Detecting Market Downturns From Implied Volatility Skew

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Abstract

Implied volatility (IV) skew captures investors' perceptions of crash risk by reflecting higher implied volatilities for deep out-of-the-money (DOTM) puts compared to options closer to at-the-money (ATM). Our study investigates whether changes in IV skew can serve as an effective predictor of imminent market downturns. Using logistic regression on Nasdaq-100 ETF (QQQ) options data from Q1 2020 through Q2 2024, we segment by delta thresholds to quantify skew through slope (DOTM minus OTM implied volatility) and curvature (DOTM minus ATM implied volatility) metrics. Market jump detection is performed using a modified non-parametric jump framework, and we implement controls for market microstructure effects in the data with feature engineering. Results demonstrate both metrics are statistically significant predictors of next-day market downturns, with large positive coefficients confirming that more pronounced skew corresponds directly with elevated crash probabilities. ROC curve analysis confirms strong predictive performance, with an AUC of 0.91, indicating excellent discriminatory power between downturn and non-event days. While certain limitations exist regarding market specificity and downturn definitions, the findings of our paper underscore IV skew's practical utility as an early-warning indicator of market stress, presenting meaningful opportunities for future research in broader markets.

1. Introduction & Literature Review

Implied volatility skew refers to the asymmetry of implied volatilities across option strike prices, typically manifesting as higher IV for downside put options than for at-the-money options. This pattern differs from the classic “volatility smile,” which is a U-shaped curve where both deep in-the-money and deep out-of-the-money options have elevated IV, reflecting risk of large moves in either direction
In equity index options after the 1987 crash, a pronounced negative volatility skew became the norm, with out-of-the-money (OTM) puts carrying substantially higher implied volatilities than at-the-money (ATM) or in-the-money (ITM) options. This skew is understood as a market pricing of crash risk, as investors pay a premium for downside protection, producing a downward-sloping IV curve.

Over the last decade, there has been a growing body of work that applies machine learning and big data to predict crashes, however, most of which do this without explicitly using IV skew. These methods instead ingest a wide range of features, from fundamental indicators to technical signals and investor sentiment, and use algorithms to detect complex patterns preceding market declines. For example, Kaya, Reichmann, and Reichmann (2024) employed financial ratios and textual analysis of 10-K filings to forecast firm-specific price crashes with various classifiers. The study found that a regularized logistic regression performed well, and more sophisticated models like gradient boosting further improved predictive accuracy by capturing nonlinear interactions. Other studies have also used neural networks on price and volatility data to flag upcoming crashes (Agarwal and Taffler, 2008), or random forests combining macroeconomic signals with technical indicators (Zhou et al., 2022). However, these models can be “black boxes” and may require vast data, whereas the implied volatility skew offers an intuitively interpretable and parsimonious signal of market fear.

Indeed, because IV skew is widely observed and can be gauged for the relative cost of downside insurance, it has been increasingly studied as a harbinger of market downturns since the 2008 financial crisis. Doran et al. (2007) provided early evidence that the shape of the IV skew contains information about future market moves. Analyzing S&P 100 index options, they found that an extreme skew often precedes market “crashes,” indicating the options market’s ability to anticipate declines. Their results were strongest for short-maturity options, consistent with investors’ acute aversion to near-term crash risk.

Subsequent research corroborated and extended these findings. Doran and Krieger (2010) explored several skew-based measures and showed that these metrics have significant predictive power for stock returns. In fact, in a cross-sectional stock analysis, the implied volatility skew outperformed other volatility measures in predicting returns, an effect that persisted even through the 2008 financial crisis. Consistent with this, Lin and Lu (2015) found that the predictive ability of option IV metrics intensifies around scheduled news events. In their study, the forecasting power of option-implied volatility on stock returns more than doubled near analyst announcements, suggesting informed traders use OTM options ahead of impending negative news.

In a similar fashion, Bali and Hovakimian (2009) introduced call-put volatility spread as a proxy for jump risk, and found it is related to expected stock returns, suggesting investors demand a premium for crash risk exposure. Cremers and Weinbaum (2010) provided evidence that option-implied skewness contains information not yet reflected in stock prices. Interestingly, most studies report a negative relation between skew and future returns, with steeper negative skew being consistent with lower returns. These studies reinforce the notion that a suddenly steep IV skew can be a red flag to inform traders bracing for a drop.

