Tomorrow's Crash Risk: Evidence from 1DTE Options

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Abstract

This paper investigates the predictive content of option-implied tail measures for forecasting next-day market crashes in the era of ultra short-dated (1DTE) options. Building on Bollerslev and Todorov (2011), we construct a model-free left-tail risk metric derived from deep out-of-the-money index puts, isolating jump risk without parametric assumptions about return distributions. Using a binary probit framework (Vilkov and Xiao, 2013; Dierkes et al., 2024), we show that the daily left-tail measure utilizing intraday option prices significantly predicts one-day-ahead extreme returns beyond the information contained in the VIX. Furthermore, we evaluate its practical relevance by employing the tail measure as a dynamic signal for adjusting leverage in daily put-writing strategies. Our results highlight that today's short-dated option prices embed a meaningful signal of tomorrow's crash risk.

Introduction

Tail risk in options markets reflects the tendency for investors to fear large, sudden losses more than steady gains, leading them to pay a premium for downside protection. As a result, options sellers are compensated for taking on this crash risk through volatility risk premia—returns earned for bearing the possibility of extreme market declines. The recent introduction of ultra-short-dated options has expanded opportunities to isolate and capture this compensation more directly. In particular, one-day-to-expiry (1DTE) out-of-the-money put options primarily compensate sellers for pure crash risk, as the diffusive component of volatility becomes negligible over such short horizons. These contracts effectively embed the market's pricing of tail events into a daily payoff structure, enabling traders to harvest the premium for insuring against abrupt, low-probability market drops.

Predicting tail risk is both crucial and inherently challenging, as market crashes are naturally rare and nonlinear. The rapid growth of ultra-short-dated put-writing and volatility-harvesting strategies has made this prediction increasingly valuable, since the convex nature of losses in short put positions can lead to large drawdowns. Anticipating the likelihood and pricing of tail events becomes essential not only for maintaining profitability but also for managing the nonlinear exposure embedded in option-selling frameworks.

Dierkes, Hollstein, Prokopczuk, and Würsig (2024) provide a comprehensive evaluation of alternative tail risk measures and their ability to forecast future market crashes and generate economic value. They find that the Bollerslev and Todorov (2011) jump-tail framework performs most effectively. The advantage of this approach lies in its simplicity—it provides a direct, model-free estimate of tail risk without relying on parametric assumptions about the return distribution. Building on their results, we extend this line of research by testing the validity of the Bollerslev–Todorov tail risk measure for one-day crash prediction in the 0DTE environment and evaluate its usefulness as a signal within daily put-writing strategies.

In the following sections, we describe the methodology used to construct the tail risk measure, present the data, evaluate the predictive power of the left-tail measure for tail events and out-of-the-money put returns, and finally examine its use as a dynamic leverage signal for 1DTE put-writing strategies.

Methodology

For capturing crash risk in 1DTE options, we focus on the methodology of (Bollerslev and Todorov 2011). Options prices contain information about the market's expectations of extreme price movements, which can be extracted without relying on strong parametric assumptions. Deep out-of-the-money put options are particularly sensitive to large negative jumps in the underlying asset, since small, continuous price changes are unlikely to generate meaningful payoffs for ultra-short maturity options. Following the framework of (Carr and Wu 2003), these short-maturity, out-of-the-money options provide a model-free way to isolate discontinuous moves, offering theoretical support for measuring the market's perception of extreme downside risk.

By constructing a left-tail measure from these options, one can capture the risk-neutral expectation of severe negative events. This approach is particularly effective for 1DTE contracts, where the contribution of ordinary price fluctuations is negligible and the option price predominantly reflects the implied probability and magnitude of a single large jump. Scaling these prices appropriately yields a model-free estimate of the left tail of the risk-neutral distribution, providing a concise indicator of immediate crash risk.

Following the (Bollerslev and Todorov 2011) approach, the left tail measure for 1DTE options is simply compressed to:

$$\mathrm{LT(Q)} \approx \frac{e^{-rT}\, P_t(K)}{T * F_t^{-}} \approx \frac{P_t(K)}{S}$$

In this expression, Pt(K) denotes the market price of a put option with strike K observed at time t, T is the time to expiration, Ft is the forward price just before T, and r is the risk-free rate. The left-tail measure LT(Q) approximates the put price divided by the underlying spot price for options immediately prior to expiration.[1] This provides a model-free estimate of the market-implied probability and magnitude of a large negative jump.

