Does the options market underreact to firms' left-tail risk?*

Bei Chen† Quan Gan‡ Aurelio Vasquez§

March 2022

Abstract

We find that firms' left-tail risk is a strong positive predictor of future returns of bear spreads, an option trading strategy that provides downside protection on the underlying. Bear spreads of high (low) left-tail risk firms earn positive (negative) returns, suggesting that the downside protection they provide is not adequately priced and the options market underreacts to firms' left-tail risk. This underreaction is stronger when the underlying stocks experience larger recent losses and are closer to their 52-week lows, and when information uncertainty and investor sentiment are high. Our finding is consistent with a behavioral rather than a risk-based explanation.

Keywords: Bear spread, Left-tail risk, Behavioral bias, Equity options, Underreaction

JEL Classification: G12, G13, G14

*The authors thank seminar participants at Tongji University, University of Sydney, and ITAM; conference participants of the Cancun Derivatives Workshop 2022; Chu Zhang, for helpful comments. Vasquez thanks the Asociación Mexicana de Cultura A.C. for financial support. Correspondence to: Quan Gan, Email: quan.gan@sydney.edu.au, Phone: +61 2 9114 0831.

†Discipline of Finance, School of Business and Management, Shanghai International Studies University. Email: beichen.finance@shisu.edu.cn.

‡Discipline of Finance, the University of Sydney Business School, the University of Sydney; Email: quan.gan@sydney.edu.au; Phone: +61 2 9114 0831; Fax: +61 2 9351 6461.

§Business School, ITAM; Email: aurelio.vasquez@itam.mx; Phone: +52 55 5628 4000.

1 Introduction

Loss aversion plays an important role in economic decisions. The utility of a loss-averse investor is steeper for losses than for gains (Kahneman and Tversky, 1979; Tversky and Kahneman, 1991). Berkelaar et al. (2004) and Jarrow and Zhao (2006) show that optimal portfolios for loss-averse investors include hedge and insurance against left-tail risk. The hedging demand of left-tail risk impacts asset prices. A growing body of literature investigates the impact of left-tail risk on the cross section of stock returns. Lu and Murray (2019) use bear spread returns constructed from Standard & Poor's (S&P) 500 index options to capture bear market risk and find that it is priced in the cross section of stock returns. Kelly and Jiang (2014) construct a tail risk factor by identifying the common fluctuation of crash events for individual firms and find that stocks with higher loadings on the tail-risk factor earn higher future returns. By contrast, Atilgan et al. (2020) show that the risk-return tradeoff between firms' left-tail risk and stock returns breaks down as firms' left-tail risk and future stock returns have a negative relation, generating the "left-tail momentum." The left-tail momentum indicates that equity investors underreact to firms' left-tail risk.

In this paper, we present evidence of underreaction to firms' left-tail risk in the equity option market by analyzing the cross-section of bear spreads returns. A bear spread, more specifically a bear put spread, is an option strategy that provides downside protection on the underlying asset. We document a positive relation between firms' left-tail risk and future bear spread returns. The portfolio with the lowest left-tail risk reports negative bear spread returns, while that with the highest left-tail risk earns positive bear spread returns. The long-short bear spread portfolio earns a monthly raw return ranging between 0.74% to 1.04% with t-statistics between 2.26 and 3.60 depending on the left-tail measure we use.

These results are robust to different methodologies and control variables. Control variables include firm characteristics such as size, book-to-market, Carhart (1997) illiquidity measure, variance risk premium and vol-of-vol, among others. We also control for ex-ante exposures of individual bear spread returns to systematic factors and left-tail factors. Using double sorts and Fama and MacBeth (1973) regressions, we show that the positive relation between bear spread returns and left tail risk is robust to all control variables. Our results also hold across different time periods, portfolio weighting schemes, daily delta-hedging, alternative definitions of the bear spread, modified Fama and MacBeth (1973) regressions proposed by Brennan et al. (1998) and the weighted least squares parameter estimation proposed by Asparouhova et al. (2013). Finally, the long-short bear spread strategy remains profitable once we account for transaction costs such as margin requirements and effective to quoted bid-ask spreads of the magnitude paid by algorithmic traders.

The large, positive long-short bear spread returns potentially represent a compensation for risk. We risk-adjust the long-short returns with equity factors, option factors, and left-tail risk factors. Equity factors include the Fama and French (1993) three factors and the Carhart (1997) momentum factor. For option factors we use the zero-beta straddle S&P 500 return proposed by Coval and Shumway (2001), the jump and volatility factors from Cremers et al. (2015), and four factors computed from the cross-section of option returns: illiquidity (Cao et al., 2022), and size, idiosyncratic volatility, and variance risk premium (Horenstein et al., 2020). Finally, bear spread portfolio returns are risk adjusted using four systematic left-tail factors: AD-Bear factor (Lu and Murray, 2019), tail risk factor (Kelly and Jiang, 2014), downside factor (Ang et al., 2006a), and a factor constructed using coskewness from Harvey and Siddique (2000). The alphas of the long-short bear spread return remain positive and significant after risk-adjusting for all these factors and are of higher magnitudes than the raw returns. Therefore, a risk-based explanation does not explain our findings.

We explore several behavioral explanations to our main finding. First, investors may underestimate the persistence of losses and underprice the risk protection provided by bear spreads. Atilgan et al. (2020) show that the left-tail momentum is stronger for stocks that experience recent large losses. They argue that investors anticipate short-term stock price mean-reversion and underestimate the persistence in left-tail risk. Empirical evidence (Driessen et al., 2013; George and Hwang, 2004) also shows that stock losses persist and option implied volatilities decrease, when stock prices are close to their 52-week low. Investors with anchoring bias underestimate the probability of downward breakthroughs toward new 52-week lows. We find that the positive relation between firms' left-tail risk and future bear spread returns is stronger when the underlying stocks experience large recent losses (left-tail momentum effect) and when stock prices are close to their 52-week low (anchoring effect). The anchoring effect alone may not offer an explanation to our main finding. But together with the left-tail momentum effect, we have strong evidence that investors' underestimation of loss persistence is one of the main sources to the underpricing of bear spreads on high left-tail risk stocks.

Second, information uncertainty may contribute to the underreaction to firms' left-tail risk. Hong et al. (2000) show that firm-specific, negative information difusses slowly and generates stock return momentum. Zhang (2006a,b) finds that information uncertainty amplifies investors' and analysts' underreaction to new information and causes greater price drift. We find that the underreaction to firms' left-tail risk is more pronounced when information uncertainty of a firm is higher. When information uncertainty is high, rational investors should demand more downside protection rather than less. Our finding of stronger bear spread underpricing when information uncertainty is high suggests that behavioral biases might be driving the underpricing.

Last, we explore whether investor sentiment explains the underpricing of bear spreads. High investor sentiment may reduce the perceived value of downside protection, causing underpricing of bear spreads. The literature shows that high investor sentiment may cause unwarranted investor optimism, overvalued stocks, and underestimated risk. Yu and Yuan (2011) find that the positive mean-variance tradeoff breaks down during high market sentiment periods. Stambaugh et al. (2012) show that a large set of anomalies in cross-sectional stock returns are amplified by high investor sentiment. Han (2008) shows that risk hedging demand, reflected by index options' implied volatility smile and risk-neutral skewness, decreases when market sentiment is high. Using the market-based sentiment index by Baker and Wurgler (2006), we find that the underreaction to firms' left-tail risk mainly happens in high investor sentiment periods. Prior literature shows that high sentiment leads to stronger overpricing of risky assets (Baker and Wurgler, 2006; Byun and Kim, 2016; Stambaugh et al., 2012). We show, as two sides of the same coin, that high sentiment also leads to stronger underpricing of bear spreads, an option strategy providing downside protection.

Our rationale of using bear spreads instead of out-of-the-money (OTM) or deep-out-of-the-money (DOTM) put options to examine left-tail risk is similar to that of Lu and Murray (2019). Bear spread, as a popular option trading strategy, is frequently used to hedge against left-tail risk. A bear spread is comprised of opposite positions in two put options. The long-short positions help mitigate the options market forces that simultaneously impact options at different strike prices. For example, Garleanu et al. (2008) show that demand pressure could cause positively correlated option price deviations from the fundamental values across strike prices. Using OTM or DOTM options alone is more prone to such options market forces and thus provides less desirable identification of left-tail risk. Moreover, from the option valuation point of view, OTM or DOTM option prices are determined by the relevant discounted conditional expectation times the tail probability, using the risk-neutral probability measure (Bates, 1991). Therefore, OTM or DOTM option prices not only capture the tail probability, but also capture the expected tail distribution of the underlying asset price. By contrast, the scaled bear spread price can be interpreted as the discounted tail probability, representing the Arrow-Debreu state price of left-tail events that is comparable in the cross-section.

Our study contributes to the growing literature of tail risk and asset prices (Atilgan et al., 2020; Campbell et al., 2008; Chabi-Yo et al., 2018; Kelly and Jiang, 2014; Lu and Murray, 2019; Van Oordt and Zhou, 2016). We document a positive relation between firms' left-tail risk and future bear spread returns. Contingent claims traded in the options market offer unique opportunities to isolate, hedge, and analyse tail risk. Using the bear spread option strategy, we show that the risk-return tradeoff breaks down as the options market underreacts to firms' left-tail risk. Option traders' behavioral biases help explain such underreaction.

Our study highlights that although investors frequently emphasize the importance of tail risk management, the protection against downsides is likely underpriced in the options market. The underpricing of bear spreads shows that adequately pricing tail risk in financial markets is more challenging than merely recognizing its importance.

The remainder of the paper proceeds as follows. Section 2 describes the data and the construction of bear spreads. Section 3 presents the main empirical results. In Section 4, we analyse potential explanations for the main findings. Section 5 presents further discussion and Section 6 concludes.

2 Data

2.1 Sample construction

Our sample period is from January 1996 to December 2017. We obtain stock price and accounting data from the Center for Research in Security Prices (CRSP) and Compustat. Option data are from OptionMetrics, which include daily closing bid and ask prices, open interest, volume, implied volatility, and option Greeks. To avoid the bid–ask bounce, the mid points of bid and ask prices are used to compute option returns.

Following previous literature (e.g. Kelly and Jiang (2014), Gao et al. (2018), and Ruan (2020)), five filters are applied to the option data: (1) The option prices are at least \$0.125; (2) the underlying stock prices are at least \$5; (3) options must have nonmissing bid and ask price quotes and positive open interests; (4) bid and ask prices must satisfy basic arbitrage bounds to filter out erroneous observations and arbitrage boundaries include: bid $>$ 0, bid $<$ ask, bid $\leq$ strike and ask $\geq$ max(0, strike price – stock price); (5) options' embedded leverage calculated following Frazzini and Pedersen (2012) is not in the top or bottom 1% of the distribution.

2.2 Bear spread construction and return

A bear spread is constructed by taking a long position in one OTM put option, denoted as PUT_1, with price P_1, strike price K_1 and delta Δ_1 and a short position in a further OTM put option, denoted as PUT_2, with price P_2, strike price K_2 and delta Δ_2 ($K_1 > K_2$ and $\Delta_1 < \Delta_2$). The bear spread generates a payoff of $K_1 - K_2$ when the stock price at expiration is below K_2 and zero when the stock price at expiration is above K_1. The bear spread payoff linearly decreases from $K_1 - K_2$ to zero when the stock price is between K_2 and K_1.

Choosing K_1 and K_2 in empirical studies deserves careful consideration. As discussed in Lu and Murray (2019), if the bear region boundary K_2 is set to be at a constant percentage below the forward price, the bear region would correspond to left-tail events with different probability when the underlying assets possess different volatility levels. To address this issue, for index option bear spreads, Lu and Murray (2019) set K_2 and K_1 to be 1.5 and 1 standard deviations below the index forward price.

Since equity options have more sparse strike prices compared to index options, we use option deltas instead of strike prices to select put options in bear spreads. Extensive literature uses Black-Scholes deltas to identify options with the same moneyness across assets as the absolute delta approximates the probability that an option will be in the money at expiration (Bali and Murray, 2013; Bollen and Whaley, 2004; Driessen et al., 2009; Jin et al., 2012; Kelly et al., 2016a,b).

The typical ranges of OTM and DOTM put option deltas are $[-0.40, -0.20)$ and $[-0.20, 0]$ (e.g. Kelly and Jiang (2014); Muravyev (2016)). We construct bear spreads with a long (short) position in PUT_1 (PUT_2) as the OTM (DOTM) put option with Δ_1 (Δ_2) closest to -0.30 (-0.10), the midpoint of the OTM (DOTM) delta range. Our results hold when we consider using a simple average or a kernel-weighted average of put options with deltas between $[-0.40, -0.20)$ and $[-0.20, 0]$ as reported in Table 8.

A bear spread has a negative delta $(\Delta_1 - \Delta_2)$, embedding an equivalent short position in the underlying stock. Therefore, unhedged bear spread returns also capture movements of the underlying stock. Atilgan et al. (2020) document a negative relation between stocks' left-tail risk and their future returns, the left-tail momentum. To remove the contribution of the underlying stocks' left-tail momentum, we use delta-hedged bear spreads in our empirical tests.[1] We use static delta-hedging as is done in other equity option studies (Bali and Murray, 2013; Byun and Kim, 2016; Goyal and Saretto, 2009).[2] Following Goyal and Saretto (2009) and Kelly and Jiang (2014), we use one-month options to construct bear spreads, and form delta-hedged bear spreads on the first trading day immediately following the third Saturday in month t and close all positions at the option maturity on the third Friday in month $t+1$.

[1] Lu and Murray (2019) show in a theoretical model that delta-hedged bear spread returns expose only to the left-tail risk. We empirically confirm that the predictability of the right-tail measure is subsumed by the left-tail measure as reported in Table IA1 in the Internet Appendix.

[2] Our results are robust to daily delta-hedging as reported in Table 8.

The return of the bear spread over $[t, t+1]$ is

$$return = \frac{(\Delta_{2,t} - \Delta_{1,t})S_{t+1} + max(K_1 - S_{t+1}, 0) - max(K_2 - S_{t+1}, 0)}{(\Delta_{2,t} - \Delta_{1,t})S_t + P_1 - P_2} - 1,$$

where P_1 (P_2), $\Delta_{1,t}$ ($\Delta_{2,t}$), and K_1 (K_2) are the price, delta, and strike price of PUT1 (PUT2), the OTM (DOTM) put at time t, and S_t (S_{t+1}) is the price of the underlying stock at time t ($t+1$, maturity).

Our sample consists of $155,003$ cross-sectional monthly returns of delta-hedged bear spreads.

2.3 Left-tail risk measures

We estimate left-tail risk using two standard measures following Atilgan et al. (2020): value-at-risk (VaR) and expected shortfall (ES). VaRx (ESx) is calculated as (the average of the observations that are less than or equal to) the x percentile of the daily returns over the past 250 trading days. As the left-tail loss measures are typically negative, we multiply these measures by -1 so that a higher value of VaR or ES corresponds to higher left-tail risk. At the portfolio formation date in month t, we compute $VaR1$, $VaR5$, $ES1$, and $ES5$ with the restriction that there are at least 200 non-missing past trading day returns.

2.4 Other variables

We construct four groups of control variables to examine the cross-section of bear spread returns. Some of these variables are commonly used when studying the cross-section of equity option returns (Bali and Murray, 2013; Byun and Kim, 2016; Cao and Han, 2013; Goyal and Saretto, 2009; Ruan, 2020).

First, we construct three variables related to firm characteristics. Firm size ($SIZE$) is the natural logarithm of the firm market capitalization observed at the end of month $t-1$. Book-to-market ratio (BTM) is the ratio of a firm's net asset's book value at the previous fiscal year-end to the market capitalization of the stock at the end of month $t-1$. Firm leverage (DTA) is the ratio of a firm's total liability to the book value of total assets at the previous fiscal year-end. Vasquez and Xiao (2020) find a negative relation between leverage and future option returns.

Second, we construct six variables related to stock returns and stock trading activities. Momentum (MOM) is the cumulative stock return from month $t-6$ to month $t-2$. Short-term reversal (REV) is the stock return in month $t-1$. Stock return skewness ($SKEW$) and kurtosis ($KURT$) are calculated using last year's daily stock return data. The two additional variables predict the cross-section of delta-hedged option returns, illiquidity and idiosyncratic volatility, according to Cao et al. (2022) and Cao and Han (2013). Illiquidity ratio ($ILLIQ$) is defined as the natural logarithm of the average ratio of the absolute daily stock return to its daily dollar trading volume multiplied by 10^8 in month $t-1$. Idiosyncratic volatility of stock returns ($IVOL$) is the standard deviation of the residuals of the daily stock excess return regressed on daily market excess return in month $t-1$.

Third, we construct three variables related to options. Variance risk premium (VRP) is the difference between the average implied volatility of ATM short-term options (with moneyness between 0.95 to 1.05 and 10 to 60 day-to-maturity) and the annualized last-quarter's daily stock return standard deviation observed at the end of month $t-1$. Goyal and Saretto (2009) show that VRP predicts future option returns. Volatility of volatility (VOV), which predicts option returns (Cao et al., 2019), is calculated following Baltussen et al. (2018) by scaling the standard deviation of ATM short-term option implied volatility by the average ATM short-term option implied volatility over month $t-1$. Risk-neutral skewness (RNS) at the end of month $t-1$ is calculated using OTM call and put options prices following Bakshi et al. (2003).

Finally, we construct six systematic risk exposure measures where three of them expose to systematic left-tail risk. These beta exposures are computed using 60-month rolling windows up to month $t-1$ where we regress the bear spread return of each firm on each of the systematic risk measures. The beta exposures to the systematic risk measures are:

- β_{Bear}: the beta exposure to the bear market risk calculated following Lu and Murray (2019)
- β_{Strad}: the beta exposure to the zero-beta straddle return of the S&P 500 computed as in Coval and Shumway (2001)
- β_{Jump} and β_{Vol}: the beta exposures to the market jump and market diffusive volatility calculated following Cremers et al. (2015)

- β_{Tail}: the beta exposure to the tail risk factor calculated following Kelly and Jiang (2014)

- $\beta_{Downside}$: the beta exposure to the downside risk factor calculated following Ang et al. (2006a)

In Section 2 of the Internet Appendix, we describe in detail the construction of each one of these beta exposures.