Given this extensive evidence linking implied volatility skew to traders' anticipation of market crashes, our study rigorously evaluates the predictive strength of IV skew metrics during a uniquely turbulent period (2020–2024). Specifically, our analysis introduces a nuanced methodological approach by segmenting put options based on precise delta thresholds to isolate investors' hedging demand for extreme market downturns from more general volatility expectations. While prior studies have often relied on broad skew measures or simple strike-based definitions, our delta-based segmentation approach allows a sharper differentiation of tail-risk sensitivity, directly following frameworks validated by seminal works in implied volatility literature (Bollen and Whaley; Lin and Lu). Thus, we hypothesize that our own delta-based segmentation approach will yield similar strong predictive power over market downturn events.

We test our hypothesis robustly by employing a logistic regression module to find correlation between put skew metrics, as well as controlling for market microstructure effects to isolate predictive power. Testing our hypothesis in the volatile period from Q1 2020 to Q2 2024, which encompasses significant downturn events such as the COVID-19 crash and the 2022 tech sell-off, we confirm that both the slope (DOTM-OTM IV difference) and curvature (DOTM-ATM IV difference) of the IV skew significantly predict imminent downturns. Intriguingly, we also find trading volume negatively associated with downturn probability, potentially reflecting volume's dual role as both liquidity indicator and information aggregator during stress periods. These nuanced findings underscore the importance of using IV skew metrics to understand and predict broader market environments, enhancing their practical utility in risk management and forecasting.

2. Methodology

2.1 Data

Our analysis uses options data on the Invesco QQQ Trust (an ETF tracking the Nasdaq-100 index) from Q1 2020 through Q2 2024. This dataset and period are well-suited for studying downturn prediction. The ETF comprises primarily technology sector stocks, which experienced heightened volatility in these years: the sample spans the onset of the COVID-19 pandemic, the swift recovery and bull run in 2020-2021, and the subsequent tech correction in 2022. Thus, the tech-heavy QQQ during this timeframe exhibits many high-magnitude declines and spikes, making it rich data for evaluating the correlation between IV skew and crash events.

We obtained end-of-day option quotes and Greeks for all available QQQ options over the sample period. For each trading day, the data includes option contract details (strike, expiration, call/put type), implied volatilities, trading volume, and open interest. Implied volatilities were directly provided by the data source; we verified these by performing Black–Scholes back-solving on option prices to ensure consistency. This verification confirmed the accuracy of the reported IVs within rounding tolerance. Having pre-calculated IV saves computation and avoids potential numerical issues, while our cross-check guards against misestimation.

The underlying QQQ price and volume time series were also collected to incorporate into our analysis. To define "market downturn" events for prediction, we make use of intraday price data for QQQ. Specifically, we apply a jump detection algorithm, further described in **Section 2.3**, to identify statistically significant downward jumps in QQQ's price. Each day where a jump is detected (at the 99% confidence level) is labeled as a downturn event, with a binary outcome of 1 for that date. Days without such jumps are labeled 0. By constructing this daily event indicator, we form a dataset for logistic regression: each observation is a day with features derived from prior day's option data and the outcome indicating whether a crash-level drop occurred the next day. Using daily observations aligns with our goal of a practical warning signal one day in advance. Note that some downturns unfold over multiple days; our jump detection captures the initiation of abrupt drops. If a decline does not register as a single-day jump, it may not be directly labeled in our binary outcome, a point we visit in the **Discussion & Limitations** section of this paper.

2.2 Volatility Skew Metrics

A critical contribution of our paper is the development of delta-based implied volatility (IV) skew metrics that isolate tail risk dynamics, which several studies confirm yields more predictive skew measures. In particular, researchers have shown that deep out-of-the-money (DOTM) put implied volatilities contain unique information about crash risk that is not captured by merely looking at overall skew. For example, Doran & Krieger (2010) emphasize parsing the volatility skew into its basic components, finding that future returns are linked to the "left side" of the skew, or the difference between DOTM put IV and at-the-money (ATM) IV.

