Economics Bulletin

Volume 45, Issue 4

Forecasting returns and risk through implied volatility: A dual-threshold investment framework

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Abstract

This study explores the non-linear relationship between implied volatility and future equity returns. We document a U-shaped link between implied volatility and ETF performance across three index pairs: VIX-SPY, VXN-QQQ, and VXD-DIA, suggesting that extreme volatility may signal market rebounds. Based on this, we develop a two-threshold trading rule that reallocates between equities and bonds. Backtesting results show that the strategy improves risk-adjusted returns and reduces drawdowns relative to a buy-and-hold approach.

The author gratefully acknowledges the valuable comments and suggestions from the two anonymous referees and the editor, Professor John P. Conley, which have greatly improved the quality of this manuscript.
Citation: Chih-hsiang Hsu, (2025) "Forecasting returns and risk through implied volatility: A dual-threshold investment framework", *Economics Bulletin*, Volume 45, Issue 4, pages 1926-1938
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Submitted: April 15, 2025. **Published:** December 30, 2025.

1. Introduction

Buy-and-hold (BnH) strategies are widely regarded as effective tools for long-term wealth accumulation (Barber & Odean, 2000; Bogle, 2017). However, such passive approaches often expose investors to substantial drawdowns during periods of elevated volatility. Given that equity returns tend to be left-skewed with fat left tails (Campbell & Hentschel, 1992; Barro, 2006), losses during market crises can disproportionately outweigh prior gains. This has motivated interest in adaptive strategies that incorporate forward-looking risk signals to protect downside exposure without fully abandoning passive investing principles.

Our strategy enhances the buy-and-hold approach by selectively exiting equities when implied volatility crosses a moderate threshold, and re-entering during extreme spikes that historically precede rebounds. Our approach utilizes implied volatility indexes as real-time signals of market sentiment. Among them, the Volatility Index (VIX), derived from S&P 500 option prices, has been widely used to forecast future market risk and returns (Whaley, 2009; Blair et al., 2001; Da & Schaumburg, 2011). Because investors often hedge with put options, the VIX captures tail-risk concerns, reinforcing its interpretation as a "fear gauge." [1]

Several studies have employed VIX-based rules to manage portfolio exposure. Pinto et al. (2015) filtered technical trading signals using the VIX, while Dolvin and Foltice (2023) proposed a single-threshold rule that rotates into bonds when the VIX exceeds a cutoff, enhancing risk-adjusted performance. Božović (2024) further confirmed that VIX-managed portfolios improve downside protection. These findings highlight the VIX's value as a tactical input, particularly for reducing losses during market stress[2]. However, these strategies often emphasize volatility reduction at the expense of long-term return, and as Kownatzki (2016) noted, the VIX may misrepresent tail risk during extreme events.

Our study introduces a dual-threshold strategy that improves upon prior approaches by recognizing a nonlinear relationship between implied volatility and future returns. Using matched pairs, VIX-SPY, VXN-QQQ, and VXD-DIA, we find a U-shaped relation: future

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[1] While the VIX is the most widely used implied volatility index derived from S&P 500 option prices, several other major equity indices have their own counterparts. In U.S. equity markets, the Nasdaq-100 has the CBOE Nasdaq Volatility Index (VXN), the Dow Jones Industrial Average uses the DJIA Volatility Index (VXD), and other markets such as the DAX, FTSE, and Nikkei also maintain similar implied volatility measures.

[2] Several studies have examined the predictive and informational content of implied volatility indices. Blair et al. (2001) and Da and Schaumburg (2011) show that the VIX has significant forecasting power for future realized volatility, often outperforming statistical models such as GARCH. Simon (2003) focuses on the VXN during the dot-com bubble, highlighting its responsiveness to sector-specific risks. Moreira and Muir (2017) propose volatility-managed portfolio strategies that dynamically scale exposure based on ex-ante risk, demonstrating substantial improvements in risk-adjusted performance.

returns decline as volatility rises from low to moderate levels, but recover when volatility becomes extreme. These turning points likely reflect market capitulation and signal rebound potential.

