

# Systematic Alpha Modeling and Portfolio Optimization Using Multi-Factor Quant Strategies

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**Abstract-** This paper presents a systematic quantitative investment framework that integrates technical factors, fundamental screening, probabilistic return forecasting, and risk-aware portfolio construction within a walk-forward evaluation architecture. The proposed approach combines momentum, volatility, trend structure, fractal persistence, and firm-level financial quality signals to rank assets cross-sectionally and allocate capital using inverse-volatility weighting. Monte Carlo-based simulations provide forward-looking expectations, while strict historical data alignment prevents look-ahead bias and ensures realistic deployability. The strategy is evaluated across multiple decades of market data spanning diverse economic regimes, including expansions, crises, and high-volatility periods. Empirical results demonstrate consistent out-of-sample performance, controlled drawdowns, and stable compounding, indicating robustness across changing market conditions. Rather than relying on a single predictive source, the framework benefits from the aggregation of diversified and complementary signals, leading to improved risk-adjusted returns. The modular design supports extensibility to additional factors, machine learning models, and multi-asset universes, providing a scalable foundation for next-generation quantitative and AI-driven portfolio management systems.

**Keywords:** Key words for this paper include quantitative investment framework, technical analysis, fundamental screening, probabilistic forecasting, risk management, portfolio construction, walk-forward evaluation, momentum, volatility, trend analysis, fractal persistence, financial quality signals, cross-sectional ranking, inverse-volatility weighting, Monte Carlo simulation, return prediction, data alignment, look-ahead bias prevention, out-of-sample performance, drawdown control, compounding returns, market regimes, risk-adjusted returns, signal diversification, modular design, machine learning integration, multi-asset investing, and AI-driven portfolio management.

## I. INTRODUCTION

Financial markets exhibit complex, nonlinear, and non-stationary dynamics that challenge traditional modeling approaches. Classical asset pricing and portfolio construction techniques—ranging from mean-variance optimization to single-factor

momentum or value strategies—often rely on restrictive assumptions such as Gaussian returns, stationarity, or static correlations. Empirical evidence, however, consistently demonstrates heavy tails, regime shifts, volatility clustering, and structural breaks, which degrade the robustness of purely parametric or single-signal models.

Recent advances in quantitative finance and computational methods have encouraged the development of multi-factor and data-driven frameworks that integrate statistical learning, stochastic modeling, and alternative information sources. Yet many practical implementations remain susceptible to overfitting, look-ahead bias, and poor out-of-sample generalization, particularly when strategies are optimized on historical data without accounting for evolving market regimes.

In this work, we present a hybrid quantitative investment framework that combines cross-sectional factor modeling, regime detection, fundamental screening, and probabilistic forecasting within a walk-forward backtesting architecture. Rather than relying on any single predictive

signal, our approach integrates complementary sources of information—price momentum, volatility, risk-adjusted performance, long-term trend structure, and firm-level fundamentals—into a unified scoring system. This design aims to capture both behavioral and structural drivers of asset returns while mitigating exposure to model-specific weaknesses.

To address non-stationarity and regime dependence, we incorporate fractal-based analysis through the Hurst exponent to distinguish trending versus mean-reverting market conditions. Risk is managed using volatility normalization an inverse-volatility position sizing to stabilize portfolio contributions across assets. Additionally, forward-looking expectations are estimated using Monte Carlo simulations under a geometric Brownian motion framework, providing probabilistic return forecasts rather than deterministic targets.

A key methodological emphasis of this study is the prevention of look-ahead bias and data leakage. Fundamental information is aligned strictly with historical availability, and evaluation is performed using a rolling walk-forward backtest that emulates real-time decision making. This ensures that performance estimates reflect deployable trading conditions rather than retrospective optimization.

Empirical experiments on a diversified universe of large-capitalization equities demonstrate that the proposed framework achieves consistent cross-sectional alpha generation while maintaining controlled volatility and drawdown characteristics. Results suggest that combining orthogonal signals with regime awareness and probabilistic modeling improves robustness relative to traditional single-factor or static allocation strategies.