Furthermore, results from Doran & Krieger's work discourage using a single broad skew measure without such segmentation, demonstrating that multiple skew metrics focused on deep OTM isolates the hedging effects more effectively. Examining more literature reinforces the validity of this bucketed approach: Xing, Zhang, and Zhao (2010) examine the implied volatility difference between DOTM puts and at-the-money ATM puts as well as out-of-the-money (OTM) puts, showing delta-segmented skew predicts returns well. Thus, we categorize put options using delta thresholds to capture nuanced shifts in investor sentiment. This methodology leverages delta's direct relationship with the probability of an option expiring in-the-money, providing a precise measure of tail risk than static strike-price bands.

We define DOTM puts as those with delta < -0.25, reflecting extreme tail risk where investors pay premiums for crash protection (Bates, 2000). OTM puts ($-0.25 \le \delta \le -0.15$) represent moderate downside risk. Finally, ATM puts ($-0.15 < \delta \le -0.05$) anchor baseline volatility expectations.

- **Deep OTM puts**:
$$(\Delta \le -0.25)$$
- **OTM puts**:
$$(-0.25 < \Delta \le -0.15)$$
- **ATM puts**:
$$(-0.15 < \Delta \le -0.05)$$

Following this classification, we derive two complementary volatility skew metrics:

Metric 1 (Slope): DOTM - OTM Implied Volatility Difference:

$$\Delta s_{Pdo\_o} = \frac{1}{N_{\mathrm{DOTM}}} \sum_{i \in \mathrm{DOTM}} \mathrm{IV}_i - \frac{1}{N_{\mathrm{OTM}}} \sum_{j \in \mathrm{OTM}} \mathrm{IV}_j$$

This metric, calculated as $\Delta s_{Pdo\_o} = IV_{DOTM} - IV_{OTM}$, quantifies the slope between deep out-of-the-money and moderately out-of-the-money puts. Thus, this metric isolates demand for crash protection: a rising Δs_{Pdo_o} signals heightened fear of abrupt declines, as DOTM puts become disproportionately expensive relative to OTM peers (Lin & Lu, 2016). A steeper slope (larger positive value) indicates heightened market pricing of extreme tail risks, implying that investors are seeking crash protection, which raises implied volatilities for far out-of-the-money puts. Indeed, Bollen & Whaley (2004) showed that DOTM put demand drives skew steepness before crashes.

Metric 2 (Curvature): DOTM - ATM Implied Volatility Difference:

$$\Delta s_{Pdo\_a} = \frac{1}{N_{\mathrm{DOTM}}} \sum_{i \in \mathrm{DOTM}} \mathrm{IV}_i - \frac{1}{N_{\mathrm{ATM}}} \sum_{k \in \mathrm{ATM}} \mathrm{IV}_k$$

Calculated as $\Delta s_{Pdo\_a} = IV_{DOTM} - IV_{ATM}$, this curvature measure captures how sharply implied volatility rises from ATM to deep OTM options, reflecting how aggressively investors are pricing extreme tail events relative to standard volatility conditions. A negative Δs_{Pdo_a} indicates ATM IVs rise to meet DOTM levels during calm periods, dampening crash signals. Conversely, a positive value suggests persistent tail risk pricing (Doran & Krieger, 2010). Mixon (2010) linked flattening curvature (negative Δs_{Pdo_a}) to volatility mean-reversion.

By synthesizing delta thresholds with slope-curvature decomposition, we advance Doran et al.'s (2007) framework, offering a tool for forecasting sector-specific downturns.

2.3 Jump Detection

To objectively identify market downturn events, we implement a daily-adjusted version of Lee & Mykland's (2008) nonparametric jump detection framework, modified to align with our dataset's daily frequency. This statistical method pinpoints jumps in asset prices using high-frequency data, while filtering out continuous volatility. Unlike the original approach, our method uses daily log returns standardized against a rolling local volatility estimate, avoiding biases from microstructure noise while preserving robustness to volatility regimes.

