Anchoring and Probability Weighting in Option Prices

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Cumulative prospect theory argues that the human decision-making process tends to improperly weight unlikely events. Another behavioral phenomenon, anchoring bias, is the failure to update beliefs away from established anchor points. In this study, we find evidence that equity option market investors both anchor to prices and incorporate a probability weighting function similar to that proposed by cumulative prospect theory. The biases result in inefficient prices for put options when firms have relatively high or relatively low implied volatilities. This has implications for the cost of hedging long portfolios and long individual equity positions. © 2017 Wiley Periodicals, Inc. Jrl Fut Mark 37:614–638, 2017

1. INTRODUCTION

Many financial studies use aspects of behavioral theories to examine phenomena observed in equity markets.[1] In this study, we employ two well-documented behavioral theories to explain the underperformance of put options with very low and very high implied volatilities relative to other put options with the same moneyness and maturities. We find evidence that equity option investors anchor to prices (or implied volatilities) and incorporate a probability weighting function similar to that proposed by cumulative prospect theory (CPT). CPT (Tversky & Kahneman, 1992), unlike standard utility theory, argues that the human decision-making process depends on relative gains and losses, not final wealth, as losses impact utility more negatively than gains of the same magnitude increase utility. The asymmetry of an

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[1]Prospect theory (Kahneman & Tversky, 1979), cumulative prospect theory (Tversky & Kahneman, 1992), mental accounting (Henderson & Peterson, 1992; Shefrin & Thaler, 1988; Thaler, 1980, 1985), and heuristics (Kahneman & Tversky, 1972; Tversky & Kahneman, 1974) have been successfully applied to many stylized facts in financial markets that are difficult to explain in a standard rational efficient markets framework (e.g., Fama, 1965, 1970; Friedman, 1953; Markowitz, 1952a,b).

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individual's utility due to gains versus losses is referred to as loss aversion. Tversky and Kahneman also contend humans are poor at internalizing event probabilities and appear to use a unique weighting function to convert an actual probability into a perceived probability which assigns a high value to low probability events, resulting in overly risk averse or risk-seeking behavior, depending upon whether the outcome of the event is a loss or a gain. Anchoring is a documented psychological bias that is independent of CPT, but it is required by CPT to determine a reference point that defines regions of gains and losses.

In addition, the literature over the past two decades presents considerable evidence that investors use anchor points in their investing decisions. Kahneman, Slovic, and Tversky (1982) define anchoring as the process of making adjustments away from a reference point (the anchor) where the adjustments are biased toward this reference point. The anchor point may come from the problem at hand (Kahneman et al., 1982) or even a random value such as the last two digits of a Social Security Number (Ariely, Loewenstein, & Prelec, 2003). Kahneman et al. (1982) and Kahneman (1992) survey studies providing evidence of anchoring by individuals. Using laboratory experiments, Myagkov and Plott (1997) and Marsat and Williams (2013) also find support for the usage of anchor points. Benartzi and Thaler (1995) contend that investors use a reference stock price, that is, the current price, as an anchor point and determine, consistent with loss aversion, that investors weigh a loss about twice as much as a similar gain.

Supporting this assertion, George and Hwang (2004) identify an investing strategy that utilizes an anchor point of a stock's 52-week high price that bests Jegadeesh and Titman's (1993) simple momentum strategy. The 52-week high price should not contain any information about a stock's future value in a weak-form efficient market. Yet, the evidence George and Hwang presents suggest investors anchor to the 52-week high and are reluctant to value the stock price above that price, even if a higher price is well justified. Bhootra and Hur (2013) strengthen the anchoring argument by demonstrating an increase in the profitability of George and Hwang's strategy by conditioning on the timing of the 52-week high anchor point, which is consistent with Grinblatt and Han's (2005) theoretical model where the purchase price of the stock serves as the investor's anchor point.[2] Similarly, Baker, Pan, and Wurgler (2012) find managers use price anchors in determining premiums paid in mergers and acquisitions.

In addition to looking for evidence of anchoring, we also investigate the tendency of individuals to improperly weight low-probability events. In general, humans tend to do a poor job of internalizing probabilities. A series of studies by Teigen (1974a,b, 1983) shows that an individual's sum of interpreted probabilities of a set of outcomes often exceeds one. Kahneman and Tversky (1984) and Tversky and Kahneman (1992), show that, under CPT, individuals overweight (underweight) small (moderate or high) probabilities. Figure 1 shows a graphical example of their findings. The perceived probability of an event, $\pi(P)$, is much higher than the actual probability, P, when P is low. Thus, when individuals apply such a weighting function to observed probabilities, it gives rise to extremely risk averse (seeking) behavior when dealing with highly improbable losses (gains) as the value of each outcome is multiplied not by an additive probability, but by a decision weight.

Another implication of a weighting function is that individuals evaluate a risk of 1 in 100,000 similarly as 1 in 10,000,000. Kunreuther, Novemsky, and Kahneman (2001) empirically confirm such a notion. The regime of extremely small probabilities is unstable, where the risks are either grossly overweighted or ignored (e.g., rounded down to zero).

[2]In the context of Grinblatt and Han's model, the concept of an anchor is important with respect to loss aversion because individuals use it as a fixed reference to determine if selling an asset (i.e., the capital gains overhang) provides pain in the form of a loss or pleasure in the form of a gain.

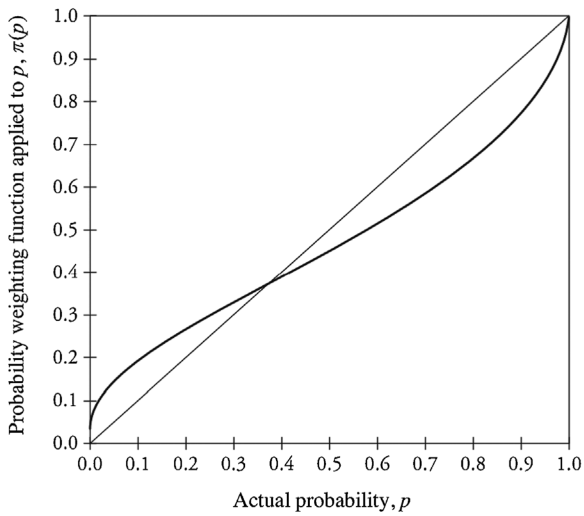

FIGURE 1

A Representation of a Probability Weighting Function From Cumulative Prospect Theory
The horizontal axis represents the actual probability (P) of an outcome and the vertical axis represents the perceived probability of an individual who applies a weighting function, π, to the actual probability. The lighter diagonal line is representative of no weighting function while the darker curved line incorporates a weighting function.

However, it is debatable whether or not individuals even seek out probabilities when making their decisions (Hogarth & Kunreuther, 1995; Huber, Wider, & Huber, 1997).

Barberis and Huang (2008) use probability weighting in their model of expected returns and demonstrate that it can explain the empirical finding that investors will pay a premium (discount) for stocks with positive (negative) skewness in their returns.[3] Barberis and Huang (2008) also posit their model can help explain other asset pricing anomalies such as initial public offering (IPO) returns, the diversification discount, private equity premiums, momentum returns, and option implied volatility skews. Additionally, De Giorgi and Legg (2012) demonstrate that probability weighting generates the large equity premium which has puzzled researchers for decades.

There are few studies in the options literature involving anchoring and probability weighting. For example, Heath, Huddart, and Lang (1999) find employees use their stock's 52-week high as a reference point to exercise their stock options.[4] Driessen, Lin, and Van Hemert (2013) show implied volatility is positively related to an underlying stock price's distance to the 52-week high price. Fodor, Doran, Carson, and Kirch (2013) show index option investors anchor to prices by showing investors purchase more put options (as a form of portfolio insurance) when the cost is low on an absolute basis but high on a relative basis. Arnold, Hilliard, and Shwartz (2007) examine the "jump memory" of S&P 500 index options after crash events and find evidence consistent with jump memory being related to loss aversion and anchoring points.[5] Additionally, Polkovnichenko and Zhao (2013), recognizing that pricing kernels estimated from option prices are inconsistent with standard kernels which include positive risk aversion and are monotonically decreasing in investor wealth,

[3]See, for example, Boyer, Mitton, and Vorkink (2010), Bali, Cakici, and Whitelaw (2011), Conrad, Dittmar, and Ghysels (2013), and Kumar (2009) for empirical evidence of skewness-seeking investors.
[4]Sautner and Weber (2009) also find employees treat their options separately from their total wealth and, consistent with the loss aversion feature of CPT, narrowly bracket them into gains and losses based on reference points.
[5]"Jump memory" is the attenuation of the implied jump intensity following a crash event.

show that empirically observed kernels are consistent with a utility model that incorporates a probability weighting function similar to the one proposed by CPT. Spalt (2013) corroborates this finding by presenting a model that demonstrates probability weighting is a key feature making option grants in pay packages desirable to nonexecutives.