Based on this empirical insight, we construct a regime-switching model with three states: Risk-On (low VIX), Risk-Off (moderate VIX), and Re-entry (very high or normalized VIX). During Risk-Off periods, equity positions are shifted into short-term government bonds (IEF). We show that this strategy achieves significantly higher returns than BnH benchmarks while maintaining comparable or lower volatility and drawdowns. Importantly, the market exit ratio remains modest (6–12%), preserving most equity exposure. To ensure that the main findings are not driven by specific parameter settings, we also conduct a robustness check by varying the threshold specifications in the dual-threshold model, confirming that the strategy's performance remains stable across different parameter choices.

Our contribution lies in uncovering the quadratic structure of the VIX-return relationship and applying it to tactical allocation. Unlike prior studies that rely on linear signals or static cutoffs, our framework dynamically captures market sentiment swings and enables more balanced decision-making.

The rest of this paper is organized as follows: Section 2 describes the data and predictive regressions; Section 3 introduces the strategy and evaluates its performance; Section 4 concludes.

2. Methodology

2.1 Data and Variables

We use daily data from 2002 to 2024 on three ETF–volatility index pairs: SPY–VIX, QQQ–VXN, and DIA–VXD. Adjusted ETF prices are sourced from Yahoo Finance and used to compute daily returns. Implied volatility indices are obtained from Investing.com.

Table I provides summary statistics for the three ETFs and their corresponding volatility indices. Among the ETFs, QQQ has the highest average return (12.96%) and volatility (24.53%), reflecting its technology-sector concentration. DIA displays the lowest volatility (18.50%) with a solid return (11.78%), while SPY has the lowest average return (9.73%) and a mid-range volatility (19.39%).

On the volatility side, VXN exhibits the highest mean (25.27%) and median (21.06%), followed by VIX and VXD. These differences reflect structural characteristics of their underlying indices: the Nasdaq-100 (QQQ) is heavily weighted toward high-growth tech stocks, resulting in greater perceived risk, while the Dow Jones (DIA) contains large-cap, traditional industrial firms with lower volatility profiles.

The extreme values, such as the VIX peaking at 82.69, typically coincide with major market stress episodes (e.g., financial crises, pandemic shocks), reinforcing their value as forward-looking risk indicators. These properties justify the use of implied volatility in both predictive regressions and the trading framework developed in later sections.

Table I. Descriptive Statistics of ETF Returns and Volatility Indexes

sample periods			
Sample Start	2000/1/3	2001/1/23	2005/11/22
Sample End	2024/12/30	2024/12/30	2024/12/30
Sample Size	6287	6021	4806
ETF return summary			
	SPY	QQQ	DIA
Annualized Return (%)	9.7322	12.9625	11.7805
Annualized Std Dev (%)	19.3917	24.5314	18.4967
Minimum Return (%)	-10.9424	-11.9788	-12.7612
Q1 Return (%)	-0.4677	-0.6241	-0.3943
Median Return (%)	0.0677	0.109	0.0736
Q3 Return (%)	0.5996	0.7825	0.5477
Maximum Return (%)	14.5198	12.1647	13.5558
volatility index summary			
	VIX	VXN	VXD
Mean	19.87	25.27	18.15
Std Dev	8.46	12.45	7.96
Minimum	9.14	10.31	2.71
Lower Quartile	13.86	16.95	13.10
Median	17.84	21.06	15.84
Upper Quartile	23.36	28.75	20.77
Maximum	82.69	82.49	74.60

Note: This table presents descriptive statistics for daily returns of SPY, QQQ, and DIA ETFs, and their corresponding implied volatility indexes (VIX, VXN, and VXD). For ETFs, we report annualized return and standard deviation, as well as key percentiles of daily returns. For volatility indexes, we report the mean, standard deviation, and distributional percentiles over the respective sample periods.

2.2 Predictive Regression

We investigate whether implied volatility indices can predict both the future returns and the future volatility of equity ETFs. The core predictive framework examines the relationship between the current level of the implied volatility index and the future behavior of the corresponding ETF over a fixed horizon h, ranging from 1 to 66 trading days.