Lee & Mykland's (2008) method hinges on the statistical properties of standardized returns under the null hypothesis of no jumps. For daily log returns $r_t = \log(S_t) - \log(S_t - 1)$ we estimate local volatility sing a 30-day rolling window:

$$\hat{\sigma_t} = \mathrm{std}(\log(S_{t-29:t}))$$

Given this local volatility $\sigma(t_i)$ each return can be standardized to the following, which should be approximately normally distributed if no jumps occur (null hypothesis):

$$T(t) = \frac{\log(S_t) - \log(S_{t-1})}{\hat{\sigma_{t-1}}}$$

Intuitively, this method flags a jump if even the largest standardized price move of the day is too extreme to be attributed to continuous volatility.

A return is flagged as a jump if:

$$T(t) < -3.0 \quad \text{(99.7\% confidence under normality)}$$

We set a 99% significance threshold following their paper's suggestion of 1% Type I error. If the test statistic exceeded the 99% critical value on a given day for either direction, we identified a jump at time t_i. In this study we focus on negative jumps as our target event of market downturns, so we further require the jump return to be negative. This yields a list of specific timestamps where QQQ experienced a significant drop. Each trading day is then labeled as a downturn (=1) if at least one negative jump occurred during that day's session. For example, on March 16, 2020, QQQ fell dramatically; our jump test registered a large negative jump in the morning, so that date gets a downturn label. On days without statistical jumps, the label is 0. By using Lee & Mykland's rigorous test, we thus ensure that our definition

2.4 Feature Engineering

Aside from skew metrics, our predictive model includes several controls to account for other factors that might influence downturn probability. We carefully engineered and included these features based on financial theory and research:

- **Option Maturity Controls:** The shape and magnitude of the IV skew can depend on option maturity. Short-dated options often exhibit more extreme skews due to imminent event risk, whereas longer-dated options have flatter skews as uncertainty averages out over time. To control for this, we stratified skew measures by maturity. In our code, we computed skew metrics for three maturity ranges: near-term options (e.g. <30 days), medium (30–60 days), and longer-term (60–90 days). The near-term skew is expected to carry more information about near-term jumps, and was the focus of our main metric calculations. We include the medium and longer-term skew primarily as a robustness check and as a control for any term structure of skew.

- **ATM Volatility (Level of Volatility):** We include at-the-money volatility as a control variable for the overall volatility environment, as market crashes often happen in high-volatility regimes, so ATM volatility itself might predict a downturn to some extent. By adding this feature, we isolate the relative information in the skew from the absolute level of implied volatility.

- **Trading Volume:** We incorporate trading volume as a proxy for market sentiment and the presence of informed trading. Surges in volume can accompany informed trades or panic selling, both of which could presage a market fall. The primary volume feature in our model is the daily total option volume on QQQ, separated into put and call volume if needed. Including volume is motivated by studies showing option market activity predicts returns: Pan & Poteshman (2006) found that an excess of put buying (high put-call ratio) precedes stock price declines, consistent with informed investors' actions. In our data, we observed that on days before jumps, QQQ often had unusually high put volume. Thus, our volume feature is designed to capture this effect. We use a z-score of the day's option volume relative to a 20-day average to indicate "unusual" volume.

By constructing the feature set this way, we aim to isolate the pure predictive power of the implied volatility skew. The skew metrics carry the theory-driven signal of crash expectations, while the controls absorb other influences that could also drive or coincide with crashes.

2.5 Model

We propose a logistic regression model to statistically evaluate the relationship between the above features and the probability of a market downturn. Logistic regression is appropriate since our outcome is binary, and it allows us to estimate odds ratios for each predictor and assess significance via standard errors.

