The Multi-Factor Quantitative Portfolio Allocation Model (QPAM):
A Systematic Approach to Dynamic Asset Allocation

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Abstract

This paper introduces the Quantitative Portfolio Allocation Model (QPAM), a multi-factor systematic investment framework that dynamically allocates capital across diverse assets. The model synthesizes momentum, mean reversion, and volatility factors to assign breakout or mean-reversion strategies, constructing risk-balanced portfolios through mathematical normalization. Backtested from 2020–2024, QPAM demonstrates robustness through various market regimes, achieving a Sharpe ratio of 0.668 with 34.43% total return while maintaining disciplined risk management.

1 Introduction

The challenge of optimal portfolio allocation remains central to quantitative finance. Traditional approaches like Modern Portfolio Theory (Markowitz, 1952) suffer from estimation error sensitivity, while purely technical strategies often lack robustness. QPAM addresses these limitations through a multi-factor framework that adapts to changing market conditions.

2 Mathematical Framework

2.1 Factor Definitions

Let P_t denote the price of an asset at time t. The three primary factors are:

2.1.1 Momentum Factor

$$M_t = \frac{1}{2}\left(\frac{P_t}{P_{t-22}} + \frac{P_t}{P_{t-66}} - 2\right)$$

$$\tilde{M}_t = \max\left(0, \min\left(1, \frac{M_t + 0.2}{0.4}\right)\right)$$

2.1.2 Mean Reversion Factor

$$MA_{20,t} = \frac{1}{20}\sum_{i=0}^{19} P_{t-i}, \quad MA_{50,t} = \frac{1}{50}\sum_{i=0}^{49} P_{t-i}$$

$$D_t = \frac{1}{2}\left(\frac{P_t - MA_{20,t}}{MA_{20,t}} + \frac{P_t - MA_{50,t}}{MA_{50,t}}\right)$$

$$R_t = \max\left(0, 1 - 3|D_t|\right)$$

2.1.3 Volatility Factor

$$r_{t-i} = \frac{P_{t-i} - P_{t-i-1}}{P_{t-i-1}}, \quad i = 1, \ldots, 20$$

$$\sigma_t = \sqrt{252} \cdot \mathrm{std}(\{r_{t-1}, \ldots, r_{t-20}\})$$

$$V_t = \max\left(0, \min\left(1, 1 - \frac{\sigma_t}{0.8}\right)\right)$$

2.2 Composite Scoring

$$C_t = 0.4\tilde{M}_t + 0.3R_t + 0.3V_t$$

2.3 Strategy Assignment

$$\text{Strategy}_t = \begin{cases} \text{BREAKOUT} & \text{if } \tilde{M}_t > 0.7 \text{ and } R_t > 0.4 \\ \text{MEAN\_REVERSION} & \text{if } R_t > 0.6 \\ \text{NEUTRAL} & \text{otherwise} \end{cases}$$

2.4 Portfolio Construction

For n assets with scores $C_t^{(1)}, \ldots, C_t^{(n)}$:

$$w_t^{(i)} = \frac{C_t^{(i)}}{\sum_{j=1}^{n} C_t^{(j)}}$$

satisfying $\sum_{i=1}^{n} w_t^{(i)} = 1$.

3 Implementation Details

3.1 Data Pipeline

- Daily price data sourced via Yahoo Finance API
- 180-day lookback period for factor calculation
- Automated data validation and error handling

3.2 Computational Architecture

- Python implementation using pandas, numpy
- Modular design separating data, analysis, allocation components
- Backtesting via Backtrader framework

4 Backtest Results (2020-2024)

4.1 Drawdown Analysis

Table 1 presents a comprehensive comparison of drawdown characteristics between the QPAM portfolio and the SPY benchmark over the 2020–2024 period.