2.2.1 Volatility Index and Future ETF Returns

The first model explores how implied volatility relates to the arithmetic average of daily ETF returns over the future horizon. The dependent variable is the arithmetic average of daily ETF returns from date *t+1* to *t+h*, denoted as:

$$\bar{R}_{t+1:t+h} = \frac{1}{h}\sum_{i=1}^{h} r_{t+i} \tag{1}$$

where r_t is the daily return of the ETF at date *t*.

The regression framework is specified as follows:

Linear specification

$$\bar{R}_{t+1:t+h} = \alpha + \beta_1 Vol\_Index_t + \varepsilon_t. \tag{2}$$

Quadratic specification

$$\bar{R}_{t+1:t+h} = \alpha + \beta_1 Vol\_Index_t + \beta_2 Vol\_Index_t^{\ 2} + \varepsilon_t. \tag{3}$$

The inclusion of the squared term allows us to detect a non-linear relationship between the implied volatility index and future ETF returns. Our results reveal a statistically significant U-shaped relationship.

Table II. Predictive Regressions of Future Returns on the Volatility Index

		R_{t+h} (SPY)		R_{t+h} (QQQ)		R_{t+h} (DIA)	
Forecast Horizon (h)	Variable	Linear	Quadratic	Linear	Quadratic	Linear	Quadratic
5	VIX_t	0.3070***	-0.4125*	-0.0536	-0.7322**	0.2823***	-0.1422
	VIX_t^2		0.0123***		0.0093**		0.0075
10	VIX_t	0.2495***	-0.4270***	-0.072	-0.6105***	0.2489***	-0.3296*
	VIX_t^2		0.0116***		0.0074***		0.0103***
22	VIX_t	0.2693***	-0.1606	-0.018	-0.5481***	0.2830***	0.0392
	VIX_t^2		0.0074***		0.0072***		0.0043**
66	VIX_t	0.1434***	0.0861	-0.0272	-0.1044	0.1424***	0.4064***
	VIX_t^2		0.001		0.0011		-0.0047***

Note: This table reports estimated coefficients from regressions of future average ETF returns on implied volatility indexes (VIX, VXN, VXD) over forecast horizons h=5,10,22,66. Both linear and quadratic specifications are estimated. Coefficients reflect the predictive relation between implied volatility and future stock returns. Significance is denoted by *, **, and *** at the 10%, 5%, and 1% levels, respectively.

Linear regressions in Table II yield mixed results: for short horizons, SPY and DIA exhibit positive coefficients, while QQQ shows negative sensitivity to VXN, suggesting rising volatility predicts lower short-term returns. These mixed signs echo long-standing debates in the literature about whether volatility signals rising risk or contrarian opportunity.

To explore potential non-linearities, we include the squared term. Across all ETFs, the quadratic term is positive and statistically significant at medium to long horizons. For example, at a 22-day horizon, the squared coefficient for SPY is 0.0009 with 5% significant level, indicating a U-shaped relation: returns fall as volatility rises from low to moderate levels but recover once volatility reaches extremes. This implies a state-dependent return dynamic, where extremely high VIX levels may signal market capitulation and subsequent recovery potential.

These findings reconcile the dual narratives in the literature: rising volatility initially signals risk-off behavior, but extremely high levels can reflect oversold markets and set the stage for recovery. This state-dependent return pattern provides the foundation for our threshold-based regime-switching strategy.

2.2.2 Volatility Index and Future ETF Volatility

We adopt the same regression framework to examine whether implied volatility predicts realized volatility over horizon h, defined as:

$$\sigma_{t+1:t+h} = \sqrt{\frac{1}{h-1}\sum_{i=1}^{h}(r_{t+i} - \bar{R}_{t+1:t+h})^2} \ . \tag{4}$$

We estimate the same linear and quadratic models, substituting $\sigma_{t+1:t+h}$ as the dependent variable. The regression framework is specified as follows:

Linear specification

$$\sigma_{t+1:t+h} = \alpha + \beta_1 Vol\_Index_t + \varepsilon_t \ . \tag{5}$$

Quadratic specification

$$\sigma_{t+1:t+h} = \alpha + \beta_1 Vol\_Index_t + \beta_2 {Vol\_Index_t}^2 + \varepsilon_t . \tag{6}$$

As shown in Table III, the linear term is consistently positive and highly significant across all

ETFs and horizons, confirming that implied volatility is a strong predictor of future risk. In the quadratic specification, the turning points (e.g., vertex ≈ 11.8 for SPY when h=5) typically lie below the median VIX, meaning that the observed VIX values are generally in the increasing portion of the curve. Thus, even with curvature, the overall relationship between implied and realized volatility remains positive throughout most of the sample.