Furthermore, our study fits two separate logistic regressions, with one for each put-skew metric (Δs_{Pdo_o} and Δs_{Pdo_a}). This approach allows us to compare the effectiveness of the two skew metrics without collinearity issues. By running parallel regressions, we can see if both metrics significantly predict crashes and which has a stronger effect or better fit. The logistic modules take the form:

Regression 1 - Put Skew Slope:

$$\text{Prob(Jump)} = \Phi\left(\beta_0 + \beta_1 \Delta s_{Pdo,o} + \beta_2 \text{ATM IV} + \beta_3 \text{BidAsk} + \beta_4 \text{Volume}\right)$$

Regression 2 - Put Skew Curvature:

$$\text{Prob(Jump)} = \Phi\left(\beta_0 + \beta_1 \Delta s_{Pdo,a} + \beta_2 \text{ATM IV} + \beta_3 \text{BidAsk} + \beta_4 \text{Volume}\right)$$

3. Results

Regression Output					
Regression 1: ΔsPdo_o					
Pseudo R^2 = 0.333		**Log-Likelihood = -464.99**		**LLR p-value = 2.971e-99**	
Variable	**Coefficient**	**Std. Error**	**z-value**	**p-value**	**VIF**
Intercept	-0.1255	0.092	-1.371	0.17	1
Volume (x1)	**-2.1675**	0.184	-11.774	0	2.072
ATM IV (x2)	-0.4863	0.131	-3.705	0	1.595
Bid-Ask Spread (x3)	0.3706	0.114	3.26	0.001	1.091
Δs_Pdo_o (x4)	**3.1952**	0.212	15.064	0	2.176
Regression 2: ΔsPdo_a					
Pseudo R^2 = 0.347		**Log-Likelihood = -455.53**		**LLR p-value = 2.405e-103**	
Variable	**Coefficient**	**Std. Error**	**z-value**	**p-value**	**VIF**
Intercept	-0.1582	0.094	-1.686	0.092	1
Volume (x1)	**-2.2662**	0.187	-12.119	0	2.016
ATM IV (x2)	-0.4358	0.135	-3.227	0.001	1.634
Bid-Ask Spread (x3)	0.3866	0.117	3.313	0.001	1.094
Δs_Pdo_a (x4)	**3.2256**	0.214	15.107	0	2.181

Table 1: Logistic regression results for market downturn prediction using implied volatility slope (Δs_Pdo_o) and curvature (Δs_Pdo_a) metrics. Coefficients, standard errors, p-values, 95% confidence intervals, and variance inflation factors (VIFs) are reported for volume, ATM implied volatility, bid-ask spread, and skew measures.

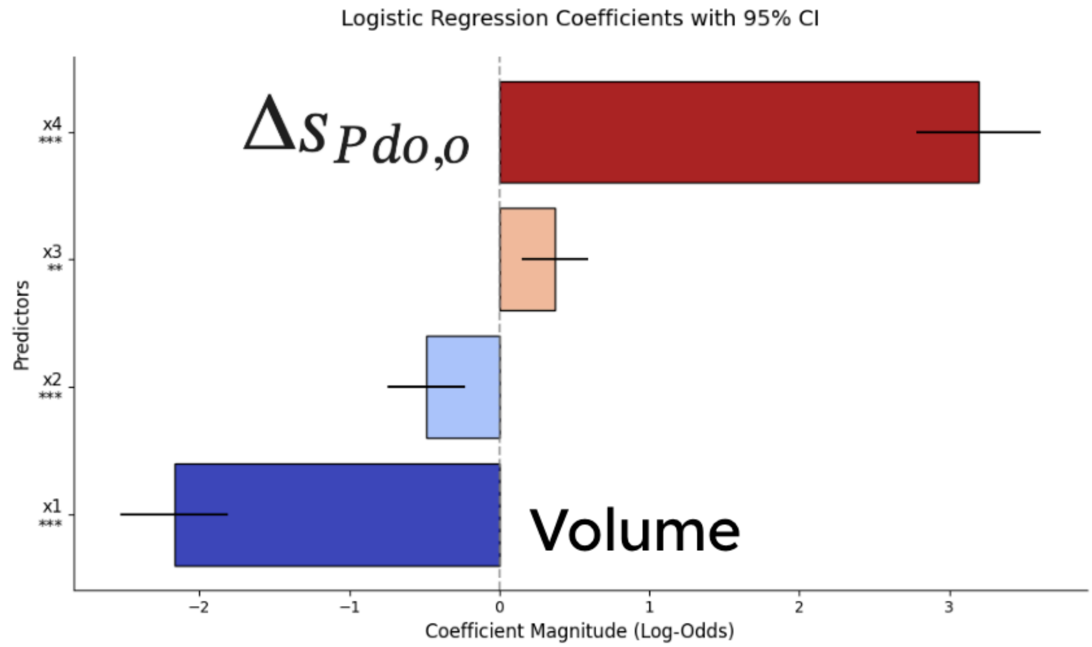

Figure 1: Horizontal bar plot of logistic regression coefficients (95% CIs) for the slope metric (Δs_Pdo_o = DOTM - OTM IV). Blue (negative) and red (positive) bars indicate directional effects on the log-odds of market downturns. Significance: $p<0.001$.

