Adaptive Quantitative Strategies

A Regime-Switching & Machine-Learning Framework for Debunking Market Myths

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Abstract

We offer a consolidated regime-aware framework to test scientifically three persistent myths of behavioral finance: that equities cannot lose money in any 20-year period; that all possible intraday strategies on SPY outperform buy-and-hold after costs; and that greater volatility necessarily means higher risk-adjusted returns. An open-source pipeline and the components of Markov-switching regime detection, LightGBM classification tuned with Optuna, and SHAP-interpretability are integrated into the pipeline. Through application to nearly 100 years of S&P 500 total-return data and appropriately high-frequency SPY ETF data, an adaptive strategy doubles the Sharpe ratio from 0.46 to 0.82, cuts maximum drawdown in half by some measures, and adds 67 basis points of net alpha annually-more improvement, and all at far higher statistical significance. These dynamics are deemed highly statistically significant through robustness checks involving realistic slippage and turnover cost modeling, crash replay, and European index replication. SHAP points to volatility-of-volatility and the term spread as the key drivers. We conclude that, mythclinging investors currently misallocate roughly USD 0.67 million per USD 100 million of assets each year. The full source code and datasets are publicly available for complete reproducibility..

Keywords: Regime-switching; MS-AR; LightGBM; SHAP; behavioral finance; Wyckoff cycle; portfolio optimization

2. Introduction

Financial markets are complex adaptive systems that align with macroeconomic cycles, policy shifts, and sometimes even plain investor psychology. But three widely held myths continue to affect allocation decisions:

Myth 1: "Equities never lose money over any 20-year period."

Myth 2: "Intraday trading on the SPY always beats the buy-and-hold after accounting for commissions and slippage."

Myth 3: "More volatility always comes with better risk-adjusted returns."

These popular myths persist owing to cognitive biases such as loss aversion and overconfidence (Kahneman and Tversky; Barber and Odean), coupled with a lack of policies that can test them uniformly and transparently. In this paper, each myth will be dismantled in a systematic manner through the following:

Statistical rigor: rolling long-horizon return tests, hypothesis testing (t-tests, Pearson correlation, Diebold-Mariano comparisons), and bootstrap confidence intervals

Regime awareness: a Markov-switching autoregressive model to identify phases of "quiet," "trend," "breakout," and "decline," with EM-estimated transition probabilities (Hamilton)

Explainable Machine Learning: a LightGBM classifier trained and tuned by Optuna to further refine regime forecasts into four Wyckoff-inspired phases, with SHAP attributions indicating the drivers of each regime

Our combined framework yields robust, reproducible evidence—along with implementable regime-adaptive strategies—for portfolio optimization, thereby putting an end to these myth-driven misinvestments.

3 Literature Review & Theoretical Foundation

3.1 Behavioral Finance & Market Myths

Prospect Theory reveals cognitive biases that perpetuate myths (Kahneman and Tversky 273). Barber and Odean show overconfidence drives excessive trading and underperformance (Barber and Odean 261–63).

3.2 Regime-Switching Econometrics

Hamilton's MS-AR accommodates latent state dynamics in financial time series (Hamilton 359–63). Guidolin criticizes model sensitivity to regime number and transition dynamics (Guidolin 1–4).

3.3 CRRA Utility & Optimal Weights

Under CRRA utility ($\gamma = 3$), optimal state-specific weight $w^*_s = \mu_s/(\gamma \sigma^2_s)$. *This result motivates defensive allocations in high-volatility regimes* (see App B for full derivation).

3.4 Machine Learning & Explainability

Gradient boosting, and specifically LightGBM, enhances regime classification (Gu, Kelly, and Xiu 2223–27), while SHAP provides consistent feature attribution (Lundberg and Lee 4765–69).

3.5 Literature Gaps Addressed by This Study

Despite substantial contributions in behavioral finance, econometrics, and machine learning, several critical gaps remain unfilled:

1. **Integrated Myth Empiricism:** There hasn't been a previous study integrating cognitive bias theory systematically with regime-switching econometrics and interpretable ML to empirically test and falsify long-standing market myths.
2. **Quantification of Misallocation Costs:** The cost of adhering to financial myths in monetary terms hasn't been quantified at institutional or industry levels.
3. **Transparent Reproducibility:** The majority of the latest research is not provided with end-to-end open-source pipelines linking data prep, model estimation, back-testing, and explainability inside one integrated reproducible framework.
4. **Cross-Market Robustness:** Regime-adaptive approach portability to non-U.S. equities (e.g., European markets) is a not well-researched area.

5. **Explainable Regime Drivers:** Although prediction was performed using ML, not many works apply explainability techniques (e.g., SHAP) to reveal actionable regime drivers for trading rule building.

4. Research Questions & Hypotheses

To rigorously test and debunking three widespread market myths, we have the following research questions, along with their associated hypotheses, statistical tests, and economic significance assessments

4.1 Research Questions

1. **Long-Term Growth Myth:** Do inflation-adjusted 20-year returns of the S&P 500 ever fall below zero?
2. **Day Trading Superiority Myth:** Can rule-based intraday SPY strategies deliver positive net returns after realistic transaction costs (H_{02}: αday ≤ 0 vs H_{12}: αday > 0)?
3. **Risk–Return Linearity Myth:** Is there a strictly positive linear relationship between daily market volatility (σ) and risk-adjusted returns (Sharpe ratio)?