From option prices in the bear spread strategy, we can compute the Arrow-Debreu state price (AD-Price) of left-tail events (Lu and Murray, 2019). If we scale the option positions in the bear spread by $K_1 - K_2$, we get a price of $(P_1 - P_2)/(K_1 - K_2)$, and a payoff of \$1 when $S_T < K_2$. Therefore, the price of the scaled bear spread should be equal to $e^{-rT}\hat{\mathbb{E}}[\mathbf{1}_{\{S_T<K_2\}}]$, where $\mathbf{1}$ is the indicator function and $\hat{\mathbb{E}}$ represents the expected value under the risk-neutral probability. The scaled bear spread price can be interpreted as the discounted risk-neutral state probability of left-tail events.

We also report the relative bid-ask spread (BA Spread) of the bear spread strategy. Since the bear spread involves buying an OTM put option and selling a DOTM put option, we compute its bid-ask spread as the sum of the difference between the ask and the bid for the two put options divided by the sum of the mid prices of these two put options.

2.5 Summary statistics

[Insert Table 1 here.]

Table 1 reports summary statistics in Panel A, characteristics of decile portfolios in Panel B, and the cross-sectional correlation matrix in Panel C. Panel A presents the summary statistics for delta-hedged bear spread returns, option characteristics for the OTM put (PUT_1) and the DOTM put (PUT_2) options that make the bear spread, left-tail risk measures, control variables, and beta exposures to systematic tail-risk factors. The reported mean, standard deviation, 25th percentile, median, and 75th percentile are computed as the time-series average of their cross-sectional values.

In Panel A, both mean and median of delta-hedged bear spread returns are negative, consistent with the negative risk premium carried by the bear spreads as they provide insurance against left-tail risk. The 75th percentile is 6.77%, indicating that at least 25% of return observations are positive. The summary statistics reveal that although on average delta-hedged bear spread returns are negative, there are still substantial occurrences of positive returns.

PUT_1 (OTM put option) and PUT_2 (DOTM put option) have median deltas of -0.30 and -0.11, close to our selection targets of -0.30 and -0.10, and the standard deviations of deltas are moderately small, suggesting a satisfactory selection result of option pairs in bear spread construction. PUT_1's mean implied volatility is 48%, which is smaller than PUT_2's mean implied volatility of 53%. This is consistent with the typical shape of the volatility smirk for put options (Xing et al., 2010).

$VaR5$ ($VaR1$) has a mean of 4.24% (6.96%), implying that on average there is a 5% (1%) probability that the daily loss that a firm experiences over the following day is 4.24%

(6.96%) or higher. $ES5$ ($ES1$) has a mean of 6.15% (9.28%), which is larger than the mean of $VaR5$ ($VaR1$) as expected.

As for the summary statistics of the control variables, the median MOM and REV are of similar magnitude to those reported in Byun and Kim (2016). The median of $ILLIQ$ and $IVOL$ are also similar to those reported in Cao and Han (2013) and Atilgan et al. (2020). The average AD-Price, the cost of insurance against extreme negative returns is 21%. An AD bear security pays off $1 when its price at expiration is in a bear state. The beta exposures to systematic tail-risk factors are on average positive for bear market risk, zero-beta market straddles, jump and volatility market risk, and are negative for the market tail risk factor and the downside risk factor.

In Panel B, we report the average of the characteristics across decile portfolios sorted by $VaR5$. $VaR5$ increases from 2.1% for decile 1 to 7.5% for decile 10. Firm size is very similar across decile portfolios but book-to-market, momentum, reversal, idiosyncratic volatility, and kurtosis increase from decile 1 to decile 10. As expected, AD-Price increases from 17.6 cents for decile 1 to 26.1 cents for decile 10. As left-tail risk increases, to buy insurance against bear states becomes more expensive. Note that our research question is different from this cost of bear state insurance; we analyse the returns of these quasi-insurance contracts, the bear spread returns.

The relative bid-ask spread is very similar across decile portfolios and is very similar to its mean at around 20%. Finally, the beta exposures to the market bear spread, the jump factor, the volatility factor, and the tail factor report a monotonic pattern across decile portfolios. In Fama and MacBeth (1973) regressions and double sorts, we show that this monotonic relation does not subsume the predictability of $VaR5$ on bear spread returns.

Panel C reports the cross-sectional correlations of firm characteristics. The correlation among the four left-tail measures is high, above 75%. $VaR5$, the main left-tail measure used in our paper, displays a high correlation with firm size (-51%), Carhart (1997) illiquidity (43%), idiosyncratic volatility (60.5%), and AD-Price (44%). The correlations (in absolute value) with the relative bid-ask spread, variance risk premium, and beta exposures to systematic left tail risk are below 10%.

In summary, Table 1 shows that the left-tail risk measures appear to be related to some control variables such as firm size, illiquidity, and idiosyncratic volatility. In the next section, we attempt to establish a cross-sectional relation between left-tail measures ($VAR5$) and bear spread returns.

3 Empirical Analysis

3.1 Univariate portfolio analysis

We conduct univariate portfolio analysis to examine the relation between left-tail risk measures and future delta-hedged bear spread returns. In month t, we form decile portfolios of delta-hedged bear spreads by sorting the underlying stocks based on one of the left-tail risk measures ($VaR1$, $VaR5$, $ES1$, $ES5$). The decile 10 (decile 1) portfolio contains delta-hedged bear spreads on stocks with the highest (lowest) left-tail risk.

We report both equal-weighted and dollar-open-interest-weighted (DOI-weighted) hold-to-maturity monthly portfolio returns. The DOI weighting puts more weight on options or option strategies with higher liquidity (open interest). Our construction of DOI weighting is similar to Cao and Han (2013) and Gao et al. (2018). The dollar-open-interest weight is calculated on the bear spread formation date as the cost of each bear spread, multiplied by the minimum of the open interests of two put options in that bear spread:

$$DOI = (PUT_1 - PUT_2) \times min(PUT_{1,OI}, PUT_{2,OI}).$$

where PUT_1 (PUT_2) and $PUT_{1,OI}$ ($PUT_{2,OI}$) are the price and the open interest of the OTM (DOTM) put option. DOI captures the maximum possible dollar open interest to form a bear spread.

Table 2 reports the time-series average monthly returns for each decile portfolio, together with the return spreads between the highest and lowest ("10-1") left-tail risk decile portfolios. To adjust for serial correlation, robust Newey-West (1987) t-statistics with 4 lags are reported in parentheses.

[Insert Table 2 here.]

Both the equal-weighted and DOI-weighted delta-hedged bear spread returns increase across decile portfolios sorted by the underlying stocks' left-tail risk measures. Deciles 1 to 3 (8 to 10), the ones with low (high) left-tail risk, report negative (positive) bear spread returns in all specifications.

In the first row, decile 1 portfolio (with the lowest $VaR5$) has an average monthly return of -0.62%, while decile 10 portfolio (with the highest $VaR5$) has an average monthly return of 0.40%. Decile portfolio returns in general increase from decile 1 to decile 10. The "10-1" monthly return spread is 1.03% (t-statistic=3.60). Portfolios sorted on $VaR1$, $ES5$, and $ES1$ exhibit a similar pattern.

The DOI-weighted portfolio returns have patterns similar to those of equal-weighted returns. When sorting by $VAR5$, the "10-1" monthly return spread is 1.04% (t-statistic=2.44). The results for $VaR1$, $ES5$, and $ES1$ are similar to those for $VaR5$.

The bear spreads with bear regions concentrated in left tails provide protection against rare events such as stock price crashes. In theory, option traders should pay adequately for such protection, accept a negative risk premium, and expect negative future returns. However, empirically we find that high decile portfolios generate higher returns than low decile portfolios and the "10-1" returns are all statistically and economically significant in both panels, indicating significant underpricing of bear spreads when left-tail risk is high.

The positive relation between firms' left-tail risk and future delta-hedged bear spread returns deserves more analyses. Since the four left-tail risk measures are highly correlated, and the empirical distribution of $VaR5$ is more well-behaved in terms of being closer to normality compared to the other three measures (Atilgan et al., 2020), we present our subsequent empirical results using $VaR5$ as the key left-tail risk measure. Next we study risk-adjusted bear spread returns when sorting by $VaR5$.

3.2 Risk-Adjusted Bear Spread Returns

We now compute the risk-adjusted returns of decile portfolios and the "10-1" portfolio. The positive relation between $VaR5$ and bear spread returns could be a manifestation of some market wide risk, a systematic left-tail risk, or an option-based systematic risk.

We regress the returns of decile portfolios and the "10-1" bear spread portfolios on various specifications of linear pricing models. We include traditional equity pricing models consisting of the Fama and French (1993) three factors and the Carhart (1997) momentum factor. We also include four systematic option factors: 1) the aggregate volatility factor measured by the zero-beta S&P 500 index ATM straddle return from Coval and Shumway (2001), 2) the jump and 3) the volatility factors calculated as in Cremers et al. (2015), and 4) the VIX volatility index.

To control for systematic left-tail risk, we risk-adjust the returns with the bear market factor (AD-BEAR) computed as in Lu and Murray (2019), the tail factor by Kelly and Jiang (2014), the downside factor by Ang et al. (2006a), and a factor constructed using coskewneess following Harvey and Siddique (2000). Finally, we control for factors that explain the cross-section of option returns. These include the illiquidity factor from options by Cao et al. (2022), and three factors from options – size, idiosyncratic volatility, and variance risk premium – as suggested by Horenstein et al. (2020). The last four factors, not to be confused with the stock factors, are computed as the long-short return of decile delta-hedged option returns sorted on each characteristic. We also risk-adjust using the coskewness model by Vanden (2006) that uses the market return, the square of the market return as well as the bear spread return of the S&P 500, its square and the product of the market return and the market bear spread return. Section 1 of the Internet Appendix contains a detailed description on the construction of these factors.

We regress bear spread portfolio returns and the "10-1" return using the following model:

$$R_{pt} = \alpha_p + \beta_p^{'} F_t + \epsilon_{pt},$$

where R_{pt} is the return of decile or "10-1" portfolios, F_t are factors, β_p is the exposure of the portfolio to the factor, and α_p captures the mispricing of the portfolio relative to the factor model.

[Insert Table 3 here.]

Table 3 reports the risk-adjusted returns. All factor models include four factors (4F): the Fama and French (1993) three factors and the Carhart (1997) momentum factor. The raw return is the equal-weighted "10-1" bear spread return reported in Table 2 that is equal to 1.03% with a significant t-statistic of 3.60. The main result in Table 3 is that all the alphas of the "10-1" bear spread returns are larger in magnitude than the raw return. For example, when we control by the AD-Bear market factor, the alpha of the "10-1" portfolio is 1.25% with a significant t-statistic of 4.76.

Next, we study the exposures, β_p, of bear spread portfolios to systematic left-tail factors. Table IA2 reports the exposures of decile portfolios. This table shows that the returns of the decile portfolio sorted by $VaR5$ are not sensitive to these systematic left-tail risk factors. The betas of decile portfolios to the AD-Bear systematic factor increase from decile 1 to decile 9, but the magnitude of the beta in decile 10 is lower than that of decile 8. Moreover, the difference in betas of deciles 10 and 1 is not statistically different from zero for all but one factor, the market return.

Only the exposure β_p of bear spread decile portfolios to the market return is negative and statistically significant for all deciles. In addition, the exposures to the market return decrease across decile portfolios and the difference in betas of deciles 10 and 1 is negative and statistically significant. Decile 10, the portfolio that provides protection against firms with the highest left tail risk, has the most negative beta of all deciles. In market downturns, the portfolio with the riskiest stocks in terms of left-tail risk, decile 10, would deliver the highest return.

We conclude that stock and option systematic factors, left-tail systematic risk factors, and factors from the cross-section of option returns do not explain the "10-1" bear spread returns. The alphas for all models are larger than the raw returns. The exposures of decile portfolios to systematic factors show no consistent patterns. Only the exposures to the market factor show a monotonic relation with bear spread decile portfolio returns.

3.3 Bivariate portfolio analysis

We investigate whether the positive relation between the underlying stocks' left-tail risk measures and future bear spread returns can be explained by other variables (firm, stock, option related, or beta exposures) using the dependent (conditional) bivariate portfolio sorting method following previous studies such as Ang et al. (2006b) and Bali et al. (2011).

In month t, we form decile portfolios of delta-hedged bear spreads by sorting the underlying stocks based on one of the control variables in Section 2.4. Then, within each decile, we form decile portfolios based on the left-tail risk measure $VaR5$. Each left-tail risk decile portfolio is then averaged across the control variable deciles.

Table 4 reports equal-weighted returns of decile portfolios, together with the raw and risk-adjusted return spreads ("10-1") between the highest and lowest $VaR5$ decile portfolios. Newey-West (1987) t-statistics are reported in parentheses.

[Insert Table 4 here.]

The "10-1" return spreads and their corresponding alphas are positive and statistically significant for all control variables. The return spreads range from 0.62% (t-statistic = 2.23) to 1.01% (t-statistic = 4.12) per month. The "10-1" five-factor alphas are statistically significant and range from 0.65% to 1.18%. The results for DOI-weighted returns display a similar pattern to the equal-weighted returns and are reported in the Internet Appendix, Table IA3.

The results indicate that after controlling for various characteristic variables, there is still a strong positive relation between firms' left-tail risk measure $VaR5$ and future returns of delta-hedged bear spreads. The return predictability of $VaR5$ cannot be explained by the characteristic variables commonly used by the literature nor by bear spread exposures to systematic and left-tail risk factors.

3.4 Fama-MacBeth regressions

We perform Fama-MacBeth (1973) regressions to formally test the positive cross-sectional relation between $VaR5$ and future bear spread returns. The dependent variable is the hold-to-maturity monthly return of delta-hedged bear spreads formed in month t and the variable of interest is $VaR5$. We use control variables defined in Section 2.4.

Table 5 presents time-series averages of the regression coefficient estimates, along with their Newey-West (1987) adjusted t-statistics in parentheses. We perform bivariate regressions with each one of the control variables and the $VaR5$ risk measure, and a multivariate regression using all control variables simultaneously.

[Insert Table 5 here.]

In the first row, we perform a univariate regression on $VaR5$. The coefficient is 0.201 (t-statistic=4.58), confirming the positive relation between $VaR5$ and future delta-hedged bear spread returns. In bivariate regressions with control variables, the coefficient of $VaR5$ decreases in most cases but remains positive and statistically significant. In the last column, we perform a multivariate regression on $VaR5$ together with all the control variables. The coefficient on $VaR5$ remains positive and statistically significant. The following variables report significant coefficients: firm size, momentum, reversal, idiosyncratic volatility, illiquidity, and variance risk premium. Larger firms, that are likely more liquid, tend to attract more attention from investors, and the protection provided by bear spreads is likely more valuable to investors. Thus the bear spreads on larger firms tend to generate lower future returns. The economic intuition is consistent with Cao and Han (2013) and Byun and Kim (2016).

The protection of left-tail risk provided by bear spreads is more valuable when such risk is harder to hedge for low liquidity or high idiosyncratic volatility stocks. Thus for highly illiquid and high idiosyncratic volatility stocks, future bear spread returns are lower. The economic intuition is consistent to Cao and Han (2013).

The coefficient on VRP is -0.026 (t-statistic=-3.49), suggesting a negative variance premium of bear spreads. This is consistent to the positive vega exposure that bear spreads carry.

The results of Table 5 indicate a strong and robust positive relation between firms' left-tail risk and future delta-hedged bear spread returns after controlling for various combinations of control variables. We also show that beta exposures of bear spread returns to systematic left-tail risk factors do not explain our results. In the next section we analyse behavioral explanations to explore how the long-short bear spread returns react during different periods like high/low sentiment, high/low economic growth, or high/low information uncertainty, among others.

4 Potential explanations

So far we show that there is a positive relation between firm measures of tail-risk like $VaR5$ and bear put spread returns. Our results cannot be explained by either risk-based factor models or beta exposures of bear spreads to systematic left-tail risk. In this section we explore potential behavioral explanations of our findings.

4.1 Persistence of losses

A behavioral explanation to the positive relation between firms' left-tail risk and future bear spread returns is that option traders underestimate the persistence of losses. From this perspective, we analyse two effects: the left-tail momentum effect and the anchoring effect. Atilgan et al. (2020) show that investors underestimate loss persistence and such underestimation contributes to the left-tail return momentum, a negative relation between firms' left-tail risk and expected equity returns. George and Hwang (2004) show that anchoring behaviour helps explain loss momentum around the 52-week low, albeit the anchoring effect being weaker than the 52-week high. Driessen et al. (2013) show that option implied volatilities decrease when stock prices approach their 52-week low, suggesting that investors underestimate persistence in risk due to the anchoring bias. The anchoring effect by itself cannot directly explain our main finding. By analyzing its impact on bear spread returns and combining with the results from the left-tail momentum effect help us to pin down the underestimation of loss persistence as one of the main behavioral sources to the positive relation between firms' left-tail risk and future bear spread returns.

To analyse the impact of these two effects, we construct two corresponding measures: 1) $\Delta VaR5$, change of $VaR5$, is the difference in $VAR5$ from month t to month $t-1$. A positive $\Delta VaR5$ implies that the 5th percentile loss computed in month t is higher than the loss computed in month $t-1$, indicating an increase in left-tail risk. 2) NL, nearness to the 52-week low, is the current stock price divided by the lowest stock price in the previous year. A lower NL indicates that the stock price is closer to its 52-week low. We expect that the positive relation between firms' left-tail risk and future bear spread returns is stronger when $\Delta VaR5$ is positive or for low levels of NL.