Data

Our primary data source is the IvyDB US - Intraday database. To construct the left-tail measure, we use the 3:45 p.m. snapshot of the SPX 1DTE volatility surface, extracting implied premium values at the −15 delta surface point. Put returns are computed from the option's 3:45 p.m. price on day t to its value at expiration on day t+1. The sample period spans March 3, 2018, through August 31, 2025; however, daily 1DTE options become consistently available only in the latter part of the sample, beginning in May 2022. For this analysis, we restrict all observations strictly to 1DTE put options.

Prediction of Crash Event

To evaluate the predictive content of the daily left-tail measure for short-horizon downside risk, we estimate binary probit regressions of the form specified in Equation (1). The dependent variable, Crash, equals one when the next-day SPX return falls more than two standard deviations below the mean, conditional on the one-day VIX. Building on prior work on testing measures of extreme risk (Vilkov and Xiao 2013; Dierkes et al. 2024), the probit specification tests whether the left-tail measure provides incremental information about realized tail events. The primary explanatory variable, left tail, reflects the one-day downside risk implied by the 1-day volatility surface, while VIX controls for market uncertainty. This framework isolates the predictive power of tail-specific risks in forecasting next-day crash likelihood.

$$Crash_{t+1} = \alpha + \beta_1\, LeftTail_t + \beta_2\, VIX_t + \varepsilon_t \qquad (1)$$

Table 1 presents the results. The coefficient on the *left tail* variable is positive and statistically significant at the 5% level, suggesting that larger left tail values are associated with a higher probability of an extreme negative return on the following trading day. This finding implies that tail-based measures of return asymmetry contain incremental information about short-term crash risk beyond the standard VIX.

By contrast, the coefficient on the *VIX* is negative and statistically insignificant, indicating that IV alone does not meaningfully explain next-day crash probability once the left-tail measure is accounted for. This is consistent with our construction of the *Crash* dependent variable, which focuses on market crashes outside of a 2-standard deviation range.

[1] Bollerslev and Todorov (2011) provide the full derivation of the risk neutral tail measure.

Next, we look to verify the left tail predictive power in actual asset returns. Out-the-money put returns are an obvious choice due to high payoffs in crash states of the world

Table 1: 1-Day Crash Risk Binary Probit Regression

Notes: Regression results for binary daily crash indicator at t+1. Independent variables *left tail* measure with *VIX* control variable captured at t. Sample covers daily data from March 2018–August 2025. Standard errors are Newey-West adjusted for autocorrelation.

variable	coef	std err	
left tail	0.2347	0.112	**
VIX	−0.0973	0.139	

** indicates significance at the 5% level.*** indicates significance at 1% level.

Prediction of OTM Put Returns

Quantile regression is particularly well-suited for analyzing OTM put returns because the return distribution is highly skewed and exhibits significant mass at the lower bound, in this case, a -100% return for worthless expiring options. Worthless options form a discrete cluster of extreme negative outcomes that violate the normality and homoskedasticity assumptions underlying ordinary least squares (OLS) estimation. In contrast, quantile regression does not assume a specific error distribution and allows the conditional relationship between explanatory variables and returns to vary across different parts of the return distribution. By focusing on extreme quantiles, the model isolates periods when put options generate large positive payoffs.

We perform quantile regressions for daily 0.75%, 1.00%, and 2.00% on 1DTE OTM put returns from March 2018 - August 2025. Regressions take the form of equation 2 below:

$$Q_\tau(PutReturn_{t+1} \mid VIX_t, LeftTail_t) = \alpha_\tau + \beta_{1,\tau}\ VIX_t + \beta_{2,\tau}\ LeftTail_t + \varepsilon_{t,\tau} \quad (2)$$

Regression results appear in Tables 2, 3, and 4. Across all moneyness levels and quantiles, the results demonstrate that the left-tail variable is a robust and statistically significant predictor of next-day OTM put returns, even after controlling for VIX. The coefficients on the left-tail measure are consistently positive and highly significant, indicating that increases in crash risk are associated with higher subsequent conditional quantiles of put returns. Moreover, the magnitude of these coefficients rises systematically with both quantile level and option moneyness—most notably for the 1.00% OTM puts at the 0.9 quantile, where the effect is strongest—suggesting that the influence of tail risk becomes more pronounced for options with the highest sensitivity to downside movements. This pattern highlights that the left-tail measure captures a distinct dimension of priced crash risk.