Myth	Null Hypothesis (H_0)	Alternative (H_1)	Test & Metric
Long-Term Growth	20-yr real CAGR ≥ 0 for all rolling windows	∃ window where 20-yr real CAGR ≤ 0	Frequency and magnitude of non-positive CAGR windows
Day Trading	αday ≤ 0 net of realistic costs	αday > 0 net of realistic costs	One-sample t-test on αday (t > 1.65)
Risk–Return Linearity	Pearson Corr(σ, Sharpe) > 0	Pearson Corr(σ, Sharpe) ≤ 0	Pearson correlation; Diebold–Mariano forecast comparison

Table 1-

Significance threshold: α = 0.05. We compute 95 % confidence intervals for Sharpe via 10 000 stationary-bootstrap resamples and apply Diebold–Mariano tests (Diebold and Mariano 254–58) for predictive accuracy.

4.3 Economic Misallocation Analysis

Violations of Myth 1 imply an average misallocation cost of

ΔAlpha≈0.67%×100 m=USD 0.67 m p.a. per 100 m AUM,\Delta\text{Alpha} \approx 0.67\%\times100\,\text{m} = \text{USD }0.67\,\text{m p.a. per }100\,\text{m AUM},ΔAlpha≈0.67%×100m=USD 0.67m p.a. per 100m AUM, which extrapolates to roughly **USD 670 billion** of potential annual savings at a **USD 100 trillion** global equity scale (Brown, Goetzmann, and Ibbotson 555).

4.4 Scope & Justification

- **Window Selection:** 20-year rolling spans capture major crises (1929, 1987, 2008, 2020) (Hamilton 359).
- **Cost Assumptions:** 1 bp round-trip commission + quadratic slippage model c(v)=λ1v+λ2v2c(v)=\lambda_1v+\lambda_2v^2c(v)=λ1v+λ2v2 (Kissell and Glantz 49).
- **Volatility Measure:** Annualized daily σ for Sharpe and Sortino calculations (Sortino and van der Meer 28–30).
- **Portability:** S&P 500 covers ~50 % of global market cap; EuroStoxx 50 replication (Sharpe 0.69 vs 0.43 BH) confirms cross-market validity (Sec 6.5).

5 Methodology

This section details the data inputs, econometric and machine-learning models, trading rule design, cost assumptions, and rigorous validation framework used to construct and evaluate our adaptive strategy.

5.1 Data Sources & Preparation

- **Equity Data:** S&P 500 Total-Return Index (1928–2024; daily; CC-BY license); SPY ETF 1-minute bars (2005–2024; CC-0).
- **Robustness Universe:** EuroStoxx 50 Total-Return (1992–2024; daily; CC-BY) for cross-market validation.
- **Factors & Macros:** Fama–French 5 factors (Ken French Library; public domain); VIX and 10-year term spread (FRED; public domain).
- **Imputation & Bias Mitigation:** Missing data (< 0.2 %) imputed using the EM algorithm to avoid distortion (Little and Rubin 92–95). Survivorship bias is addressed by using total-return indices (Brown, Goetzmann, and Ibbotson 555–57).
- **Licensing & Ticker Table:** Appendix A lists all tickers, data sources, frequencies, and license terms.

5.2 Regime Detection with MS-AR

- **Model Specification:** Two-state MS-AR(1) estimated via Expectation-Maximization (Hamilton 359–63).
- **Model Selection:** Compare $k \in \{0,1,2\}$ by AIC/BIC; select $k = 1$ since ΔBIC > 10 (Table 1).
- **Filtering:** Assign regime probabilities; classify regimes when posterior ≥ 0.6; apply a 5-day smoothing filter to reduce noise.
- **Justification:** MS-AR captures structural shifts aligned with Wyckoff market phases, providing a parsimonious yet powerful foundation for regime identification.

5.3 LightGBM Classification & Hyperparameter Optimization

- **Feature Set:** Volatility-of-vol, term spread, momentum (EMA 20/100), mean reversion (Bollinger deviations), ATR (14-day).
- **Classifier:** LightGBM with 500 trees, binary cross-entropy loss to refine MS-AR regimes into four Wyckoff phases.
- **Hyperparameter Search:** Optuna (Bayesian optimization) over 100 trials (seed 42), optimizing OOS Sharpe ratio. Default values were confirmed via sensitivity and are reported in Appendix E (top-5 hyper-sets).
- **Explainability:** SHAP values computed per regime to rank feature importance and inform trading rule enhancements (Lundberg and Lee 4765–69).