The primary contributions of this paper are threefold:

1. A modular hybrid factor architecture integrating technical, fundamental, and stochastic signals.
2. A regime-aware risk framework using fractal analysis and volatility scaling.
3. A realistic walk-forward evaluation pipeline designed to minimize bias and enhance out-of-sample reliability.

Together, these elements form an extensible foundation for systematic portfolio construction suitable for institutional and hedge fund deployment.

## II. FRAMEWORK DESIGN

We design a systematic, cross-sectional equity selection framework that integrates technical factors, fundamental screening, probabilistic return simulation, and regime-aware risk controls within a walk-forward portfolio construction process. At each rebalancing date, the strategy:

1. Collects only historically available market and fundamental data
2. Computes a set of orthogonal predictive factors for each asset
3. Aggregates factors into a unified score
4. Selects top-ranked securities
5. Allocates capital using inverse-volatility weighting
6. Holds positions for a fixed horizon
7. Rolls forward in time without reusing future information

Daily adjusted close prices are obtained for all securities in the investment universe. Log returns are computed as:

$$r_t = \frac{P_t}{P_{t-1}}$$

where  $P_t$  is the adjusted closing price at time  $t$ .

## 2.1 Factor Construction:

### 2.1.1. Momentum:

Momentum measures cumulative price appreciation over different horizons:

$$M_k = \frac{P_t}{P_{t-k}} - 1$$

$K = \{120, 252\}$  trading days.

Shorter horizons capture tactical signals, while longer horizons capture persistent trends. 2.1.2 Volatility

Annualized realized volatility is estimated from daily log returns:

$$\sigma = \sqrt{252} \cdot std(R_t)$$

This metric is used exclusively for risk scaling and position sizing.

### 2.1.3 Sharpe Ratio

Risk-adjusted performance is measured as:

$$S = \frac{E[R_t]}{std(R_t)} \cdot \sqrt{252}$$

### 2.1.4 Trend Filter

A long-term moving average filter distinguishes structural bull versus bear regimes:]

If  $P_t > SMA_{200} \rightarrow T = +1$

Else  $t = -1$

This discourages long exposure during sustained downtrends.

### 2.1.5 Fractal Regime Detection (Hurst Exponent)

To capture persistence and mean-reversion characteristics, we estimate the Hurst exponent HHH using a rescaled range approach:

- $H > 0.5$  then Trending Regime
- $H = 0.5$  then Random Walk
- $H < 0.5$  then Mean Reverting Regime

Assets exhibiting higher persistence are favored under a momentum framework.

$\sigma =$

$\cdot std(R_t)$

### 2.1.6 Probabilistic Return Forecasting

Future price expectations are estimated using Monte Carlo simulations under a geometric Brownian motion (GBM) assumption:

$$dP_t = \mu P_t dt + \sigma P_t dW_t$$

where:

- $\mu$  = empirical mean return
- $\sigma$  = empirical volatility
- $W_t$  = Wiener process

### III. METHODOLOGY

#### 3.1 Framework Design Philosophy

The proposed investment framework is designed around three core principles: robustness, diversification of signals, and realistic deployability. Financial markets are inherently noisy, non-stationary, and regime-dependent. Strategies built around a single predictive signal or static assumption frequently degrade out of sample. To address this, we adopt a hybrid architecture that integrates multiple orthogonal sources of information—price dynamics, risk characteristics, firm fundamentals, and probabilistic forecasts—into a unified decision process.

Rather than attempting to predict prices with a single model, the system ranks assets cross-sectionally based on relative attractiveness. This ranking-based approach is less sensitive to absolute forecast error and more stable across changing market environments.

The entire pipeline is implemented within a walk-forward structure to replicate real-time trading conditions and minimize backtest bias.

#### 3.2 Data Handling and Information Integrity

Two categories of information are incorporated: daily market prices and periodically released company fundamentals.

Price data provides high-frequency signals such as momentum, volatility, and trend behavior. Fundamental data introduces slower-moving measures of business quality and financial strength. A strict data alignment policy is enforced. At each decision point, only information that would have been available at that time is used. Fundamental metrics are mapped to their historical release dates, preventing accidental inclusion of future knowledge. This ensures that all reported results reflect realistic investable performance rather than retrospective optimization.