To test our conjecture, we first sort bear spreads into two subsamples according to the signs of $\Delta VaR5$ of the underlying stocks: $\Delta VaR5 > 0$ and $\Delta VaR5 <= 0$. Similarly, we sort bear spreads into tercile subsamples according to the value of NL of the underlying stocks: low NL, mid NL, and high NL. Then, within each subsample, we further sort bear spreads into deciles based on the left-tail risk measure $VaR5$.

Table 6 reports the time-series average monthly returns for the highest and lowest $VaR5$ decile portfolios in each subsample, together with the return spreads ("10-1") and their corresponding five-factor alphas. Newey-West (1987) adjusted t-statistics are reported in parentheses.

[Insert Table 6 here.]

Panel A presents results for the sorts based on $\Delta VaR5$. For equal weighted returns the "10-1" return spreads and the alphas are positive and statistically significant for both subsamples. The magnitudes of the "10-1" return spread and the corresponding alpha are larger for the "$\Delta VaR5 > 0$" subsample than for the "$\Delta VaR5 <= 0$" subsample.

For DOI-weighted portfolios, when $\Delta VaR5 > 0$, the "10-1" return spread is 1.64% (t-statistic=3.01). For $\Delta VaR5 \leq 0$, both the "10-1" return spread and the alpha remain positive but are statistically insignificant. The positive relation between $VaR5$ and future bear spread returns is only significant for the "$\Delta VaR5 > 0$" subsample.

Combining the results for equal-weighted and DOI-weighted portfolios, Panel A shows a strong and consistent positive relation between $VaR5$ and future delta-hedged bear spread returns when $\Delta VaR5$ is positive. Since stocks that have experienced recent large losses are more likely to experience similar large losses in the near future (stock price's left-tail risk momentum), the protection provided by the bear spreads on these stocks should be more valuable. However, option traders seem to underestimate the left-tail risk persistence and underprice the bear spreads on the stocks with high recent extreme losses, showing a left-tail risk momentum effect.

Panel B presents results for the sorts based on NL, the nearest to 52-week low price. For equal-weighted and DOI-weighted portfolios, only the low and medium NL subsamples report a positive and significant "10-1" returns and alphas. In addition, the "10-1" bear spread return is the largest for the low NL subgroup. In the high NL subsample, the "10-1" return spread and alphas are positive but mostly insignificant.

The results for equal-weighted and DOI-weighted portfolios in Panel B show that the underestimation of the left-tail risk in the options market is stronger when the stock price is nearer to its 52-week low. Option traders anchor their loss expectation around the 52-week low and underestimate the persistence of stock price decline, leading to a stronger positive relation between firms' left-tail risk and future bear spread returns. consistent with with Driessen et al. (2013) as option traders' underestimation to the chance of downward breakthroughs leads to a stronger underpricing of bear spreads when stock prices approach their 52-week low, showing an anchoring effect.

Overall, the results in Table 6 suggest that both the left-tail momentum effect and the anchoring effect have strong impact on the underpricing of bear spreads. The existence of both effects indicates that one of the driving forces of the underreaction to firms' left-tail risk in the options market is option traders' underestimation of loss persistence.

4.2 Information uncertainty

Prior literature (Hong et al., 2000; Jiang et al., 2005; Kumar, 2009; Zhang, 2006a,b) shows that information uncertainty amplifies investor behavioural biases. In particular, high information uncertainty may lead to investors' slow reaction to news (especially bad news), causing predictable price drift or momentum.

Following the literature, we construct five information uncertainty proxies: 1) $SIZE$ is the market capitalization; 2) AC is analyst coverage; 3) $DISP$, analysts' forecast dispersion, is the standard deviation of the analysts' forecasts scaled by the stock price in the previous quarter; 4) $TURN$ is the stock return turnover; and 5) AGE, firm age, denotes the number of years that the firms are listed on Compustat at the previous year-end. Zhang (2006a) uses all five proxies to measure information uncertainty. Hirshleifer and Teoh (2003) use firm size and analyst coverage as proxies for investor inattention. Kumar (2009) uses firm age to measure valuation uncertainty. Taking into account conceptual overlap and mixed interpretation of proxies between information uncertainty, investor inattention, and valuation uncertainty, we use small firm size, young firm age, low analyst coverage, and high dispersion in analyst forecasts as proxies of high information uncertainty. We expect that high information uncertainty amplifies the positive relation between left-tail risk and future bear spread returns.

The previous results from the multivariate Fama and MacBeth (1973) regression in Table 5 show that $SIZE$ is a significant predictor of bear spread returns in the presence of $VaR5$ and additional control variables. In addition, there is a highly negative correlation between $SIZE$ and $VAR5$ of -51%. For this reason, we first investigate the role of $SIZE$ on the predictability of bear spread returns using double sorts. First we sort the sample into $SIZE$ quintiles, and then into $VaR5$ deciles.

[Insert Table 7 here.]

Table 7 Panel A reports the returns for deciles 1 and 10, and the return and alpha spreads for the "10-1" portfolio across $SIZE$ quintiles. The results show that the return spreads are more pronounced for the low-size quintiles compared to the high-size quintiles. More importantly, our results are robust across all $SIZE$ quintiles; all "10-1" spread returns are positive and significant.

Next, we use the methodology by Hong et al. (2000) to compute the residual value of three information uncertainty variables after orthogonalizing to $SIZE$. The three information variables are analyst coverage (AC), analysts' forecast dispersion ($DISP$), and stock return turnover ($TURN$). We denote their residual values by AC_{res}, $DISP_{res}$, and $TURN_{res}$.[3] We compute the residual from the cross-sectional regression of the logarithm of each variable on the logarithm of firm's market capitalization in the previous quarter.

Table 7, Panel B reports the "10-1" portfolio returns for the four information uncertainty

[3]We do not take the residual of AGE because firm age is only available since 1972 and it could bias downwards the age measure for firms created before 1972.

measures. The "10-1" portfolio returns remain positive and statistically significant. In addition, the positive relation between bear spread returns and left-tail risk is larger when information uncertainty is high. That is when analyst coverage is low, analyst forecast dispersion is high, stock return turnover is high, and firm age is low.

Overall, the positive relation between firms' left-tail risk and the future bear spread returns is stronger in the high information uncertainty environment. As information uncertainty usually amplifies investors' behavioral biases such as investor underreaction to bad news, our finding suggests that the options market underreacts to firms' left-tail risk.

4.3 Investor sentiment

Sentiment is a biased investor belief conditional on available information (Barberis et al., 1998). Asset mispricing and risk underestimation are more likely to happen during the high investor sentiment periods (Baker and Wurgler, 2006; Byun and Kim, 2016; Lemmon and Ni, 2014; Stambaugh et al., 2012; Yu and Yuan, 2011). Stambaugh et al. (2012) show that high investor sentiment contributes to the significant profits from the short legs of long-short strategies building upon a large set of anomalies. Byun and Kim (2016) document that the overvaluation of lottery-like options is attributable to high investor sentiment. While prior literature focuses more on the overpricing of risky assets, the underpricing of safer, protective assets may also happen when investor sentiment is high.

Complementary to prior literature, we analyse potential, more pronounced underpricing for bear spread, a protective option strategy, in high sentiment periods. We use the monthly market-based sentiment index (BW sentiment index) constructed by Baker and Wurgler (2006) to classify high and low investor sentiment months. A high (low) sentiment month occurs when the value of the BW sentiment index in the previous month is above (below) the median value for the sample period. Within the subsample with high (low) sentiment months, we form decile portfolios of delta-hedged bear spreads based on $VaR5$ and calculate the time-series average monthly returns for decile portfolios.

Table 8 reports the returns for the highest and lowest $VaR5$ decile portfolios, together with the return spreads ("10-1"). Newey-West (1987) t-statistics are reported in parentheses.

[Insert Table 8 here.]

The results show that the "10-1" bear spread returns are larger during high-sentiment periods. When market sentiment is high, option traders might tend to overlook downside risk and underprice the downside protection provided by bear spreads.

[Insert Figure 1 here.]

To further understand the relation between the "10-1" bear spread return during high-sentiment periods, we plot in Figure 1 the cumulative "10-1" bear spread return and highlight the periods of high sentiment. We observe that in periods of high sentiment, the "10-1" cumulative return increases as previously reported.

Our finding, together with the prior research on risky asset overpricing in high sentiment periods, supports the economic intuition that overvaluation in risky assets and undervaluation in safer, protective assets may happen at the same time (Acharya and Naqvi, 2019). Han (2008) shows that when market sentiment is high, the index option volatility smile is flatter and the risk-neutral skewness of index return extracted from the index option prices is less negative, suggesting decreased risk hedging demand. Our results are consistent with Han (2008) as low hedging demand leads to stronger underpricing of bear spreads during high market sentiment periods.

5 Robustness

In this section, we further explore the predictability of $VaR5$ on bear spread returns. First, we examine that the results are robust for different subsamples such as earnings announcement periods, business cycles and high/low volatility periods, among others. Second, we consider different weighting methods to calculate the bear spread return. Third, we analyse the profitability of the "10-1" bear spread return when accounting for transaction costs.

5.1 Subsamples: earnings announcements and before/after crisis

We study the impact of earnings announcements on bear spread returns sorted by $VAR5$. Engelberg et al. (2018) report that stock return anomalies are six times larger during earnings announcement days. Dubinsky et al. (2019) document that earnings announcements induce substantial uncertainty as implied volatility increases before earnings announcements and decreases afterwards. To confirm that our results are not driven by earnings announcements, we separate the monthly return sample into two subgroups: months with and without earnings announcements. Table 8 shows that the "10-1" return spread for both subgroups are positive and significant and are larger in subgroups without earnings announcements. Our results are robust to periods with and without earnings announcements.

Next, to analyse the impact of the global financial crisis on bear spread returns, we divide the sample into two subperiods: from 1996 to 2007 and from 2008 to 2017. As reported in Table 8, the "10-1" bear spread return is positive and significant in the two subperiods, but is larger in magnitude in the period 1996-2007 at 1.52% with a t-statistic of 3.48. The relation between bear spread returns and left-tail risk holds for the two subperiods.

In conclusion, the relation between delta-hedged bear spread returns and left-tail risk holds for different subsamples.

5.2 Business cycles and volatility

The impact of business cycles or periods with high volatility can potently be linked to our findings. We now study bear spread returns for subperiods with high/low volatility and high/low economic growth. We choose these subsamples based on the median value of the VIX and zero for CFNAI. VIX is the volatility index from the CBOE and the Chicago Fed National Activity Index (CFNAI) is a monthly index designed to gauge overall economic activity and related inflationary pressure. CFNAI is used as a market-wide indicator to examine the performance of trading strategies during high/low economic growth periods (Atilgan et al., 2020; Bali and Murray, 2013).

[Insert Figure 2 here.]

In Figure 2 we visualize the relation of the cumulative "10-1" bear spread return with levels of volatility (Panel A) and with business cycles (Panel B). We produce two time-series graphs where we highlight in grey the periods of high volatility and high economic growth. For Panel A when the VIX level is above the sample median, we label the current month as "high-VIX period"; for Panel B when CFNAI is above 0, we label the current month as "high-economic growth period."

Panels A and B of Figure 2 report the results for the cumulative "10-1" bear spread return under different levels of VIX and CFNAI. From 1997 to 2004, a period of high volatility, the cumulative bear spread return increased. However, in the two subperiods of low volatility (2004-2007 and 2012-2017) the cumulative bear spread return also increased. The visual analysis of economic growth does not show a clear pattern. Overall, no clear pattern is graphically observed.

To further understand the impact of high/low volatility and high/low economic growth, we perform univariate sorts of bear spread returns on $VAR5$ for these subperiods. Table 8 reports decile portfolio returns and the "10-1" bear spread return. We show that the "10-1" bear spread returns remain positive and significant across all subsamples, and returns are larger in periods of high volatility and low economic growth.

We conclude that bear spread returns hold across business cycles and volatility periods.

5.3 Bear spread weighting schemes

In all previous analyses we construct the bear spread with a long (short) position in PUT_1 (PUT_2) as the OTM (DOTM) put option with Δ_1 (Δ_2) closest to -0.30 (-0.10), the midpoint of the OTM (DOTM) delta range. The ranges of OTM and DOTM put option deltas are $[-0.40, -0.20)$ and $[-0.20, 0]$. In this subsection we consider using the simple average and the kernel-weighted average of all put options with deltas between $[-0.40, -0.20)$ for OTM puts and $[-0.20, 0]$ for DOTM puts, to reduce potential sample bias.

Table 8 reports univariate sorts for the two weighting schemes. We show that the positive relation between the delta-hedged bear spread returns and $VaR5$ persists using different methods to construct the bear spreads. The return spreads remain significantly positive and of similar magnitudes to the results in Table 2.

5.4 Daily delta-hedging

We verify the robustness of our findings to an alternative delta-hedging methodology. Thus far we have only considered buy-and-hold returns of the bear spread returns. The bear spread is delta neutral only when the position is opened since we do not rebalance the delta-hedge as time goes by. We now adjust the delta-hedge on a daily basis and compound the daily returns over the given month to obtain a monthly return.

The results based on daily delta-hedging are reported in Table 8. All decile portfolio returns are positive and the "10-1" bear spread returns remain positive and significant. Our results are confirmed when using daily delta hedging.

5.5 Modified Fama-Macbeth regressions and weighted least squares

In the main analysis we use the traditional Fama and MacBeth (1973) regressions. We now use the modified Fama and MacBeth (1973) regressions proposed by Brennan et al. (1998) and the weighted least squares (WLS) parameter estimation proposed by Asparouhova et al. (2013).

The Brennan et al. (1998) methodology first regresses delta-hedged bear spread returns on an all factor's model, and then performs the following Fama and MacBeth (1973) regression to correct for the error-in-variables problem. In our setting, the methodology is as follows:

$$r_{i,t} - \hat{\beta}_i F_t = \gamma_{0,t} + \gamma_{1,t}^{'} VaR5_{i,t} + \phi_t^{'} Z_{i,t-1} + \epsilon_{i,t},$$

where $r_{i,t}$ is the delta-hedged bear spread return for each security i at time t, F_t include all systematic factors from Table 3, $Z_{i,t-1}$ are the characteristics for each stock i at time $t-1$. The $\hat{\beta}_i$ are estimated in the first stage for each stock i using the entire sample. In the second stage, for each month t, a regression is run with the bear spread return and the factors on the left-hand side and $VaR5$ along with the other variables on the right-hand side. Table IA4 reports the second stage estimation results. Using the modified Fama and MacBeth (1973) regressions, the coefficient on $VaR5$ remains positive and statistically significant and of similar magnitude to the original one.

In the WLS estimation, each return is weighted by either the dollar open interest of the bear spread, or by the stock market capitalization. WLS estimation puts more weights on bear spread returns with higher liquidity or higher firm value, reducing the bias caused by illiquid contracts. The third and fourth columns in Table IA4 show that the coefficients of $VaR5$ are positive and significant with t-statistic above 3.57.

Both modified Fama-Macbeth regressions and WLS estimation confirm our main results.

5.6 Transaction costs

Transaction costs play an important role in option transactions. In Table 1 we report that the average relative bid-ask spread of bear spread is 20% and in Table 2 we report that "10-1" delta-hedged bear spread monthly return is 1.03%. Comparing these two numbers, the long-short bear spread profitability seems not plausible. However, we should compare the bid-ask spread to the raw bear spread return. Table IA5 reports raw bear spread returns without delta-hedging sorted on the left-tail risk measures. When sorting by $VaR5$, the "10-1" bear spread return without delta-hedging is 11.52% with a t-statistic of 3.60. Therefore, a profitable strategy would require an effective bid-ask spread of about 50% of the quoted spread for the "10-1" strategy to remain profitable. Below we perform a rigorous analysis on the impact of transaction costs on delta-hedged bear spread returns.

To reduce the impact of transaction costs, we follow previous studies such as Goyal and Saretto (2009), Bali and Murray (2013), and Cao et al. (2022) and hold the position for one month without rebalancing the delta hedges. We also hold the position until maturity to avoid paying the option bid-ask spreads and receive the underlying stock at maturity instead. To account for transaction costs, we buy at the ask and sell at the bid and we measure option transaction costs by the effective bid-ask spread when selling and buying the put options. Thus far we assume that the effective spread is equal to zero—i.e., option returns are computed with a price equal to the midpoint of the bid and ask quotes. Since Optionmetrics does not provide effective bid-ask spread, we assume an effective option spread that is equal to 0%, 10%, 25%, and 50% of the quoted spread.

We also account for the margin requirement required when writing options. The option strategy involves holding delta-shares of the underlying stock for one short unit of a DOTM put option and a long unit of an OTM put option. We follow the CBOE initial margin requirement for a delta-hedged bear spread position, which is "for the same underlying instrument and, as applicable, the same index multiplier; the amount by which the long put (short call) aggregate exercise price is below the short put (long call) aggregate exercise price. Long side must be paid for in full. Proceeds from short option sale may be applied", and "50% requirement on long stock position". We assume the margin cost is the cost of borrowing the additional capital to meet the margin requirement over the holding period which is one month (Weinbaum et al., 2020). We compute an adjusted return to account for the margin requirements of the delta-hedged bear spread as follows

$$return = \frac{(\Delta_{2,t} - \Delta_{1,t})S_T + max(K_1 - S_T, 0) - max(K_2 - S_T, 0) - \frac{r}{12}M}{(\Delta_{2,t} - \Delta_{1,t})S_t + PUT1 - PUT2} - 1,$$

where $PUT1$ ($PUT2$), $\Delta_{1,t}$ ($\Delta_{2,t}$), and K_1 (K_2) are the price, delta, and strike price of the

the OTM (DOTM) put at time t, S_t (S_T) is the price of the underlying stock at time t (T, Maturity), r is the 1-month Libor rate, and M is the CBOE required margin.