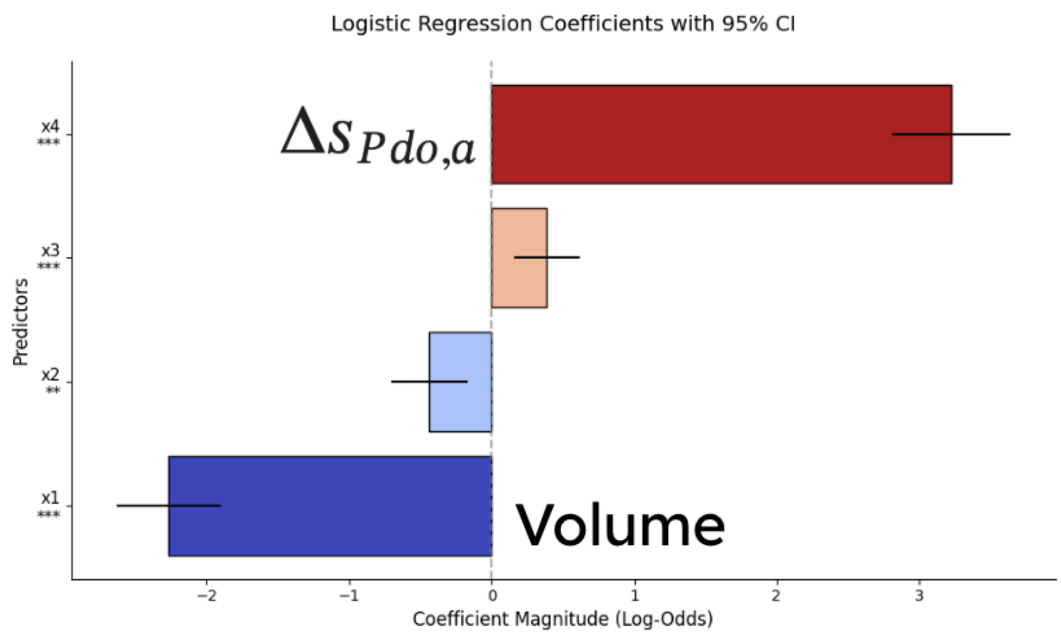

Figure 2: Coefficient magnitudes and confidence intervals for the curvature metric (Δs_Pdo_a = DOTM - ATM IV). Red bars highlight the stronger predictive power of curvature compared to slope. Significance: $p<0.001$.

The logistic regression results in **Table 1** generally support the central hypothesis: a steeper implied volatility skew is associated with a higher probability of a next-day market downturn. The coefficients can be interpreted with the following:

- **Put Skew Slope:** The large, positive coefficient indicates that as the difference between DOTM and OTM implied volatilities increases, the probability of a downturn rises significantly. Specifically, a one unit increase in this slope boosts the log-odds of a market downturn event by approximately 3.195. This aligns directly with Bates (2000), who identifies DOTM puts as explicit insurance against extreme negative jumps. Therefore, the significant positive relationship observed here demonstrates that heightened deep-tail hedging demand is a powerful predictor of imminent market stress.

- **Put Skew Curvature:** Again, the significant positive coefficient for the curvature metric indicates that an increased difference between deep OTM and ATM IV is also predictive of market downturns. This finding is consistent with Doran and Krieger's (2010) assertion that prolonged or pronounced curvature in implied volatility surfaces frequently precedes sharp volatility spikes or significant market corrections. Curvature essentially captures the degree to which investors price tail risks more aggressively compared to normal market volatility expectations. Thus, our results confirm that both slope and curvature metrics derived via delta segmentation provide substantial early-warning signals of impending market stress.