Together, these findings support the use of implied volatility not only for anticipating returns, but also for gauging short-term risk. The dual predictive role of the VIX family justifies its use in our regime-switching strategy introduced in the next section.

Table III. Predictive Regressions of Future Returns Volatility on the Volatility Index

		$\sigma_{t+1:t+h}$ (SPY)		$\sigma_{t+1:t+h}$ (QQQ)		$\sigma_{t+1:t+h}$ (DIA)	
Forecast Horizon (h)	Variable	Linear	Quardratic	Linear	Quardratic	Linear	Quardratic
5	VIX_t	11.5998***	-7.8510***	9.8234***	-0.9826	13.4687***	-11.0141***
	${VIX_t}^2$		0.3328***		0.1478***		0.4344***
10	VIX_t	11.5980***	-4.9634***	10.3283***	-0.3671	13.2665***	-7.1130***
	${VIX_t}^2$		0.2833***		0.1463***		0.3616***
22	VIX_t	9.8854***	-1.0832**	9.7993***	-0.0496	10.9057***	-1.1906
	${VIX_t}^2$		0.1876***		0.1347***		0.2146***
66	VIX_t	6.1972***	2.3436***	7.4973***	2.4721***	6.2319***	2.1307***
	${VIX_t}^2$		0.0659***		0.0687***		0.0728***

Note: This table reports regression results where the dependent variable is the future volatility (standard deviation) of ETF returns over horizons h=5,10,22,66 days. Implied volatility indexes are used as predictors under both linear and quadratic specifications. Results assess the extent to which implied volatility forecasts future market risk.

3. Strategy Construction and Backtesting

Building on the nonlinear predictive patterns identified in Section 2, we propose a regime-switching strategy that modifies a traditional buy-and-hold (BnH) approach. The strategy remains invested in equities most of the time, temporarily reallocating to bonds during periods of elevated implied volatility. Our central hypothesis is that timely exits—triggered by volatility signals—can improve the risk-return profile of passive investing without excessive trading or risk exposure.

3.1 Strategy Construction and Volatility Thresholds

The strategy uses a dual-threshold rule to define three regimes:

- **Risk-On:** Volatility is below the “middle” threshold; the portfolio is fully invested in equities.

- **Risk-Off:** Volatility exceeds the "middle" but remains below the "upper" threshold; the portfolio switches to bonds (IEF).
- **Re-entry:** Volatility either exceeds the "upper" threshold or falls below the long-term average; equity exposure resumes.

These dynamic thresholds are calculated based on rolling 240-day historical averages ($\mu_{240,t}$) and standard deviations ($\sigma_{240,t}$) of the respective implied volatility index: $\mathrm{upper}_t = \mu_{240,t} + 2 \times \sigma_{240,t}$, $\mathrm{middle}_t = \mu_{240,t} + 1 \times \sigma_{240,t}$, and $\mathrm{lower}_t = \mu_{240,t}$.

This structure captures both rising risk and panic-induced reversals. Our goal is to improve upon Dolvin and Foltice's (2023) single-threshold model, which may exit the market prematurely and frequently. In contrast, our approach minimizes exit frequency while enhancing timing precision.

It is worth noting that the three threshold parameters used in this study primarily serve as a proof of concept, demonstrating the potential of the dual-threshold framework in capturing market panic rebounds. Our main objective is to improve upon the single-threshold method proposed by Dolvin and Foltice (2023), which may lead to excessively frequent market exits during volatility spikes, thereby missing the long-term excess returns of the equity market. In contrast, our strategy aims to provide a more balanced framework for long-term investors, protecting capital without overly sacrificing market participation.[3]

3.2 Backtesting and Results

We evaluate the proposed strategy through historical backtesting using daily ETF returns up to December 2024. The benchmark is a buy-and-hold (BnH) strategy maintaining full equity exposure in SPY, QQQ, or DIA. For simplicity, we assume no transaction costs and immediate execution at market close.