The one parameter in an option pricing formula, such as the Black and Scholes (1973) model, that cannot be directly observed is the volatility of the stock price. Implied volatility is the volatility of the stock which, when substituted into the Black–Scholes formula, gives a theoretical option price equal to the observed market price. Changes in investor assumptions about volatility can have a dramatic effect on an option's price. Thus, implied volatility is a forward-looking measure of the future volatility of the stock over the term of the option. By contrast, historical volatilities, such as standard deviations, are backward looking. Consequently, traders use implied volatilities to gauge the market's opinion about the volatility of a particular stock. The information content of implied volatility is examined in multiple studies.[6] It has also been observed in equity markets that implied volatility is generally a convex function of strike price. This phenomenon is known as the volatility smile and has been repeatedly documented in the literature.[7] Prior to the October 1987 market crash, there was no significant volatility smile. Rubinstein (1994) refers to this phenomenon as "crash-o-phobia," alluding to the strong demand for put options on the S&P 500 index to hedge against market crashes. Several studies conclude that the premium on put options for downside risk is very high (Bliss & Panigirtzoglou, 2004; Engle & Rosenberg, 2002; Jackwerth, 2000). A recent study by Israelov and Nielsen (2015) supports anchoring as a possible explanation. In particular, the authors suggest that put options' low prices during calm market periods give the illusion of value, arguing that the frequency of "black swan" events required to rationalize option purchases is unreasonably large.

In this study, we find evidence that equity option market investors anchor to prices and incorporate a probability weighting function similar to that proposed by CPT. Specifically, we show put option prices are inefficient when firm implied volatilities are relatively high or relatively low. We focus on put options in this study due to their use as insurance against price decreases for long portfolios or individual equity positions (Trennepohl, Booth, & Tehranian, 1988). Investors are more likely to entertain call option prices periodically when they have positive sentiment for a stock. In contrast, an investor who has a long portfolio or long position in an individual equity is likely to continually assess put option prices as they consider insuring their positions. To the degree that an investor is more risk averse, this will become increasingly so. It is necessary that prices are regularly surveyed if we are to assume investors anchor prices at specific levels.

As expected, when implied volatilities are higher (lower), options are more (less) likely to be exercised. While the ordering of prices, or implied volatilities, with respect to exercise probabilities is correct, we find prices are too high when implied volatilities are very low or very high. To demonstrate this, we examine option returns for 30-, 60-, and 90-day options after dividing firms based on implied volatilities. Option returns are always lowest for the extreme implied volatility quintiles and are significantly negative.

Investors with long positions in equities will continually examine option prices and decide whether to hedge based on how prices relate to their estimates of future volatilities. In the case of low implied volatilities, we find evidence consistent with inefficient prices through

[6]For example, Christensen and Prabhala (1998) find that the volatility implied by S&P 100 index option prices outperforms past volatility in forecasting future index volatility. Diavatopoulos, Doran, and Peterson (2008) find that implied idiosyncratic volatility is a stronger predictor of future idiosyncratic volatility than idiosyncratic volatility forecasts from statistical models. Doran, Fodor, and Jiang (2013) provide evidence that implied volatility spreads contain information about both firm fundamentals and option mispricing.

[7]See, for example, Aït-Sahalia and Lo (1998), Rubinstein (1994), and Jackwerth and Rubinstein (1996).

anchoring. When investors evaluate prices, they fail to properly estimate future volatilities. They assess prices on an absolute basis rather than relative to a sound estimate of future volatilities. Since implied volatilities are mean-reverting, unlike equity prices which drift upward, investors may anchor to the mean implied volatility level. Thus, options with very low implied volatilities are likely to not be low enough as investors bias them toward the mean. This would result in contemporaneously high option prices and low future returns.

In the case of high implied volatilities, we explain the apparently inefficient prices through CPT. When implied volatilities are high, investors improperly weight the low probability event of a large price decrease, consistent with CPT. Because investors are risk averse, their fear of losses on long portfolios or individual equities due to large, market-wide, or specific price decreases will increase as implied volatilities increase. To the degree that investors are more fearful of price decreases, they will purchase more put options, all else equal.[8] If prices increase for put options, investors will buy fewer put options, all else equal. These two effects are offsetting in the case of higher implied volatilities. CPT suggests the first effect will dominate the second as investors will improperly overestimate the probability of large price decreases and demand more than a rational level of put options. This will cause prices to increase to inefficiently high levels and low future returns. Alternatively, if investors exhibited an anchoring bias in options with very high implied volatility, the bias would be toward the mean and the options would be underpriced, leading to high future returns. We find evidence to support the presence of CPT, not anchoring, in option prices with high implied volatilities.

The rest of the paper is as follows. In Section 2, we describe the data, variable definitions, and methodology. In Section 3, we report results. Section 4 concludes.

2. DATA AND METHODOLOGY

We collect data on option prices, strike prices, exercise dates, open interest, and implied volatilities from OptionMetrics. Our sample period is from January, 1996 to September, 2013. On the day of each month where options are available with exactly 32 (62, 92) days until expiration, we identify our put options for study.[9] On each observation date, we find the out-of-the-money (OTM) put option available that is closest to at-the-money status and denote this option as the "closest" OTM match. If possible, we also consider descending strike price options in search of a "second closest" OTM put option match. Our general question of study considers whether, as these put options approach expiration, subsequent performance varies based on the implied volatility levels of these puts. We consider whether these puts are more likely to eventually finish in the money on day 0, based on their implied volatility on the initial observation date. More importantly, we consider whether the returns of the "closest OTM" and "second closest OTM" put options vary, over the (-32,-2) [(-62,-2), (-92,-2)] period,[10] based on the implied volatility level on the observation date. By comparing options with similar moneyness and maturities, we isolate the effects of implied volatility differences (e.g., we are not testing the effects of the implied volatility smile or time value of the options).

[8]Brennan (1995) suggests prospect theory leads investors to demand products that limit losses or produce a "money-back guarantee."

[9]Thus, the beginning and ending observation dates for the 32-, 62-, and 92-day put performances all differ from one another. This also means the weighted implied volatilities (to be discussed) at the beginning of the various performance periods all differ slightly.

[10]Given the data difficulty in evaluating returns at the exact expiration (day 0), we measure returns through the end of trading day 2.

We measure our primary variable of study, the put option implied volatility level at the beginning of our performance measurement window, by using the weighted average implied volatilities of all OTM put options, with exactly 32 (62, 92) days until expiration, with the weighting done by the open interest of these put options. We denote this measure WIV. We seek to track performance of OTM put options based on their WIV levels. In order to include an observation in our analysis, the "closest OTM put" or "second closest OTM put" match may only be used if the OTM put has an open interest of at least 100 contracts, as noted in OptionMetrics on day -32 (-62, -92), and a midpoint price (between bid and ask) of at least $0.25.

In order to determine the moneyness status of our option observations, stock price data and identification information are taken from CRSP. This allows for the determination of whether "closest OTM" and "second closest OTM" put option matches are eventually exercisable on day 0. Furthermore, observations must have stock prices of at least $5 on day -32 (-62, -92), must trade on the NYSE, NASDAQ, or AMEX, and must have CRSP share codes of 10 or 11. Market capitalization and returns data are also taken from CRSP for the construction of control measures. Book value information is taken from Compustat for the construction of the book-to-market equity ratio. Compustat data are also used to measure short-interest concentration. SEC 13F filings provide data on institutional ownership of shares. We also take daily VIX data from the CBOE website for further analyses.

For much of our investigation, firm-date observations are sorted into quintiles, each month, on day -32 (-62, -92)[11] based on WIV level so that we might track subsequent performance of "closest match" and "second closest match" OTM puts. We first use this sorted WIV approach to consider whether the open interest of firm-date puts, relative to calls, varies based on the underlying WIV level. We construct OTMPutOI (OTMCallOI) to be the sum of the open interest of all put (call) options with at least 30 days until expiration, and we consider the ratio of these totals by WIV quintile. We also determine whether OTM put options closest and second closest to ATM status on day -32 (-62, -92) are eventually exercisable on day 0, based on the underlying WIV quintile sorts. We then determine whether OTM put options closest and second closest to ATM status on day -32 (-62, -92) differ in return performance over their holding periods, ending on day 2, based on the underlying WIV quintile sorts.

To control for the effects of timing, as well as factors widely considered to impact option returns, we then shift to a fixed-effects regression framework and include control measures, particularly inspired by Goyal and Saretto (2009).

As our variable of study is the open-interest weighted put option implied volatility (WIV), we create WIV quintiles, each month, by segmenting the sample of firm dates into equal quintiles based on the put open-interest WIV. WIVQ1 (WIVQ5) is a dummy variable indicating whether a firm-date observation has a weighted implied volatility in the lowest (highest) quintile among available observations on that date. $(HV_t - IV_t)$ is analogous to the measure found in Goyal and Saretto (2009), constructed as the log difference of the historical, annualized volatility of the firm-date observation based on daily stock returns from the prior trading year, minus the implied volatility of the option whose return performance is analyzed. Size (log of market capitalization), Mom (momentum), Skew (skewness), and Kurt (kurtosis) of stock returns are all calculated using the prior year's daily CRSP data, with the exception of 6 months of data used to calculate Mom as in Goyal and Saretto (2009). The BtoM (book-to-market) calculation utilizes Compustat data and is calculated as in Fama and French (1993). We augment the Goyal and Saretto model with short interest (as put options are a viable substitute to shorting equity shares, especially when there are short sale constraints) and institutional ownership (to separate the effects of institutional owners who are unlikely to exhibit the same behavioral biases as retail investors). Short Interest (ShortInt)

[11]Days -32, -62, and -92 are all unique from one another each month.