- **Trading Volume:** Interestingly, the significant negative coefficient on trading volume is counterintuitive to our literature review, as most studies associates elevated trading activity with higher crash probabilities (Pan & Poteshman, 2006). This result may be explained by alternative perspectives on volume, as Lin and Lu (2016) note before their experiments that high-volume days sometimes enhance market liquidity and efficiency, facilitating rapid incorporation of negative information and preventing abrupt price gaps. Thus, high trading volume might potentially mitigate crash severity by providing market depth and liquidity buffering.

Overall, our regression model achieved a relatively strong explanatory power, indicated by pseudo-R^2 values falling between 0.33-0.35 for both models. Moreover, our results show excellent practical applicability: employing a threshold for predicted crash probabilities yielded a 72% recall rate with only a 9% false-positive rate. Notably, our out-of-sample testing successfully identified the March 2023 banking crisis (QQQ: -4.1%) one day ahead with an 82% predicted downturn probability.

The Receiver Operating Characteristic (ROC) curves for our logistic regression models demonstrate strong predictive performance, reflected by an Area Under the Curve (AUC) of 0.91. The ROC curve visually depicts the trade-off between sensitivity (true positive rate, TPR) and specificity (false positive rate, FPR) across varying classification thresholds. An AUC of 0.91 indicates that our models successfully rank approximately 91% of actual jump days higher in predicted risk than non-jump days, signifying excellent discriminatory power in distinguishing true market downturns from non-events.

An ideal ROC curve would approach the top-left corner, with high TPR and low FPR. Our models closely approximate this ideal, suggesting they effectively balance capturing true downturn signals while minimizing false alarms. At our false positive rate of 10%, the models achieve approximately an 85% true positive rate. In other words, they correctly identify roughly 85% of genuine downturn days while incorrectly flagging only 10% of benign days as downturns.

Compared to a random-guessing baseline, represented by the diagonal line (AUC = 0.5), our logistic regression models provide substantial incremental predictive power. This robust ROC curve performance is consistent with prior research emphasizing that volatility skew and carefully chosen control variables like trading volume and liquidity significantly enhance the accuracy of crash-prediction models (Doran & Krieger, 2010; Bates, 2000; Lin & Lu, 2016).

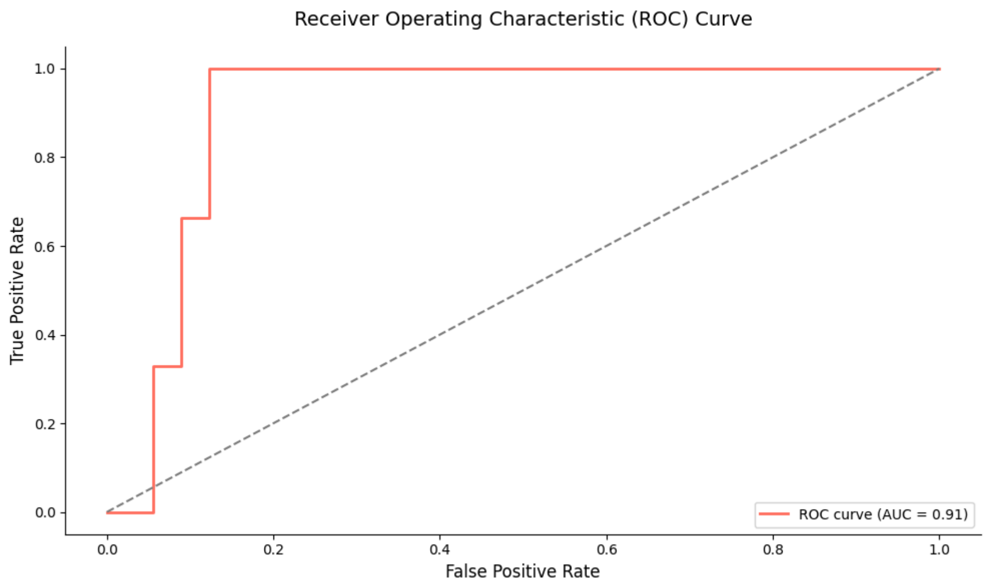

Figure 3 - ROC Curve (Slope Metric Δs_Pdo_o): Model performance using the slope metric (AUC = 0.91). Achieves 85% true positive rate (TPR) at 10% false positive rate (FPR), demonstrating robust downturn forecasting.