For instance, the coefficient of 0.0592 on the left-tail variable for the 1.00% OTM put at the 0.9 quantile implies that, holding VIX constant, a one-unit increase in the left-tail measure is associated with a 0.0592 increase in the conditional 90th percentile of next-day put returns. In other words, if the left-tail measure rises by one standard unit, the upper quantile of put returns shifts upward by approximately 5.92 percentage points. This effect reflects how higher implied crash risk expands the right tail of the conditional return distribution, leading to more extreme positive outcomes for put returns and signaling greater compensation during crash events.

Table 2: Quantile Regression Results for Put Returns 0.75% OTM

Notes: Table reports quantile regression results for t+1 0.75% OTM put returns at the 0.8, 0.85, and 0.9 quantiles. Dependent variables are previous day's VIX level and left tail indicator. Each entry shows coefficient with standard error in parentheses. * indicates significance at the 10% level, ** indicates significance at 5% level, *** indicates significance at 1% level.

	Quantile 0.8	**Quantile 0.85**	**Quantile 0.9**
VIX	0.0303 (0.002)***	0.0878 (0.005)***	0.1260 (0.096)
lt	0.0190 (0.003)***	0.0219 (0.007)***	0.0413 (0.126)
Pseudo R^2	0.0070	0.0203	0.0071

Table 3: Quantile Regression Results for Put Returns 1.00% OTM

Notes: Table reports quantile regression results for t+1 0.750.8, 0.85, and 0.9 quantiles. Dependent variables are previous day's VIX level and left tail indicator. Each entry shows coefficient with standard error in parentheses. * indicates significance at the 10% level, ** indicates significance at 5% level, *** indicates significance at 1% level.

	Quantile 0.8	Quantile 0.85	Quantile 0.9
VIX	0.0066 (0.001)***	0.0394 (0.002)***	0.1575 (0.010)***
lt	0.0097 (0.001)***	0.0226 (0.003)***	0.0592 (0.013)***
Pseudo R^2	0.0004	0.0084	0.0220

Table 4: Quantile Regression Results for Put Returns 2.00% OTM

Notes: Table reports quantile regression results for t+1 2.00% OTM put returns at the 0.95 and 0.98 quantiles. Dependent variables are previous day's VIX level and left tail indicator. Each entry shows coefficient with standard error in parentheses. * indicates significance at the 10% level, ** indicates significance at 5% level, *** indicates significance at 1% level.

	Quantile 0.95	Quantile 0.98
VIX	0.0985 (0.003)***	0.4025 (0.023)***
lt	0.0164 (0.004)***	0.3437 (0.031)***
Pseudo R^2	0.0387	0.0568

The relatively low pseudo-R squared values observed across the quantile regressions are consistent with expectations for option return data. OTM put returns are inherently noisy and most options expire worthless; a large share of the variation in returns reflects stochastic realizations. In this context, even modest R-squared values are informative.

However, a high positive correlation between the *VIX* and the *left tail* variable introduces a potential multicollinearity concern, as both capture elements of jump risk. This high collinearity can inflate standard errors. To address this, we orthogonalize the left tail variable with respect to the VIX, effectively isolating the component of tail risk that is not linearly explained by *VIX*. The resulting orthogonalized series, denoted *lt_orth*, captures variation in the volatility surface unique to the crash risk.

The quantile regression results in Table 5 demonstrate that even after this orthogonalization, the *lt_orth* variable remains positive and statistically significant across the 0.95 and 0.98 quantiles. The magnitude of the coefficients suggests that the orthogonalized tail component continues to exert a meaningful influence on the conditional upper quantiles of put returns.[2]

Table 5: Quantile Regression on Put Returns 2.00% OTM with Orthogonal Left Tail

Notes: Table reports quantile regression results for t+1 1.00% OTM put returns at the 0.95 and 0.98 quantiles. Dependent variables are previous day's VIX level and orthogonalized left tail indicator. Each entry shows coefficient with standard error in parentheses. * indicates significance at the 10% level, ** indicates significance at 5% level, *** indicates significance at 1% level.

