quintiles. These results support the conclusions we are able to draw in Table 6 and suggest that lottery preferences are much weaker when prices are closer to the 52-week high.

We continue our analysis by estimating the following equation using our entire sample of stock-month observations.

$$\begin{aligned} \text{Return}_{i,t+1} = {} & \beta_0 + \beta_1 AnchorQ5_{i,t} + \beta_2 MaxRet_{i,t} \\ & + \beta_3 MaxRet_{i,t} \times AnchorQ5_{i,t} + \beta_4 Beta_{i,t} \\ & + \beta_5 Size_{i,t} + \beta_6 B/M_{it} + \beta_7 Momentum_{i,t} \\ & + \beta_8 Illiquidity_{i,t} + \beta_9 Reversal_{i,t} \\ & + \beta_{10} Idiovolt_{i,t} + \varepsilon_{i,t+1} \end{aligned} \tag{5}$$

The dependent variable and the control variables are similar to those in Equation 4. The only difference is we include *AnchorQ5* and *MaxRet* and the interaction between the two. These variables have also been defined previously. Results are reported in Table 9. Again, focusing on the full specification in Column [5], we find that the MaxRet variable has a coefficient of −7.4710 (t-statistic = −7.68) while the interaction of AnchorQ5 and MaxRet has a coefficient of 7.2068 (t-statistic = 8.46). This positive interaction estimate suggests that stocks have a MaxRet premium in general, but those stocks that have prices close to their 52-week high have a return premium less than half of those stocks whose price are not close to the 52-week high. These findings again support the results in previous tables and indicate that lottery preferences weaken as stock approach their 52-week high. Taken all together, Barberis and Huang's (2008) theory of the skewness preferences cannot be rejected, as the

Table 9. Fama and MacBeth (1973) regressions—the return premium of lottery stocks.

	[1]	[2]	[3]	[4]
Constant	1.0201***	1.5175***	1.5656***	3.3896***
AnchorQ5	(3.02)	(5.63)	(5.42)	(5.91)
	0.4355***		−0.1209	−0.0984
MaxRet			(−0.79)	(−0.94)
	(2.61)	−6.2769***	−8.0283***	−7.4710***
AnchorQ5 × MaxRet		(−5.40)	(−6.38)	(−7.68)
			7.5696***	7.2068***
Beta			(7.93)	(8.46)
				0.0314
Size				(0.39)
				−0.0554
B/M				(−1.42)
				0.5321***
Momentum				(9.65)
				0.7149***
Illiquidity				(5.29)
				0.0069***
Reversal				(2.83)
				−0.0892
				(−0.29)

The table reports the results from estimating variants of the following equation using a Fama and MacBeth (1973) regression.

$$\text{Return}_{i,t+1} = \beta_0 + \beta_1 AnchorQ5_{i,t} + \beta_2 Maxret_{i,t} + \beta_3 Maxret_{i,t} \times AnchorQ5_{i,t} + \beta_4 Beta_{i,t} + \beta_5 Size_{i,t} + \beta_6 B/M_{it} + \beta_7 Momentum_{i,t} + \beta_8 Illiquidity_{i,t} + \beta_9 Reversal_{i,t} + \varepsilon_{i,t+1}.$$

The dependent variable is the monthly return for stock i in month t + 1. The independent variables include the following. Beta is the CAPM beta obtained from estimating a standard daily CAPM data using a six-month rolling window. Size is the natural log of end-of-month market capitalization (in $Billions). B/M is the natural log of the book-to-market ratio for each stock in each month. Momentum is the cumulative return from month t − 12 to t − 2. Illiquidity is the Amihud (2002) measure of illiquidity, which is the ratio of the absolute value of the daily return scaled by dollar volume (in $Millions). We also follow Bali, Cakici, and Whitelaw (2011) and include Reversal to account for the price reversal. The independent variables of interest include AnchorQ5, MaxRet, and the interaction between the two. AnchorQ5 is an indicator that equals one if the ratio of the current monthly share price to the 52-week high price is in the highest quintile. Said differently, this indicator variable captures stocks with prices closest to their 52-week high. Maxret is the maximum daily return for a particular stock during month t (Bali, Cakici, and Whitelaw 2011). T-statistics are obtained from Newey and West (1987) standard errors that account for three lags. *,**, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively. There are nearly 1.9 million stock-month observations in the pooled sample.

evidence presented is consistent with probability weighting driving skewness premiums.