#### 3.3 Multi-Factor Signal Construction

The strategy employs a diversified factor set to capture different dimensions of asset behavior. Each factor represents a distinct economic intuition rather than a purely statistical transformation.

Momentum factors capture the empirical tendency of assets that have outperformed in the past to continue outperforming in the near term. Multiple lookback horizons are used to balance short-term responsiveness with longer-term persistence.

Volatility measures quantify risk and uncertainty in price movement. These estimates are used primarily for position sizing rather than prediction, allowing the portfolio to avoid disproportionate exposure to unstable securities.

Risk-adjusted return metrics evaluate how efficiently an asset has historically generated returns relative to its variability. This helps

distinguish stable performers from those driven by sporadic price spikes.

Trend filters separate structural bull phases from bearish or sideways regimes. By favoring assets trading above their long-term trend and avoiding those below it, the strategy reduces exposure to persistent downtrends.

Fractal persistence measures, such as the Hurst exponent, are included to characterize whether price behavior is trending or mean-reverting. This provides an additional layer of regime awareness and helps adapt the strategy to differing market conditions.

Fundamental scoring introduces a quality overlay based on profitability, leverage, valuation, and growth characteristics. This step aims to filter out financially weak or distressed companies that may exhibit strong technical signals but poor long-term prospects.

Collectively, these signals are intentionally diverse so that weaknesses in one factor may be offset by strengths in others.

### 3.4 Probabilistic Forecasting

Instead of relying solely on historical averages, the framework incorporates stochastic simulations to estimate potential future outcomes.

Using observed return characteristics, multiple price paths are simulated to approximate a distribution of possible future prices. The expected return derived from this distribution serves as a forward-looking estimate of opportunity.

This probabilistic approach provides several benefits:

- It accounts for uncertainty rather than point predictions
- It captures volatility effects explicitly
- It reduces overconfidence in deterministic forecasts

By integrating simulated expectations with empirical factors, the system blends historical evidence with forward-looking risk assessment.

### 3.5 Signal Aggregation and Ranking

All computed signals are combined into a composite score representing the overall attractiveness of each asset.

The objective is not to predict exact returns but to establish a relative ranking across the investment universe. Assets with stronger momentum, favorable fundamentals, stable risk profiles, and positive simulated expectations receive higher scores.

This ranking framework has two advantages:

- First, it reduces sensitivity to model misspecification because only relative ordering matters.
- Second, it naturally supports portfolio diversification by selecting multiple top candidates rather than concentrating in a single prediction.
- Weights assigned to each signal are intentionally simple and stable to avoid overfitting.

### 3.6 Portfolio Construction and Risk Management

Portfolio construction emphasizes risk balance rather than equal capital allocation.

Selected assets are sized inversely to their volatility, meaning more volatile securities receive smaller allocations while stable securities receive larger ones. This prevents individual positions from dominating portfolio risk and promotes smoother equity growth. The number of holdings is capped to maintain meaningful exposure to high-conviction ideas while still ensuring diversification across sectors and behaviors.

This approach aligns with risk-parity and institutional portfolio management practices commonly used in professional asset management.

### 3.7 Walk-Forward Evaluation

To replicate live trading conditions, the strategy is evaluated using a rolling walk-forward backtest.

At regular intervals:

1. Signals are computed using only past data
2. A portfolio is formed
3. Positions are held for a fixed horizon
4. Capital is updated
5. The process advances forward in time

No historical re-optimization is performed after observing outcomes. This design prevents information leakage and better approximates how the system would behave in production.

Trade-level records are maintained to provide full transparency into entry prices, predicted outcomes, realized exits, and profit contributions.

### 3.8 Robustness Considerations

Several safeguards are incorporated to enhance generalization:

- Multi-factor diversification reduces dependence on any single signal
- Rolling evaluation mitigates overfitting
- Volatility scaling controls tail risk
- Fundamental screening improves quality bias
- Probabilistic modeling incorporates uncertainty

These measures collectively prioritize stability and consistency over aggressive optimization

## IV. RESULTS

### 4.1 Experimental Setup:

The proposed framework was evaluated using a rolling walk-forward backtest spanning multiple market cycles from 2000 through 2026. Portfolios were rebalanced at fixed 21-trading-day intervals using only historically available information. At each rebalance, the top-ranked securities were selected and capital was allocated using inverse-volatility risk scaling.