Since bear spreads may contain OTM put options with high bid-ask spreads and low prices, the bid-ask spread will be large relative to the price and thus the returns are measured with potentially large errors. To alleviate this concern, we create bear spread subsamples that contain put options with low relative bid-ask spread. We present the results for subsamples under different levels of the relative bid-ask spreads: below 10%, 20%, 30%, and for the full sample. Note that the 25th, the 50th (median), and the 75th percentile of the relative bid-ask spread are 11.1%, 17.5%, and 25.7%. Therefore our subsamples should capture about the same percentiles of the sample data.

[Insert Table 9 here.]

Table 9 examines the impact of transaction costs (and margin requirements) on the profitability of the bear spread trading strategy and reports the "10-1" bear spread returns. The column "Full-sample" with 0% effective to quoted spread replicates the results from Table 2 when sorting by $VaR5$. When using the full sample, the effective to quoted spread must be below 25% for the bear spread trading strategy to be profitable. If the effective to quoted spread is equal to 50%, the relative bid-ask spread of bear spread must be below 20% for the "10-1" strategy to remain profitable.

When accounting for margin requirements and an effective to quoted spread of 25% the "10-1" strategy is profitable for the full sample. Muravyev and Pearson (2020) document that algorithmic traders pay on average 25% of the effective to quoted spread. We conclude that the bear spread trading strategy is profitable for algorithmic traders able to trade at low effective spreads. The impact of margin requirements on our trading strategy is negligible.

6 Conclusion

Understanding the hedging and pricing of tail risk is vital in asset pricing. Practitioners in financial markets also emphasize their loss aversion against investment downsides. Adequately estimating and pricing firms' left-tail risk is important for equity investors, option traders, and well-functioned financial markets in general.

Using bear put spreads with bear regions concentrated on firms' left-tail, we show that firms' left-tail risk is a strong positive predictor of future bear spread returns. We conduct comprehensive tests to show that risk-based explanations cannot explain our findings. Our finding suggests that the option market underreacts to firms' left-tail risk and does not adequately price in such risk.

Behavioral biases help to explain the underreaction to firms' left-tail risk. We show that underreaction is stronger for stocks with larger recent losses and closer to their 52-week lowest price, suggesting that option traders do not adequately factor in the persistence of losses. Higher information uncertainty amplifies investor underreaction to bad news, leading to stronger bear spread underpricing. Investor sentiment also has significant impact on left-tail risk underreaction; we show that the underreaction mainly happens during high market sentiment periods.

Bear spreads provide protection against downsides and such protection should be priced adequately in the options market. Our finding suggests that, although the loss aversion against left-tail risk plays an important role in financial markets, option traders fail to demand adequate price premium for bear spreads to compensate for firms' left-tail risk.

Our study contributes to the literature by using an option trading strategy, bear spread, to isolate and analyse firms' left-tail risk and showing that merely recognizing the importance of left-tail risk is not enough, investors need overcome behavioral biases to adequately price left-tail risk.

References

Viral Acharya and Hassan Naqvi. On reaching for yield and the coexistence of bubbles and negative bubbles. *Journal of Financial Intermediation*, 38:1–10, 2019.

Andrew Ang, Joseph Chen, and Yuhang Xing. Downside risk. *The Review of Financial Studies*, 19(4):1191–1239, 2006a.

Andrew Ang, Robert J Hodrick, Yuhang Xing, and Xiaoyan Zhang. The cross-section of volatility and expected returns. *Journal of Finance*, 61(1):259–299, 2006b.

Elena Asparouhova, Hendrik Bessembinder, and Ivalina Kalcheva. Noisy prices and inference regarding returns. *The Journal of Finance*, 68(2):665–714, 2013.

Yigit Atilgan, Turan G Bali, K Ozgur Demirtas, and A Doruk Gunaydin. Left-tail momentum: Underreaction to bad news, costly arbitrage and equity returns. *Journal of Financial Economics*, 135(3):725–753, 2020.

Malcolm Baker and Jeffrey Wurgler. Investor sentiment and the cross-section of stock returns. *Journal of Finance*, 61(4):1645–1680, 2006.

Gurdip Bakshi, Nikunj Kapadia, and Dilip Madan. Stock return characteristics, skew laws, and the differential pricing of individual equity options. *The Review of Financial Studies*, 16(1):101–143, 2003.

Turan G Bali and Scott Murray. Does risk-neutral skewness predict the cross section of equity option portfolio returns? *Journal of Financial and Quantitative Analysis*, 48(4): 1145–1171, 2013.

Turan G Bali, Nusret Cakici, and Robert F Whitelaw. Maxing out: Stocks as lotteries and the cross-section of expected returns. *Journal of Financial Economics*, 99(2):427–446, 2011.

Guido Baltussen, Sjoerd Van Bekkum, and Bart Van Der Grient. Unknown unknowns: uncertainty about risk and stock returns. *Journal of Financial and Quantitative Analysis*, 53(4):1615–1651, 2018.

Nicholas Barberis, Andrei Shleifer, and Robert Vishny. A model of investor sentiment. *Journal of Financial Economics*, 49(3):307–343, 1998.

David S Bates. The crash of 87: was it expected?the evidence from options markets. *Journal of Finance*, 46(3):1009–1044, 1991.

Arjan B Berkelaar, Roy Kouwenberg, and Thierry Post. Optimal portfolio choice under loss aversion. *Review of Economics and Statistics*, 86(4):973–987, 2004.

Nicolas PB Bollen and Robert E Whaley. Does net buying pressure affect the shape of implied volatility functions? *Journal of Finance*, 59(2):711–753, 2004.

Michael J Brennan, Tarun Chordia, and Avanidhar Subrahmanyam. Alternative factor specifications, security characteristics, and the cross-section of expected stock returns. *Journal of Financial Economics*, 49(3):345–373, 1998.

Suk-Joon Byun and Da-Hea Kim. Gambling preference and individual equity option returns. *Journal of Financial Economics*, 122(1):155–174, 2016.

John Y Campbell, Jens Hilscher, and Jan Szilagyi. In search of distress risk. *The Journal of Finance*, 63(6):2899–2939, 2008.

Jie Cao and Bing Han. Cross section of option returns and idiosyncratic stock volatility. *Journal of Financial Economics*, 108(1):231–249, 2013.

Jie Cao, Aurelio Vasquez, Xiao Xiao, and Xintong Zhan. Volatility uncertainty and the cross-section of option returns. *Available at SSRN 3178263*, 2019.

Jie Cao, Bing Han, Xintong Zhan, and Qing Tong. Option return predictability. *The Review of Financial Studies*, 35(3):1394–1442, 2022.

Mark M Carhart. On persistence in mutual fund performance. *Journal of Finance*, 52(1): 57–82, 1997.

Fousseni Chabi-Yo, Stefan Ruenzi, and Florian Weigert. Crash sensitivity and cross-section of expected stock returns. *Journal of Financial and Quantitative Analysis*, 53(3):1059–1100, 2018.

Joshua D Coval and Tyler Shumway. Expected option returns. *Journal of Finance*, 56(3): 983–1009, 2001.

Martijn Cremers, Michael Halling, and David Weinbaum. Aggregate jump and volatility risk in the cross-section of stock returns. *The Journal of Finance*, 70(2):577–614, 2015.

Joost Driessen, Pascal J Maenhout, and Grigory Vilkov. The price of correlation risk: Evidence from equity options. *Journal of Finance*, 64(3):1377–1406, 2009.

Joost Driessen, Tse-Chun Lin, and Otto Van Hemert. How the 52-week high and low affect option-implied volatilities and stock return moments. *Review of Finance*, 17(1):369–401, 2013.

Andrew Dubinsky, Michael Johannes, Andreas Kaeck, and Norman J Seeger. Option pricing of earnings announcement risks. *The Review of Financial Studies*, 32(2):646–687, 2019.

Joseph Engelberg, R David McLean, and Jeffrey Pontiff. Anomalies and news. *The Journal of Finance*, 73(5):1971–2001, 2018.

Eugene F Fama and Kenneth R French. Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, 33(1):3–56, 1993.

Eugene F Fama and James D MacBeth. Risk, return, and equilibrium: Empirical tests. *Journal of Political Economy*, 81(3):607–636, 1973.

Andrea Frazzini and Lasse H Pedersen. Embedded leverage. *NBER Working Paper Series No. 18558*, 2012.

Chao Gao, Yuhang Xing, and Xiaoyan Zhang. Anticipating uncertainty: straddles around earnings announcements. *Journal of Financial and Quantitative Analysis*, 53(6):2587–2617, 2018.

Nicolae Garleanu, Lasse Heje Pedersen, and Allen M Poteshman. Demand-based option pricing. *The Review of Financial Studies*, 22(10):4259–4299, 2008.

Thomas J George and Chuan-Yang Hwang. The 52-week high and momentum investing. *Journal of Finance*, 59(5):2145–2176, 2004.

Amit Goyal and Alessio Saretto. Cross-section of option returns and volatility. *Journal of Financial Economics*, 94(2):310–326, 2009.

Bing Han. Investor sentiment and option prices. *Review of Financial Studies*, 21(1):387–414, 2008.

Campbell R Harvey and Akhtar Siddique. Time-varying conditional skewness and the market risk premium. *Research in Banking and Finance*, 1(1):27–60, 2000.

David Hirshleifer and Siew Hong Teoh. Limited attention, information disclosure, and financial reporting. *Journal of Accounting and Economics*, 36(1-3):337–386, 2003.

Harrison Hong, Terence Lim, and Jeremy C Stein. Bad news travels slowly: Size, analyst coverage, and the profitability of momentum strategies. *Journal of Finance*, 55(1):265–295, 2000.

Alex R Horenstein, Aurelio Vasquez, and Xiao Xiao. Common factors in equity option returns. *Available at SSRN 3290363*, 2020.

Robert Jarrow and Feng Zhao. Downside loss aversion and portfolio management. *Management Science*, 52(4):558–566, 2006.

Guohua Jiang, Charles MC Lee, and Yi Zhang. Information uncertainty and expected returns. *Review of Accounting Studies*, 10(2-3):185–221, 2005.

Wen Jin, Joshua Livnat, and Yuan Zhang. Option prices leading equity prices: Do option traders have an information advantage? *Journal of Accounting Research*, 50(2):401–432, 2012.

Daniel Kahneman and Amos Tversky. Prospect theory: An analysis of decision under risk. *Econometrica*, 47(2):263–292, 1979.

Bryan Kelly and Hao Jiang. Tail risk and asset prices. *The Review of Financial Studies*, 27 (10):2841–2871, 2014.

Bryan Kelly, Hanno Lustig, and Stijn Van Nieuwerburgh. Too-systemic-to-fail: What option markets imply about sector-wide government guarantees. *American Economic Review*, 106 (6):1278–1319, 2016a.

Bryan Kelly, L'uboš Pástor, and Pietro Veronesi. The price of political uncertainty: Theory and evidence from the option market. *Journal of Finance*, 71(5):2417–2480, 2016b.

Alok Kumar. Hard-to-value stocks, behavioral biases, and informed trading. *Journal of Financial and Quantitative Analysis*, 44(6):1375–1401, 2009.

Michael Lemmon and Sophie Xiaoyan Ni. Differences in trading and pricing between stock and index options. *Management Science*, 60(8):1985–2001, 2014.

Zhongjin Lu and Scott Murray. Bear beta. *Journal of Financial Economics*, 131(3):736–760, 2019.

Dmitriy Muravyev. Order flow and expected option returns. *Journal of Finance*, 71(2): 673–708, 2016.

Dmitriy Muravyev and Neil D Pearson. Options trading costs are lower than you think. *The Review of Financial Studies*, 33(11):4973–5014, 2020.

Whitney K Newey and Kenneth D West. A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. *Econometrica*, 55(3):703–708, 1987.

Xinfeng Ruan. Volatility-of-volatility and the cross-section of option returns. *Journal of Financial Markets*, 48:100492, 2020.

Robert F Stambaugh, Jianfeng Yu, and Yu Yuan. The short of it: Investor sentiment and anomalies. *Journal of Financial Economics*, 104(2):288–302, 2012.

Amos Tversky and Daniel Kahneman. Loss aversion in riskless choice: A reference-dependent model. *Quarterly Journal of Economics*, 106(4):1039–1061, 1991.

Maarten Van Oordt and Chen Zhou. Systematic tail risk. *Journal of Financial and Quantitative Analysis*, 51(2):685–705, 2016.

Joel M Vanden. Option coskewness and capital asset pricing. *The Review of Financial Studies*, 19(4):1279–1320, 2006.

Aurelio Vasquez and Xiao Xiao. Default risk and option returns. *Available at SSRN 2667930*, 2020.

David Weinbaum, Andy Fodor, Dmitriy Muravyev, and Martijn Cremers. Option trading activity, news releases, and stock return predictability. *Working Paper*, 2020.

Yuhang Xing, Xiaoyan Zhang, and Rui Zhao. What does the individual option volatility smirk tell us about future equity returns? *Journal of Financial and Quantitative Analysis*, 45(3):641–662, 2010.

Jianfeng Yu and Yu Yuan. Investor sentiment and the mean–variance relation. *Journal of Financial Economics*, 100(2):367–381, 2011.

X Frank Zhang. Information uncertainty and stock returns. *Journal of Finance*, 61(1): 105–137, 2006a.

X Frank Zhang. Information uncertainty and analyst forecast behavior. *Contemporary Accounting Research*, 23(2):565–590, 2006b.

Figure 1: Sentiment and Cumulative Bear Spread Strategy Return

This figure reports the time-series of the cumulative "10-1" bear spread return. Each month, decile portfolios of delta-hedged bear spreads are formed and held to maturity by sorting underlying stocks by $VaR5$. $VaR5$ is the 5% value-at-risk that corresponds to -1 times the 5th percentile of daily returns in the past year. The "10-1" portfolio is the spread between decile 10 portfolio (with the highest left-tail risk metric) and decile 1 portfolio (with the lowest left-tail risk metric). The shaded areas capture periods of high sentiment. Sentiment is the market-wide sentiment constructed by Baker and Wurgler (2006). A high-sentiment period is selected when the sentiment level is above its sample median (zero). The sample period is from January 1996 to December 2017 for stocks in the OptionMetrics database.

High Sentiment vs. Low Sentiment

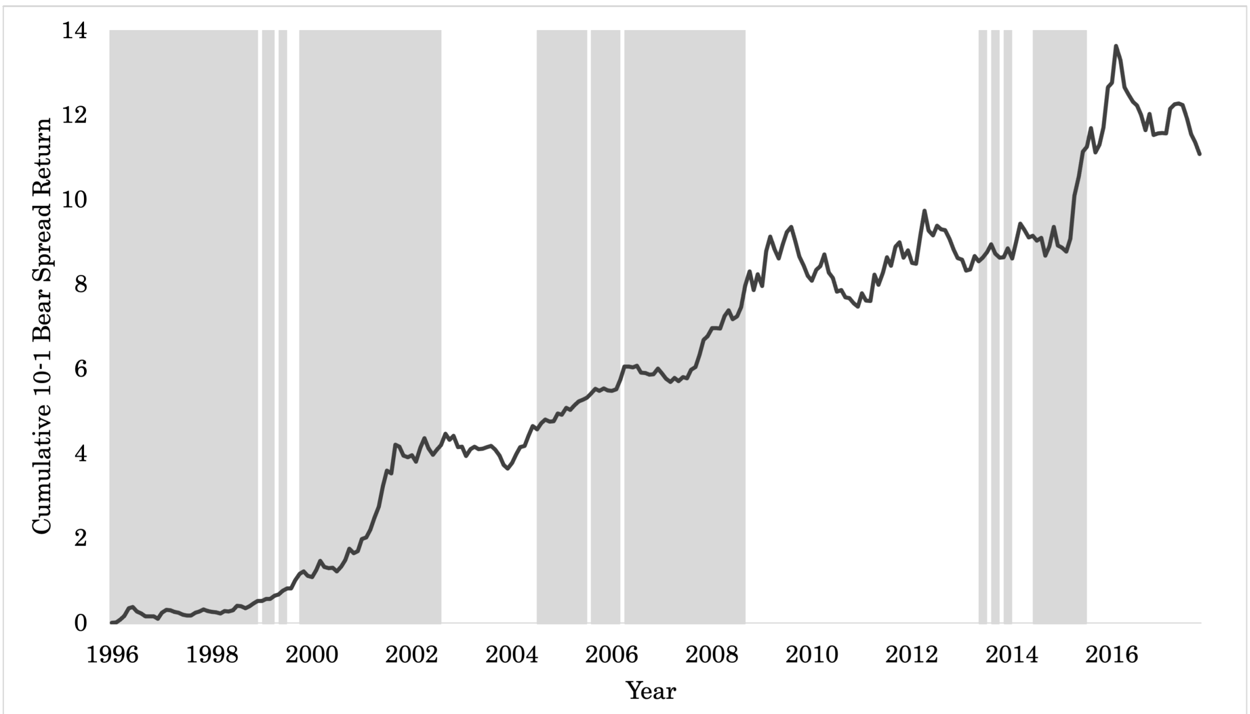
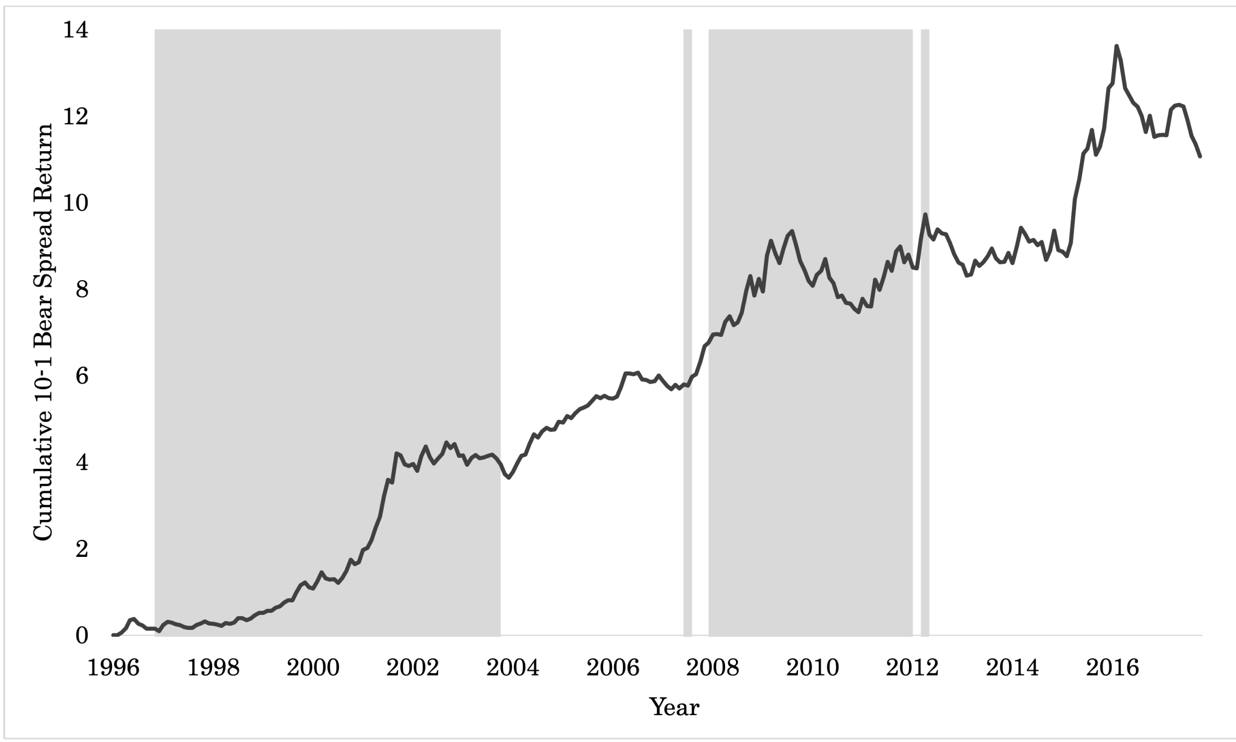


