Volatility Regimes and Trend-Following Performance in U.S. Equities

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Abstract

This paper evaluates how a simple trend-following rule behaves across volatility regimes in U.S. equities. The baseline strategy is long when price is above its 50-day simple moving average and in cash otherwise, with monthly rebalancing and 10 basis points transaction costs. Volatility regimes are defined using annualized 21-day realized volatility and out-of-sample expanding-window quantiles (low: below 25th percentile, high: above 75th percentile). On SPY from 1993-04-12 to 2026-02-12, the trend strategy has lower unconditional return than buy-and-hold (CAGR 3.83% vs. 8.68%) but materially lower max drawdown (-36.46% vs. -56.47%). Regime-conditional results show strongest strategy performance in low-volatility periods and weaker relative performance in normal and high-volatility periods. A bootstrap test of high-minus-normal Sharpe difference yields 0.10 with p-value 0.794, indicating weak statistical evidence for a meaningful difference in this sample.

1 Introduction

A standard claim in trend-following is that performance varies materially by market state, with the strongest behavior often tied to persistent directional moves and weaker behavior in choppy transitions. This paper studies the following question: *How sensitive is trend-following performance to volatility regimes in U.S. equities?*

The design is intentionally minimal to isolate the regime effect: a single trend rule, explicit friction assumptions, and out-of-sample regime classification. The setup is motivated by prior momentum and trend literature [2, 3, 1].

2 Data and Methodology

2.1 Data

The primary instrument is SPY (S&P 500 ETF). Robustness checks use QQQ and IWM. Daily OHLCV history is sourced from Yahoo Finance via `yfinance`. The SPY analysis sample spans 1993-04-12 to 2026-02-12.

2.2 Signal and Regime Definitions

The baseline trading signal is

$$\text{Signal}_t = ⊮\{P_t > \text{SMA}_{50,t}\}. \tag{1}$$

The position at time t uses lagged signal information consistent with end-of-period execution.

Realized volatility is computed as annualized 21-day rolling standard deviation of daily returns:

$$\sigma_t = \sqrt{252}\,\mathrm{Std}(r_{t-20:t}). \tag{2}$$

Regimes are assigned using expanding-window quantiles to avoid look-ahead bias:

- Low volatility: $\sigma_t < Q_{0.25,t}$
- Normal volatility: $Q_{0.25,t} \le \sigma_t \le Q_{0.75,t}$
- High volatility: $\sigma_t > Q_{0.75,t}$

2.3 Backtest Protocol

The backtest uses monthly rebalancing and 10 bps cost per unit position change. Performance is reported via CAGR, annualized volatility, Sharpe, Sortino, Calmar, win rate, and max drawdown. Regime-conditional performance is computed separately by volatility state. A walk-forward procedure uses 24-month train and 6-month test windows (61 out-of-sample periods). Statistical significance is assessed with 500 bootstrap resamples for high-vs-normal Sharpe differences.

3 Results

3.1 Unconditional Performance (SPY)

Table 1: Unconditional performance, SPY (1993-04-12 to 2026-02-12)

Metric	Trend Strategy	Buy and Hold
CAGR	3.83%	8.68%
Sharpe	0.322	0.465
Max drawdown	-36.46%	-56.47%
Volatility	11.90%	18.68%
Sortino	0.334	0.595
Calmar	0.105	0.154
Win rate	34.80%	53.66%
Sharpe CI (95%)	[-0.007, 0.725]	N/A

The trend strategy reduces downside depth but gives up significant long-run return versus passive exposure.

3.2 Conditional Performance by Volatility Regime

Table 2: Regime-conditional performance, SPY

Regime	Avg vol	Strategy Sharpe	Benchmark Sharpe	Strategy CAGR	Benchmark CAGR	Count
Low	7.96%	1.548	1.739	12.62%	15.00%	1988
Normal	13.60%	0.111	0.433	0.62%	5.23%	3780
High	26.00%	0.215	0.447	2.10%	9.07%	2469

The strategy underperforms buy-and-hold in high-volatility periods by roughly 6.97 percentage points annualized. The high-minus-normal Sharpe difference is 0.10 with p-value 0.794, providing weak evidence of regime Sharpe separation in this sample.