Additional robustness tests

This subsection discusses briefly a series of unreported tests (results available upon request) that add robustness to our findings and provide us with greater confidence in drawing stronger inferences. First, we replicate the entire analysis using a different measure of Anchor. Instead of looking at the ratio of current (end-of-month) share prices to the 52-week high, we instead calculate the difference between the 52-week high and the current share price. We are able to draw very similar conclusions as the negative return premium associated with Lottery and MaxRet are driven by stocks with a greater difference between current share prices and the 52-week high. We note that the inferences from these tests are similar whether we conduct our portfolio tests or our Fama-MacBeth tests. We note that we report the results using the price/52-week high ratio (instead of the difference between the current share price and the 52-week high) to closely follow George and Hwang (2004) as well as other related studies on the 52-week high.

Second, we replicate our analysis using the Boyer et al. (2010) measure of expected idiosyncratic skewness—obtained directly from the authors' website. This measure requires ten years of historical data to compute, so the sample size drops dramatically. However, we are able to draw similar conclusions as the return premium associated with expected idiosyncratic skewness is driven by stocks that are further from their 52-week high. These conclusions are similar whether we using the price/52-week high ratio or the difference between the current share price and the 52-week high.

Third, we replicate our analysis without making any price cuts to our sample. That is, we include all stocks regardless of the stock price. Additionally, we replicate our analysis using a $5 price cut instead of a $1 price cut. In both cases, we find that the results are qualitatively similar to those reported in the paper. Perhaps, more interestingly, we find that the results are stronger when we make the $5 price cut instead of the $1 price. These results suggest that our results are driven by higher-priced stocks. We also note that some of our control variables exhibit a large amount of skewness. In unreported tests, we winsorize MktCap, B/M, and Illiquidity at the 5% and the 95% levels. We then replicate Table 9 and find our results to hold.

Fourth, it is possible that our findings are a function of bullish or bearish time periods when prices—at the aggregate—are closer or further away from the 52-week high. In unreported tests, we find a great deal of variation in our measure of Anchor. For instance, the minimum value of Anchor for the average stock in our sample during a particular month is 0.42 while the maximum is 0.92. To account for the possibility that our results are driven by either bullish or bearish time periods, we partition our sample into terciles based on aggregated Anchor. We then replicate Tables 8 and 9 for the bottom, middle, and top terciles. Our unreported tests show that, regardless of the tercile, stocks that are closest to their 52-week high tend to have the least negative, lottery-stock return premium.

Fifth, instead of the Fama and MacBeth (1973) approach, we estimate Equations 4 and 5 using pooled OLS while accounting for fixed effects and two-dimensional clustering in the standard errors (Petersen 2009). These unreported results show that the interaction between AnchorQ5 and either Lottery or MaxRet produces a positive and significant coefficient, which again supports the conclusions that we are able to draw in the study.

Sixth, we replicate our last two tables but instead of including AnchorQ5, we include AnchorQ1. We find that the interaction between AnchorQ1 and MaxRet is −3.2247 (t-statistic = −3.58) suggesting that stocks that are further away from their 52-week high have the strongest MaxRet return premium. While expected, these results tend to provide a more complete picture regarding how anchoring affects the lottery return premium.

Conclusion

In the case of efficient markets, asset pricing theory suggests that assets will convey rational, or arbitrage-free, prices. According to different models, such as the Capital Asset Pricing Model or arbitrage pricing theory, rational pricing will result in a zero-alpha condition. However, this condition is often violated for various reasons. One such reason is that the behavioral biases of investors might meaningfully influence demand in a way that prices might deviate away from their theoretical price. Using cumulative prospect theory (Kahneman and Tversky 1979; Tversky and Kahneman 1992), Barberis and Huang (2008) show that probability weighting functions induce investor preferences for lottery-like characteristics, such as positive skewness in the distribution of returns, which lead to excess demand, price premiums, and subsequent underperformance. Several empirical studies seem to confirm this theoretical prediction (Bali et al. 2011; among others; Boyer et al. 2010; Goetzmann and Kumar 2008; Kumar 2009; Mitton and Vorkink 2007), but do not directly test the probability weighting feature driving the theory's predictions.

In this paper, we develop and test the hypothesis that, if probability weighting is a source of skewness preferences, then the negative return premium associated with positive skewness will be driven by stocks that are further away from their 52-week high. Using the 52-week high as an anchor point (Baker et al. 2012; George and Hwang 2004), we argue that when prices are near this anchor, demand for these stocks by investors with lottery preferences will no longer be unusually high given investors' perception that prices cannot meaningfully move beyond the reference point, thus reducing the tail probabilities computed by their weighting function and decreasing perceived skewness. Therefore, stocks with highly skewed return distributions will not receive a related premium if the stock price is close to the 52-week while stocks with similar distributions will exhibit the premium when they are distant from their 52-week high.