TABLE I
Summary Statistics and Correlations

Panel A: Summary Statistics

	Mean	*Median*	*St. Dev*
$HV_t - IV_t$	−0.0281	−0.0309	0.1906
Size	15.3667	15.2671	1.5284
BtoM	0.4912	0.3285	12.4772
Mom	0.1202	0.0707	0.4569
Skew	0.2615	0.2138	1.2577
Kurt	5.9978	2.5776	12.4097
ShortInt	0.0641	0.0379	0.0736
InstOwn	0.7366	0.7592	0.2207
WIV	0.5692	0.5109	0.2612

Panel B: Correlations

	$HV_t - IV_t$	*Size*	*BtoM*	*Mom*	*Skew*	*Kurt*	*ShortInt*	*InstOwn*	*WIVQ1*
$HV_t - IV_t$									
Size	0.022								
BtoM	0.052	−0.003							
Mom	0.256	−0.024	0.005						
Skew	0.171	−0.04	−0.015	0.208					
Kurt	0.205	−0.079	−0.001	0.040	0.370				
ShortInt	−0.093	−0.272	−0.003	0.007	0.036	0.082			
InstOwn	−0.044	−0.19	0.003	−0.048	−0.042	0.015	0.384		
WIVQ1	0.043	0.314	−0.004	−0.059	−0.037	−0.063	−0.294	−0.081	
WIVQ5	−0.122	−0.175	0.003	0.066	0.097	0.116	0.374	−0.093	−0.249

This table presents Pearson correlation coefficients between the measures of interest and control variables. Our variable of study is the open-interest weighted put option implied volatility (WIV). The WIV quintiles are created, each month, by segmenting the sample of firm dates into equal quintiles based on the put open-interest WIV. WIVQ1 (WIVQ5) is a dummy variable indicating whether a firm-date observation has a weighted implied volatility in the lowest (highest) quintile among available observations on that date. ($HV_t - IV_t$) is analogous to the measure found in Goyal and Saretto (2009), constructed as the log difference of the historical, annualized volatility of the firm-date observation based on daily stock returns from the prior trading year, minus the implied volatility of the option whose return performance is analyzed. Size (log of market capitalization), Mom (momentum), Skew (skewness), and Kurt (kurtosis) of stock returns are all calculated using the prior year's daily CRSP data, with the exception of 6 months of data used to calculate Mom as in Goyal and Saretto (2009). The BtoM (book-to-market) calculation utilizes Compustat data and is calculated as in Fama and French (1993). Short Interest (ShortInt) is the proportion of shares outstanding, from CRSP, which are held short, as measured in Compustat. Institutional Ownership (InstOwn) is the institutional ownership ratio as noted in SEC 13f filings. Option observations must have Optionmetrics open interest of at least 100 and a midpoint put price of at least \$0.25 in order for an observation to be included. Underlying stocks must trade on the NYSE, NASDAQ, or AMEX, have CRSP share codes of 10 or 11, and have prices of at least \$5 for an observation to be included. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The sample period is from January, 1996 through September, 2013.

is the number shares held short, as measured in Compustat, as a proportion of total shares outstanding. Institutional Ownership (InstOwn) is the proportion of shares held by institutional owners, as reported to the SEC in Form 13F filings, relative to the total shares outstanding.

Table I provides summary statistics and Pearson correlation coefficients between the variables of interest (WIVQ1 and WIVQ5) and controls.[12]

[12]For brevity, we present only the correlation matrix for the sample of options with 32 days until expiration. Correlation matrices for the samples of options with 62 and 92 days until expiration are nearly identical.

All correlations among potential predictors have magnitude less than 0.4, and most correlations are less than 0.1. Given these modest correlations, we proceed to a fixed-effect regression framework to measure the impact of high and low WIV status in the presence of controls. Our regression framework is

$$\begin{aligned}\text{PutRet}_t = {} & b0 + b1(\text{HV} - \text{IV})_{\text{it}} + b2\Big(\text{Size}_{\text{it}}) + b3(\text{BtoM}_{\text{it}}) + b4(\text{Mom}_{\text{it}}) + b5(\text{Skew}_{\text{it}}) \\ & + b6(\text{Kurt}_{\text{it}}) + b7(\text{ShortInt}) + b8(\text{InstOwn}) + b9(\text{WIV Q1}_{\text{it}}) + b10(\text{WIV Q5}_{\text{it}}) + \varepsilon_{\text{it}}\end{aligned} \tag{1}$$

The $b9$ and $b10$ coefficients show the average difference in the returns of the put options in the WIVQ1 and WIVQ5 groups, respectively, compare to groups WIVQ2 through WIVQ4 after controlling for firm-specific characteristics. A negative estimate of $b9$ is consistent with anchoring bias in group WIVQ1, while a negative estimate of $b10$ is consistent with probability weighting in group WIVQ5.

We also investigate the possibility of earning abnormal returns using a trading strategy that goes long put options in the WIVQ2 through WIVQ4 categories and short options in either the WIVQ1 or WIVQ5 category. To account for transaction costs, options are purchased at the ask price and sold at the bid price. We also estimate the alphas from these self-funding put option portfolios using the following factor model based on Fama and French (2015):

$$\begin{aligned}\text{PortRet}_t = {} & \alpha + \beta_1(\text{Mkt} - \text{Rf})_t + \beta_2(\text{SMB}_t) + \beta_3(\text{HML}_t) + \beta_4(\text{RMW}_t) + \beta_5(\text{CMA}_t) \\ & + \beta_6(\text{ORF}_t) + \varepsilon_t\end{aligned} \tag{2}$$

PortRet_t is the time t return of the long-short put options portfolio, Mkt-Rf is the market risk premium, and SMB, HML, RMW, and CMA are factor portfolio returns based on size, book-to market equity ratio, operating profitability, and asset investment, respectively. The alpha (α) represents abnormal returns not explained by the model. Broadie et al. (2009), Coval and Shumway (2001), and Vanden (2006) show option-based strategies produce returns that are unique compared those that are equity based. Our approach to control for these types of returns is similar to that of Diavatopoulos, Doran, Fodor, and Peterson (2012), which uses straddles on the S&P 500 as a systematic risk factor. Thus, we include another factor to capture systematic options returns, ORF, which is the return on an at-the-money straddle on the S&P 500.

3. EMPIRICAL RESULTS

In Table II, we first examine relative open interest of call and put options based on implied volatility levels. For all observations with non-zero call and put open interest, we calculate the ratio of put open interest to call open interest after sorting the sample into quintiles based on weighted implied volatilities. We separately consider this relative open-interest metric for options expiring in 32, 62, and 92 days.

We generally observe lower put-to-call open-interest ratios for higher implied volatility quintiles. When the highest levels of volatility are present, there tends to be less open interest in put options than when implied volatilities are lower, though put open interest still exceeds call open interest. For options with 32 and 92 days to expiration, respectively, put/call open-interest ratios are 4.13 and 4.50, respectively, for the lowest implied volatility quintiles, lower than any other quintile. Ratios are 6.04 and 7.78, respectively, for the highest implied volatility quintiles. For options with 62 days to expiration, the ratio is slightly lower for the

TABLE II
Relative Put/Call Open Interest by Implied Volatility

Panel A: OTMPutOI/OTMCallOI, 32 Days Until Expiration					
	WIV 32-Day Q1	*WIV 32-Day Q2*	*WIV 32-Day Q3*	*WIV 32-Day Q4*	*WIV 32-Day Q5*
Mean	6.04	6.16	6.71	5.31	4.13
Median	1.18	1.12	1.03	0.91	0.69
n	16,726	16,844	16,835	16,838	16,765
Panel B: OTMPutOI/OTMCallOI, 62 Days Until Expiration					
	WIV 62-Day Q1	*WIV 62-Day Q2*	*WIV 62-Day Q3*	*WIV 62-Day Q4*	*WIV 62-Day Q5*
Mean	5.92	7.14	6.88	5.22	5.62
Median	1.02	1.04	0.96	0.85	0.66
n	8461	8568	8561	8568	8496
Panel C: OTMPutOI/OTMCallOI, 92 Days Until Expiration					
	WIV 92-Day Q1	*WIV 92-Day Q2*	*WIV 92-Day Q3*	*WIV 92-Day Q4*	*WIV 92-Day Q5*
Mean	7.78	5.96	5.09	5.11	4.50
Median	1.08	1.07	0.98	0.87	0.67
n	8953	9071	9065	9069	8996

OTMPutOI/OTMCallOI is the ratio of the sum of all open interest of OTM put options, with given times until expiration (32 days in Panel A, 62 days in Panel B, 92 days in Panel C), to the sum of all open interest of OTM call options for these firms with the same number of days until expiration. We consider whether OTMPutOI/OTMCallOI varies based on the underlying level of open-interest weighted put implied volatility (WIV) on observation firm dates. WIV is calculated based on all puts with exactly 32 (62, 92) days until option expiration in Panel A (Panels B and C). The WIV quintiles are created, each month, by segmenting the date's sample of firms into equal quintiles based on the put, open-interest WIV. On each observation date, there must be an out-of-the-money (OTM) put available that has initial open interest of at least 100 and an initial midpoint price of at least $0.25 in order for the observation to be included in the analysis. Underlying stocks must trade on the NYSE, NASDAQ, or AMEX, have CRSP share codes of 10 or 11, and have prices of at least $5 for an observation to be included. The sample period is from January, 1996 through September, 2013.

fourth implied volatility quintile than the fifth, but the general trend suggests higher implied volatility is associated with relatively lower open interest in put options.