	Quantile 0.95	Quantile 0.98
VIX	0.1092 (0.001)***	0.5727 (0.006)***
lt_orth	0.0178 (0.004)***	0.1601 (0.021)***
Pseudo R^2	0.0421	0.0505

Given we have demonstrated the statistical significance of the left tail variable for crash risk prediction and put returns, we turn next to providing economic evidence via cash-secured put strategies.

Dynamic Put-Write Strategies

In this section, we evaluate the power of the left tail as a signal in cash secured put strategies. This strategy involves selling an OTM put and holding cash collateral equivalent to the strike. Strategies sell 1-DTE puts and hold to expiration, with rolling of contracts occurring every trading day.

The approach we utilize to test the economic value of the daily left tail signal is dynamic linear. Consistent with other approaches in the literature (Wysocki 2025), we scale the number of short put contracts linearly based on the percentile rank of the left tail measure over a rolling 252 previous trading days, represented by the formula below:

$$r_{t+1} = \frac{P(K) - max(0, K - S_{t+1})}{K - P(K)} \left(2 \cdot (1 - Prank(LT(Q)_t))\right)$$

[2] Regression results were similar across other OTM put moneyness levels. They were omitted for brevity.

Where r(t+1) is the put write portfolio return, P(K) is the put price, K is the strike of the short put, S(t+1) is SPX close price on the following trading day, and Prank (LT(Q)) is the percentile rank of the left tail measure.

The minimum applied leverage is 0, and maximum leverage is 2. The fundamental idea is to de-leverage when crash risk is high and increase leverage when crash risk is low. Table 7 and Table 8 compare the performance statistics of the static and dynamic leveraged strategies of 0.75% & 1.00% OTM put write strategies, respectively.

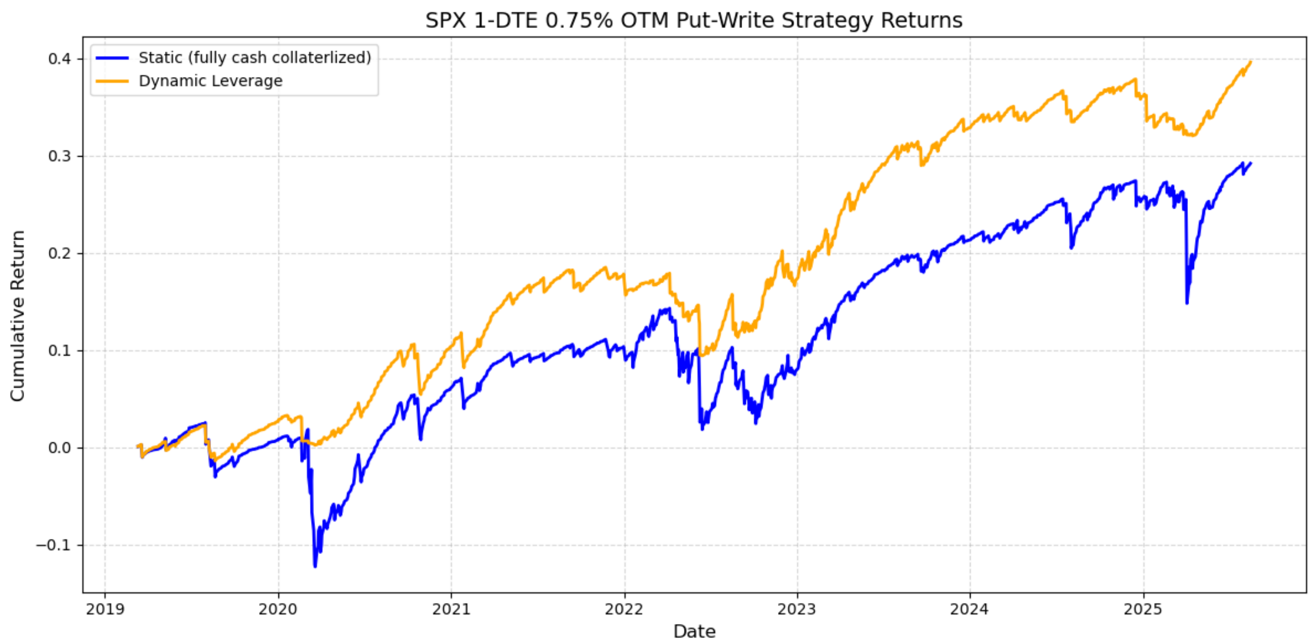
Table 6: Performance Statistics: 0.75% OTM 1-DTE Put Write Strategies