Figure 2: Volatility, Business Cycles, and Cumulative Bear Spread Returns

These figures report the time-series of the cumulative "10-1" bear spread return. Each month, decile portfolios of delta-hedged bear spreads are formed and held to maturity by sorting underlying stocks by $VaR5$. $VaR5$ is the 5% value-at-risk that corresponds to -1 times the 5th percentile of daily returns in the past year. The "10-1" portfolio is the spread between decile 10 portfolio (with the highest left-tail risk metric) and decile 1 portfolio (with the lowest left-tail risk metric). The shaded areas capture periods of high volatility in Panel A and high economic growth in Panel B. VIX is the volatility index from the CBOE and Chicago Fed National Activity Index (CFNAI) is a monthly index designed to gauge overall economic activity and related inflationary pressure. A high volatility period (high economic-growth period) is selected when the VIX level (CFNAI level) is above its sample median (zero). The sample period is from January 1996 to December 2017 for stocks in the OptionMetrics database.

Panel A: High Volatility (VIX) vs. Low VIX



Panel B: High Economic-Growth (CFNAI) vs. Low CFNAI

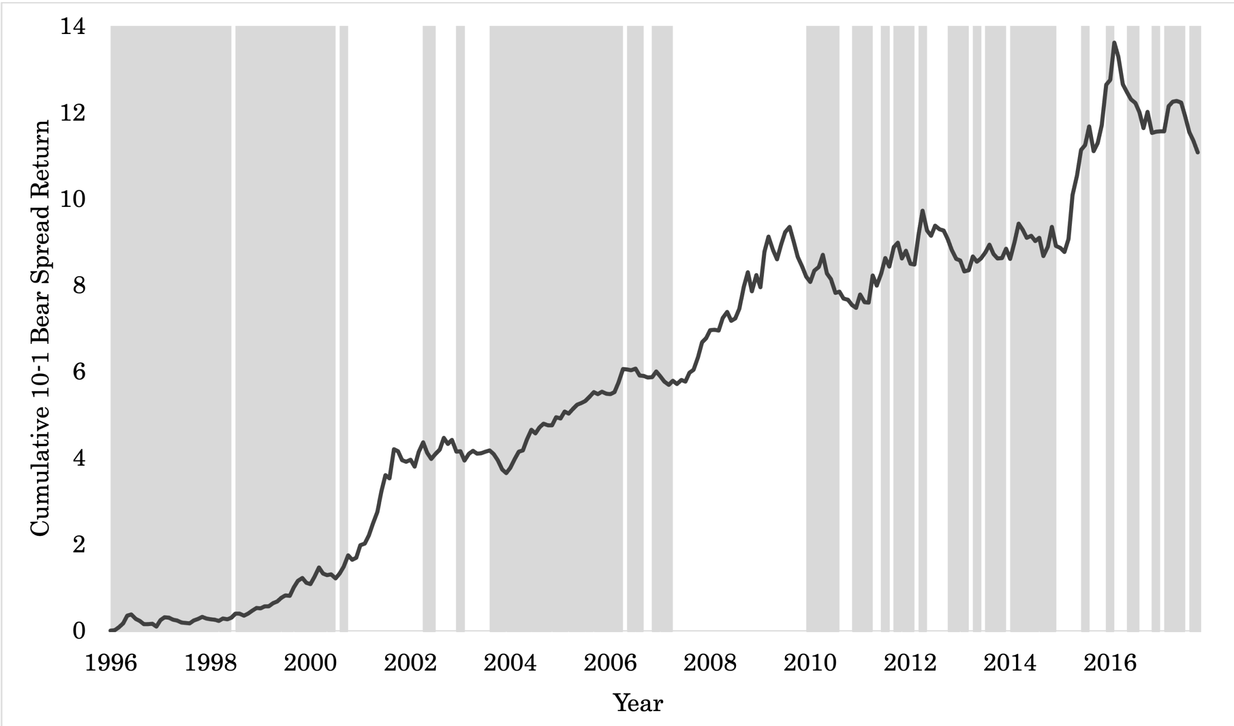


Table 1: Summary Statistics

Panel A of this table presents descriptive statistics for delta-hedged bear spread returns (in %), characteristics of put options in the bear spreads, the left-tail risk measures, and other variables that include control variables. Panel B reports the characteristics of 10 portfolios sorted by the 5% value-at-risk, $VaR5$, that corresponds to -1 times the 5th percentile of daily returns in the past year. Panel C reports the correlations (in %) of the characteristics. The left-tail risk measures are the 5% (1%) value-at-risk, $VaR5$ ($VaR1$), that corresponds to 5th (1st) percentile of daily returns in the past year; the expected shortfall, $ES5$ ($ES1$), is calculated as -1 times the average of the returns below the 5th (1st) percentile of daily returns in the past year. The characteristics are SIZE (market capitalization); BTM (book-to-market ratio); DTA (firm leverage); MOM (momentum computed as the return over the previous six months); REV (reversal which is the return over the previous month); ILLIQ (logarithm of Carhart illiquidity); IVOL (idiosyncratic volatility); SKEW and KURT (skewness and kurtosis from one year of daily returns); VRP (variance risk premium as in Goyal and Saretto (2009)); VOV (vol-of-vol as in Baltussen et al. (2018)); RNS (risk-neutral skewness). We use 60-month rolling windows to compute the exposures of individual bear spread returns to the following systematic risk factors: zero-beta straddle (β_{Strad}) from Coval and Shumway (2001), jump and volatility factors (β_{Jump} and β_{Vol}) as in Cremers et al. (2015), the bear market factor (β_{Bear}) following Lu and Murray (2019), the tail factor (β_{Tail}) as in Kelly and Jiang (2014), and the downside factor ($\beta_{Downside}$) following Ang et al. (2006a). We also report the AD-Price (Price of the Arrow-Debreu security); and BA spread (average bid-ask spread of the two put options in the bear spread). Statistics are computed as the time-series averages of the monthly cross-sectional means, standard deviations and percentiles. The sample period is from January 1996 to December 2017 for stocks in the OptionMetrics database.

Panel A: Summary Statistics

	Mean	Std Dev	25th	Median	75th
Delta-hedged bear spread returns					
	-0.166	13.22	-8.55	-1.74	6.77
Option characteristics					
PUT_1					
Delta	-0.304	0.047	-0.339	-0.304	-0.268
Implied Volatility	0.476	0.204	0.333	0.439	0.574
PUT_2					
Delta	-0.116	0.032	-0.136	-0.111	-0.092
Implied Volatility	0.527	0.221	0.374	0.487	0.629
Left-tail risk variables					
VaR5	0.042	0.016	0.030	0.040	0.052
VaR1	0.070	0.028	0.049	0.064	0.085
ES5	0.062	0.024	0.043	0.057	0.075
ES1	0.093	0.044	0.061	0.083	0.113
Other variables					
SIZE	22.230	1.576	21.094	22.179	23.303
BTM	4.507	49.701	0.349	0.689	1.427
DTA	0.185	0.194	0.023	0.143	0.281
MOM	0.151	0.338	-0.041	0.126	0.306
REV	0.028	0.133	-0.045	0.020	0.090
ILLIQ	-7.960	1.563	-9.033	-8.017	-6.886
IVOL	0.022	0.013	0.013	0.019	0.026
SKEW	0.235	1.217	-0.176	0.181	0.590
KURT	8.605	11.117	4.156	5.464	8.635
VRP	0.092	0.269	-0.064	0.092	0.253
VOV	0.099	0.064	0.058	0.085	0.124
RNS	-0.625	0.580	-0.952	-0.559	-0.221
β_{Bear}	0.155	1.043	-0.356	0.097	0.624
β_{Strad}	0.042	0.099	-0.002	0.041	0.085
β_{Jump}	0.052	0.464	-0.134	0.048	0.232
β_{Vol}	0.027	0.825	-0.277	0.021	0.337
β_{Tail}	-0.045	0.949	-0.462	-0.023	0.400
$\beta_{Downside}$	-0.604	2.981	-1.203	-0.621	-0.018
AD-Price	0.210	0.054	0.174	0.206	0.241
BA Spread	0.200	0.126	0.111	0.175	0.257

Panel B: Characteristics of Decile Portfolios

	1	2	3	4	5	6	7	8	9	10
VaR5	0.021	0.026	0.029	0.033	0.037	0.041	0.046	0.051	0.059	0.075
SIZE	23.551	23.308	23.023	22.674	22.371	22.091	21.849	21.633	21.348	20.865
BTM	2.628	3.148	3.598	3.352	3.022	2.974	2.809	3.208	6.540	11.399
DTA	0.212	0.201	0.196	0.190	0.183	0.182	0.173	0.172	0.172	0.165
MOM	0.106	0.112	0.116	0.122	0.138	0.151	0.165	0.168	0.180	0.237
REV	0.021	0.022	0.025	0.026	0.032	0.034	0.034	0.040	0.038	0.050
ILLIQ	-9.072	-8.798	-8.557	-8.256	-8.018	-7.791	-7.563	-7.390	-7.150	-6.847
IVOL	0.011	0.013	0.015	0.017	0.019	0.021	0.023	0.026	0.030	0.037
SKEW	0.194	0.151	0.134	0.121	0.177	0.202	0.213	0.247	0.331	0.533
KURT	7.863	8.091	8.413	8.759	8.774	8.689	8.914	8.735	9.521	10.073
VRP	0.023	0.020	0.019	0.018	0.017	0.015	0.012	0.008	0.001	-0.015
VOV	0.081	0.083	0.083	0.084	0.084	0.084	0.085	0.085	0.085	0.088
RNS	-0.989	-0.826	-0.736	-0.680	-0.612	-0.577	-0.530	-0.523	-0.512	-0.513
β_{Bear}	0.090	0.083	0.119	0.110	0.133	0.144	0.172	0.198	0.205	0.301
β_{Strad}	0.037	0.041	0.041	0.040	0.041	0.043	0.043	0.046	0.047	0.044
β_{Jump}	0.032	0.043	0.046	0.029	0.033	0.049	0.062	0.061	0.063	0.104
β_{Vol}	0.026	0.021	0.031	0.011	0.013	0.002	-0.008	0.026	0.061	0.090
β_{Tail}	-0.021	-0.002	-0.026	-0.009	-0.010	-0.033	-0.049	-0.105	-0.085	-0.108
$\beta_{Downside}$	-0.486	-0.556	-0.567	-0.619	-0.732	-0.654	-0.670	-0.622	-0.681	-0.450
AD-Price	0.176	0.183	0.189	0.196	0.204	0.211	0.218	0.227	0.239	0.261
BA spread	0.206	0.198	0.198	0.198	0.197	0.199	0.200	0.200	0.202	0.205

Panel C: Correlations

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
1-VaR5	100																						
2-VaR1	89																						
3-ES5	87.7	74.6																					
4-ES1	96.5	93	92.7																				
5-SIZE	-50.9	-52.1	-47.3	-53.1																			
6-MOM	5.3	9.4	-0.1	5.2	-6.4																		
7-REV	2.4	4	0.9	2.6	-4.2	0.6																	
8-ILLIQ	42.9	43.5	40.4	44.9	-88.6	4.8	8.1																
9-BTM	-4.3	-4.8	-4.4	-4.8	-1.9	-4.3	-1.9	2.1															
10-DTA	-6.5	-6.6	-7	-7.1	1.4	-0.6	0	-0.4	0.9														
11-KURT	12.3	4.2	31.8	18	-12.8	8	5.2	12.2	-2.4	-0.2													
12-SKEW	-0.2	9.3	-19.7	-4.4	-7.6	27.3	13.7	8.1	-1.6	1.1	31.6												
13-RNS	14.1	16.5	12.9	15.4	-33.4	6.6	7.1	33.8	-3.8	-2.1	3	2.8											
14-IVOL	60.5	60.7	57.7	63.2	-39.9	8.3	15.5	36.5	-4.3	-3.9	21	12.2	13.3										
15-VRP	-5.6	-4.4	-7.4	-6.2	-4.3	1.8	-13.7	3	-1.3	1.5	-8.9	-3.2	0.6	-59									
16-VOV	7.2	2.9	10.8	7.4	-2.5	-0.2	0.2	0.3	-0.3	0.5	15	4	-5.7	22.1	-15.5								
17-AD-Price	43.9	46.4	40.1	46.1	-40.1	5.2	-0.9	36.7	-2.2	-4.1	7.2	5.3	28.6	37.4	2	2.5							
18-BA Spread	1.4	-0.4	3.3	1.6	-37.7	-1.5	1.9	46.9	1.8	4.3	7.8	2.9	27.1	1.8	2.4	4.5	-5.7						
19-β_{Bear}	9.8	12.3	7.4	10.4	-12.1	-5.1	-2.7	11.4	1.5	1.3	0.3	3.0	2.4	5.5	1.5	0.8	7.8	4.8					
20-β_{Strad}	2.1	3.7	1.5	2.7	-4.7	-0.9	-0.9	3.7	-1.8	1.1	-0.7	2.8	0.2	2.1	0.5	0.6	3.1	1.9	42.0				
21-β_{Jump}	3.1	4.7	1.4	3.2	-1.4	-0.3	0.4	-1.1	-1.8	-0.9	-0.5	0.9	0.4	1.9	0.0	-0.7	2.1	-1.4	6.9	24.7			
22-β_{Vol}	-0.4	1.6	-0.9	0.2	0.8	0.9	0.3	-2.2	-1.3	2.1	-0.3	1.5	-1.5	-0.1	-0.1	-0.3	0.8	-1.3	10.4	19.4	15.7		
23-β_{Tail}	-4.8	-4.6	-4.3	-4.6	4.8	2.4	1.7	-5.8	-2.3	-0.1	-1.3	-0.8	0.1	-3.1	-2.2	-1.2	-4.1	-2.2	-31.3	-19.2	-10.0	-5.5	
24-$\beta_{Downside}$	-3.5	-5.3	-2.1	-3.9	3.4	1.9	1.4	-1.8	1.6	1.1	2.6	-1.2	-0.1	0.2	-0.5	0.3	-1.8	-1.6	-29.7	-18.0	-2.7	-5.4	9.3

Table 2: Univariate Portfolio Analysis

This table reports the time-series average monthly returns (in %), equal-weighted and dollar-open-interest-weighted, for the delta-hedged bear spread decile portfolios sorted on the left-tail risk measures ($VaR5$, $VaR1$, $ES5$, $ES1$), along with the return spreads ("10-1") and the associated alpha spreads between decile 10 portfolio (with the highest left-tail risk metric) and decile 1 portfolio (with the lowest left-tail risk metric). The left-tail risk measures are the 5% (1%) value-at-risk, $VaR5$ ($VaR1$), that corresponds to -1 times the 5th (1st) percentile of daily returns in the past year, and expected shortfall, $ES5$ ($ES1$), is the calculated as -1 times the average of the returns below the 5th (1st) percentile of daily returns in the past year. Each month t, decile portfolios of delta-hedged bear spreads are formed and held to maturity by sorting underlying stocks on one of the left-tail risk measures. The dollar open interest weight is calculated as the minimum of the open interests of the two puts in each bear spread, multiplied by the cost of the bear spread. Newey-West (1987) adjusted t-statistics are presented in parentheses. The sample period is from January 1996 to December 2017 for stocks in the OptionMetrics database.