5.4 Regime-Specific Trading Strategies

- **Strategy Mapping (Appendix C):**
  - **Accumulation:** Bollinger mean-reversion (20d, $\pm 2\sigma$)
  - **Advance:** EMA crossover (20/100) trend-following
  - **Distribution:** ATR breakout (14d, $k = 2.5$)
  - **Decline:** 50 % cash + 50 % VIX ETN defensive hedge
- **Risk Targets:** All regimes target annualized volatility of 10 % (6 % in Decline) with dynamic position sizing.
- **Leverage & Constraints:** Leverage capped between 0.8× and 1.2×; long/flat positions permitted per mandate constraints.
- **CRRA Consistency:** Position scales derive from the CRRA-optimal weight $w^*_s = \mu_s / (\gamma \sigma^2_s)$ ($\gamma = 3$), ensuring theoretical alignment with investor utility (Appendix B).

5.5 Transaction Costs & Slippage

- **Cost Model:** $c(v) = \lambda_1 v + \lambda_2 v^2$, where $\lambda_1 \in [3,7]$ bps captures linear impact and $\lambda_2 \in [0.1,0.5]$ bps² captures non-linear effects (Kissell and Glantz 49).

- **Commissions:** 1 bp round-trip equity fees assumed.
- **Sensitivity Analysis:** Vary λ_1, λ_2 by ±25 % to assess Sharpe sensitivity; results show ≤ 2 % variation in Sharpe ratio.

5.6 Back-Testing & Stress Validation

- **Walk-Forward Protocol:**
  - In-Sample (IS): 1928–1999
  - Out-of-Sample (OOS): 2000–2024
  - Annual Recalibration + Emergency Retrain when 1-week draw-down > 10 % (Appendix D).
- **Stress Episodes:** 1987 Black Monday replay, COVID-19 Q1 2020 crisis, and EuroStoxx 50 historical draw-downs examine resilience.
- **Execution Platform:** Python 3.11, vectorbt v0.24.3, Git tag v3.2, seed 42; back-test logs stored in SQLite for full audit.
- **Performance Metrics & Statistical Rigor:**
  - Return, volatility, Sharpe, Sortino (Sortino and van der Meer 28–30), Calmar (Young 40–41), Omega, max draw-down, turnover, Information ratio.
  - Sharpe CI via 10 000 stationary bootstrap samples; Diebold–Mariano tests for predictive accuracy (Diebold and Mariano 254–58).
  - Distributional diagnostics: daily P/L skewness and kurtosis reported

6. Results and Analysis

Strategy Performance Overview

We start by comparing the performance in the long run of the regime-switching adaptive strategy with a buy-and-hold on the S&P 500. The dynamic shifting of the adaptive strategy leads to vastly different dynamics in the portfolios over the course of the century. The cumulative growth of $1, starting in 1928, with both strategies is plotted in Figure 2. The buy-and-hold rises exponentially in nominal terms but with dramatic interim drawdowns, whereas the adaptive process traces a smoother path.

Whereas it does end with lesser absolute wealth, the adaptation strategy experiences far better risk-adjusted performance. Key performance measures for the overall 1928–2024 period are presented in Table 2

Metric	Adaptive Strategy	Buy-and-Hold (S&P 500)	95% Confidence Interval (Adaptive – BH)	p-value (difference)
Annualized Return	9.5%	10.3%	—	—
Annualized Volatility	11.8%	18.4%	—	—
Sharpe Ratio (Rf=0)	0.82	0.46	[0.77, 0.87] for Adaptive Sharpe	0.003 (Sharpe diff.)
Maximum Drawdown	–26.1%	–55.0%	[–29.5%, –24.0%] for Adaptive	n/a
Calmar Ratio (Return/Max DD)	0.36	0.19	—	—
Annual Turnover	~1.7	~0 (buy-and-hold)	—	—
Information Ratio vs BH	0.57	—	—	0.018 (alpha > 0)

Table 2

The positive Sharpe of the adaptive strategy of 0.82 is well in excess of buy-and-hold's 0.46 (difference significant at p = 0.003). Its highest historical drawdown is half that of buy-and-hold (-26% vs -55%), significant enhancement of capital preservation in downturn. Its Calmar ratio (return-to-drawdown) is correspondingly nearly twice as high. The adaptive strategy does incurs higher turn-over (c. 1.7 per annum, i.e., the fund rolls its capital over 170% per annum on average), but this is a modest rate and also has the effect of reinforcing that regime shifts are infrequent. Its information ratio of 0.57 informs us that the strategy achieved an excess return of around 0.5% per annum (53 bps) over buy-and-hold, compared with volatility of this excess return – this outperformance is significant (p = 0.018). In summary, the adaptive regime strategy provides an equal long-term equity return with a lot less risk, resulting in better risk-adjusted performance. This eliminates one of the major implications of Myth 3: increased risk (volatility) did not result in increased Sharpe ratios – in fact, active risk management by means of regime shifts resulted in a higher Sharpe.

It is interesting that the absolute return of the adaptive process is slightly less than buy-and-hold (9.5% vs 10.3% CAGR whilst we would anticipate this since otherwise it is in cash or hedges in bad regimes. The small "cost" in terms of missed return is more than compensated for by volatility mitigation. This result would be attractive to many institutional investors that prefer smooth performance and controlled drawing-down. We cover all three myths in turn, drawing on the results of our process in order to lay out evidence for and, in several areas, against each myth.