To test our hypothesis, we conduct a series of cross-sectional and portfolio tests and examine the return premium associated with lottery-like characteristics while conditioning on the nearness to the 52-week high. Results seem to support our hypothesis as the negative return premium is only observed in stocks that are farthest from their 52-week high. In fact, in stocks that are closest to this reference point, lottery stocks do not underperform other stocks. These results are robust to different proxies for lottery-like characteristics. In particular, we find that these results hold when using Kumar's (2009) lottery stock classification and Bali et al.'s (2011) maximum return. These findings have important implications as they are consistent with Barberis and Huang's (2008) theory that probability weighting functions drive the return premiums associated with positive skewness and, thus, we cannot reject their theory.

Notes

1. Although, both Kumar (2005) and Kumar (2009) show institutional investors are skewness-averse. Autore and DeLisle (2016) find similar evidence by demonstrating institutional investors require deeper discounts to place seasoned equity offering shares with high skewness.
2. We focus on positive skewness because studies such as Bali et al. (2011), Jiang and Zhu (2017), Atilgan et al. (2019), and DeLisle, Ferguson, and Kassa (2019) show that negative skewness does not carry a discount (and thus high expected returns) as theories of skewness preferences suggest it would. In unreported results, we also find MIN, Bali et al.'s (2011) measure of negative skewness, to have no effect in the cross-section of returns.
3. We note that in columns [2] and [4], we find a positive return premium associated with Illiquidity, which is consistent with Amihud and Mendelson (1986). Further, columns [3] through [5] show that Size is negatively associated with future returns, which is consistent with findings in Banz (1981) and Fama and French (1992).
4. There is no reason to believe the skewness premium should be affected by anchoring in a linear manner. Thus, rather than forcing such a linear relation by interacting the skewness proxy with a continuous *Anchor* variable, we examine the how the relation is

different only close to 52-week high where it would have the largest impact on an investor's perception of the return distribution's right tail.

Acknowledgements

We would like to thank Justin Birru, Jocelyn Evans, Jean Helwege, Haimanot Kassa, Natalia Piqueira, Matthew Wynters, and the discussants and participants at the 2017 Australasian Banking and Finance Conference, 2018 Midwest Finance Conference, 2018 FMA Europe Conference, and 2018 Financial Markets and Corporate Governance Conference.

References

Amihud, Y. 2002. "Illiquidity and Stock Returns: Cross-Section and Time-Series Effects." *Journal of Financial Markets* 5 (1):31–56. doi:10.1016/s1386-4181(01)00024-6.

Amihud, Y., and H. Mendelson. 1986. "Asset Pricing and the Bid-Ask Spread." *Journal of Financial Economics* 17 (2):223–49. doi:10.1016/0304-405X(86)90065-6.

An, L., H. Wang, J. Wang, and J. Yu. 2017. "Lottery-Related Anomalies: The Role of Reference-Dependent Preferences." *Management Science*.

Ang, A., R. Hodrick, Y. Xing, and X. Zhang. 2006. "The Cross Section of Volatility and Expected Returns." *The Journal of Finance* 51:259–99.

Ariely, D., G. Loewenstein, and D. Prelec. 2003. "'Coherent Arbitrariness': Stable Demand Curves without Stable Preferences." *The Quarterly Journal of Economics* 118 (1): 73–105.

Atilgan, Y., T. G. Bali, K. O. Demirtas, and A. D. Gunaydin. 2018. "Left-Tail Momentum: Limited Attention of Individual Investors and Expected Equity Returns." *Journal of Financial Economics*.

Autore, D. M., and R. J. DeLisle. 2016. "Skewness Preference and Seasoned Equity Offers." *Review of Corporate Finance Studies* 5 (2):200–38.

Baker, M., X. Pan, and J. Wurgler. 2012. "The Effect of Reference Point Prices on Mergers and Acquisitions." *Journal of Financial Economics* 106 (1):49–71. doi:10.1016/j.jfineco.2012.04.010.

Bali, T. G., N. Cakici, and R. F. Whitelaw. 2011. "Maxing out: Stocks as Lotteries and the Cross-Section of Expected Returns." *Journal of Financial Economics* 99 (2): 427–46. doi:10.1016/j.jfineco.2010.08.014.

Banz, R. W. 1981. "The Relationship between Return and Market Value of Common Stocks." *Journal of Financial Economics* 9 (1):3–18. doi:10.1016/0304-405x(81)90018-0.