Metric	(Static)	(Dynamic Lev.)
Mean Daily Return	0.000218	0.000270
Std Daily Return	0.00536	0.00318
Annualized Volatility	0.0851	0.0505
Sharpe Ratio (Annual)	0.527	1.149
Sortino Ratio (Annual)	0.310	0.655
Max Drawdown	-0.145	-0.0767
Cumulative Return	0.292	0.396
Skew	-3.858	-4.201
Kurtosis	25.743	24.133
% Positive Days	85.65	85.01
Median Daily Return	0.000850	0.000734

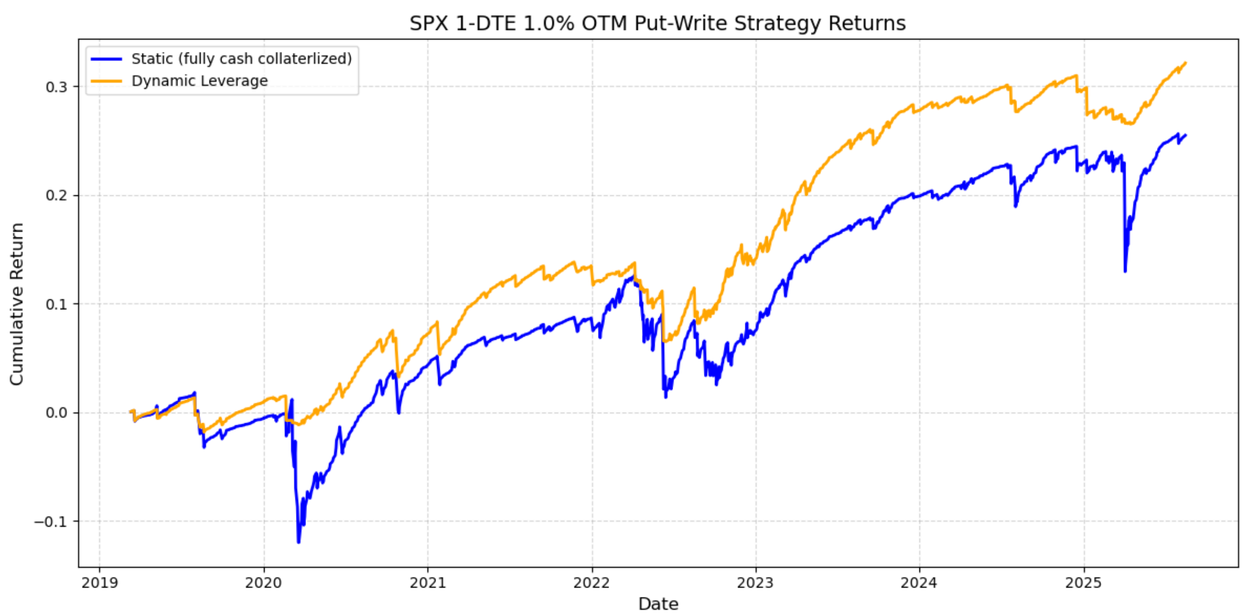
Table 7: Performance Statistics: 1% OTM 1-DTE Put Write Strategies

Metric	(Static)	(Dynamic Lev.)
Mean Daily Return	0.00019	0.00023
Std Daily Return	0.00488	0.00263
Annualized Volatility	0.0775	0.0417
Sharpe Ratio (Annual)	0.500	1.134
Sortino Ratio (Annual)	0.258	0.563
Max Drawdown	-0.1386	-0.0648
Cumulative Return	0.2571	0.3259
Skew	-4.424	-4.986
Kurtosis	33.696	34.206
% Positive Days	88.50	87.87
Median Daily Return	0.00063	0.00052