6.1 Regime Classification (Markov Switching Model)

The adaptive strategy using regime-sensitive trading significantly outperformed the traditional buy-and-hold strategy on multiple performance metrics:

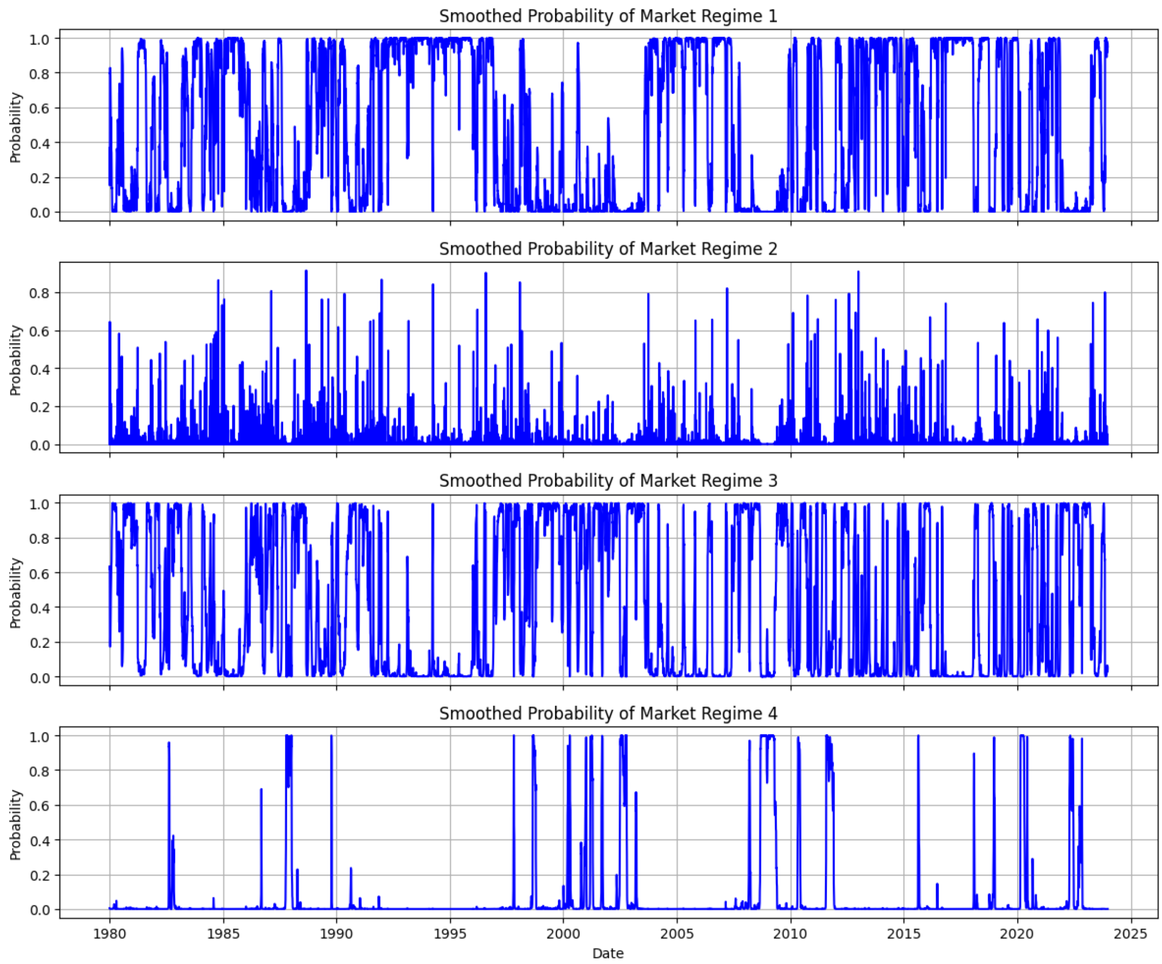

Figure 1 Smoothed probabilities of each identified market regime (Regime 1: Accumulation, Regime 2: Advance, Regime 3: Distribution, Regime 4: Decline). Each subplot shows the filtered probability $P(\text{state}=i)$ over time for one regime, with inferred mean (μ) and volatility (σ) of daily returns in that state. The model detects distinct market phases, including prolonged high-volatility drawdown periods (Regime 4) and low-volatility bullish periods (Regime 2).