We do not explicitly know trader types, but it is plausible that potential hedgers, who are risk averse, would be more likely to enter long put positions when implied volatilities, and prices, are low. This is a potential explanation for high put open-interest levels, relative to call open interest, when implied volatilities are low. When implied volatilities are high, the more consistent levels of put and call open interest may be explained by relatively more attention from risk seeking, speculative investors who are more likely to trade when exercise probabilities, and corresponding implied volatilities and prices, are higher. Given investors use both put and call options to speculate, an increase in speculation should increase open interest in both put and call options. This should not cause an imbalance in open interest, as is the case when implied volatilities are low.

We next test whether differing relative open-interest levels represent rational investor choices or behavioral biases. Specifically, we consider the case of put options as two potential biases exist. First, the finding of relatively higher put open interest when implied volatilities are low may indicate an anchoring bias where potential hedgers see lower associated put option prices and purchase these options without properly considering exercise probabilities and expected returns associated with these options. While prices may be low on an absolute basis, sufficiently low exercise probabilities would mean the insurance provided by the put options is relatively expensive. Table III examines exercise probabilities across implied volatility quintiles.

A behavioral bias may also be observed when implied volatilities are high, though this is not necessarily reflected in relative put/call open-interest levels. As potential hedgers are risk averse, they may be willing to overpay for options when implied volatility levels are high. If these investors believe higher implied volatility levels are indicative of higher future volatility, they may make the decision to buy put options without properly considering the price of options. This can be explained by CPT and the overweighting of low-probability events. To

TABLE III
Put Option Exercise Frequency by Implied Volatility

Panel A: Buying Puts With 32 Days Until Expiration and Holding 30 Days

	WIV 32-Day Q1	*WIV 32-Day Q2*	*WIV 32-Day Q3*	*WIV 32-Day Q4*	*WIV 32-Day Q5*	*(Q5–Q1)*
Closest OTM put exercise %	18.80	20.52	21.89	24.01	26.20	7.40***
n	16,726	16,844	16,835	16,838	16,765	
2nd closest OTM put exercise %	11.45	13.58	16.34	17.37	19.02	7.57***
n	6612	6722	6720	6720	6645	

Panel B: Buying Puts With 62 Days Until Expiration and Holding 60 Days

	WIV 62-Day Q1	*WIV 62-Day Q2*	*WIV 62-Day Q3*	*WIV 62-Day Q4*	*WIV 62-Day Q5*	*(Q5–Q1)*
Closest OTM put exercise %	18.20	21.13	22.51	25.20	27.48	9.28***
n	8461	8568	8561	8568	8496	
2nd closest OTM put exercise %	10.90	13.36	15.25	17.71	19.42	8.52***
n	4485	4596	4584	4595	4522	

Panel C: Buying Puts With 92 Days Until Expiration and Holding 90 Days

	WIV 92-Day Q1	*WIV 92-Day Q2*	*WIV 92-Day Q3*	*WIV 92-Day Q4*	*WIV 92-Day Q5*	*(Q5–Q1)*
Closest OTM put exercise %	20.12	22.51	24.89	27.53	30.36	10.24***
n	8953	9071	9065	9069	8996	
2nd closest OTM put exercise %	12.43	14.62	17.60	19.30	22.29	9.86***
n	5343	5430	5454	5430	5382	

This table presents the frequency of OTM put option eventual expiration in the money, based on the underlying level of open-interest weighted put option implied volatility (WIV). WIV is calculated based on all puts with exactly 32 (62, 92) days until option expiration in Panel A (Panels B and C). The WIV quintiles are created, each month, by segmenting the sample of firm dates, into equal quintiles based on the put open-interest WIV. On each observation date, we find the out-of-the-money (OTM) put available that is closest to at-the-money status and denote this option the "closest" match. If possible, we also consider descending strike price puts in search of a "second closest" OTM put match. To be included in the sample, put matches must have initial Optionmetrics open interest of at least 100 and initial midpoint prices of at least $0.25. Underlying stocks must trade on the NYSE, NASDAQ, or AMEX, have CRSP share codes of 10 or 11, and have prices of at least $5 for an observation to be included. *** denotes statistical significance at the 1% level to the difference of proportions test comparing frequency of in-the-money expiration for puts in WIV quintile 5 and WIV quintile 1. The sample period is from January, 1996 through September, 2013.

determine if investors are overpaying for put options when implied volatilities are high, we calculate put option returns across weighted implied volatility quintiles. These results are presented later in Table IV.

Table III presents the probability of option exercise based on put option implied volatility, days to expiration, and nearness to ATM. As hedgers are most likely to purchase

TABLE IV
Put Returns by Implied Volatility

Panel A: Buying Puts With 32 Days Until Expiration and Holding 30 Days							
	WIV 32-Day Q1	*WIV 32-Day Q2*	*WIV 32-Day Q3*	*WIV 32-Day Q4*	*WIV 32-Day Q5*	*Q1–Q(2–4)*	*Q5–Q(2–4)*
Closest OTM put mean return	−0.134	−0.092	−0.074	−0.065	−0.104	−0.057**	−0.027
n	16,726	16,844	16,835	16,838	16,765		
2nd closest OTM put mean return	−0.145	−0.127	−0.071	−0.055	−0.118	−0.061	−0.034
n	6612	6722	6720	6720	6645		
Panel B: Buying Puts With 62 Days Until Expiration and Holding 60 Days							
	WIV 62-Day Q1	*WIV 62-Day Q2*	*WIV 62-Day Q3*	*WIV 62-Day Q4*	*WIV 62-Day Q5*	*Q1–Q(2–4)*	*Q5–Q(2–4)*
Closest OTM put mean return	−0.221	−0.151	−0.129	−0.093	−0.189	−0.097***	−0.065**
n	8461	8568	8561	8568	8496		
2nd closest OTM put mean return	−0.198	−0.119	−0.069	−0.027	−0.150	−0.126**	−0.078*
n	4485	4596	4584	4595	4522		
Panel C: Buying Puts With 92 Days Until Expiration and Holding 90 Days							
	WIV 92-Day Q1	*WIV 92-Day Q2*	*WIV 92-Day Q3*	*WIV 92-Day Q4*	*WIV 92-Day Q5*	*Q1–Q(2–4)*	*Q5–Q(2–4)*
Closest OTM put mean return	−0.178	−0.147	−0.078	−0.095	−0.161	−0.071**	−0.054**
n	8953	9071	9065	9069	8996		
2nd closest OTM put mean return	−0.192	−0.138	0.033	−0.034	−0.138	−0.146***	−0.093**
n	5343	5430	5454	5430	5382		

In this table, we consider OTM put option returns, based on the underlying level of open-interest weighted put option implied volatility (WIV). WIV is calculated based on all puts with exactly 32 (62, 92) days until option expiration in Panel A (Panels B and C). The WIV quintiles are created, each month, by segmenting the sample of firm dates into equal quintiles based on the put open-interest WIV. On each observation date, we find the out-of-the-money (OTM) put available that is closest to at-the-money status and denote this option the "closest" match. If possible, we also consider descending strike price puts in search of a "second closest" OTM put match. To be included in the sample, put matches must have initial Optionmetrics open interest of at least 100 and initial midpoint prices of at least \$0.25. Underlying stocks must trade on the NYSE, NASDAQ, or AMEX, have CRSP share codes of 10 or 11, and have prices of at least \$5 for an observation to be included. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively, for the difference of means tests comparing WIV quintile 1 and WIV quintile 5 performance, respectively, to the performance of puts in WIV quintiles 2, 3, and 4. The sample period is from January, 1996 through September, 2013.

OTM options, we examine returns to the two OTM options for each firm/month combination that are closest to ATM status.

If traders are acting rationally with respect to pricing, as reflected in WIVs, exercise probabilities should be higher in higher weighted implied volatility quintiles than in lower WIV quintiles. For each of the six groups formed based on time to expiration and nearness to ATM status, exercise probabilities are increasing from the lowest to highest put IV quintile and these increases are relatively monotonic.

Although this is evidence of rational pricing, with respect to ordering, across implied volatility quintiles, it does not necessarily mean prices are efficient. For example, it may be that in the highest WIV quintile, options are most likely to be exercised, but still have a large positive or negative average return because WIVs, while high relative to other firm days, are too low or too high. The same could be argued for the lowest quintile or other quintiles. To test for the efficiency of prices, we need to examine returns to these options.

In Table IV, options returns are presented after dividing firms into the same WIV groups of Table III, based on status of nearness to ATM and time to expiration.

As seen in Panel A, for options with 32 days to expiration, returns for each group are negative. This is not surprising because option sellers face a riskier payoff structure than do option buyers and demand from hedgers has been shown to increase put option prices and lead to lower returns (relative to call option returns). Consistent with this notion, Panels B and C also show that returns are negative in 19 of 20 cases for longer term puts.

If an anchoring bias exists where demand for put options is irrationally high when absolute prices are low (the lowest weighted implied volatility quintiles), returns should be relatively low for these firm days. The same is true if CPT is driving potential hedgers to be willing to pay inefficiently high prices when large underlying asset price changes are more likely (the highest weighted implied volatility quintiles). We expect put option returns will be lowest in the lowest and highest implied volatility quintiles due to the presence of these biases.