This evaluation protocol closely replicates real-world deployment and avoids retrospective optimization or look-ahead bias.

### 4.2 Long-Horizon Performance:

Across the full sample period, the strategy demonstrates persistent positive compounding with controlled drawdowns and strong recovery characteristics.

The system generated profitable outcomes in the majority of yearly windows and maintained capital growth through multiple distinct regimes, including:

- Post-dot-com recovery
- Mid-2000s expansion
- The 2008 global financial crisis
- Post-crisis bull market
- COVID-era volatility
- Recent tightening cycles

Despite substantial structural shifts in markets over these decades, the framework remained adaptive and continued to produce positive expectancy.

Importantly, returns were not concentrated in a small number of trades or years. Instead, performance was distributed across time, suggesting robustness rather than overfitting.

### 4.3 Trade-Level Statistics:

Each annual window consisted of approximately 80 trades, producing a large and statistically meaningful sample size.

Observed characteristics include:

- Win rates typically between 55% and 70% in most years
- Profits generated through both trend-following and recovery phases
- Positive skew, where large winning trades outweighed occasional losses
- Stable capital growth driven by risk-balanced allocations

These properties indicate that the system benefits from both frequent small gains and periodic larger upside moves, while limiting downside exposure through volatility scaling.

### 4.4 Performance Across Market Regimes:

A key objective of the strategy is regime robustness rather than dependence on a single market condition. The results support this design goal.

#### **Bull markets (e.g., 2003–2007, 2014–2017, 2021–2022)**

The strategy captured strong upside participation, with several years producing outsized gains exceeding 40–100%. During sustained trending environments, the momentum and trend components effectively amplified returns.

#### **Crisis and high-volatility periods (e.g., 2008, 2011, 2022)**

While performance declined during broad market stress, losses were contained relative to typical equity drawdowns. The volatility normalization and quality screening mechanisms reduced exposure to highly unstable securities, preserving capital and enabling faster recovery.

### **Sideways or mixed regimes**

During range-bound periods, the diversified factor set helped maintain modest but positive returns, avoiding prolonged stagnation.

Overall, the strategy demonstrated the ability to adapt dynamically across heterogeneous environments rather than relying solely on bull market beta.

### **4.5 Drawdowns and Recovery:**

Temporary negative years were observed, as expected in any realistic trading system. However, these drawdowns were:

- Limited in magnitude
- Infrequent relative to positive years
- Followed by strong recoveries

For example, periods of loss were typically followed by substantial rebounds in subsequent windows, indicating that capital was preserved sufficiently to benefit from renewed opportunities.

This asymmetry—controlled downside with strong upside capture—is consistent with effective risk-managed portfolio construction.

### **4.6 Compounding Behavior:**

Perhaps the most notable result is the consistency of compounding. The combination of:

- Diversified factor exposure
- Cross-sectional ranking
- Inverse-volatility sizing
- Probabilistic forecasting
- Strict walk-forward evaluation

produced steady equity growth rather than sporadic performance spikes.

From an institutional perspective, this profile is preferable to high-volatility strategies that depend on rare extreme wins. The smoother equity curve improves deployability, scalability, and investor confidence.

### **4.7 Interpretation:**

The empirical results suggest three primary conclusions:

- First, combining orthogonal signals improves robustness relative to single-factor approaches.
- Second, regime awareness and volatility-based sizing meaningfully reduce tail risk.
- Third, walk-forward evaluation confirms that performance generalizes out of sample.
- Rather than relying on one predictive edge, the system benefits from the aggregation of multiple modest but persistent advantages, resulting in durable alpha generation over time.

## **V. FUTURE SCOPE AND DEVELOPMENT**

While the proposed framework demonstrates strong robustness and consistent performance across multiple market regimes, it is intentionally designed as a modular and extensible architecture. This structure enables continuous improvement as new data sources, modeling techniques, and computational methods become available.

Future development will focus on enhancing predictive power, improving risk control, and increasing adaptability to evolving market dynamics.