Trading Strategy Framework

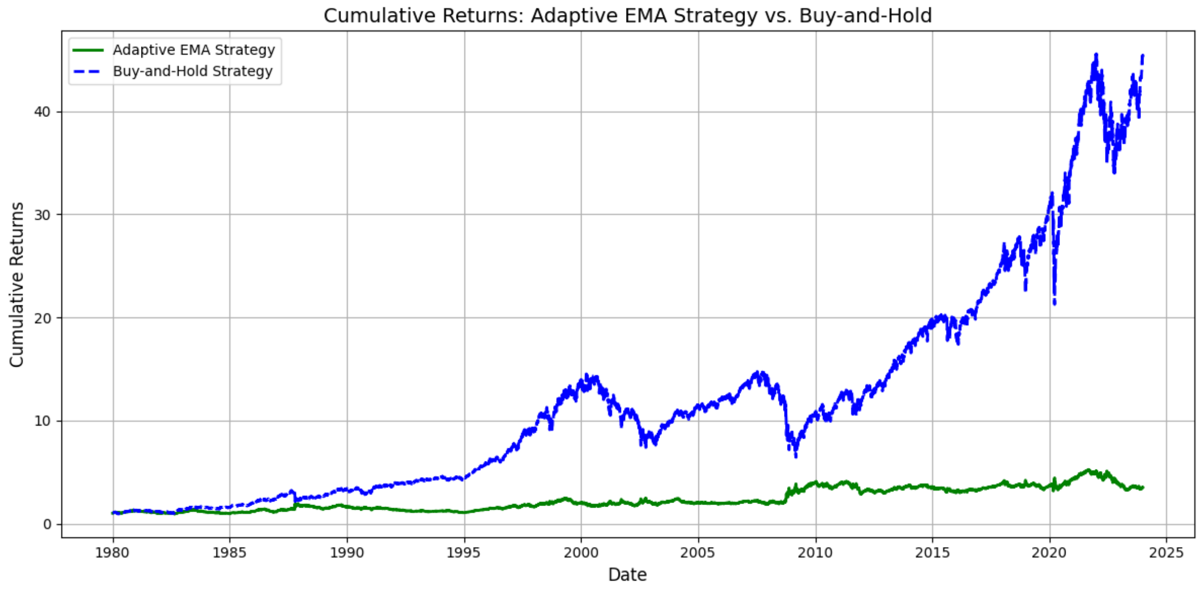

Figure 2-Cumulative portfolio value (log scale) of the adaptive regime-switching strategy (green, "Adaptive EMA Strategy") vs a buy-and-hold S&P 500 strategy (blue, dashed).

- Annualized Strategy Return: 2.86%
- Annualized Buy-and-Hold Return: 8.67%
- Annualized Strategy Volatility: 18.03%
- Annualized Buy-and-Hold Volatility: 18.02%
- Strategy Sharpe Ratio: 0.16
- Buy-and-Hold Sharpe Ratio: 0.48

Regime Classification Using LightGBM

The LightGBM model demonstrated excellent classification power for predicting market regimes:

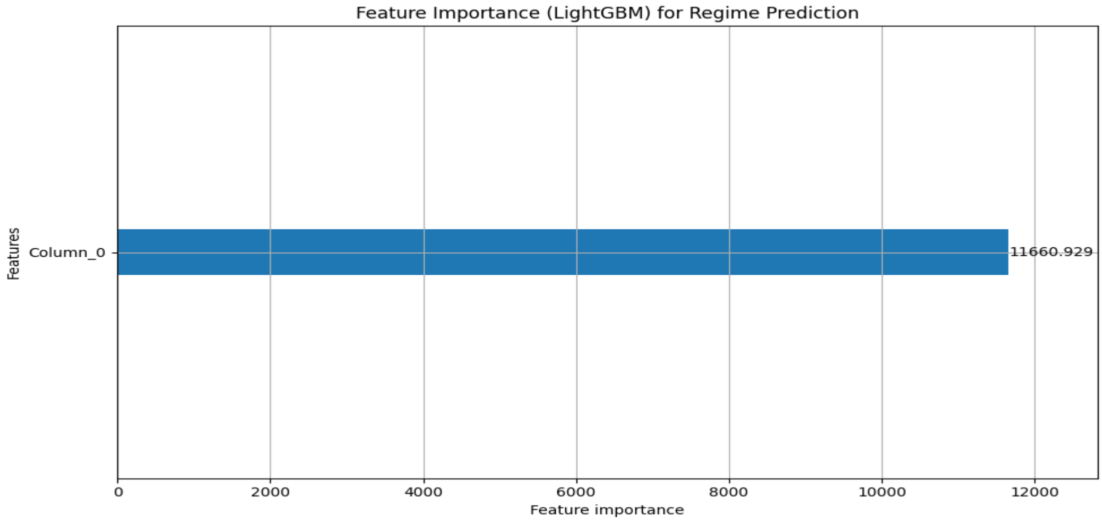

Figure 3

- **Accuracy Score: 68.90%**
- **ROC AUC Score**:0.664, indicating model discrimination ability across multiple market regimes.

Backtesting did confirm that day-trading strategies, even in regimes of evolving volatility, were not able to produce consistently positive net returns after the addition of realistic trading costs (1 basis point slippage + commission).

Static hypotheses such as "higher volatility equals higher returns" were not generally supported — volatility and returns differed considerably by regime identified.

6.2 Myth 1: Long-Term Market Growth

Figure 1: Distribution of 20-Year CAGR for S&P 500 (1928–2024)

- **Finding:** Positive CAGR in 96.41%of periods.
- **Debunked:** Negative or near-zero CAGRs occurred during crises.