For 32-day options, we observe increasing returns from the lowest WIV quintile to the fourth quintile, then a sharp increase in the highest WIV quintile. If option prices are efficient under all implied volatility conditions, returns should not vary across WIV quintiles. Though differences are only statistically significant in one of four cases (the 32-day options), returns are lower for the lowest WIV quintile (compared to the middle three quintiles) by 5.7% and 6.1%, respectively, for put options closest to ATM and one strike price lower, respectively. For the highest WIV quintile, these differences relative to the middle three quintiles are 2.7% and 3.4%, respectively. This pattern of returns suggests the presence of an anchoring bias when implied volatilities are low and biases due to CPT when implied volatilities are high.

In Panels B and C, results are presented for options with 62 and 92 days to expiration. The results in the two panels are consistent with our hypotheses and findings in Panel A but are much more pronounced and statistically significant in all cases. The finding of stronger results for longer term options is not surprising as hedgers are less likely to use short-term options relative to longer term options (Bakshi, Cao, & Chen, 2000; Block & Gallagher, 1986; Geczy, Minton, & Schrand, 1997). For both times to expiration, and both moneyness categories, the lowest put option returns occur in the highest and lowest WIV quintiles. For both the highest and lowest quintiles, mean returns are significantly lower than return means for the middle three quintiles. Magnitudes of differences range from 6.5% to 14.6%. This is consistent with our hypotheses related to anchoring and CPT and option pricing.

We explain the low returns for the lowest WIV quintiles (ranging from −17.8% to −22.1%) as evidence of an anchoring bias. Given these firm days have the lowest put implied volatilities, they also have lower put option prices, relative to expiration dates, in other WIV quintiles. In other words, prices are low on an absolute basis. Table III showed these options are least likely to be exercised, but relative pricing can only be considered by examining option returns. The large negative option returns suggest these options are overpriced on a relative basis. We argue that, because prices are low on an absolute basis, hedgers will increase purchasing and bid up prices to an unreasonably high level, relative to efficient prices, because their pricing expectations are anchored to a higher average option price. If put option prices are absolutely low, traders will see this as inexpensive insurance though they know it is unlikely to be needed. Even when the price in inefficiently high, if WIVs are low then traders will judge the price as absolutely low if anchored to a higher mean price and they may, therefore, overpay.

The low returns for the highest WIV quintiles (ranging from −13.8% to −18.9%) are consistent with CPT in put option pricing. When WIVs are high, options are more likely to be exercised. In an ordinal sense, options are priced efficiently as options with higher probabilities of exercise are more expensive, but again, option returns must be used to test for efficiency of prices. CPT suggests traders will improperly weight low probability events. Low returns for high weighted implied volatility quintiles suggest hedgers are overweighting the probability of a large price decrease in the underlying asset and are thus willing to overpay for put options.

Although it is more likely options will be exercised when WIVs are high, this is still a low probability event that occurs for between 19.0% and 30.4% of high implied volatility quintile firm days. When pricing options, buyers and sellers consider the probability of a price change large enough to profit (or justify the need for insurance) and also the expected magnitude of these price changes. The large negative returns for put options suggest traders improperly estimate the probability of large price changes (the low probability event), expecting these large price changes will occur more often and/or to a greater degree than is realized. This leads to prices which are too high and inefficient.

From a hedging perspective, traders with long positions place upward pressure on prices, leading to inefficiently expensive puts as a result of behavioral biases when implied volatility are very high or very low. This is observed in returns for high and low implied volatility quintiles that tend to be significantly lower than when implied volatilities are not at extreme levels.

Table IV results suggest investors should not be tempted to hedge because put options are cheap on an absolute basis. Though this insurance is cheap, it is unlikely to be needed and is extremely costly when evaluating returns. When implied volatilities are low, the corresponding probabilities of large price changes are overestimated. Results also suggest that buying put options when implied volatilities are high will be costly. In this case, investors may be best served by protecting themselves against large potential losses on the underlying assets by exiting these positions if possible. While they may be correct in judging that protection against large losses is more likely to be needed, this protection is overpriced relative to the likelihood of a large price change. In both cases, option buyers are losing and option sellers are earning greater profits.

To test the robustness of these results, while considering factors shown in previous works which influence option returns, we present fixed-effects regressions in Table V.[13]

Results are presented for options with 32, 62, and 92 days to expiration in Panels A, B, and C, respectively. The variables of most interest are separate, binary variables which designate if a firm-day is in the highest (WIV5) or lowest (WIV1) WIV quintile. Our control variables are a measure of IV relative to historical volatility as in Goyal and Saretto (2009), firm size, book-to-market equity, momentum, skewness, kurtosis, short interest level, and institutional ownership. Coefficients of these control variables have the expected signs based on past works.

The findings in Table V, relative to weighted implied volatility, are consistent with those in Table III and support the presence of behavioral biases in pricing put options when implied volatilities are at the extremes (either relatively high or relatively low). For 32-day options, coefficients of WIV1 are negative for both moneyness groups, but

[13]Consistent with the low correlations between the independent variables shown in Table I, all variance inflation factors (VIFs) from the regressions are below 5 which indicates multicollinearity is not a concern.

TABLE V
Fixed-Effect Regressions of Put Option Returns on Firm Characteristics

Panel A: 30-Day Returns

	OTM Match Closest to ATM		OTM Match 2nd Closest to ATM	
	Coefficient	*t-Statistic*	*Coefficient*	*t-Statistic*
$HV_t - IV_t$	0.593	9.25***	0.653	6.16***
Size	−0.504	−1.91**	−0.812	−2.01**
BtoM	−0.009	−0.83	−0.024	−0.81
Mom	−0.068	−2.61***	−0.160	−3.37***
Skew	−0.019	−2.72***	−0.013	−0.85
Kurt	−0.003	−4.67***	−0.004	−2.96***
ShortInt	0.146	1.09	−0.292	−1.13
InstOwn	0.061	1.24	0.122	1.18
WIVQ1	−0.054	−2.63***	−0.087	−2.11**
WIVQ5	0.021	0.81	0.064	1.22
	$n = 76{,}492$		$n = 32{,}738$	

Panel B: 60-Day Returns

	OTM Match Closest to ATM		OTM Match 2nd Closest to ATM	
	Coefficient	*t-Statistic*	*Coefficient*	*t-Statistic*
$HV_t - IV_t$	0.623	6.77***	0.709	4.44
Size	−0.299	−3.05***	−0.313	−3.06***
BtoM	0.002	0.11	−0.003	−0.12
Mom	−0.118	−3.22***	−0.079	−1.18
Skew	−0.008	−0.99	−0.026	−1.44
Kurt	−0.002	−2.08**	−0.004	−2.04**
ShortInt	0.437	2.44	−0.401	−1.19
InstOwn	0.054	0.89	0.039	0.31
WIVQ1	−0.048	−1.97**	−0.077	−2.01**
WIVQ5	−0.056	−1.79*	−0.061	−1.41
	$n = 38{,}181$		$n = 20{,}933$	

Panel C: 90-Day Returns

	OTM Match Closest to ATM		OTM Match 2nd Closest to ATM	
	Coefficient	*t-Statistic*	*Coefficient*	*t-Statistic*
$HV_t - IV_t$	0.569	6.29***	0.626	4.09***
Size	−0.340	−3.20***	−0.223	−2.41**
BtoM	0.003	0.24	−0.002	−0.09
Mom	−0.054	−1.57	−0.048	−0.83
Skew	−0.004	−0.47	−0.013	−0.82
Kurt	−0.001	−1.43	−0.001	−0.37
ShortInt	0.481	2.85***	0.295	1.00
InstOwn	0.115	2.02**	0.134	1.22
WIVQ1	−0.046	−2.06**	−0.094	−2.07**

continued

TABLE V
(Continued)

	Panel C: 90-Day Returns			
	OTM Match Closest to ATM		*OTM Match 2nd Closest to ATM*	
	Coefficient	*t-Statistic*	*Coefficient*	*t-Statistic*
WIVQ5	−0.052	−1.78*	−0.086	−1.80*
	$n = 43{,}789$		$n = 25{,}279$	

This table presents coefficients with *t*-values and significance levels for the fixed-effects regression framework which models: $\text{PutRet}_t = b1(\text{HV}_t - \text{IV}_t) + b2(\text{Size}_t) + b3(\text{BtoM}_t) + b4(\text{Mom}_t) + b5(\text{Skew}_t) + b6(\text{Kurt}_t) + b7(\text{ShortInt}) + b8(\text{InstOwn}) + b9(\text{WIVQ1}_t) + b10(\text{WIVQ5}_t)$. On the day each month where puts are available with expirations 32 (62, 92) days hence, we consider the 30-day (60-day, 90-day) returns of these puts as our dependent variable in Panel A (Panels B and C). On each observation date, we find the out-of-the-money (OTM) put available that is closest to at-the-money status and denote this option the "closest" match. If possible, we also consider descending strike price puts in search of a "second closest" OTM put match. Our variable of study is the open-interest weighted put option implied volatility (WIV). The WIV quintiles are created, each month, by segmenting the sample of firm dates into equal quintiles based on the put open-interest WIV. WIVQ1 (WIVQ5) is a dummy variable indicating whether a firm-date observation has a weighted implied volatility in the lowest (highest) quintile amongst available observations on that date. We include control measures to our regression specification. ($\text{HV}_t - \text{IV}_t$) is analogous to the measure found in Goyal and Saretto (2009), constructed as the log difference of the historical, annualized volatility of the firm-date observation based on daily stock returns from the prior trading year, minus the implied volatility of the option whose return performance is analyzed. Size (log of market capitalization), Mom (momentum), Skew (skewness), and Kurt (kurtosis) of stock returns are all calculated using the prior year's daily CRSP data, with the exception of 6 months of data used to calculate Mom as in Goyal and Saretto (2009). The BtoM (book-to-market) calculation utilizes Compustat data and is calculated as in Fama and French (1993). Short Interest (ShortInt) is the proportion of shares outstanding, from CRSP, which are held short, as measured in Compustat. Institutional Ownership (InstOwn) is the institutional ownership ratio as noted in SEC 13f filings. Option observations must have Optionmetrics open interest of at least 100 and a midpoint put price of at least $0.25 in order for an observation to be included. Underlying stocks must trade on the NYSE, NASDAQ, or AMEX, have CRSP share codes of 10 or 11, and have prices of at least $5 for an observation to be included. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The sample period is from January, 1996 through September, 2013.