3.3 Transition, Walk-Forward, and Cross-Asset Robustness

Regime transitions are persistent (e.g., low-to-low 93.21%, normal-to-normal 93.94%, high-to-high 96.19%). Walk-forward out-of-sample performance remains consistent with full-sample behavior (OOS CAGR 3.61%, OOS Sharpe 0.325, OOS max drawdown -33.22%; 61 test periods).

Table 3: Cross-asset robustness (unconditional)

Asset	Trend CAGR	Trend Sharpe	Buy and Hold CAGR	Buy and Hold Sharpe
QQQ	7.29%	0.419	9.42%	0.350
IWM	3.23%	0.204	6.65%	0.278

A parameter sweep of SMA windows (20, 50, 100, 150, 200) shows low-volatility Sharpe is consistently stronger than high-volatility Sharpe.

4 Figures

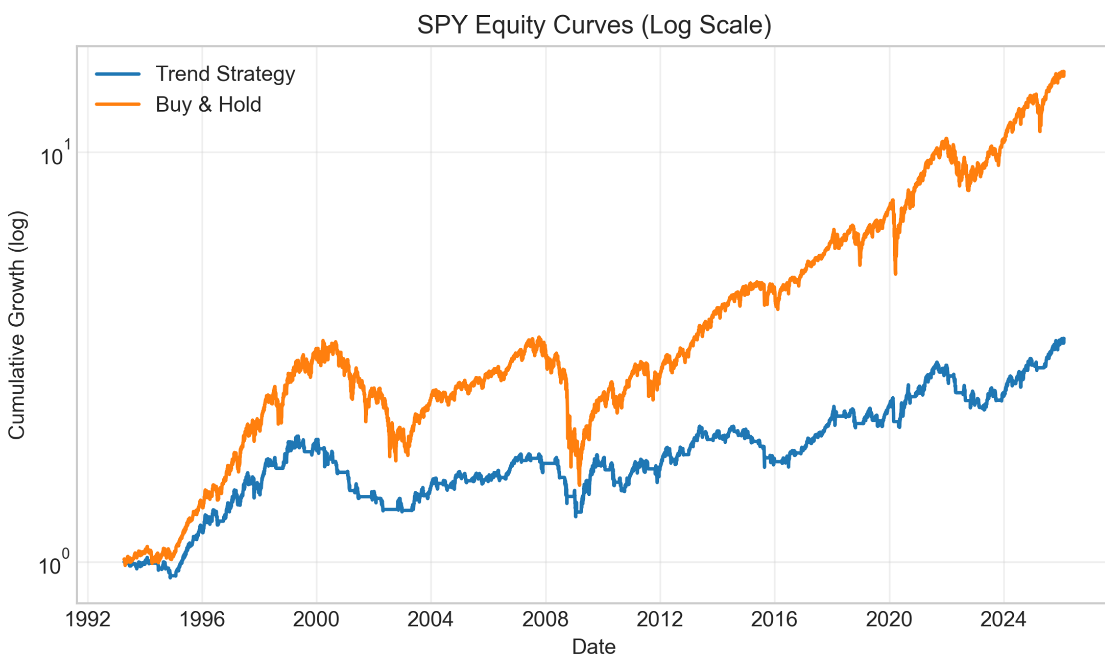

Figure 1: SPY equity curves (log scale).