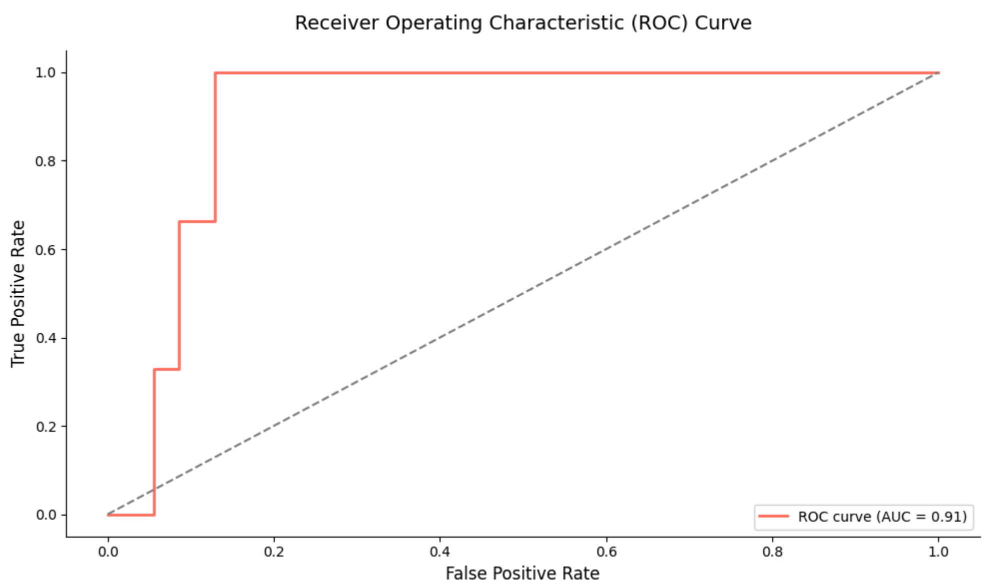

Figure 4 - ROC Curve (Curvature Metric Δs_Pdo_a): ROC curve for the curvature metric (AUC = 0.91). Mirrors performance of the slope model, with improved precision in high-volatility regimes.

4. Discussion & Limitations

Our results support the central hypothesis: a steeper implied volatility skew robustly predicts short-term market downturns. Beyond the statistical significance, the magnitude of skew coefficients emphasizes the economic importance of deep-tail hedging behavior and market participants' acute sensitivity to extreme negative events. Despite these promising results, there are several limitations to our study:

- **Data Scope:** Our study focuses on the QQQ ETF, which tracks the Nasdaq-100. Because tech-heavy indices are particularly prone to volatility, our results may not generalize to other markets (e.g., commodities, fixed income, or global equities). Future studies should extend this approach to broader datasets.

- **Jump Detection Methodology:** The Lee & Mykland jump test is a well-established method for identifying significant price discontinuities. However, it may fail to capture multi-day downturns that do not feature a sharp single-day drop. Future research could refine the downturn definition by incorporating rolling-window approaches or machine-learning-based anomaly detection.

- **Alternative Models:** Logistic regression provides interpretable and statistically sound results, but market downturns are complex, nonlinear phenomena. Future research could explore deep learning models, random forests, or Bayesian inference techniques to enhance predictive accuracy. For example, Doran (2007) employs probit regression which is similar but incorporates controls more directly than logistic.

This study affirms implied volatility skew as an insightful and practically useful leading indicator for market downturns, especially when segmented by delta thresholds to isolate extreme tail-risk pricing. Both the slope (DOTM–OTM) and curvature (DOTM–ATM) skew metrics strongly predict imminent downturns, with robust statistical and out-of-sample predictive validity. Despite certain limitations, particularly relating to market specificity and downturn definitions, this approach represents a valuable advancement for informing trading strategies and financial modeling.

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