significant only for options closest to ATM. Coefficients of WIV5 are positive with low *t*-statistics. Again, a lack of convincing findings for the shortest term options is not surprising as hedgers tend to use longer term options. For the remaining four moneyness/maturity groups, binary variables for both low- and high-WIV groups are negative and significant with the exception of second-closest to ATM puts for the 62-day options, which has a negative coefficient just shy of statistical significance. This is evidence that options are overpriced when WIVs are low or high and that this finding is not driven by other factors shown in previous works to have power in predicting option returns.

We next examine differences between the implied volatilities of the put options used in previous analysis and implied volatilities of corresponding calls (i.e., those of the same expiration date and strike price). We calculate call and put implied volatilities separately using open-interest weighting, then calculate the difference as call implied volatility less put implied volatility. The results are shown in Table VI.

Although put-call parity would suggest identical implied volatility levels for these calls and puts, our results show higher implied volatility levels for put options, reflected in negative implied volatility differences.

Most interesting is the finding that put implied volatilities are highest relative to call implied volatilities at the highest implied volatility levels. These consistently higher prices for put options, relative to call options, are more evidence that put options are overpriced when implied volatilities are high, but are also evidence that call options are priced more efficiently under high implied volatility conditions. We find negative differences in the low implied

TABLE VI
Put/Call Implied Volatility Differences by Implied Volatility

Panel A: Buying Puts With 32 Days Until Expiration

	Put WIV 32-Day Q1	*Put WIV 32-Day Q2*	*Put WIV 32-Day Q3*	*Put WIV 32-Day Q4*	*Put WIV 32-Day Q5*
Closest OTM put, mean	−0.007	−0.009	−0.011	−0.017	−0.034
n	16,726	16,844	16,835	16,838	16,765
2nd closest OTM put, mean	−0.008	−0.012	−0.017	−0.023	−0.045
n	6612	6722	6720	6720	6645

Panel B: Buying Puts With 62 Days Until Expiration

	Put WIV 62-Day Q1	*Put WIV 62-Day Q2*	*Put WIV 62-Day Q3*	*Put WIV 62-Day Q4*	*Put WIV 62-Day Q5*
Closest OTM put, mean	−0.006	−0.009	−0.011	−0.015	−0.034
n	8461	8568	8561	8568	8496
2nd closest OTM put, mean	−0.005	−0.010	−0.012	−0.019	−0.039
n	4485	4596	4584	4595	4522

Panel C: Buying Puts With 92 Days Until Expiration

	Put WIV 92-Day Q1	*Put WIV 92-Day Q2*	*Put WIV 92-Day Q3*	*Put WIV 92-Day Q4*	*Put WIV 92-Day Q5*
Closest OTM put, mean	−0.007	−0.009	−0.010	−0.012	−0.030
n	8953	9071	9065	9069	8996
2nd closest OTM put, mean	−0.007	−0.008	−0.011	−0.015	−0.036
n	5343	5430	5454	5430	5382

In this table, we consider put versus call implied volatility discrepancies, based on the underlying level of put, open-interest weighted implied volatilities (WIV). On the day each month where options are available with exactly 32 (62, 92) days until expiration we consider the relative implied volatilities of calls and puts with identical strike prices in Panel A (Panels B and C). On each observation date, we find the out-of-the-money (OTM) put available that is closest to at-the-money status and denote this option the "closest" match. If possible, we also consider descending strike price options in search of a "second closest" OTM put match. Thus, the matching call options for determining the differences in implied volatility are generally the in-the-money (ITM) call option closest to ATM status and the ITM call option second closest to ATM status. We take the simple difference of the implied volaties of the corresponding call and put options (IVCall-IVPut). We calculate the mean values of these differences per quintile of our original measure, WIV (open-interest weighted implied volatility of puts). To be included in the sample, the put options of observations must have initial Optionmetrics open interest of at least 100 and midpoint prices of at least $0.25. Underlying stocks must trade on the NYSE, NASDAQ, or AMEX, have CRSP share codes of 10 or 11, and have prices of at least $5 for an observation to be included. The sample period is from January, 1996 through September, 2013.

volatility quintile as well, but they are small in magnitude and consistent with past works, suggesting normal hedging pressure causes put options to be slightly more expensive than call options. Smaller implied volatility differences when implied volatilities are low, coupled with poor put option returns, suggest that an anchoring bias may also be present for call options. Uninformed option investors tend to buy call options. These investors may also see low absolute pricing as an attractive investment due to improperly considering the lower probability of price movements large enough to profit.

TABLE VII
Put Option Prices by Implied Volatility

Panel A: Means of (Put Price/Underlying Price), Puts With 32 Days Until Expiration					
	WIV 32-Day Q1	*WIV 32-Day Q2*	*WIV 32-Day Q3*	*WIV 32-Day Q4*	*WIV 32-Day Q5*
Closest OTM P/stock price	0.013	0.018	0.023	0.029	0.043
n	16,726	16,844	16,835	16,838	16,765
2nd closest OTM P/stock price	0.009	0.013	0.017	0.022	0.032
n	6612	6722	6720	6720	6645
Panel B: Means of (Put Price/Underlying Price), Puts With 62 Days Until Expiration					
	WIV 62-Day Q1	*WIV 62-Day Q2*	*WIV 62-Day Q3*	*WIV 62-Day Q4*	*WIV 62-Day Q5*
Closest OTM P/stock price	0.019	0.026	0.032	0.041	0.059
n	8461	8568	8561	8568	8496
2nd closest OTM P/stock price	0.013	0.017	0.021	0.028	0.041
n	4485	4596	4584	4595	4522
Panel C: Means of (Put Price/Underlying Price), Puts With 92 Days Until Expiration					
	WIV 92-Day Q1	*WIV 92-Day Q2*	*WIV 92-Day Q3*	*WIV 92-Day Q4*	*WIV 92-Day Q5*
Closest OTM P/stock price	0.024	0.032	0.041	0.051	0.072
n	8953	9071	9065	9069	8996
2nd closest OTM P/stock price	0.015	0.021	0.027	0.034	0.049
n	5343	5430	5454	5430	5382

In this table, we consider the relative prices of out-of-the-money (OTM) put options to their underlying stock prices based on the level of open-interest weighted put option implied volatility (WIV). Put prices are expressed as a proportion of each put's underlying stock price. Mean relative put prices are shown after splitting the sample into WIV quintiles. WIV is calculated based on all puts with exactly 32 (62, 92) days until option expiration in Panel A (Panels B and C). The WIV quintiles are created, each month, by segmenting the sample of firm dates into equal quintiles based on the put open-interest WIV. On each observation date, we find the out-of-the-money (OTM) put available that is closest to at-the-money status and denote this option the "closest" match. If possible, we also consider descending strike price puts in search of a "second closest" OTM put match. To be included in the sample, put matches must have initial Optionmetrics open interest of at least 100 and initial midpoint prices of at least $0.25. Underlying stocks must trade on the NYSE, NASDAQ, or AMEX, have CRSP share codes of 10 or 11, and have prices of at least $5 for an observation to be included. The sample period is from January, 1996 through September, 2013.

Table VII presents the average cost of hedging as a percentage of underlying asset prices. As in Tables III and IV, observations are sorted into quintiles based on implied volatilities. The mean percentage of underlying asset price that the put option premium represents is then presented within each quintile for the 32-, 62- and 92-day-to-expiration options nearest ATM status and one strike price lower.

Table VII presents an easily interpretable representation of the cost of hedging. In Table IV, we observed the relatively poor returns of put options for firm days in the lowest and highest implied volatility quintiles. While it is clear that option returns are poor, examining the cost of hedging as a percentage of underlying asset prices is also telling. Using OTM puts closest to ATM status in the highest implied volatility quintiles, the cost of a 32-day hedge is

4.3% of underlying asset value. About 62- and 92-day premiums are 5.9% and 7.2% of underlying asset value, respectively. This is a striking result as hedging repeatedly over a 1-year period using 92-day options, the cheapest method, would cost over 28.8% of underlying asset value when implied volatilities are at their lowest.