Equal-Weighted Returns												
	1	2	3	4	5	6	7	8	9	10	10-1	t-stat
VaR5	-0.62	-0.46	-0.37	-0.19	-0.13	-0.11	0.18	0.17	0.09	0.40	1.03	(3.60)
VaR1	-0.61	-0.43	-0.36	-0.17	-0.13	-0.07	0.09	0.16	0.16	0.30	0.91	(3.33)
ES5	-0.61	-0.44	-0.40	-0.14	-0.19	-0.06	0.13	0.20	0.13	0.30	0.91	(3.41)
ES1	-0.60	-0.44	-0.33	-0.23	-0.02	-0.05	0.13	0.11	0.24	0.14	0.74	(3.48)

Dollar-Open-Interest-Weighted Returns												
	1	2	3	4	5	6	7	8	9	10	10-1	t-stat
VaR5	-0.59	-0.38	-0.23	-0.18	0.16	0.06	0.12	-0.14	0.01	0.45	1.04	(2.44)
VaR1	-0.55	-0.53	-0.25	-0.05	0.33	0.13	-0.14	-0.15	0.52	0.27	0.83	(2.26)
ES5	-0.53	-0.41	-0.40	0.10	-0.10	0.21	-0.10	0.09	0.12	0.46	0.99	(2.35)
ES1	-0.56	-0.38	-0.15	-0.04	0.07	-0.25	0.01	0.27	0.50	0.29	0.85	(2.61)

Table 3: Risk-Adjusted Returns

This table reports the time-series average equal-weighted monthly returns (in %) for the delta-hedged bear spread decile portfolios sorted on the left-tail risk measure $VaR5$, along with the return spreads ("10-1") and the associated alpha spreads between decile 10 portfolio (with the highest left-tail risk metric) and decile 1 portfolio (with the lowest left-tail risk metric). $VaR5$ is the 5% value-at-risk that corresponds to -1 times the 5th percentile of daily returns in the past year. CAPM alphas are calculated after adjusting for CAPM market risk factor; four-factor (4F) alphas are calculated after adjusting for Fama-French three factors and Carhart (1997) momentum factor; the ZB Straddle is the zero-beta straddle return from Coval and Shumway (2001); the jump and volatility factors (Jump and Vol) are computed as in Cremers et al. (2015); the bear market factor (AD-BEAR) following Lu and Murray (2019); the VIX is the monthly return of the VIX volatility index; the Tail factor following Kelly and Jiang (2014); Downside following Ang et al. (2006a); Coskewness factor computed following Harvey and Siddique (2000); illiquidity factor on options (ILLLIQ) calculated following Cao et al. (2022); the three factors from options are the size, idiosyncratic volatility, and variance risk premium factors from delta-hedged option returns following Horenstein et al. (2020). Vanden's alpha is computed following Vanden (2006). Newey and West (1987) adjusted t-statistics are presented in parentheses. The sample period is from January 1996 to December 2017 for stocks in the OptionMetrics database.

	1	2	3	4	5	6	7	8	9	10	10-1	(t-stat)
Raw Return	-0.62	-0.46	-0.37	-0.19	-0.13	-0.11	0.18	0.17	0.09	0.40	1.03	(3.60)
CAPM alpha	-0.52	-0.35	-0.25	-0.06	0.04	0.07	0.36	0.36	0.28	0.72	1.23	(4.59)
4F alpha	-0.50	-0.36	-0.25	-0.08	0.03	0.03	0.28	0.25	0.16	0.68	1.18	(4.62)
4F+ZB Straddle alpha	-0.28	-0.14	-0.05	0.20	0.31	0.28	0.56	0.56	0.38	0.89	1.17	(4.42)
4F+Jump+Vol. alpha	-0.41	-0.27	-0.19	0.04	0.16	0.16	0.40	0.39	0.31	0.77	1.18	(4.50)
4F+AD-BEAR alpha	-0.49	-0.34	-0.22	-0.02	0.09	0.07	0.34	0.37	0.28	0.76	1.25	(4.76)
4F+VIX alpha	-0.49	-0.33	-0.22	-0.05	0.08	0.08	0.32	0.29	0.23	0.72	1.21	(4.62)
4F+Tail factor alpha	-0.50	-0.35	-0.24	-0.09	0.05	0.03	0.28	0.25	0.17	0.70	1.20	(4.65)
4F+Downside alpha	-0.48	-0.33	-0.21	-0.05	0.06	0.05	0.30	0.27	0.20	0.73	1.21	(4.57)
4F+Coskew alpha	-0.52	-0.37	-0.26	-0.08	0.02	0.00	0.25	0.21	0.11	0.66	1.18	(4.29)
4F+Illiquidity alpha	-0.58	-0.49	-0.26	-0.22	0.03	-0.18	0.19	0.22	0.12	0.75	1.33	(3.69)
4F+3F Option's alpha	-0.26	0.01	0.26	-0.03	0.41	0.44	0.69	0.54	0.42	1.01	1.27	(2.27)
All factors' alpha	0.01	0.24	0.53	0.36	0.72	0.70	1.03	0.95	0.64	1.21	1.20	(2.24)
Vanden's alpha	-1.03	-0.92	-0.81	-0.81	-0.65	-0.66	-0.19	-0.25	-0.31	0.36	1.38	(4.16)

Table 4: Bivariate Portfolio Analysis

This table presents results (in %) for equal-weighted delta-hedged bear spread portfolios based on bivariate dependent sorts of one (firm-specific, stock-related or option related) characteristic variable and $VaR5$. In month t, decile portfolios of delta-hedged bear spreads are formed by sorting underlying stocks based on one of the characteristic variables. Then within each decile, additional decile portfolios of delta-hedged bear spreads are formed by sorting underlying stocks based on $VaR5$ observed in the previous year. Each $VaR5$ decile portfolio is then averaged over the control characteristic deciles. This table reports the raw returns for equal-weighted decile portfolios thus obtained, and the return spreads and associated alpha spreads for decile 10 portfolio (highest $VaR5$) and decile 1 portfolio (lowest $VaR5$). Five-factor alphas are calculated after adjusting for Fama-French three factors, Carhart (1997) momentum factor, and Coval and Shumway (2001) systematic volatility factor. $VaR5$ is the 5% value-at-risk that corresponds to -1 times the 5th percentile of daily returns in the past year. Control variables are SIZE (market capitalization); BTM (book-to-market ratio); DTA (firm leverage); MOM (momentum computed as the return over the previous six months); REV (reversal which is the return over the previous month); ILLIQ (logarithm of Carhart illiquidity); IVOL (idiosyncratic volatility); SKEW and KURT (skewness and kurtosis from one year of daily returns); VRP (variance risk premium as in Goyal and Saretto (2009)); VOV (vol-of-vol as in Baltussen et al. (2018)); RNS is risk-neutral skewness. We use 60-month rolling windows to compute the exposures of individual bear spread returns to the following systematic risk factors: zero-beta straddle (β_{Strad}) from Coval and Shumway (2001), jump and volatility factors (β_{Jump} and β_{Vol}) as in Cremers et al. (2015), the bear market factor (β_{Bear}) following Lu and Murray (2019), the tail factor (β_{Tail}) as in Kelly and Jiang (2014), and the downside factor ($\beta_{Downside}$) following Ang et al. (2006a). Newey and West (1987) adjusted t-statistics are presented in parentheses. The sample period is from January 1996 to December 2017 for stocks in the OptionMetrics database.

	1	2	3	4	5	6	7	8	9	10	10-1	(t-stat)	5F Alpha	(t-stat)
SIZE	-0.56	-0.47	-0.16	-0.20	-0.19	-0.09	0.11	-0.02	0.24	0.30	0.86	(3.89)	0.94	(4.55)
BTM	-0.54	-0.38	-0.31	-0.19	-0.08	-0.01	-0.13	0.09	0.13	0.10	0.67	(3.65)	0.69	(3.93)
DTA	-0.51	-0.28	-0.36	-0.23	-0.02	0.03	0.01	0.03	0.14	0.10	0.65	(2.97)	0.71	(3.48)
MOM	-0.44	-0.29	-0.24	-0.23	-0.20	0.05	0.03	0.01	0.01	0.21	0.64	(3.05)	0.72	(3.72)
REV	-0.58	-0.44	-0.34	-0.26	-0.10	-0.06	0.02	0.07	0.11	0.51	1.09	(4.99)	1.18	(5.86)
ILLIQ	-0.60	-0.36	-0.34	-0.23	-0.18	-0.07	0.01	0.17	0.15	0.41	1.01	(4.12)	1.13	(4.95)
IVOL	-0.61	-0.37	-0.33	-0.23	-0.05	-0.01	0.01	-0.01	0.11	0.40	0.73	(4.46)	0.83	(4.87)
SKEW	-0.61	-0.35	-0.38	-0.29	-0.12	0.04	0.10	0.23	0.05	0.33	0.94	(3.73)	1.11	(4.82)
KURT	-0.35	-0.27	-0.40	-0.16	0.05	0.04	0.14	0.03	0.01	0.47	0.82	(1.94)	1.09	(2.83)
VRP	-0.59	-0.39	-0.37	-0.28	-0.20	0.09	-0.04	0.02	0.17	0.34	0.93	(3.56)	1.04	(4.31)
VOV	-0.63	-0.45	-0.29	-0.17	-0.18	0.02	0.12	0.10	0.05	0.17	0.79	(2.85)	0.97	(3.78)
RNS	-0.59	-0.36	-0.13	-0.12	-0.01	0.18	-0.01	-0.07	0.26	0.46	0.85	(3.23)	0.91	(3.59)
β_{Bear}	-0.53	-0.48	-0.38	-0.17	-0.23	-0.18	0.01	-0.14	-0.18	0.09	0.63	(2.50)	0.80	(3.47)
β_{Srad}	-0.56	-0.45	-0.31	-0.27	-0.21	-0.12	-0.29	-0.14	-0.10	0.26	0.82	(2.94)	0.91	(3.53)
β_{Jump}	-0.58	-0.44	-0.32	-0.40	-0.23	-0.14	-0.17	-0.02	-0.10	0.19	0.77	(2.51)	0.87	(3.01)
β_{Vol}	-0.53	-0.39	-0.35	-0.22	-0.22	-0.18	-0.15	-0.23	-0.06	0.15	0.68	(2.61)	0.85	(3.28)
β_{Tail}	-0.56	-0.48	-0.30	-0.25	-0.15	-0.26	-0.10	-0.17	0.00	0.05	0.62	(2.23)	0.65	(2.48)
β_{Down}	-0.55	-0.39	-0.39	-0.28	-0.19	-0.26	-0.11	-0.12	-0.22	0.27	0.82	(2.92)	1.01	(3.60)

Table 5: Fama-MacBeth Regressions

The table presents the results of Fama and MacBeth (1973) regressions of monthly delta-hedged bear spread returns on $VaR5$ and control variables. $VaR5$ is the 5% value-at-risk that corresponds to -1 times the 5th percentile of daily returns in the past year. Control variables are SIZE (market capitalization); BTM (book-to-market ratio); DTA (firm leverage); MOM (momentum computed as the return over the previous six months); REV (reversal which is the return over the previous month); ILLIQ (logarithm of Carhart illiquidity); IVOL (idiosyncratic volatility); SKEW and KURT (skewness and kurtosis from one year of daily returns); VRP (variance risk premium as in Goyal and Saretto (2009)); VOV (vol-of-vol as in Baltussen et al. (2018)); RNS (risk-neutral skewness). We use 60-month rolling windows to compute the exposures of individual bear spread returns to the following systematic risk factors: zero-beta straddle (β_{Strad}) from Coval and Shumway (2001), jump and volatility factors (β_{Jump} and β_{Vol}) as in Cremers et al. (2015), the bear market factor (β_{Bear}) following Lu and Murray (2019), the tail factor (β_{Tail}) as in Kelly and Jiang (2014), and the downside factor (β_{Down}) following Ang et al. (2006a). The first two columns report the results for the univariate regression of delta-hedged bear spread returns on $VaR5$, and the regressions of delta-hedged bear spread returns on $VaR5$ and each of the control variables. The third column reports the adjusted R-squared of the univariate and bivariate regressions. The last column reports the results of the multivariate regression of delta-hedged bear spread returns on $VaR5$ and all the control variables. Coefficients are time-series averages and the associated Newey and West (1987) t-statistics are reported in parentheses. The sample period is from January 1996 to December 2017 for stocks in the OptionMetrics database.

	Bivariate Regressions			Multivariate
	Coefficient on VaR5	Coefficient on Control	Adj. R^2	Regression
VaR5	0.201		1.32%	0.267
	(4.58)			(4.20)
SIZE	0.210	0.000	1.47%	-0.003
	(4.64)	(0.82)		(-3.42)
BTM	0.118	0.000	1.33%	0.000
	(2.63)	(1.04)		(1.02)
DTA	0.128	-0.002	1.41%	0.001
	(2.74)	(-1.16)		(0.57)
MOM	0.172	-0.002	1.90%	-0.004
	(3.98)	(-1.43)		(-1.82)
REV	0.186	-0.004	1.83%	-0.007
	(4.26)	(-1.03)		(-1.70)
ILLIQ	0.239	-0.001	1.54%	-0.002
	(5.13)	(-3.55)		(-2.76)
IVOL	0.235	-0.113	1.81%	-0.548
	(5.11)	(-2.85)		(-4.73)
SKEW	0.182	-0.001	1.50%	0.001
	(4.18)	(-1.80)		(1.08)
KURT	0.183	0.000	1.53%	0.000
	(4.15)	(-2.53)		(1.56)
VRP	0.143	-0.002	1.68%	-0.026
	(3.21)	(-0.90)		(-3.49)
VOV	0.154	-0.008	1.47%	0.012
	(3.46)	(-0.98)		(1.10)
RNS	0.184	-0.001	1.58%	-0.001
	(3.69)	(-1.10)		(-0.61)
β_{Bear}	0.141	0.001	1.93%	0.000
	(2.78)	(2.12)		(-0.33)
β_{Strad}	0.163	-0.002	1.64%	0.002
	(3.00)	(-0.43)		(0.37)
β_{Jump}	0.159	0.000	1.69%	0.001
	(2.91)	(0.07)		(1.34)
β_{Vol}	0.159	0.000	1.80%	-0.001
	(2.92)	(0.60)		(-0.58)
β_{Tail}	0.163	0.001	1.72%	0.000
	(2.98)	(1.89)		(0.13)
β_{Down}	0.164	0.000	1.70%	0.000
	(2.99)	(1.15)		(1.23)
Adj. R^2				5.75%

Table 6: Persistence of Left-Tail Risk

This table presents equal-weighted and dollar-open-interest-weighted return (in %) comparisons between bear spread decile portfolios sorted based on the monthly change in $VaR5$ (ΔVaR) in Panel A and the nearness to 52-week low (NL) in Panel B. $VaR5$ is the 5% value-at-risk that corresponds to -1 times the 5th percentile of daily returns in the past year. ΔVaR is defined as the difference between $VaR5$ in month t and month $t-1$. NL is calculated as the the previous month-end stock price divided by the minimum price in the previous year. Delta-hedged bear spread portfolios are sorted into $\Delta VaR > 0$ and $\Delta VaR \leq 0$ groups or NL terciles. Then decile portfolios are formed based on $VaR5$ within each group or tercile. The returns for decile 10 and decile 1 portfolios, the return spread ("10-1") and its associated five-factor alpha are reported. Five-factor alphas are calculated after adjusting for Fama-French three factors, Carhart (1997) momentum factor, and Coval and Shumway (2001) systematic volatility factor. Newey and West (1987) adjusted t-statistics are presented in parentheses. The sample period is from January 1996 to December 2017 for stocks in the OptionMetrics database.

Panel A: Sorts based on ΔVaR

	Equal-weighted		Dollar-open-interest-weighted	
	ΔVaR >0	ΔVaR <=0	ΔVaR >0	ΔVaR <=0
1	-0.53	-0.64	-0.56	-0.44
10	0.48	0.15	1.08	-0.28
10-1	1.02	0.79	1.64	0.16
(t-stat)	(2.76)	(2.70)	(3.01)	(0.43)
Five-factor alpha	1.12	0.87	1.77	0.25
(t-stat)	(2.85)	(3.34)	(3.11)	(0.59)

Panel B: Sorts based on nearest to 52-week low (NL)

	Equal-weighted			Dollar-open-interest-weighted		
	Low NL	Mid NL	High NL	Low NL	Mid NL	High NL
1	-0.65	-0.68	-0.21	-0.55	-0.67	-0.62
10	0.47	0.04	0.31	1.48	0.52	-0.17
10-1	1.12	0.72	0.52	2.04	1.19	0.46
(t-stat)	(3.28)	(2.74)	(1.45)	(3.74)	(2.63)	(0.73)
Five-factor alpha	1.23	0.83	0.76	2.21	1.34	0.55
(t-stat)	(3.26)	(3.58)	(2.05)	(4.02)	(3.03)	(0.78)

Table 7: Information Uncertainty

This table presents equal-weighted and dollar-open-interest-weighted return (in %) comparisons between bear spread decile portfolios in subsamples sorted based on quintiles by size in Panel A, and, in Panel B, four information uncertainty proxies: analyst coverage residual (AC_{res}), analysts' forecast dispersion residual ($DISP_{res}$), turnover residual ($TURN_{res}$) and firm age (AGE). AC_{res}, $DISP_{res}$, and $TURN_{res}$ are calculated as the residuals from the cross-sectional regression of the corresponding values on the logarithm of firm's market capitalization in the previous quarter. Decile portfolios are formed based on the underlying stocks' $VaR5$ within each subsample. $VaR5$ is the 5% value-at-risk that corresponds to -1 times the 5th percentile of daily returns in the past year. The returns for decile 10 and decile 1 portfolios, the return spread ("10-1"), and its associated five-factor alpha are reported. Five-factor alphas are calculated after adjusting for Fama-French three factors, Carhart (1997) momentum factor, and Coval and Shumway (2001) systematic volatility factor. Newey and West (1987) adjusted t-statistics are presented in parentheses. The sample period is from January 1996 to December 2017 for stocks in the OptionMetrics database.