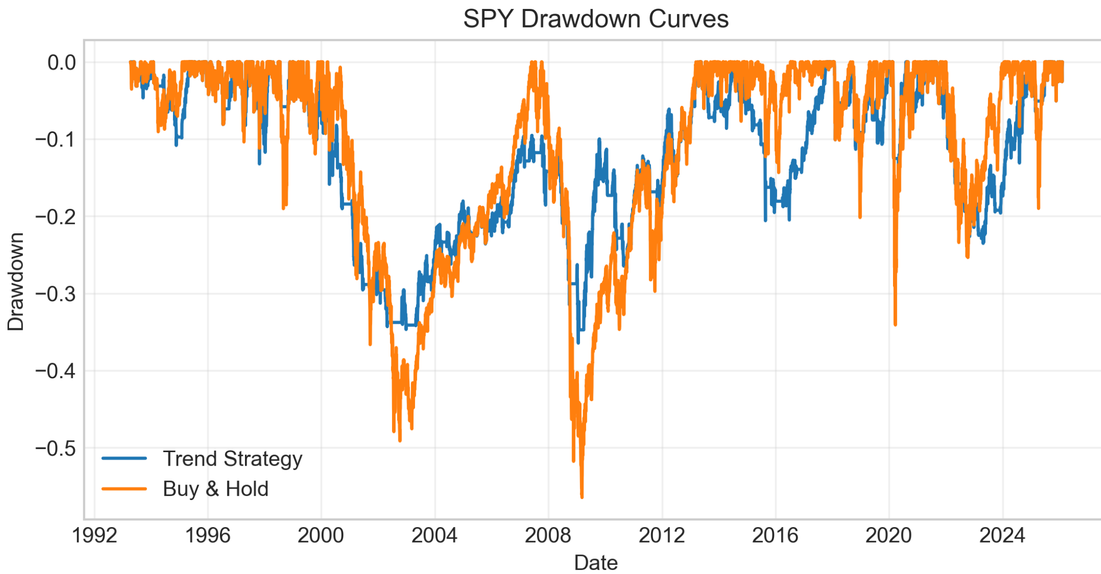

Figure 2: SPY drawdown curves.

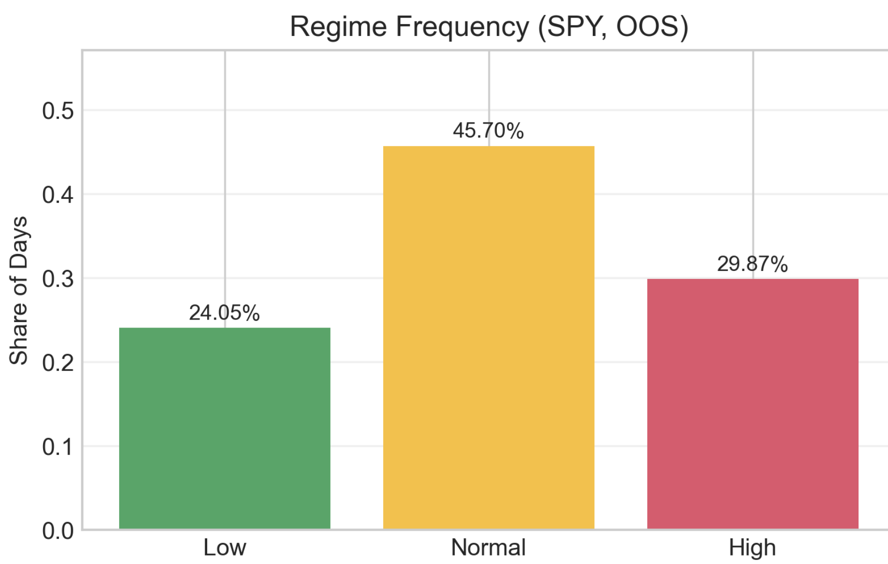

Figure 3: Regime frequency under out-of-sample quantile classification.