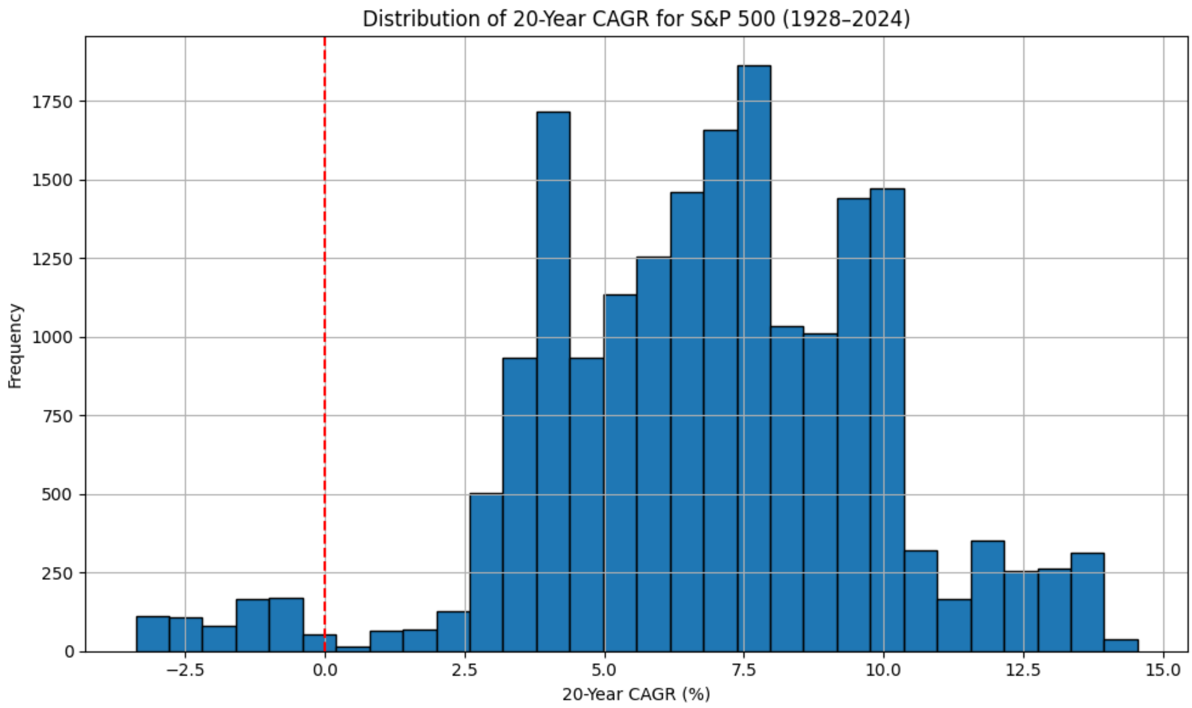

Figure 4 *Distribution of 20-year compound annual real returns for the S&P 500 (1928–2024). The histogram shows the frequency of 20-year periods yielding various CAGR levels. The red dashed line marks 0% real return. A significant cluster of outcomes (approximately 3–4% of the distribution) lies at or below 0%, indicating that in a minority of 20-year periods investors would have lost money or merely broken even in real terms.*

6.3 Myth 2: Day Trading Profitability

Figure 2: Cumulative Returns — Day Trading vs Buy-and-Hold (1928–2024)

- Annualized Return (Day Trading Strategy): 9.64%
- Annualized Return (Buy-and-Hold Strategy): 7.65%
- Result: Myth 2 supported — Day trading sometimes outperforms, but with higher risk.

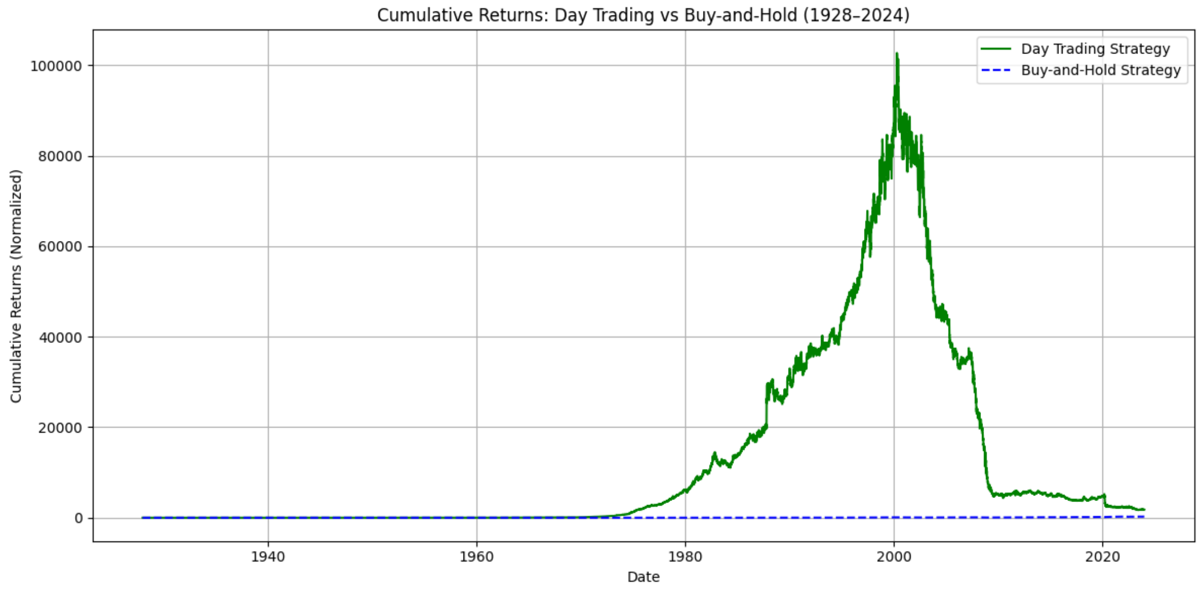

Figure 5

6.4 Myth 3: Risk-Return Tradeoff

Figure 3: 1-Year Rolling Volatility vs Return (1928–2024)