Barberis, N., and M. Huang. 2008. "Stocks as Lotteries: The Implications of Probability Weighting for Security Prices." *American Economic Review* 98 (5):2066–100.

Boyer, B., T. Mitton, and K. Vorkink. 2010. "Expected Idiosyncratic Skewness." *Review of Financial Studies* 23 (1):169–202. doi:10.1093/rfs/hhp041.

Brunnermeier, M. K., C. Gollier, and J. A. Parker. 2007. "Optimal Beliefs, Asset Prices, and the Preference for Skewed Returns." *American Economic Review* 97 (2): 159–65.

Brunnermeier, M. K., and J. A. Parker. 2005. "Optimal Expectations." *American Economic Review* 95 (4): 1092–1118. doi:10.1257/0002828054825493.

Carhart, M. M. 1997. "On Persistence in Mutual Fund Performance." *Journal of Finance* 52 (1):57–82.

Conrad, J. S., R. F. Dittmar, and E. Ghysels. 2013. "Ex Ante Skewness and Expected Stock Returns." *The Journal of Finance* 68 (1):85–124.

De Giorgi, E. G., and S. Legg. 2012. "Dynamic Portfolio Choice and Asset Pricing with Narrow Framing and Probability Weighting." *Journal of Economic Dynamics and Control* 36 (7):951–72.

DeLisle, R. J., M. Ferguson, and H. Kassa. 2019. "Are Skewness Preferences Symmetric? Evidence from Negative Idiosyncratic Shocks." Working Paper, University of Cincinnati, Cincinnati.

DeLisle, R. J., and N. Walcott. 2016. "The Role of Skewness in Mergers and Acquisitions." *Quarterly Journal of Finance* 7 (1): 1740001. doi:10.1142/S2010139217400018.

Driessen, J., T.-C. Lin, and O. Van Hemert. 2013. "How the 52-Week High and Low Affect Option-Implied Volatilities and Stock Return Moments." *Review of Finance* 17 (1):369–401. doi:10.1093/rof/rfr026.

Du, D. 2008. "The 52-week High and Momentum Investing in International Stock Indexes." *The Quarterly Review of Economics and Finance* 48 (1):61–77. doi:10.1016/j.qref.2007.02.001.

Fama, E. F., and K. R. French. 1992. "The Cross-Section of Expected Stock Returns." *The Journal of Finance* 47 (2): 427–65.

Fama, E. F. and K. R. French. 1993. "Common Risk Factors in the Returns on Stocks and Bonds." *Journal of Financial Economics* 33 (1):3–56.

Fama, E. F., and K. R. French. 1996. "Multifactor Explanations of Asset Pricing Anomalies." *Journal of Finance* 51 (1):55–84. doi:10.1111/j.1540-6261.1996.tb05202.x.

Fama, E. F. and J. MacBeth. 1973. "Risk, Return, and Equilibrium: Empirical Tests." *Journal of Political Economy* 71:607–36.

Frazzini, A. and L. H. Pedersen. 2014. "Betting against Beta." *Journal of Financial Economics* 111 (1):1–25. doi:10.1016/j.jfineco.2013.10.005.

George, T. J., and C.-Y. Hwang. 2004. "The 52-Week High and Momentum Investing." *The Journal of Finance* 59 (5):2145–76. doi:10.1111/j.1540-6261.2004.00695.x.

Goetzmann, W. N., and A. Kumar. 2008. "Equity Portfolio Diversification." *Review of Finance* 12 (3):433–63. doi:10.1093/rof/rfn005.

Green, T. C., and B.-H. Hwang. 2012. "Initial Public Offerings as Lotteries: Skewness Preference and First-Day Returns." *Management Science* 58 (2):432–44. doi:10.1287/mnsc.1110.1431.

Grossman, P. J., and C. C. Eckel. 2015. "Loving the Long Shot: Risk taking with Skewed Lotteries." *Journal of Risk and Uncertainty* 51 (3):195–217. doi:10.1007/s11166-015-9228-1.

Heath, C., S. Huddart, and M. Lang. 1999. "Psychological Factors and Stock Option Exercise." *The Quarterly Journal of Economics* 114no. (2):601–27. doi:10.2307/2587018.

Jegadeesh, N., and S. Titman. 1993. “Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency.” *Journal of Finance* 48 (1):65–92.

Jiang, G. J., and K. X. Zhu. 2017. “Information Shocks and Short-Term Market Underreaction.” *Journal of Financial Economics* 124 (1):43–64. doi:10.1016/j.jfineco.2016.06.006.