Key performance metrics include annualized return, volatility, downside deviation, Sharpe ratio, and maximum drawdown. Additionally, we report the Market Exit Ratio, the proportion of days the strategy is in the Risk-Off state, to highlight the minimal extent of deviation from passive investing.

Table IV compares ETF returns across Risk-On and Risk-Off regimes. Across all three ETFs, returns during Risk-Off periods are significantly lower than those during Risk-On periods. For

[3] As the primary aim of this study is to conceptually refine the single-threshold strategy proposed by Dolvin and Foltice (2023), this paper does not attempt to optimize the threshold parameters. The dual-threshold framework is intended to demonstrate the potential benefit of selectively timing re-entries to address the shortcomings of overly frequent exits in high-volatility conditions.

instance, SPY exhibits a daily return of –0.09% in Risk-Off states, compared to 0.0563% in Risk-On states. The two-sample t-statistic for SPY equals –2.1822 and is statistically significant at the 5% level, indicating that the return differential is not due to random variation. Similar patterns are observed for QQQ and DIA, confirming the strategy's effectiveness in identifying periods of heightened downside risk.

Regarding volatility and downside risk, the evidence is more mixed. For SPY and QQQ, the strategy yields lower daily volatility compared to the buy-and-hold benchmark: 1.0563% versus 1.1977% for SPY, and 1.1551% versus 1.4051% for QQQ. In contrast, for DIA, the strategy exhibits higher volatility than the benchmark, with daily standard deviations of 1.4078% and 1.1157%, respectively. Downside deviation shows a similar pattern across ETFs, suggesting that while the strategy reliably enhances returns, it does not consistently reduce overall portfolio risk.

Table IV. ETF Performance During Risk-Off vs Risk-On Periods

ETF	SPY		QQQ		DIA	
	Risk-Off	Risk-On	Risk-Off	Risk-On	Risk-Off	Risk-On
Mean ETF Return	-0.09	0.0563	-0.0385	0.0761	-0.1161	0.0664
difference (%)	-0.1463		-0.1146		-0.1825	
T-Statistic	-2.1822**		-1.6783*		-3.5886***	
Return Std (%)	1.0563	1.1977	1.1551	1.4051	1.4078	1.1157
Levene Statistic (Std)	0.2126		8.6811**		85.159***	
Return Semi-Std (%)	0.814	0.972	0.9012	1.0555	0.9718	0.9323
Levene Statistic (Semi-Std)	0.0448		3.1478*		18.487***	

Note: This table compares mean returns, standard deviations, and downside risk of ETFs during Risk-On and Risk-Off regimes as defined by VIX-based thresholds. T-statistics test for mean return differences, and Levene statistics assess variance equality between regimes.

Table V summarizes the full-sample performance of the proposed regime-switching strategy compared to the buy-and-hold benchmark for SPY, QQQ, and DIA. Despite minimal deviations from the benchmark, quantified by market exit ratios of 5.94% for SPY, 7.94% for QQQ, and 12.25% for DIA, the strategy consistently delivers superior return performance. For example, the annualized return for SPY increases from 11.99% under buy-and-hold to 13.83% under the strategy. Correspondingly, the Sharpe ratio improves from 52.91 to 64.01.

Importantly, these gains are achieved without substantially increasing portfolio risk. Volatility and downside risk metrics under the strategy are generally comparable to those of the benchmark, and maximum drawdowns are notably reduced. During Risk-Off periods, the portfolio reallocates to IEF, a short-term government bond ETF, which serves to preserve capital during episodes of elevated implied volatility.

These results support the central premise of this study: that small, well-timed departures from passive equity exposure, guided by a nonlinear interpretation of volatility signals, can enhance long-term performance while maintaining effective risk control. In contrast to earlier VIX-based strategies that focus primarily on risk mitigation, such as those proposed by Dolvin and Foltice (2023) and Božović (2024), our approach achieves meaningful improvements in return without sacrificing the core strengths of passive investing.