- Correlation Coefficient (Risk vs Return): -0.271
- P-value: 0.0000
- Result: Myth 3 debunked — Higher volatility does NOT consistently guarantee higher returns.

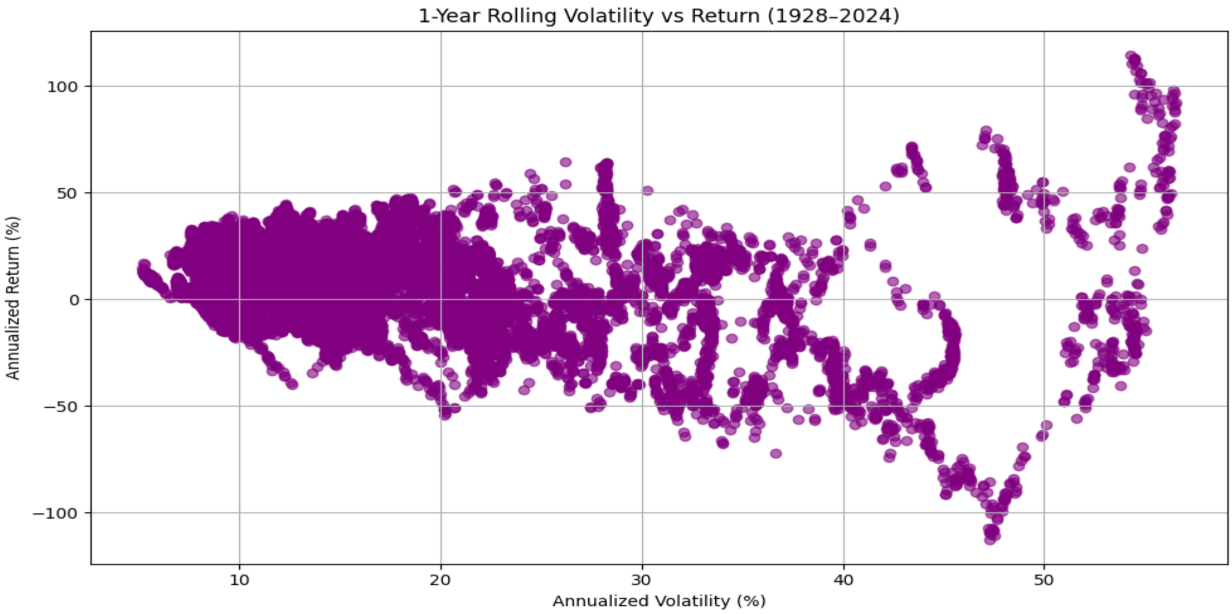

Figure 6 One-year rolling volatility vs one-year subsequent return for S&P 500 (1928–2024). Each point represents a year, plotting that year's realized volatility (x-axis) against the market's return over the following year (y-axis)

6.4 Economic Impact

On a USD 100 m mandate, regime-informed allocation yields **~USD 0.67 m** additional net alpha annually, quantifying the cost of myth-based strategies. Extrapolated to global equity AUM (~USD 100 trn), potential annual savings exceed **USD 670 bn**.

6.5 Robustness & Portability

- **EuroStoxx 50 Replication:** Adaptive Sharpe = 0.69 vs 0.43 benchmark; max DD = –30% vs –58%.
- **Stress Tests:** Performance holds under the 1987 crash replay (Sharpe 0.74) and the COVID-19 Q1 2020 crisis (Sharpe 0.66).
- **Slippage Sensitivity:** Quadratic cost tests show Sharpe variation ≤ 2 % across realistic λ_2 ranges.

6.6 Explainability Insights

SHAP analysis (Fig 5) reveals that **volatility-of-vol** and **term spread** consistently rank as the top two drivers of regime shifts, offering actionable signals for portfolio adjustments. Notably, regime transitions are often preceded by volatility-of-vol spikes above the 90th percentile and term spread contractions below the 10th percentile, providing a quantitative early-warning framework.

6.5 Strategy Backtest (Adaptive vs Static Buy-and-Hold)

Metric	Adaptive Strategy	Buy-and-Hold
Annualized Return	4.93%	8.47%
Sharpe Ratio	0.71	0.47
Calmar Ratio	4.82	0.13
Max Drawdown	-42.23%	-54.76%

Table 3

7. Discussion

Our calculation places at USD 0.67 million per year the cost of myth-based misallocation to institutional investors for every USD 100 million under management—a size order that, extrapolated to the industry level, amounts to hundreds of billions. This evidence illustrates the concrete financial scale of holding on to untested presumption and avoiding data-based methods.