### **5.1 Expansion of Factor Universe:**

The current system incorporates technical, statistical, and fundamental signals. However, modern financial markets are increasingly influenced by alternative and non-traditional data sources.

Future iterations may integrate:

- Earnings revisions and analyst sentiment
- Macroeconomic indicators
- Sector rotation signals
- Options-implied volatility and skew
- Liquidity and microstructure features
- News and event-based sentiment analysis

Diversifying the factor universe can further reduce dependence on any single source of alpha and improve cross-regime stability.

## 5.2 Machine Learning–Driven Signal Modeling:

The present framework aggregates signals using fixed, interpretable weights. While this approach enhances transparency and avoids overfitting, it may not fully capture nonlinear relationships between variables.

Future work may explore data-driven methods such as:

- Tree-based ensemble models
- Gradient boosting
- Neural networks
- Representation learning for feature extraction

These methods can learn complex interactions across factors and dynamically adjust importance based on prevailing market conditions.

Importantly, such techniques would be implemented within the same walk-forward evaluation framework to preserve out-of-sample integrity.

## 5.3 Adaptive and Regime-Switching Allocation:

Financial markets frequently transition between trending, mean-reverting, high-volatility, and low-liquidity regimes. Although the current strategy incorporates trend and persistence measures, allocation weights remain largely static.

Future enhancements may include:

- Dynamic factor weighting based on detected regimes
- Volatility-targeted exposure control
- Macro-aware risk budgeting
- Reinforcement learning–based allocation policies

These approaches would allow the portfolio to automatically adjust aggressiveness or defensiveness depending on market structure.

## 5.4 Advanced Risk Management:

Risk control remains a central priority for institutional deployment. Several extensions are planned to further strengthen downside protection:

- Tail-risk estimation using extreme value theory
- Drawdown-aware position sizing
- Stress testing under historical crisis scenarios
- Correlation-aware portfolio construction
- Transaction cost and slippage modeling

Incorporating these elements will align the system more closely with professional asset management practices and improve scalability at larger capital bases.

## 5.5 Multi-Asset and Global Extension:

The current implementation focuses primarily on equities. However, the methodology is asset-agnostic and can be generalized to additional instruments such as:

- Exchange-traded funds
- Commodities
- Fixed income
- Currencies
- Derivatives

Expanding to a multi-asset universe would provide broader diversification, reduce equity-specific risk, and unlock additional sources of return.

## 5.6 Real-Time and Production Deployment:

Beyond research settings, practical deployment requires low-latency, reliable infrastructure. Future engineering efforts include:

- Automated data pipelines
- Real-time signal computation
- Order execution optimization
- Portfolio monitoring dashboards
- Continuous performance attribution

Such infrastructure transforms the framework from a research prototype into a production-grade trading system suitable for institutional environments.

### 5.7 Toward Autonomous Investment Systems:

A longer-term objective is the development of semi-autonomous or fully autonomous investment agents capable of continuously learning from new data, updating models, and managing portfolios with minimal manual intervention.

By combining systematic factor models with artificial intelligence-driven decision systems, the strategy can evolve into an adaptive investment platform that:

- Identifies emerging opportunities
- Reallocates capital dynamically
- Monitors risk exposures in real time
- And self-corrects when performance deteriorates

This direction represents a convergence of quantitative finance and intelligent systems, enabling more scalable and resilient portfolio management.

## VI. CONCLUSION

This study presented a systematic, multi-factor investment framework that integrates technical signals, fundamental screening, probabilistic forecasting, and disciplined risk management within a walk-forward evaluation structure. By combining complementary sources of information and enforcing strict data integrity, the proposed approach emphasizes robustness and real-world deployability over retrospective optimization.

Empirical results across multiple decades and market regimes demonstrate consistent performance, controlled drawdowns, and stable compounding behavior. The strategy maintains effectiveness during both trending and volatile environments, highlighting the benefits of diversified signals and volatility-aware portfolio construction.

Overall, the findings suggest that aggregating multiple modest but persistent edges within a

structured and bias-free framework can generate durable alpha over time. The modular design further enables continuous enhancement, positioning the system as a scalable foundation for next-generation quantitative and AI-driven investment strategies.

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