Table V. Performance Summary of VIX-Based Risk Regime Strategy vs Buy-and-Hold

	SPY		QQQ		DIA	
Metric	**Strategy**	**BnH**	**Strategy**	**BnH**	**Strategy**	**BnH**
Annualized Return (%)	13.83	11.99	18.43	16.88	15.91	11.12
Annualized Volatility (%)	18.5	18.89	21.49	22.03	16.83	18.37
Annualized Downside Risk (%)	15.01	15.16	16.32	16.47	13.96	14.98
Market Exit Ratio (%)	5.94	--	7.94	--	12.25	--
Sharpe Ratio	64.01	52.91	76.45	67.63	82.62	49.57
Max Drawdown (%)	-55.15	-55.19	-51.98	-53.4	-41.71	-51.87
T-Statistic (Returns)	1.7801 *		1.2145		2.2806 **	
Levene Statistic (Std)	2.9783 *		5.0340 **		22.0133 ***	
Levene Statistic (Semi-Std)	0.0448		3.1478 *		18.487 ***	

Note: This table summarizes the annualized performance of the dual-threshold strategy versus a passive buy-and-hold benchmark across ETFs. Reported metrics include returns, standard deviations, downside risk, Sharpe ratios, maximum drawdowns, and Market Exit Ratios (percentage of days in Risk-Off). Risk-Off periods are allocated to short-term government bonds (IEF). Statistical tests evaluate return and variance differences.

Although the reduction in volatility is less pronounced for DIA, this outcome reflects the characteristics of its underlying index composition. The DIA index primarily comprises large, mature industrial firms that naturally exhibit lower baseline volatility compared to SPY and QQQ. Consequently, the potential for further volatility reduction through regime switching is inherently limited. Nevertheless, the strategy still improves the Sharpe ratio and mitigates drawdowns, indicating that its risk-adjusted performance remains robust across assets with different volatility structures.

From a practical perspective, the strategy's low trading frequency also suggests that transaction costs would have a negligible impact on performance. As shown in Table V, the market-exit ratios of 6 to 12% imply only a few portfolio reallocations per year. Most of the time, the portfolio remains fully invested in equities and only temporarily exits the market when implied volatility rises. Even under reasonable assumptions for bid–ask spreads or brokerage commissions, the overall reduction in annualized returns would be limited. Therefore, the performance improvements observed in the empirical results are unlikely to be driven by the omission of transaction costs.

To check the robustness to threshold specification, Table VI displays the results of the sensitivity analysis using alternative combinations of the middle and upper thresholds (m, u). In the baseline strategy reported in Table V, the volatility thresholds are defined based on 240-day rolling statistics of each implied volatility index. Specifically, the upper and middle thresholds are calculated as $\mathrm{upper}_t = \mu_{240,t} + 2\sigma_{240,t}$ and $\mathrm{middle}_t = \mu_{240,t} + 1\sigma_{240,t}$, where $\mu_{240,t}$ and $\sigma_{240,t}$ denote the 240-day rolling mean and standard deviation of the implied volatility index, respectively, and the lower bound corresponds to $\mathrm{lower}_t = \mu_{240,t}$. These dynamic thresholds determine the switching points between equity and bond positions in the dual-threshold strategy.

To verify that the results are not sensitive to a particular parameter choice, we vary the middle and upper thresholds within a reasonable range of (m, u) combinations. The results, summarized in Table VI, indicate that the dual-threshold strategy consistently outperforms the buy-and-hold benchmark across all parameter settings. The baseline case $(m = 1, u = 2)$ remains representative of the overall performance. The annualized returns and Sharpe ratios range from 13% to 19% and 62% to 84%, respectively, across all ETFs, while the market-exit ratio stays within the range from 4% to 12%. These findings confirm that the superior risk-adjusted performance of the strategy is not driven by excessive trading frequency, and the results are robust to reasonable variations in the threshold parameters.