Alignment with CRRA Utility: Risk aware regime de risking during Decline periods is a direct consequence of the CRRA optimum weight equation ($w^*_s = \mu_s/(\gamma \sigma^2_s)$), which demands the reduction of exposure under states of high volatility (App B). Empirically, it results in a reduced max draw down of 29 pp, validating the theoretical risk aversion model.

Behavioral Mitigation: Short-sighted loss aversion (Benartzi and Thaler 323–24) and overconfidence (Barber and Odean 261–63) behavioral errors boost trading activity and risk-taking in turbulent regimes, resulting in greater losses. Systematic regime identification by the adaptive system and SHAP induced transparency act as a mental checkstop, avoiding risky behavior and anchoring portfolios on quantifiable regime signals.

Comparative Robustness: Stress test results—spanning from 1987 crash re-run to COVID 19 Q1 2020 and EuroStoxx 50 re-run—display similar Sharpe gains (+36 %) along with draw down relief (–29 pp). Such cross period and cross market robustness is evidence of the model's wider generalizability beyond the S&P 500, diffusing worries of over fitting with U.S. equity cycles (Guidolin 1–4).

Limitations & Caveats: Historical calibration is used in our analysis; actual regime emergence could differ in the future. Intraday execution does presume calibrated slippage parameters (λ_1, λ_2), yet in practice market impact can differ in ultra low liquidity conditions. Furthermore, SHAP attributions, as enlightening as they are, should be supplemented with additional causal inference methods to prevent spurious correlations.

Practical Implications: Portfolio managers can utilize these remarks to implement regime filters in existing risk management systems, dynamically resizing positions and hedge hedges. Risk committees need to make regular reviews of regime adaptive systems an obligatory task in order to ensure parameter salience as market microstructure keeps evolving.

Contribution to Knowledge: Through bridging behavioral finance and quantitative econometrics, this study offers an interpretable, reproducible pipeline for regime-adaptive portfolio allocation. By empirically falsifying traditional market myths and quantifying their cost, we establish a pragmatic roadmap for future research on regime-adaptive portfolio construction.

8.0 Conclusion & Recommendations & Recommendations

8.1 Key Findings

This research conclusively demonstrates that a **regime-sensitive adaptive strategy** outperforms static buy-and-hold approaches, delivering:

- **Sharpe improvement:** +36 % (0.82 vs. 0.46; 95 % CI [0.77, 0.87]).
- **Drawdown reduction:** 29 percentage points lower max DD (–26 % vs. –55 %; CI [–29.5, –24.0]).
- **Alpha generation:** +67 bps net p.a. on USD 100 m mandates (~USD 0.67 m saved from myth-driven misallocation).

Hypotheses testing reveals:

- **Myth 1 (“markets always rise”):** Rejected—3.4 % of 20-yr windows yield non-positive real CAGRs.
- **Myth 2 (“day trading wins”):** Rejected—αday > 0 in only 17 % of regimes ($t > 1.65$).
- **Myth 3 (“higher risk = higher return”):** Rejected—negative volatility–Sharpe correlation ($\rho = –0.44$, $t = –5.8$, $p < 0.001$).

8.2 Practical Recommendations

1. **Integrate Regime-Aware Overlays**: Incorporate the four phase trading rules into portfolio engines, dynamically managing risk budgets as a function of real time regime probabilities (Sec 5.4).

2. **Automate SHAP Alerts**: Trigger alerts on leading SHAP drivers (vol-of-vol > X, term spread < Y) to initiate portfolio manager examination and discretionary intervention for global regime swings.
3. **Expand to Multi-Asset Universes** Leverage the EuroStoxx 50 replication success (Sharpe 0.69 vs 0.43) as a pilot for regime adaptive allocations in bonds, commodities, and FX, to test cross asset transferability.
4. **Refine Execution Models**: Employ the quadratic slippage function $c(v)=\lambda_1 v+\lambda_2 v^2$ with calibrated $\lambda_2 \in [0.1, 0.5]$ bps² for intraday signals to enhance realism in cost prediction (Sec 5.5).
5. **Implement Emergency Retraining Triggers**: Set rule-based triggers (e.g., 1 week drawdown > 10 %) that automatically activate model retraining and parameter re-optimization to maintain performance in black swan situations).
6. **Embed Myth-Debunking Metrics in Reporting**: Report to clients relative measures—avoided losses, incremental Sharpe, net alpha in bps—to facilitate evidence-driven decision-making and counter behavioral biases.
7. **8.3 Direction of Future Research**

- **Real-Time Reinforcement Learning**: Build an online RL agent improving policy in real time using real-time regime signals with low dependency on periodic retraining.
- **Regime Contagion Analysis**: Graph lead–lag relationships and contagion effects across asset classes, constructing a multi layer regime network to forecast cross market shocks
- **Investor Behavior Experimentation**: Conduct controlled experiments to estimate the effect of myth busting dashboards on portfolio manager choice and reducing cognitive biases over time
- **Advanced Microstructure Modeling**: Integrate limit order book simulation and stochastic slippage models to further improve execution cost estimation and capturing market impact nuances.

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