Panel A: Size

	Equal-weighted					DOI-weighted				
	Low Size	2	3	4	High Size	Low Size	2	3	4	High Size
1	-0.22	-0.46	-0.57	-0.55	-0.74	-0.68	-0.73	-0.64	-0.68	-0.54
10	0.81	0.33	0.32	0.00	-0.06	1.10	0.69	0.56	0.03	0.00
10-1	1.04	0.79	0.89	0.54	0.67	1.78	1.42	1.21	0.71	0.54
(t-stat)	(2.68)	(2.28)	(2.14)	(1.71)	(2.46)	(2.68)	(2.28)	(2.14)	(1.71)	(2.46)
5F alpha	1.11	0.68	0.93	0.65	0.66	1.63	1.46	1.41	0.71	0.70
(t-stat)	(2.79)	(1.97)	(2.16)	(2.36)	(2.26)	(2.21)	(2.37)	(2.35)	(1.73)	(1.45)

Panel B: Other measures of information uncertainty

	Equal-weighted portfolio							
	Low AC_{res}	High AC_{res}	Low $DISP_{res}$	High $DISP_{res}$	Low $TURN_{res}$	High $TURN_{res}$	Low AGE	High AGE
1	-0.61	-0.51	-0.65	-0.70	-0.71	-0.28	-0.57	-0.69
10	0.52	0.07	0.10	0.31	-0.25	0.65	0.75	0.19
10-1	1.13	0.59	0.75	1.01	0.46	0.93	1.32	0.88
(t-stat)	(3.94)	(2.15)	(2.41)	(3.44)	(1.92)	(3.27)	(4.22)	(3.19)
5F alpha	1.28	0.81	0.94	1.07	0.57	1.00	1.44	1.02
(t-stat)	(4.72)	(2.77)	(3.41)	(3.40)	(2.38)	(3.66)	(5.11)	(3.79)

	DOI-weighted portfolio							
	Low AC_{res}	High AC_{res}	Low $DISP_{res}$	High $DISP_{res}$	Low $TURN_{res}$	High $TURN_{res}$	Low AGE	High AGE
1	-0.62	-0.37	-0.49	-0.61	-0.68	-0.30	-0.43	-0.73
10	0.74	0.49	-0.53	0.83	-0.65	0.86	1.50	-0.12
10-1	1.36	0.86	-0.04	1.44	0.02	1.17	1.93	0.61
(t-stat)	(2.22)	(2.11)	(-0.11)	(2.81)	(0.06)	(2.55)	(4.40)	(1.26)
5F alpha	1.52	1.14	0.10	1.89	0.21	1.45	2.00	0.95
(t-stat)	(2.67)	(2.69)	(0.26)	(3.23)	(0.56)	(2.76)	(4.66)	(2.03)

Table 8: Robustness Tests

This table reports the time-series average monthly returns (in %) for equal-weighted delta-hedged bear spread decile portfolios sorted on the left-tail risk measure $VaR5$ for different subsamples. $VaR5$ is the 5% value-at-risk that corresponds to -1 times the 5th percentile of daily returns in the past year. We report the following subsamples: for periods of high and low sentiment; from 1996-2007 and 2008-2017; for period with and without earnings announcement days (with/without EAD); for periods of high and low volatility VIX; for periods of high and low economic growth (CFNAI). Sentiment is the market-wide sentiment constructed by Baker and Wurgler (2006), VIX is the volatility index from the CBOE, and Chicago Fed National Activity Index (CFNAI) is a monthly index designed to gauge overall economic activity and related inflationary pressure. A high-sentiment period and a high volatility period (high economic-growth period) are selected when the sentiment level or the VIX level (CFNAI level) are above their sample median (zero). The prices of the put options in the bear spread are weighted using simple average or kernel-weighted average. To construct the bear spread, we take the average of all put options within the range $[-0.40, -0.20)$ and $[-0.20, 0]$ for the OTM and the DOTM put options. We also report bear spread returns using daily rebalancing. Newey and West (1987) adjusted t-statistics are presented in parentheses. The sample period is from January 1996 to December 2017 for stocks in the OptionMetrics database.

	1	2	3	4	5	6	7	8	9	10	10-1	(t-stat)
Low Sent.	-0.61	-0.54	-0.47	-0.47	-0.32	-0.29	-0.10	-0.18	-0.44	-0.08	0.52	(1.67)
High Sent.	-0.57	-0.33	-0.23	0.11	0.08	0.08	0.45	0.50	0.63	0.85	1.42	(3.25)
1996-2007	-0.84	-0.59	-0.40	-0.14	-0.12	-0.04	0.42	0.42	0.36	0.68	1.52	(3.48)
2008-2017	-0.33	-0.24	-0.27	-0.19	-0.10	-0.13	-0.07	-0.06	-0.16	0.15	0.48	(1.65)
With EAD	-0.38	-0.35	-0.06	-0.07	0.28	0.26	0.39	0.27	0.34	0.57	0.95	(3.15)
Without EAD	-0.65	-0.53	-0.51	-0.36	-0.19	-0.22	0.00	0.02	-0.11	0.63	1.28	(3.61)
Low VIX	-0.43	-0.24	-0.19	-0.09	-0.17	0.06	0.31	0.17	-0.02	0.22	0.65	(1.82)
High VIX	-0.82	-0.68	-0.54	-0.30	-0.09	-0.28	0.04	0.16	0.19	0.59	1.41	(3.30)
Low CFNAI	-0.59	-0.43	-0.40	-0.27	-0.01	-0.04	-0.03	0.06	0.17	0.78	1.37	(3.31)
High CFNAI	-0.66	-0.49	-0.34	-0.12	-0.26	-0.17	0.38	0.27	0.01	0.04	0.69	(2.17)
Simple avg.	-0.58	-0.45	-0.36	-0.16	-0.13	-0.12	0.21	0.21	0.13	0.42	1.00	(3.55)
Kernel avg.	-0.57	-0.45	-0.35	-0.15	-0.10	-0.09	0.24	0.24	0.15	0.45	1.02	(3.50)
Daily rebalance	1.96	1.69	1.74	1.85	2.17	2.49	2.62	2.73	2.86	3.76	1.80	(2.46)

Table 9: Transaction Costs

This table examines the impact of transaction costs (bid-ask spreads and margin requirements) on the profitability of the "10-1" delta-hedged bear spread return (in %) sorted on $VaR5$. $VaR5$ is the 5% value-at-risk that corresponds to -1 times the 5th percentile of daily returns in the past year. We report "10-1" delta-hedged bear spread returns for different ratios of the effective bid-ask spread to the quoted bis-ask spread: 0% (No cost), 10%, 25%, and 50%, and for different relative bid-ask spreads: lower than 10%, lower than 20%, lower than 30%, and for the full sample. The margin requirement adjusted return is computed using the initial option margin requirements of the CBOE. Following Weinbaum et al. (2020), the margin cost equals the cost of borrowing the additional capital to meet the margin requirement. Portfolios are equal-weighted and dollar-open-interest-weighted. Each month t, decile portfolios of delta-hedged bear spreads are formed and held to maturity by sorting underlying stocks on the $VaR5$ left-tail measure. Newey and West (1987) adjusted t-statistics are presented in parentheses. The sample period is from 1996 to 2017 for stocks in the OptionMetrics database.

	Equal-weighted				DOI-weighted			
Effective to Quoted Spr.	Relative spread<0.1	Relative spread<0.2	Relative spread<0.3	Full sample	Relative spread<0.1	Relative spread<0.2	Relative spread<0.3	Full sample
0% (No cost)	1.08	1.22	0.96	1.03	0.88	1.22	1.08	1.04
	(2.72)	(3.97)	(3.26)	(3.60)	(1.80)	(2.55)	(2.55)	(2.44)
10%	1.03	1.12	0.84	0.84	0.83	1.14	0.99	0.92
	(2.60)	(3.69)	(2.84)	(2.94)	(1.70)	(2.39)	(2.32)	(2.17)
25%	0.93	0.98	0.66	0.57	0.73	1.02	0.85	0.73
	(2.39)	(3.24)	(2.25)	(1.98)	(1.51)	(2.14)	(2.03)	(1.74)
50%	0.82	0.76	0.35	0.15	0.64	0.83	0.59	0.42
	(2.10)	(2.53)	(1.22)	(0.50)	(1.33)	(1.75)	(1.41)	(1.01)
25%+Margin	0.93	0.98	0.66	0.57	0.73	1.02	0.85	0.73
	(2.38)	(3.23)	(2.25)	(1.98)	(1.51)	(2.14)	(2.03)	(1.74)
Obs.	35,390	89,825	122,454	155,003	35,390	89,825	122,454	155,003

Internet Appendix for "Does the options market underreact to firms' left-tail risk?"

1 Factor Construction

1.1 Zero-Beta Straddle Factor: ZB Straddle

The zero-beta straddle or systematic volatility factor (ZB Straddle) is calculated as the return of the zero-beta S&P 500 straddles following Coval and Shumway (2001). Each month, we form zero-beta S&P 500 straddle portfolios based on information available on the first trading day (usually a Monday) immediately following the expiration of the previous one month options. All options are to expire on the Saturday immediately following the third Friday in the next calendar month. Among these options with one month to maturity, we select the pair of call and put options that are closest to at-the-money (ATM). After next month expiration, we select a new pair of call and put contracts that are at that time closest to ATM and have one month to expiration.

We take the midpoint of the bid-ask spread and calculate monthly holding-period returns for each option. Following Coval and Shumway (2001), we calculate the zero-beta straddle return as:

$$r_{zb-straddle} = \frac{-C\beta_c + S}{P\beta_c - C\beta_c + S} r_c + \frac{P\beta_c}{P\beta_c - C\beta_c + S} r_p,$$

where C (P) is the call (put) price, S is the index price, β_c is the market beta of the call option, and r_c (r_p) is the holding-period return of the call (put) option.

The average monthly return of the zero-beta straddle is -10.75%, which is equivalent to the result in Coval and Shumway (2001) of -3.15% per week.

1.2 Jump and Volatility Factors

The jump and diffusive volatility factors (Jump and Vol) are calculated following Cremers et al. (2015). We form the jump risk factor portfolio and the diffusive volatility risk factor portfolio using S&P 500 index options. At the close of the trading on a given date, we form one short-dated zero-beta ATM straddle, and one long-dated zero-beta ATM straddle, by picking the call and put option pair that is closest to being ATM among all options that expire in the next calendar month (for the short-dated options required in the strategies) and the calendar month that follows (for the long-dated options). We hold each position for one trading day, and pick new option pairs the next day.

The jump risk factor portfolio consists of a long position of 1 contract in the short-dated zero-beta ATM straddle, and a short position of y_1 contracts in the long-dated zero-beta ATM straddles; y_1 is chosen to make the overall portfolio vega neutral. The diffusive volatility risk factor portfolio consists of a long position of 1 contract in the long-dated zero-beta ATM straddle, and a short position of y_2 contracts in the short-dated zero-beta ATM straddles; y_2 is chosen to make the overall portfolio gamma neutral. We cumulate the daily returns for these two risk factor portfolios during each month to obtain the jump and volatility risk factors at a monthly frequency. The daily return of the jump (diffusive volatility) risk factor portfolio is -0.11% (-0.05%), consistent with the negative risk premium arguments in Cremers et al. (2015). The correlation between the jump and the diffusive volatility risk factors is 0.19, indicating a moderately low correlation.

1.3 Arrow-Debreu Bear Factor: AD-BEAR

The bear market factor (AD-BEAR) is calculated following Lu and Murray (2019). We create the bear market factor portfolio using the S&P 500 index options expiring on the third Friday of the subsequent calendar month. We form the bear market factor portfolio by taking a long position in the out-of-the-money (OTM) put option with strike price to be one standard deviation below the index forward price, and a short position in the deep out-of-the-money (DOTM) put option with strike price to be 1.5 standard deviations below the index forward price. The standard deviation of the market return is the level of VIX divided by one hundred multiplied by the square root of the time to expiration. We define the price of both put options to be the dollar trading volume-weighted average price of puts with strikes within a 0.25 standard deviation range of the target strike.

At the end of each week, we calculate the buy and hold return of the bear market factor portfolio over the next five trading days. We pick a new option pair at the end of each week. We subtract the five-day risk-free rate from the five-day buy-and-hold bear market factor portfolio return to get the excess return for the five day period. As in Lu and Murray (2019), we scale the bear excess returns so that the standard deviation of the scaled bear excess returns is equal to that of the market excess returns. We cumulate weekly returns for the bear portfolio during each month to obtain the bear market risk factor at a monthly frequency. The average monthly return of the bear market portfolio is -1.33%, which is similar to the results in Lu and Murray (2019) of -0.28% per week.

1.4 Tail Risk Factor

To calculate the tail risk factor (Tail), first, we estimate the tail risk time series following Kelly and Jiang (2014). Second, we estimate the tail loading for each stock by regressing stock excess return on the tail risk time series. The regressions use the most recent 120 months of data. Third, stocks are sorted into decile portfolios based on their estimated tail risk loadings. We calculate the tail risk factor as the equal-weighted returns of the portfolio that is long stocks in the decile 10 portfolio and short stocks in the decile 1 portfolio. By construction, this is the factor that can be traded.

1.5 Downside Risk Factor

To calculate the downside risk factor (Downside), first, we calculate the downside beta following Ang et al. (2006a). Each month t for each stock, we regress each stock's excess return on the market's excess return when the market excess return is below its average during the time period. The regression uses the daily data in the last 12 months.

Second, we calculate the downside risk factor by sorting all stocks into decile portfolios based on an ascending sort of downside beta in each month t, and calculating the equal-weighted excess return in month $t+1$ for a portfolio that is long stocks in decile 10 and short stocks in decile 1.

1.6 Coskewness Risk Factor

To calculate the coskewness risk factor (Coskew), first, we calculate the coskewness beta following Harvey and Siddique (2000) for each stock in each month t as:

$$\beta_{coskewness} = \frac{E[(r_i - \mu_i)(r_m - \mu_m)^2]}{\sqrt{var(r_i)}var(r_m)},$$

where r_i and μ_i (r_m and μ_m) are the excess return and the average excess return of each security i (the market). The regression uses the daily data in the last 12 months.

Second, we calculate the coskewness risk factor (Coskew) by sorting all stocks into decile portfolios based on an ascending sort of $\beta_{coskewness}$ in each month t, and calculating the equal-weighted excess return in month $t+1$ for a portfolio that is long stocks in the decile 10 portfolio and short stocks in the decile 1 portfolio.

1.7 Vanden's Alpha

Vanden (2006) develops the coskewness risk factor model that includes higher-order moments of the market return and the market option return. The coskewness model incorporates not only the market return and the square of the market return but also the option return, the square of the option return, and the product of the market and the option returns. For the option return, we use the market bear spread return computed as in Lu and Murray (2019). Additionally the model includes the Fama-French factors and the momentum factor.

1.8 Option Factors: Illiquidity, Idiosyncratic Volatility, Variance Risk Premium, and Size

Cao et al. (2022) and Horenstein et al. (2020) document four factors that drive the cross-section of delta-hedged option returns. These factors are similar to the ones in the stock market, the only difference is that they are computed from the cross-section of option returns. To construct the factors, every month we sort by one of the characteristics and form decile portfolios of delta-hedged option returns. The factor is the long-short portfolio which is the portfolio that buys portfolio 10 and sells portfolio 1.

2 Left-Tail Risk Exposures Construction

2.1 Exposure to the Market Bear Spread: β_{Bear}

The exposure of the individual bear spreads to the market bear spread is calculated following Lu and Murray (2019). We run a time series regression of the delta-hedged bear spread returns in each month for each stock on the contemporaneous AD-BEAR return and the contemporaneous excess market return. The regression uses monthly data in the last 5 years, and we require at least 10 valid observations. The exposure to the AD-BEAR return is denoted by β_{Bear}.

2.2 Exposure to the Zero-Beta Straddle Factor: β_{Strad}

To calculate the exposure to the zero-beta straddle factor (β_{Strad}), we run a time series regression of the delta-hedged bear spread returns in each month for each stock on the contemporaneous zero-beta straddle return. The regression uses monthly data in last 5 years, and we require at least 10 valid observations for estimation. The exposure to the zero-beta straddle return is denoted by β_{Strad}.

2.3 Exposure to the Jump Factor and the Vol Factor: β_{Jump} and β_{Vol}

We estimate β_{Jump} and β_{Vol} following Cremers et al. (2015) by estimating regressions in each month for each stock using monthly returns over rolling annual periods. The delta-hedged bear spread return is regressed on the contemporaneous excess market return, the lagged excess market return, the jump (volatility) factor return, and the lagged jump (volatility) factor return. To calculate β_{Jump} (β_{Vol}), we use the sum of the betas estimated for the jump (volatility) factor, and the lagged jump (volatility) factor.

2.4 Exposure to the Tail Factor: β_{Tail}

To calculate β_{Tail}, we run a time series regression of the delta-hedged bear spread returns in each month for each stock on the contemporaneous tail risk factor. The regression uses monthly data in last 5 years, and we require at least 10 valid observations for estimation. The exposure to the tail risk factor return is denoted by β_{Tail}.

2.5 Exposure to the Downside Factor: $\beta_{Downside}$

To calculate $\beta_{Downside}$, we run a time series regression of the delta-hedged bear spread returns in each month for each stock on the contemporaneous market excess return when the market excess return is below the average market excess return during the time period. The regression uses monthly data in last 5 years, and we require at least 10 valid observations for estimation. The exposure to the market factor return is denoted by $\beta_{Downside}$.

Table IA1: Left-Tail vs. Right-Tail Risk

The table presents the results of Fama and MacBeth (1973) regressions of monthly delta-hedged bear spread returns on VaR5 residual, VaR95, and control variables in regressions (1) and (2), and on VaR95 residual, VaR5, and the control variables in regressions (3) and (4). VaR5 (VaR95) is the 5% (95%) value-at-risk that corresponds to -1 times the 5th (95th) percentile of daily returns in the past year. VaR5 residual (VaR95 residual) is calculated by orthogonalizing VaR5 (VaR95) via monthly cross-sectional regressions of VaR5 (VaR95) on VaR95 (VaR5). The residual terms from these regressions are denoted as VaR5 residual (VaR95 residual). Control variables are SIZE (market capitalization); BTM (book-to-market ratio); DTA (firm leverage); MOM (momentum computed as the return over the previous six months); REV (reversal which is the return over the previous month); ILLIQ (logarithm of Carhart illiquidity); IVOL (idiosyncratic volatility); SKEW and KURT (skewness and kurtosis from one year of daily returns); VRP (variance risk premium as in Goyal and Saretto (2009)); VOV (vol-of-vol as in Baltussen et al. (2018)); RNS (risk-neutral skewness). Coefficients are time-series averages, and the associated Newey and West (1987) *t*-statistics are reported in parentheses. The sample period is from January 1996 to December 2017 for stocks in the OptionMetrics database.