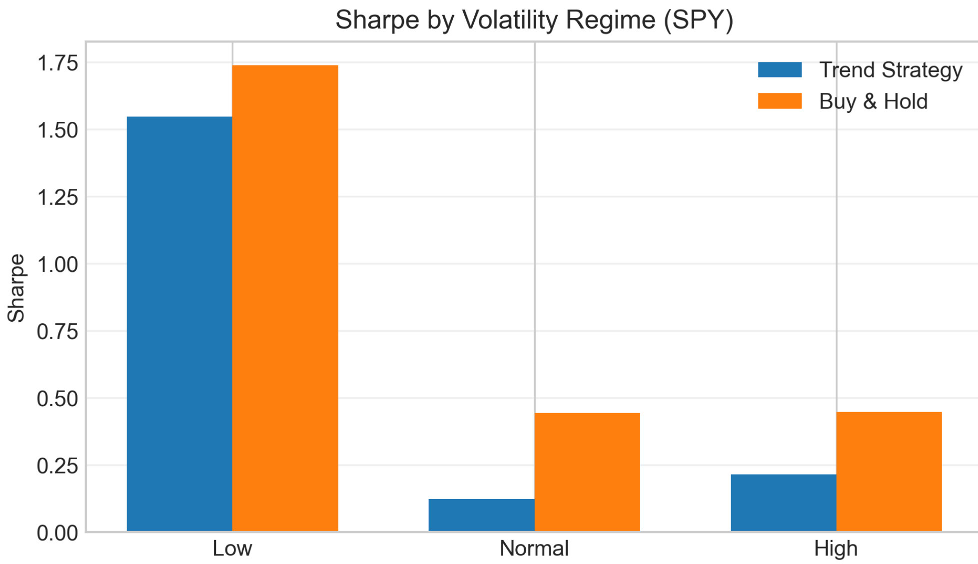

Figure 4: Strategy and benchmark Sharpe by volatility regime.

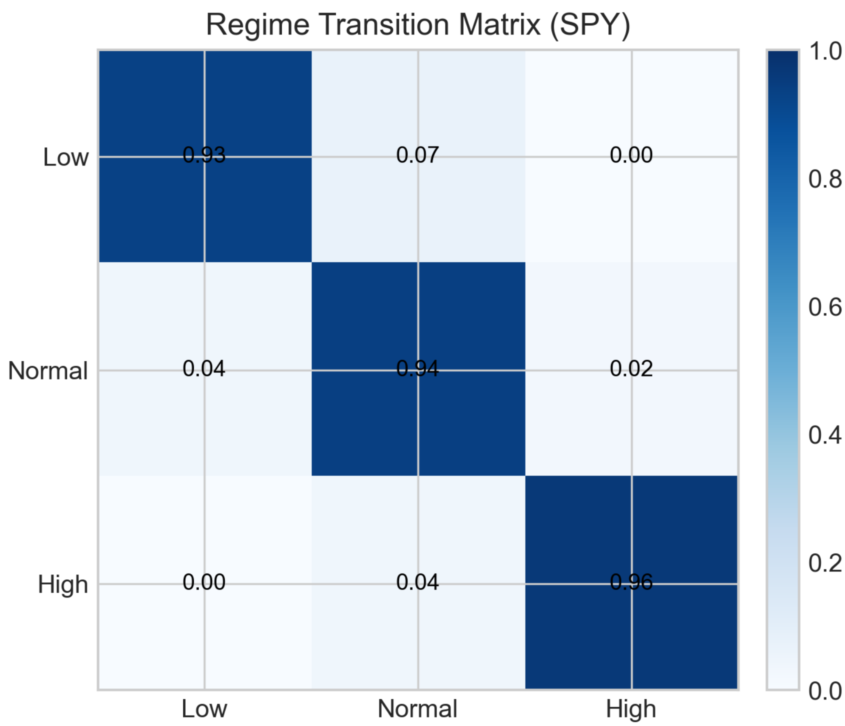

Figure 5: Volatility regime transition matrix.