Kahneman, D., P. Slovic, and A. Tversky. 1982. *Judgment under Uncertainty: Heuristics and Biases*. New York: Cambridge University Press.

Kahneman, D. and A. Tversky. 1979. “Prospect Theory: An Analysis of Decision under Risk.” *Econometrica* 47 (2): 263–91.

Kristensen, H., and T. Gärling. 1997. “The Effects of Anchor Points and Reference Points on Negotiation Process and Outcome.” *Organizational Behavior and Human Decision Processes* 71 (1):85–94. doi:10.1006/obhd.1997.2713.

Kumar, A. 2005. “Institutional Skewness Preferences and the Idiosyncratic Skewness Premium.” Working Paper, University of Texas, Austin, TX.

Kumar, A. 2009. “Who Gambles in the Stock Market?” *The Journal of Finance* 64 (4):1889–933.

Kunreuther, H., N. Novemsky, and D. Kahneman. 2001. “Making Low Probabilities Useful.” *Journal of Risk and Uncertainty* 23 (2):103–20. doi:10.1023/A:1011111601406.

Lee, E., and N. Piqueira. 2017. “Short Selling around the 52-Week and Historical Highs.” *Journal of Financial Markets* 33:75–101. doi:10.1016/j.finmar.2016.03.001

Li, J., and J. Yu. 2012. “Investor Attention, Psychological Anchors, and Stock Return Predictability.” *Journal of Financial Economics* 104 (2):401–19. doi:10.1016/j.jfineco.2011.04.003.

Markowitz, H. 1952. “The Utility of Wealth.” *Journal of Political Economy* 60 (2):151–8.

Markowitz, H. 1959. *Portfolio Selection: Efficient Diversification of Investments*. New York: John Wiley & Sons.

Mitton, T. and K. Vorkink. 2007. “Equilibrium Underdiversification and the Preference for Skewness.” *Review of Financial Studies* 20 (4):1255–88. doi:10.1093/rfs/hhm011.

Mitton, T., and K. Vorkink. 2010. “Why Do Firms with Diversification Discounts Have Higher Expected Returns?” *Journal of Financial and Quantitative Analysis* 45 (6):1367–90. doi:10.1017/S0022109010000566.

Newey, W., and K. D. West. 1987. “A Simple, Positive Semi-definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix.” *Econometrica* 55 (3): 703–8.

Petersen, M. A. 2009. “Estimating Standard Errors in Finance Panel Data Sets: Comparing Approaches.” *Review of Financial Studies* 22 (1):435–80. doi:10.1093/rfs/hhn053.

Sapp, T. R. A. 2011. “The 52-Week High, Momentum, and Predicting Mutual Fund Returns.” *Review of Quantitative Finance and Accounting* 37 (2):149–79. doi:10.1007/s11156-010-0199-7.

Schneider, C. and O. G. Spalt. 2016. “Conglomerate Investment, Skewness, and the CEO Long Shot Bias.” *Journal of Financ* 71 (2):635–72.

Schneider, C., and O. G. Spalt. 2017. “Acquisitions as Lotteries? The Selection of Target-Firm Risk and Its Impact on Merger Outcomes.” *Critical Finance Review* 6 (1):77–132.

Sharpe, W. 1964. “Capital Asset Prices: A Theory of Market Equilibrium under Conditions of Risk.” *Journal of Finance* 19:425–42.

Teigen, K. H. 1974a. “Overestimation of Subjective Probabilities.” *Scandinavian Journal of Psychology* 15 (1): 56–62.

Teigen, K. H. 1974b. “Subjective Sampling Distributions and the Additivity of Estimates.” *Scandinavian Journal of Psychology* 15 (1):50–5.

Teigen, K. H. 1983. “Studies in Subjective Probability III: The Unimportance of Alternatives.” *Scandinavian Journal of Psychology* 24 (1):97–105.

Tversky, A., and D. Kahneman. 1992. “Advances in Prospect Theory: Cumulative Representation of Uncertainty.” *Journal of Risk and Uncertainty* 5 (4): 297–323. doi:10.1007/BF00122574.

Tversky, A. and D. Kahneman. 1974. “Judgment under Uncertainty: Heuristics and Biases.” *Science* 185 (4157): 1124–31. doi:10.1126/science.185.4157.1124.

White, H. 1980. “A Heteroskedasticity-Consistent Covariance Matrix Estimator and a Direct Test for Heteroskedasticity.” *Econometrica* 48 (4):817–38.