	(1)	(2)	(3)	(4)
VaR5			0.201	0.223
			(4.66)	(3.30)
VaR5 residual	0.252	0.179		
	(2.99)	(1.98)		
VaR95	0.137	0.175		
	(4.12)	(3.21)		
VaR95 residual			-0.073	0.025
			(-1.15)	(0.35)
SIZE		-0.004		-0.004
		(-4.24)		(-4.24)
BTM		0.000		0.000
		(1.28)		(1.28)
DTA		-0.004		-0.004
		(-1.45)		(-1.45)
MOM		-0.002		-0.002
		(-0.88)		(-0.88)
REV		0.000		0.000
		(0.02)		(0.02)
ILLIQ		-0.003		-0.003
		(-4.09)		(-4.09)
IVOL		-0.287		-0.287
		(-2.76)		(-2.76)
SKEW		0.000		0.000
		(0.21)		(0.21)
KURT		0.000		0.000
		(-1.84)		(-1.84)
VRP		-0.014		-0.014
		(-2.10)		(-2.10)
VOV		-0.002		-0.002
		(-0.18)		(-0.18)
RNS		-0.001		-0.001
		(-0.72)		(-0.72)
Adj. R^2	1.8%	5.0%	1.8%	5.0%

Table IA2: Exposures to Systematic Factors

This table reports the post-formation exposures to the systematic left-tail risk measures of each bear spread decile portfolio sorted by VaR5. The post-formation beta exposures are calculated for each of the decile portfolio as the slope coefficients on each of the systematic left-tail risk factor from a regression of the delta-hedged bear spread portfolio returns on the contemporaneous market return and each factor return. Factors are the ZB Straddle is the zero-beta straddle return from Coval and Shumway (2001); the jump and volatility factors (Jump and Vol) are computed as in Cremers et al. (2015); the bear market factor (AD-BEAR) following Lu and Murray (2019); the VIX is the monthly return of the VIX volatility index; the Tail factor following Kelly and Jiang (2014); Downside factor following Ang et al. (2006a); Coskewness factor computed following Harvey and Siddique (2000). The difference between the post-formation betas of decile 10 and decile 1 portfolios is reported in the last column. The sample period is from January 1996 to December 2017 for stocks in the OptionMetrics database.

Exposures	1	2	3	4	5	6	7	8	9	10	10-1
MKT	-0.001	-0.001	-0.001	-0.001	-0.002	-0.002	-0.002	-0.002	-0.002	-0.003	-0.002
(t-stat)	(-3.45)	(-2.79)	(-3.38)	(-3.70)	(-4.68)	(-4.77)	(-4.48)	(-4.15)	(-3.20)	(-5.80)	(-3.29)
ZB Straddle	0.017	0.016	0.015	0.021	0.020	0.018	0.021	0.023	0.017	0.016	0.000
(t-stat)	(5.80)	(4.44)	(4.11)	(7.48)	(6.86)	(5.67)	(5.62)	(4.93)	(2.49)	(2.68)	(-0.06)
Jump	0.024	0.016	0.009	0.027	0.031	0.035	0.030	0.035	0.042	0.022	-0.002
(t-stat)	(2.90)	(1.98)	(0.94)	(2.40)	(2.56)	(2.55)	(1.95)	(2.00)	(1.97)	(1.06)	(-0.08)
Vol	0.022	0.036	0.025	0.039	0.036	0.023	0.029	0.040	0.022	0.043	0.021
(t-stat)	(1.42)	(2.17)	(1.48)	(2.11)	(1.91)	(1.06)	(1.22)	(1.55)	(0.72)	(1.22)	(0.63)
AD-BEAR	0.015	0.028	0.029	0.070	0.072	0.039	0.069	0.134	0.133	0.093	0.078
(t-stat)	(0.42)	(0.80)	(0.66)	(1.76)	(1.65)	(0.73)	(1.31)	(2.18)	(1.61)	(1.34)	(1.16)
Tail	-0.010	-0.022	-0.026	-0.001	-0.031	-0.005	-0.018	-0.031	-0.040	-0.022	-0.012
(t-stat)	(-0.38)	(-0.96)	(-0.91)	(-0.03)	(-0.92)	(-0.21)	(-0.52)	(-0.68)	(-0.84)	(-0.55)	(-0.24)
VIX	0.033	0.071	0.064	0.092	0.140	0.127	0.122	0.133	0.193	0.091	0.057
(t-stat)	(1.03)	(1.78)	(1.32)	(1.80)	(2.61)	(2.33)	(1.96)	(1.72)	(2.40)	(1.16)	(0.79)
Downside	0.035	0.044	0.053	0.046	0.043	0.020	0.017	0.013	0.039	0.043	0.008
(t-stat)	(2.21)	(2.61)	(3.49)	(2.77)	(1.95)	(1.13)	(0.61)	(0.41)	(1.06)	(1.31)	(0.22)
Coskew	-0.024	-0.022	-0.024	-0.014	-0.032	-0.042	-0.052	-0.060	-0.081	-0.004	0.021
(t-stat)	(-1.09)	(-0.79)	(-0.76)	(-0.50)	(-0.92)	(-1.58)	(-1.22)	(-1.27)	(-1.32)	(-0.06)	(0.32)

Table IA3: Bivariate Portfolio Analysis: Dollar-Open-Interest-Weighted

This table presents results (in %) for dollar-open-interest-weighted delta-hedged bear spread portfolios based on bivariate dependent sorts of one (firm-specific, stock-related or option related) characteristic variable and $VaR5$. In month t, decile portfolios of delta-hedged bear spreads are formed by sorting underlying stocks based on one of the characteristic variables. Then within each decile, additional decile portfolios of delta-hedged bear spreads are formed by sorting underlying stocks based on $VaR5$ observed in the previous year. Each $VaR5$ decile portfolio is then averaged over the control characteristic deciles. This table reports the raw returns for equal-weighted decile portfolios thus obtained, and the return spreads and associated alpha spreads for decile 10 portfolio (highest $VaR5$) and decile 1 portfolio (lowest $VaR5$). Five-factor alphas are calculated after adjusting for Fama-French three factors, Carhart (1997) momentum factor, and Coval and Shumway (2001) systematic volatility factor. $VaR5$ is the 5% value-at-risk that corresponds to -1 times the 5th percentile of daily returns in the past year. Control variables are SIZE (market capitalization); BTM (book-to-market ratio); DTA (firm leverage); MOM (momentum computed as the return over the previous six months); REV (reversal which is the return over the previous month); ILLIQ (logarithm of Carhart illiquidity); IVOL (idiosyncratic volatility); SKEW and KURT (skewness and kurtosis from one year of daily returns); VRP (variance risk premium as in Goyal and Saretto (2009)); VOV (vol-of-vol as in Baltussen et al. (2018)); RNS is risk-neutral skewness. We use 60-month rolling windows to compute the exposures of individual bear spread returns to the following systematic risk factors: zero-beta straddle (β_{Strad}) from Coval and Shumway (2001), jump and volatility factors (β_{Jump} and β_{Vol}) as in Cremers et al. (2015), the bear market factor (β_{Bear}) following Lu and Murray (2019), the tail factor (β_{Tail}) as in Kelly and Jiang (2014), and the downside factor ($\beta_{Downside}$) following Ang et al. (2006a). Newey and West (1987) adjusted t-statistics are presented in parentheses. The sample period is from January 1996 to December 2017 for stocks in the OptionMetrics database.

	1	2	3	4	5	6	7	8	9	10	10-1	(t-stat)	5F Alpha	(t-stat)
SIZE	-0.76	-0.41	-0.28	-0.30	-0.39	-0.23	-0.11	0.08	0.17	0.21	0.97	(3.26)	1.07	(3.62)
BTM	-0.42	-0.38	0.01	0.04	-0.09	0.03	-0.12	0.12	0.08	0.28	0.50	(1.49)	0.65	(2.18)
DTA	-0.54	-0.20	0.06	-0.28	0.00	0.42	0.07	-0.01	0.08	0.18	0.62	(2.27)	0.68	(2.54)
MOM	-0.29	-0.32	-0.13	-0.14	-0.40	0.14	-0.08	-0.02	-0.26	0.56	0.85	(2.45)	1.04	(3.02)
REV	-0.45	-0.40	-0.17	-0.22	0.27	-0.21	0.12	0.01	0.07	0.60	1.06	(2.91)	1.17	(3.31)
ILLIQ	-0.90	-0.14	-0.42	-0.37	-0.28	0.06	-0.11	0.13	0.15	0.26	1.16	(3.44)	1.26	(3.92)
IVOL	-0.46	0.06	-0.32	-0.14	-0.07	-0.04	-0.27	-0.29	0.12	0.57	0.58	(2.42)	0.81	(3.11)
SKEW	-0.35	-0.27	-0.40	-0.16	0.05	0.04	0.14	0.03	0.01	0.47	0.82	(1.94)	1.09	(2.83)
KURT	-0.42	-0.29	-0.32	-0.25	0.01	0.35	0.14	0.13	0.06	0.21	0.63	(1.60)	0.96	(2.60)
VRP	-0.61	-0.01	-0.37	-0.35	0.04	0.19	0.07	0.19	0.10	0.11	0.72	(1.77)	0.88	(2.20)
VOV	-0.46	-0.25	-0.28	-0.21	0.17	0.20	0.01	-0.07	0.05	0.26	0.72	(1.82)	0.93	(2.32)
RNS	-0.42	-0.58	-0.20	-0.01	0.16	0.43	-0.31	-0.18	0.18	0.39	0.84	(2.30)	0.77	(2.08)
β_{Bear}	-0.57	-0.58	-0.42	-0.19	-0.26	-0.08	-0.17	-0.34	-0.39	0.26	0.82	(2.19)	1.20	(3.34)
β_{Strad}	-0.59	-0.41	-0.26	-0.31	-0.30	-0.07	-0.37	-0.23	-0.26	0.14	0.73	(1.96)	1.04	(2.79)
β_{Jump}	-0.49	-0.63	-0.33	-0.33	-0.01	-0.19	-0.20	-0.06	-0.44	0.05	0.55	(1.43)	0.93	(2.45)
β_{Vol}	-0.57	-0.31	-0.47	-0.47	0.18	-0.15	-0.32	-0.43	-0.44	0.28	0.86	(2.35)	1.36	(3.88)
β_{Tail}	-0.51	-0.61	-0.21	-0.16	-0.39	-0.04	-0.24	-0.41	-0.10	0.12	0.63	(1.70)	0.78	(2.15)
β_{Down}	-0.60	-0.46	-0.52	-0.17	-0.42	-0.27	0.06	0.03	-0.56	0.11	0.71	(2.03)	1.12	(3.32)

Table IA4: Modified Fama-Macbeth Regressions and Weigthed Least Squares Regressions

This table presents the results of Fama and MacBeth (1973) regressions (FM) of monthly delta-hedged bear spread returns on VaR5 and control variables. In the Modified FM model, the delta-hedged bear spread returns are first regressed on all factors in Table 3, and then the cross-sectional regressions are conducted as follows: $r_{i,t} - \beta_i F_i = \gamma_{0,t} + \gamma_{1,t} VaR5_{i,t-1} + \phi_t Z_{i,t-1} + e_{i,t}$ where $r_{i,t}$ is the return on the delta-hedged bear spread observed for stock i at quarter t, β_i is a vector of estimated factor loadings of the stock i's delta-hedged bear spread returns, F_i is a vector of factors, $VaR5_{i,t-1}$ is one of the stock i's left-tail risk characteristics observed in quarter t-1, and $Z_{i,t-1}$ is a vector of controls. In the weighted least squares model (WLS), each monthly regression is estimated using the WLS methodology following Asparouhova et al. (2013). The dollar open interest (DOI) of the options and the last month-end stock market capitalization are used as the weight assigned to each observation respectively. VaR5 is the 5% value-at-risk that corresponds to -1 times the 5th percentile of daily returns in the past year. Control variables are SIZE (market capitalization); BTM (book-to-market ratio); DTA (firm leverage); MOM (momentum computed as the return over the previous six months); REV (reversal which is the return over the previous month); ILLIQ (logarithm of Carhart illiquidity); IVOL (idiosyncratic volatility); SKEW and KURT (skewness and kurtosis from one year of daily returns); VRP (variance risk premium as in Goyal and Saretto (2009)); VOV (vol-of-vol as in Baltussen et al. (2018)); RNS (risk-neutral skewness). We use 60-month rolling windows to compute the exposures of individual bear spread returns to the following systematic risk factors: zero-beta straddle (β_{Strad}) from Coval and Shumway (2001), jump and volatility factors (β_{Jump} and β_{Vol}) as in Cremers et al. (2015), the bear market factor (β_{Bear}) following Lu and Murray (2019), the tail factor (β_{Tail}) as in Kelly and Jiang (2014), and the downside factor (β_{Down}) following Ang et al. (2006a). Coefficients are time-series averages and the associated Newey and West (1987) t-statistics are reported under the coefficients. The last row reports the average adjusted R-squared. The sample period is from January 1996 to December 2017 for stocks in the OptionMetrics database.

	Modified FM	WLS (DOI-weighted)	WLS (mkt-weighted)
VaR5	0.276	0.261	0.351
	(3.64)	(2.23)	(4.21)
SIZE	-0.004	-0.003	-0.002
	(-3.63)	(-1.65)	(-1.29)
BTM	0.000	0.000	0.000
	(2.15)	(0.81)	(1.32)
DTA	0.001	0.004	0.005
	(0.52)	(1.05)	(1.93)
MOM	-0.003	-0.001	-0.006
	(-1.15)	(-0.26)	(-2.22)
REV	-0.004	-0.015	-0.014
	(-0.96)	(-2.11)	(-2.47)
ILLIQ	-0.003	-0.002	-0.001
	(-2.66)	(-1.07)	(-1.01)
IVOL	-0.660	-0.574	-0.437
	(-5.86)	(-3.04)	(-2.71)
SKEW	0.000	0.001	0.000
	(0.68)	(0.97)	(0.38)
KURT	0.000	0.000	0.000
	(1.83)	(1.58)	(0.54)
VRP	-0.030	-0.025	-0.014
	(-3.86)	(-2.17)	(-1.33)
VOV	0.002	0.016	0.010
	(0.24)	(0.80)	(0.60)
RNS	-0.002	-0.003	-0.002
	(-2.12)	(-1.56)	(-1.12)
β_{Bear}	0.003	0.001	0.002
	(1.37)	(0.69)	(1.05)
β_{Strad}	0.026	0.007	0.000
	(2.21)	(0.56)	(-0.01)
β_{Jump}	0.003	-0.004	0.001
	(2.26)	(-1.47)	(0.26)
β_{Vol}	0.001	0.001	0.001
	(1.19)	(0.98)	(0.95)
β_{Tail}	0.003	0.000	0.001
	(2.75)	(0.23)	(1.36)
β_{Down}	0.000	0.002	0.000
	(0.92)	(2.41)	(0.00)
Adj. R^2	6.8%	31.0%	15.0%

Table IA5: Univariate Portfolio Analysis of Raw Bear Spread Returns

This table reports the time-series average monthly returns (in %), equal-weighted and dollar-open-interest-weighted, for the raw bear spread decile portfolios sorted on the left-tail risk measures ($VaR5$, $VaR1$, $ES5$, $ES1$), along with the return spreads ("10-1") and the associated alpha spreads between decile 10 portfolio (with the highest left-tail risk metric) and decile 1 portfolio (with the lowest left-tail risk metric). The left-tail risk measures are the 5% (1%) value-at-risk, $VaR5$ ($VaR1$), that corresponds to -1 times the 5th (1st) percentile of daily returns in the past year, and expected shortfall, $ES5$ ($ES1$), is the calculated as -1 times the average of the returns below the 5th (1st) percentile of daily returns in the past year. Each month t, decile portfolios of delta-hedged bear spreads are formed and held to maturity by sorting underlying stocks on one of the left-tail risk measures. The dollar open interest weight is calculated as the minimum of the open interests of the two puts in each bear spread, multiplied by the cost of the bear spread. Newey and West (1987) adjusted t-statistics are presented in parentheses. The sample period is from January 1996 to December 2017 for stocks in the OptionMetrics database.

	Equal-Weighted Returns											
	1	2	3	4	5	6	7	8	9	10	10-1	t-stat
VaR5	-7.56	-6.95	-5.07	-2.49	-1.07	0.88	2.30	0.76	1.85	3.96	11.52	(3.60)
VaR1	-6.23	-7.29	-5.44	-2.52	0.14	1.50	1.93	0.10	2.29	2.13	8.35	(3.33)
ES5	-6.46	-7.65	-6.22	-0.98	-0.88	2.46	0.54	0.48	2.30	2.57	9.03	(3.41)
ES1	-7.41	-5.25	-4.49	-2.87	1.75	0.74	0.39	1.10	1.94	0.80	8.21	(3.48)

	Dollar-Open-Interest-Weighted Returns											
	1	2	3	4	5	6	7	8	9	10	10-1	t-stat
VaR5	-6.20	-7.94	-4.74	-4.51	3.41	-0.23	2.29	0.44	2.46	3.44	9.64	(2.44)
VaR1	-4.64	-10.96	-7.67	1.04	4.27	-0.06	0.06	-0.37	2.74	2.99	7.63	(2.26)
ES5	-5.74	-7.93	-4.96	0.55	-1.54	3.91	-0.30	0.35	4.33	2.85	8.60	(2.35)
ES1	-8.74	-3.69	-1.34	-0.98	-1.59	-2.25	0.02	2.09	3.42	2.76	11.50	(2.61)