When implied volatilities are high, overly costly hedging can also be observed by examining changes in percentage prices from low to high WIV quintiles. If we consider options nearest the money with 92 days to expiration, the cost of hedging in the lowest implied volatility quintile is 2.4%, on average. As we move to the second, third, and fourth WIV quintiles, the percentage prices increase to 3.2%, 4.1%, and 5.1%, respectively. When moving from the fourth quintile to the highest quintile, the average percentage price increases substantially from 5.1% to 7.2%, a change more than twice as large as moving from any other quintile to the next. In all cases, price changes are reasonably monotonic until moving from the fourth to fifth WIV quintile when this large increase is observed. When considering option prices as a percentage of underlying asset prices, it becomes very clear that hedging is extremely expensive when implied volatilities are relatively high.

It is more difficult to demonstrate the relative expensiveness of hedging when implied volatilities are low because, by construction, put option premiums represent the lowest percentage of underlying asset price in this case. We, however, observe strong evidence of anchoring. The costs of hedging for 32-, 62-, and 92-day puts, respectively, using OTM options closest to ATM status are 0.9%, 1.3%, and 1.5%, respectively. Though the cost of hedging as a percentage of underlying asset value is very low, the expected return for these options is poor, as shown in Table IV.[14]

Table VII presents further evidence that investors fearing poor performance for individual equities due to high future volatility may be better served to exit positions, if possible, when implied volatilities are extremely high. In this environment, extremely large positive returns would be necessary to overcome the cost of the hedge. An investor with a minimal level of sophistication who is concerned that a large price decrease will occur would be unlikely to simultaneously judge the probability of a large price increase to be high enough to justify hedging in this environment.

Table VIII presents put options returns as in Table IV, but rather than sorting the sample based on weighted implied volatilities, days are sorted by the VIX market volatility index. Rather than using relative levels of firm implied volatilities to divide firm days, market implied volatility is used to characterize the general volatility sentiment in the market. The findings in Table VIII are consistent with those in Table IV in that options in the extreme VIX quintiles tend to significantly underperform those in the middle three quintiles. In 10 of 12 cases, average extreme quintile returns are lower than the average for the middle three quintiles, and eight of these differences are significant. This less careful division of firm days suggests previously presented results are robust and also provides some evidence that when VIX is high or low many put options are overpriced. Option sellers benefit in these cases due to behavior biases of options buyers.

Panel A of Table IX presents averages of time series returns for portfolios formed by taking long positions in put options with implied volatilities in low (WIVQ1), middle (WIVQ2 through WIVQ4), and high (WIVQ5) quintiles of implied volatilities. As in previous analysis, we examine OTM options with moneyness closest and second closest to ATM and 32, 62, and 92 days maturities. For each period, the return of all options in quintile groups are averaged to form the equal-weighted portfolio mean returns. Averages of these time series returns for these three portfolios are presented for each of the six maturity/moneyness groups (18 portfolios total). In addition, in each return period, we calculate differences between the "middle" portfolio returns (WIVQ2–WIVQ4) and both the high (WIVQ5) and low (WIVQ1) portfolio returns and report the means of these differences in the last two columns of Panel A.

[14]For all tables, results for ATM options are consistent with those presented for one strike price OTM options.

TABLE VIII
Put Option Returns by VIX

Panel A: Buying Puts With 32 Days Until Expiration and Holding 30 Days							
	VIX Q1	*VIX Q2*	*VIX Q3*	*VIX Q4*	*VIX Q5*	*Q1−Q(2–4)*	*Q5−Q(2–4)*
Closest OTM put mean	−0.319	0.031	0.134	−0.289	−0.037	−0.278***	0.004
n	16,784	16,627	17,307	16,362	16,928		
2nd closest OTM put mean	−0.235	0.135	−0.104	−0.354	0.029	−0.127	0.137
n	6687	6711	6744	6586	6691		
Panel B: Buying Puts With 62 Days Until Expiration and Holding 60 Days							
	VIX Q1	*VIX Q2*	*VIX Q3*	*VIX Q4*	*VIX Q5*	*Q1−Q(2–4)*	*Q5−Q(2–4)*
Closest OTM put mean	−0.380	0.053	0.088	−0.231	−0.312	−0.350***	−0.282**
n	8571	8460	8560	8546	8517		
2nd closest OTM put mean	−0.470	0.165	0.360	−0.429	−0.161	−0.502***	−0.193
n	4762	4361	4567	4528	4564		
Panel C: Buying Puts With 92 Days Until Expiration and Holding 90 Days							
	VIX Q1	*VIX Q2*	*VIX Q3*	*VIX Q4*	*VIX Q5*	*Q1−Q(2–4)*	*Q5−Q(2–4)*
Closest OTM put mean	−0.350	−0.262	0.237	0.081	−0.373	−0.369***	−0.392***
n	9125	9191	9079	8699	9060		
2nd closest OTM put mean	−0.392	−0.213	0.299	0.219	−0.384	−0.494***	−0.486***
n	5448	5369	5400	5471	5351		

In this table, we consider OTM put option returns, based on the underlying level of VIX. VIX is noted on relevant days from the CBOE website when there are put options with exactly 32 (62, 92) days until expiration in Panel A (Panels B and C). The VIX quintiles are created by pooling all observations. On each observation date, we find the out-of-the-money (OTM) put available that is closest to at-the-money status and denote this option the "closest" match. If possible, we also consider descending strike price puts in search of a "second closest" OTM put match. To be included in the sample, put matches must have initial Optionmetrics open interest of at least 100 and initial midpoint prices of at least $0.25. Underlying stocks must trade on the NYSE, NASDAQ, or AMEX, have CRSP share codes of 10 or 11, and have prices of at least $5 for an observation to be included. *** and ** denote statistical significance at the 1% and 5% levels, respectively, for the difference of means tests comparing VIX quintile 1 and VIX quintile 5 performance, respectively, to the performance of puts in VIX quintiles 2–4. The sample period is from January, 1996 through September, 2013.

Returns for each of the 18 put option portfolios are negative and statistically significant at the 1% level. All 12 of the difference in mean tests are positive, and 8 of them are significant at least at the 5% level. Consistent with earlier results, only one of four average differenced returns are significant for the shortest term options with average monthly returns ranging from 1.1% to 6.8%. Seven of eight average differenced returns are positive when longer term options are used. Average monthly differenced returns for portfolios using 62-day options, calculated by dividing average period returns by two, range from 1.4% to 5.3%. For 92-day options, dividing average period returns by three, average monthly differenced returns range from 2.0% to 4.6%. Overall, average monthly returns for difference-in-portfolios means are 3.4% per month. These results suggest that taking short positions in inefficiently priced WIVQ1 and WIVQ5 options and long positions in options from WIVQ2-4 is potentially a highly profitable trading strategy.[15]

[15]Although higher returns may be earned on average by simply shorting Q1 or Q5 options compared to long-short portfolio returns, this would be a riskier strategy that would not be hedged in any manner.

TABLE IX
Time Series of Option Portfolio Returns

Panel A

32-Day Put Returns

OTM Match	*Q1*	*Q(2–4)*	*Q5*	*Q(2–4)–Q1*	*Q(2–4)–Q5*
Closest	−0.183***	−0.115***	−0.149***	0.068**	0.034
t-statistic	(−11.55)	(−8.85)	(−10.27)	(2.50)	(1.55)
2nd-closest	−0.222***	−0.186***	−0.197***	0.036	0.011
t-statistic	(−14.68)	(−10.10)	(−12.42)	(1.18)	(0.77)

62-Day Put Returns

	Q1	*Q(2–4)*	*Q5*	*Q(2–4)–Q1*	*Q(2–4)–Q5*
Closest	−0.241***	−0.150***	−0.197***	0.091***	0.047***
t-statistic	(−16.74)	(9.20)	(−12.75)	(4.15)	(2.87)
2nd-closest	−0.244***	−0.138***	−0.166***	0.106***	0.028
t-statistic	−(12.93)	(−7.62)	(−9.83)	(6.29)	(1.25)

92-Day Put Returns

	Q1	*Q(2–4)*	*Q5*	*Q(2–4)–Q1*	*Q(2–4)–Q5*
Closest	−0.225***	−0.144***	−0.204***	0.081***	0.060**
t-statistic	(−14.09)	(−11.16)	(−13.45)	(2.78)	(2.30)
2nd-closest	−0.258***	−0.119***	−0.201***	0.139***	0.082***
t-statistic	(−13.70)	(−7.98)	(−10.35)	(5.99)	(3.04)

Panel B

Panel B1: WIV Quintile 32-Day Put Option Long-Short Portfolios' Risk-Adjusted Returns

	Closest OTM Match, Q(2–4)–Q1	*t-Statistic*	*2nd-Closest OTM Match, Q(2–4)–Q1*	*t-Statistic*	*Closest OTM Match, Q(2–4)–Q5*	*t-Statistic*	*2nd-Closest OTM Match, Q(2–4)–Q5*	*t-Statistic*
α	0.031***	(3.12)	0.040*	(1.71)	0.022	(1.01)	0.019	(0.77)
Mkt – Rf	14.227***	(15.23)	7.025***	(13.49)	10.125***	(14.88)	6.211***	(11.79)
SMB	3.103**	(2.14)	1.663	(1.20)	5.495***	(5.01)	2.740***	(2.67)
HML	−3.175*	(−1.81)	−1.41	(−0.94)	−1.304	(−0.83)	−0.676	(−0.45)
RMW	7.236***	(3.27)	2.556***	(3.08)	−1.157	(−0.97)	−0.524	(−0.38)
CMA	4.164**	(1.99)	1.359	(1.28)	−0.945	(−0.55)	−0.492	(−0.34)
ORF	−0.524***	(−7.14)	−0.317***	(−6.693)	−0.251***	(−5.00)	−0.319***	(−4.99)