Despite operating at lower absolute volatility, the dynamic strategy delivers both higher mean and cumulative returns, leading to substantially improved risk-adjusted performance. For the 1.00% OTM strategy, the mean daily return rises from 0.00019 to 0.00023 and cumulative return from 0.2571 to 0.3259, while annualized volatility declines from 0.0775 to 0.0417. Similarly, for the 0.75% OTM case, mean daily return increases from 0.000218 to 0.000270 and cumulative return from 0.292 to 0.396, accompanied by a drop in annualized volatility from 0.0851 to 0.0505. Consequently, the annualized Sharpe ratio more than doubles—from 0.50 to 1.13 and from 0.53 to 1.15, respectively—indicating that returns per unit of risk improve markedly when leverage is dynamically scaled based on left-tail risk. The Sortino ratio follows a similar pattern, improving from 0.26 to 0.56 in the 1.00% OTM case and from 0.31 to 0.66 in the 0.75% OTM case, reflecting enhanced downside-adjusted efficiency. The dynamic strategy also experiences a significantly smaller maximum drawdown—declining from –13.9% to –6.5% and from –14.5% to –7.7%—illustrating improved capital preservation during crashes. The charts below illustrate the historical cumulative returns of each strategy.



Source: OptionMetrics IvyDB US - Intraday



Source: OptionMetrics IvyDB US - Intraday

Distributional statistics further highlight the asymmetric nature of short-dated put writing. Both the static and dynamic strategies exhibit pronounced negative skewness (around –4 to –5) and extreme kurtosis (ranging from 25 to over 34), consistent with the payoff structure's exposure to infrequent but large losses. Importantly, despite a slightly higher absolute skewness in the dynamic strategy (–4.99 vs. –4.42 in the

1.00% OTM case), the lower standard deviation implies that these tail events remain proportionally rare. Overall, the results demonstrate that dynamic leverage improves efficiency and drawdown control without amplifying tail asymmetry, supporting the notion that left-tail-based scaling enhances the risk-return tradeoff in systematic short-volatility strategies.

Conclusion

This paper examines the informational and economic value of a model-free left-tail measure derived from ultra-short-dated (1DTE) option prices. Building on Bollerslev and Todorov's (2011) jump-tail framework and subsequent validation by Dierkes et al. (2024), we demonstrate that deep out-of-the-money put prices on one-day maturities contain concentrated information about market-implied crash risk. The simplicity of this measure—requiring no parametric assumptions about the return distribution—makes it particularly suited for modern high-frequency options markets.

Empirically, the left-tail measure exhibits strong predictive power for both realized tail events and next-day out-of-the-money put returns. Probit tests reveal that increases in the measure significantly raise the probability of observing large negative returns, even after controlling for the VIX. Complementary quantile regressions further confirm that the measure forecasts the upper conditional quantiles of put returns, indicating that it captures risk premia specifically associated with crash exposure. Importantly, the measure retains its significance even after orthogonalization against the VIX, underscoring that it isolates a distinct dimension of tail-specific risk.

From an economic perspective, integrating the left-tail measure into a dynamic put-writing framework substantially enhances portfolio efficiency. Scaling exposure linearly between zero and two times based on the percentile rank of the left-tail measure improves both absolute and risk-adjusted returns while materially reducing drawdowns. The findings suggest that conditioning short-volatility strategies on near-term crash risk yields higher Sharpe and Sortino ratios without increasing downside asymmetry.

Overall, this study extends prior research on option-implied tail risk by demonstrating its relevance in the ultra-short maturity era. The evidence supports the view that nonparametric, tail-focused indicators derived from option prices can meaningfully enhance prediction of crash events and tactical allocation within short-maturity volatility strategies.

References

Bollerslev, Tim, and Viktor Todorov. 2011. “Tails, Fears, and Risk Premia.” The Journal of Finance 66 (6): 2165–2211.

Carr, Peter, and Liuren Wu. 2003. “What Type of Process Underlies Options? A Simple Robust Test.” The Journal of Finance 58 (6): 2581–2610.

Dierkes, Maik, Fabian Hollstein, Marcel Prokopczuk, and Christoph Matthias Würsig. 2024. “Measuring Tail Risk.” Journal of Econometrics 241 (2): 105769. https://doi.org/10.1016/j.jeconom.2024.105769.

Vilkov, Grigory, and Yan Xiao. 2013. “Option-Implied Information and Predictability of Extreme Returns.” Unpublished manuscript.

Wysocki, Maciej. 2025. “Sizing the Risk: Kelly, VIX, and Hybrid Approaches in Put-Writing on Index Options.” arXiv preprint arXiv:2508.16598.