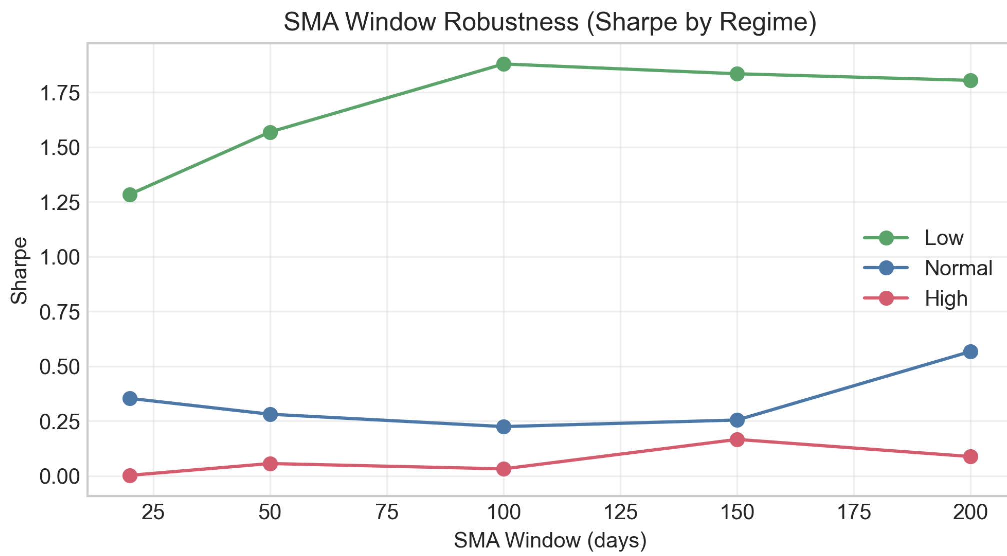

Figure 6: SMA parameter sweep: regime Sharpe sensitivity.

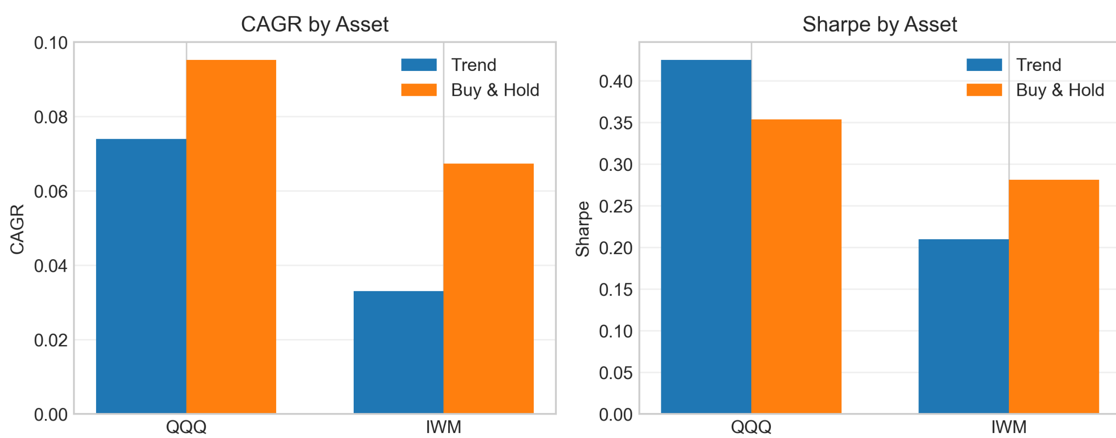

Figure 7: Cross-asset robustness for CAGR and Sharpe (QQQ, IWM).

5 Limitations

The analysis focuses on three liquid ETFs and one simple signal family. Data quality depends on Yahoo Finance history and may omit effects tied to delistings or implementation microstructure. The strategy is long/cash only and does not include leverage, position sizing, or risk targeting. Bootstrap inference is non-parametric but still sample-dependent.

6 Conclusion

In this sample, the 50-day trend-following rule is volatility-state dependent. It reduces drawdown magnitude versus buy-and-hold but does not deliver superior unconditional return. Relative performance is strongest in low-volatility states and weaker in normal and high-volatility states. Out-of-sample walk-forward results are directionally consistent with full-sample findings.

References

[1] Gary Antonacci. *Dual Momentum Investing: An Innovative Strategy for Higher Returns with Lower Risk*. McGraw-Hill, 2014.

[2] Narasimhan Jegadeesh and Sheridan Titman. Returns to buying winners and selling losers: Implications for stock market efficiency. *The Journal of Finance*, 48(1):65–91, 1993.

[3] Tobias J. Moskowitz, Yao Hua Ooi, and Lasse Heje Pedersen. Time series momentum. *Journal of Financial Economics*, 104(2):228–250, 2012.