Panel B2: WIV Quintile 62-Day Put Option Long-Short Portfolios' Risk-Adjusted Returns

	Closest OTM Match, Q(2–4)–Q1	*t-Statistic*	*2nd-Closest OTM Match, Q(2–4)–Q1*	*t-Statistic*	*Closest OTM Match, Q(2–4)–Q5*	*t-Statistic*	*2nd-Closest OTM Match, Q(2–4)–Q5*	*t-Statistic*
α	0.057***	(6.70)	0.069***	(4.04)	0.039***	(2.99)	0.024	(1.61)

continued

TABLE IX
(Continued)

Panel B2: WIV Quintile 62-Day Put Option Long-Short Portfolios' Risk-Adjusted Returns

	Closest OTM Match, Q(2–4)–Q1	*t-Statistic*	*2nd-Closest OTM Match, Q(2–4)–Q1*	*t-Statistic*	*Closest OTM Match, Q(2–4)–Q5*	*t-Statistic*	*2nd-Closest OTM Match, Q(2–4)–Q5*	*t-Statistic*
Mkt – Rf	10.485***	(14.79)	9.74***	(15.86)	6.226***	(11.71)	4.983***	(8.20)
SMB	2.298**	(2.38)	1.325	(0.91)	5.959***	(6.21)	2.872***	(2.94)
HML	−1.274	(−0.91)	0.984	(0.55)	−0.035	(−0.02)	0.348	(0.34)
RMW	4.371***	(3.66)	2.055**	(2.43)	−2.018*	(−1.66)	−1.025	(−0.97)
CMA	1.773	(1.06)	0.835	(0.59)	−1.935	(−1.00)	−1.448*	(−1.65)
ORF	−0.813***	(−13.55)	−0.558***	(−10.72)	−0.287***	(−4.85)	−0.258***	(−4.16)

Panel B3: WIV Quintile 92-Day Put Option Long-Short Portfolios' Risk-Adjusted Returns

	Closest OTM Match, Q(2–4)–Q1	*t-Statistic*	*2nd-Closest OTM Match, Q(2–4)–Q1*	*t-Statistic*	*Closest OTM Match, Q(2–4)–Q5*	*t-Statistic*	*2nd-Closest OTM Match, Q(2–4)–Q5*	*t-Statistic*
α	0.036***	(3.75)	0.088***	(8.22)	0.040***	(3.73)	0.055***	(5.50)
Mkt – Rf	12.189***	(14.87)	7.303***	(12.94)	7.356***	(10.02)	4.246***	(8.57)
SMB	3.119***	(2.97)	1.444	(1.45)	4.017***	(5.36)	2.539***	(3.26)
HML	−1.659	(−1.00)	0.446	(0.22)	−0.477	(−0.56)	0.099	(0.09)
RMW	3.977***	(3.32)	2.866**	(2.52)	−0.453	(−0.64)	−0.202	(−0.27)
CMA	0.836	(0.55)	−0.381	(−0.29)	−0.942	(−0.95)	−1.075	(−1.49)
ORF	−0.752***	(−10.27)	−0.589***	(−9.94)	−0.356***	(−5.24)	−0.239***	(−4.47)

Panel A of this table presents times series mean returns of portfolios of options constructed by purchasing the put options in the appropriate quintile of implied volatilities. The last two columns present the differences in means between the middle quintiles and the end quintiles. Panel B displays the results from regressing these returns of long-short portfolios on the factor model presented in Equation (2). The portfolios are formed by taking long positions in put options with implied volatilities in quartiles 2 through 4 (Q2–4) and shorting either the put options in the lowest quintile (WIVQ1) or highest quintile (WIVQ5). Results are presented for OTM options with moneyness closest and second closest to ATM and 32, 62, and 92 days maturities. Options are purchased at the ask price and sold at the bid price to account for transaction costs. The factor model is a Fama-French (2015) five-factor model augmented with a systematic option return factor, ORF, which is the returns of an ATM straddle on the S&P 500. There are 213 monthly observations (January 1996 through September 2013) in each regression estimation. Robust *t*-statistics are presented in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table IX Panel B presents the results from regressing the returns of long-short put options portfolios on the factor model presented in Equation (2). The portfolio returns represent the profits from a self-funding trading strategy that is long put options with implied volatilities in quintiles 2 through 4 (WIQ2–WIV4) and short either the put options in the lowest quintile (WIVQ1) or highest quintile (WIVQ5). The daily factor returns are compounded over the same number of days as the options are held to maintain consistency. In all maturity and moneyness strategies, the option portfolio returns load significantly on the market risk premium and also on the systematic option return factor, indicating the importance of controlling for the uniqueness of option returns. Consistent with Panel A, alphas are positive for all twelve strategies. The portfolios short options in the WIVQ1 group have five alphas statistically significant at the 1% level and one alpha at the 10% level. The alphas range from 1.2% per month (3.6%/3 months for the closest OTM 92-day options) to 4.0% per month (second closest OTM, 32-day options). This evidence supports the anchoring hypothesis in all the moneyness and maturity groups.

The portfolios short the options in the WIVQ5 group have three alphas statistically significant at the 1% level and three that are statistically insignificant. Both 32-day options strategies and the second closest OTM 62-day options strategies produce statistically insignificant alphas that range from 1.9% per month to 2.2% per month. The significant alphas, ranging from 1.95% per month (3.9%/2 months) to 1.83% per month −5.5%/3 months), reside with both the 92-day options and closest OTM 62-day option strategies, again consistent with Panel A. The results are consistent with probability weighting being more extreme in the longer term options, where actual probabilities are more difficult to discern. The result of negative abnormal returns from options with high implied volatilities is not supportive of anchoring. Anchoring would bias the implied volatility downward in this group of options, which would result in abnormally positive returns.[16]

Profits to the two trading strategies presented in Table IX are persistent over our sample period. There are a few reasonable explanations for this persistence. It is possible market participants are not aware of the mispricing created by the behavioral biases we document, or that actions of traders subject to these biases overwhelm rational traders. Assuming the market is aware of the documented inefficiencies but are unwilling to trade in a manner to eliminate abnormal returns, there are distinct possible explanations for persistent abnormal returns when implied volatilities are high and low. When implied volatilities are high, option writers may require expected returns that are disproportionately large to write these options. This may be due to concerns regarding jump events or decreased confidence with estimates for future volatility. When implied volatilities and option premiums are low, option writers may view expected profits as too low relative to the inherent risk of writing options. Additionally, the option writers may bear a cost of hedging their positions in the equities market (e.g., since a put writer is synthetically long, a delta hedge would require a short equity position, which incurs borrowing costs). Thus, arbitrageurs aware of these pricing inefficiencies do not employ enough capital to correct the mispricing because they perceive the costs or risks as too high.

4. CONCLUSION

We extend prior research by demonstrating the presence of anchoring and cumulative prospect theory (CPT) in option prices. Equity option market investors anchor to prices and incorporate a probability weighting function similar to that proposed by CPT, that is, overestimating the chance of low probability events. The presence of these biases causes put option prices to be inefficiently high, thus leading to large negative option returns. From a hedging or portfolio insurance perspective, the price of insurance via put options is unduly high when implied volatilities are low (and investors anchor to higher prices near the mean price) and when implied volatilities are high (and fearful investors overestimate the probability of a large price decrease).

Implied volatilities are higher (lower) when options are more (less) likely to be exercised, showing some rationality in the pricing of put options. However, prices are generally too high when implied volatilities are either very low or very high. This is evidenced by the most negative option returns for 30-, 60-, and 90-day options occurring in the highest and lowest weighted implied volatility quintiles, compared to put options with similar moneyness status and maturities but with implied volatilities closer to the mean. Further evidence is present when comparing implied volatility to future realized volatilities.

When implied volatilities are low, we find evidence of inefficient pricing through anchoring due to investors failing to properly adjust the implied volatility away from the

[16]This implication is analogous to the 52-week high anomaly in equities documented by George and Hwang (2004).

mean. By biasing the price upward and not lowering the implied volatility enough, the resulting returns are quite negative. A trading strategy that shorts put options with the lowest implied volatilities and purchases put options with implied volatilities closer to the mean earns an average monthly risk-adjusted alpha of 3.4% per month.

When implied volatilities are high, we explain high prices with CPT where investors improperly weight the probability of a large price decrease. As implied volatilities increase, investors are more fearful of price decreases and will tend to purchase more options. Higher option prices should have an offsetting effect. However, CPT suggests the first effect will dominate the second as investors will overestimate the chance of a large price decrease and purchase more put options, driving up prices to a level which leads to poor returns. A trading strategy that shorts put options with the highest implied volatilities and purchases put options with implied volatilities closer to the mean earns an average monthly alpha of 1.7% per month. However, the alphas are only significant with longer term maturities where probabilities are more difficult to determine and, thus, weighted probabilities are more likely to deviate from actual probabilities.

Overall, our results show that put option prices are inefficiently high when implied volatility levels are at either extreme and provide evidence that this consistent with the behavioral theories of anchoring and CPT. Prices at extreme implied volatility levels cannot be justified by realized volatilities nor exercise probabilities.

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