Table VI. Sensitivity of Strategy Performance to Alternative Threshold Parameters

ETF	m	u	Ann. Ret.	Ann. Vol.	Sharpe Ratio	Max Drawdown	Market Exit Ratio
SPY	0.5	1.5	15.32	18.5	66.0	–54.80	5.09
	1	1.5	14.18	18.3	64.5	–55.00	4.18
	0.5	2	16.09	18.4	67.2	–55.10	5.87
	1	**2**	**13.84**	**18.5**	**64.0**	**–55.15**	**5.94**
	1.5	2	13.45	18.7	62.8	–55.30	5.18
	0.5	2.5	16.13	18.3	67.4	–55.20	6.31
	1	2.5	13.96	18.6	63.7	–55.30	6.47
	1.5	2.5	13.19	18.8	62.4	–55.40	6.08
QQQ	0.5	1.5	19.55	21.5	76.8	–52.00	8.37
	1	1.5	19.10	21.3	76.3	–52.10	5.55
	0.5	2	19.80	21.6	77.1	–52.00	9.43
	1	**2**	**18.43**	**21.5**	**76.5**	**–51.98**	**7.94**
	1.5	2	17.73	21.7	74.8	–52.20	6.22
	0.5	2.5	19.18	21.5	76.9	–52.00	11.52
	1	2.5	16.96	21.8	73.4	–52.30	10.07
	1.5	2.5	15.24	22.0	71.1	–52.40	10.23
DIA	0.5	1.5	17.99	16.8	82.9	–41.71	11.69
	1	1.5	15.98	16.8	80.0	–41.71	9.58
	0.5	2	18.71	16.9	83.7	–41.71	14.75
	1	**2**	**15.91**	**16.8**	**82.6**	**–41.71**	**12.25**
	1.5	2	15.35	16.9	79.5	–41.80	9.77
	0.5	2.5	19.39	16.9	84.3	–41.70	18.52
	1	2.5	16.02	17.0	80.8	–41.80	16.08
	1.5	2.5	15.04	17.0	78.9	–41.80	13.19

Notes: This table reports the results of the sensitivity analysis for alternative threshold parameters (m, u), where m and u represent the middle and upper bounds of the implied volatility thresholds, respectively. These thresholds are dynamically determined based on the 240-day rolling mean $(\mu_{240,t})$ and standard deviation $(\sigma_{240,t})$ of each implied volatility index, such that

$$\text{upper}_t = \mu_{240,t} + u\sigma_{240,t}, \quad \text{middle}_t = \mu_{240,t} + m\sigma_{240,t}, \quad \text{lower}_t = \mu_{240,t}..$$

The baseline specification uses $(m = 1, u = 2)$, as shown in Table V. These thresholds define the switching points between equity and bond positions in the dual-threshold strategy. The results confirm that the strategy's superior performance is robust to reasonable variations in these parameters.

4. Conclusion

This study explores the predictive relationship between implied volatility and future ETF performance, and introduces a regime-switching strategy based on a nonlinear interpretation of VIX signals. While prior work emphasizes de-risking during volatility spikes, our results reveal a U-shaped relationship between implied volatility and future returns—suggesting that extreme fear may precede market rebounds.

Motivated by this finding, we design a dual-threshold strategy that reduces risk exposure when volatility rises, but selectively re-enters equities during extreme conditions. Backtesting shows that this approach outperforms a passive buy-and-hold benchmark across major ETFs, achieving higher Sharpe ratios and lower drawdowns without increasing volatility. The results remain consistent across alternative threshold settings.

Our contribution lies in translating nonlinear volatility—return dynamics into a practical allocation rule that preserves the core advantages of passive investing while enhancing risk-adjusted returns. Future work may incorporate bond market volatility measures such as the MOVE index to capture cross-market risk transmission and improve the robustness of the allocation framework. While the proposed model is primarily an allocation strategy rather than a direct hedging approach, it could be integrated with hedging instruments or multi-asset portfolios in future research to further enhance risk management effectiveness.[4]

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[4] Although this study focuses on equity ETFs, we also experimented with gold as an alternative safe-haven asset. Specifically, we examined strategies that replace bonds with gold ETFs and applied the CBOE Gold Volatility Index (GVZ) as a predictive signal for gold-related ETFs. However, both extensions produced weaker performance, likely because gold prices are affected by a broader range of factors, including policy interventions, global demand conditions, and currency dynamics. These results reinforced our focus on equity markets while suggesting that extending this framework to other asset classes remains a promising avenue for future research.

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