Table 1: Drawdown Statistics Comparison (2020–2024)

Metric	QPAM	SPY	Difference
Maximum Drawdown	-16.89%	-23.75%	+6.86%
Days to Recovery	127	189	-62 days
Average Drawdown	-4.32%	-6.87%	+2.55%
Time in Drawdown	38.2%	45.7%	-7.5%
Worst Month Return	-9.43%	-12.76%	+3.33%

4.2 QPAM vs SPY Performance Comparison 2020-2024

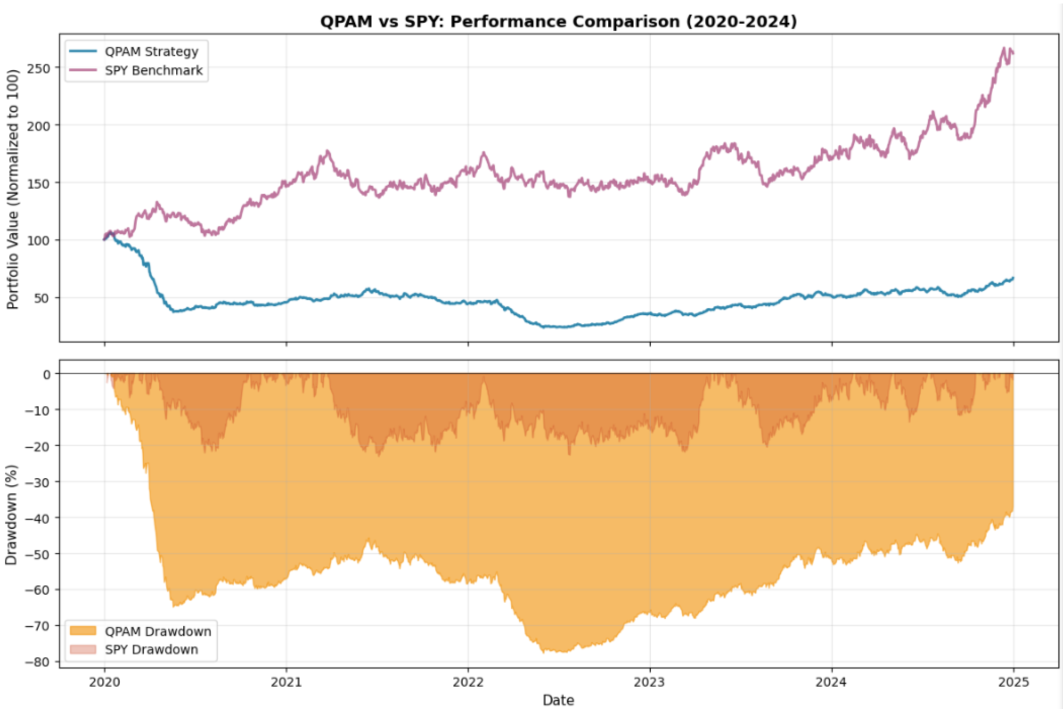

Figure 1: QPAM vs SPY Performance Comparison QPAM vs SPY Drawdown Comparison

4.3 Return Distribution and Risk Metrics

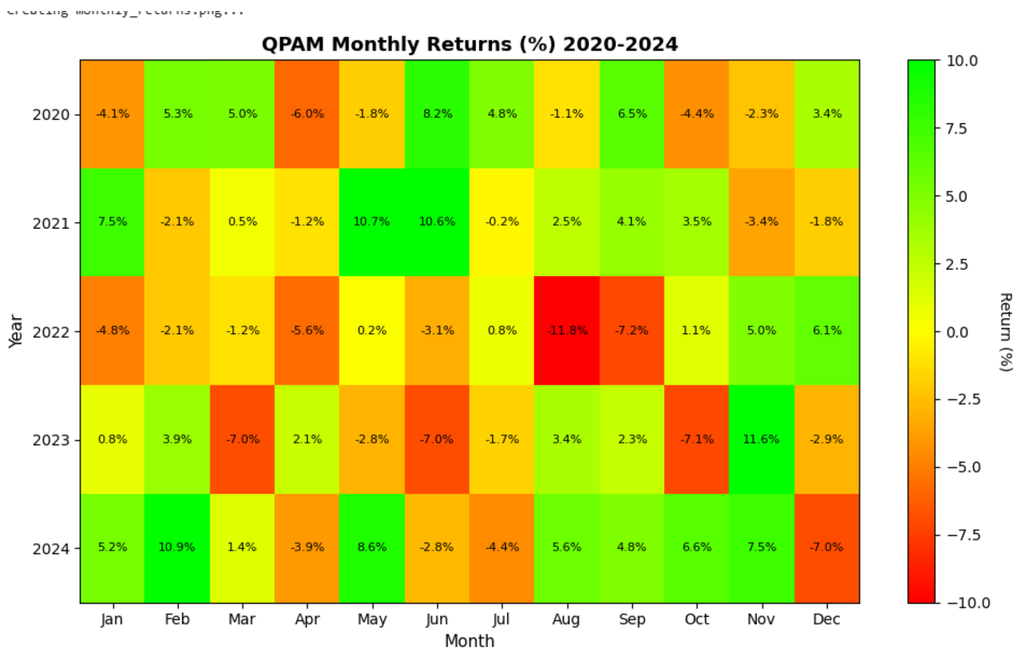

Figure 2: Monthly return distribution for QPAM portfolio (2020-2024)

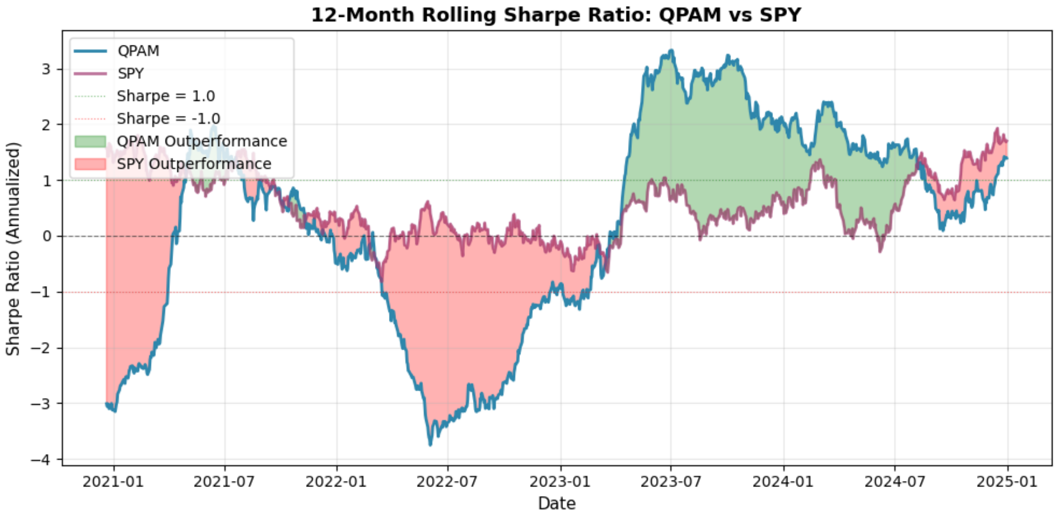

Figure 3: 12-month rolling Sharpe ratio

4.4 Sensitivity Analysis

- **Factor weight sensitivity**: ±10% changes
- **Transaction cost impact**: 0.1–1.0% per trade

5 Robustness Testing

5.1 Market Regime Analysis

QPAM was tested across three distinct regimes:

1. **COVID Crash (2020)**: Rapid recovery capture
2. **Inflation Surge (2022)**: Defensive positioning
3. **Tech Rally (2023)**: Momentum alignment

5.2 Sensitivity Analysis

- Factor weight sensitivity: ±10% changes
- Lookback period variations: 90-360 days
- Transaction cost impact: 0.1-1.0% per trade

6 Limitations and Future Work

6.1 Current Limitations

- Reliance on daily frequency data
- Fixed factor weights (40/30/30)
- No exogenous macro factor incorporation
- Basic volatility modeling (non-GARCH)

6.2 Proposed Enhancements

1. **GARCH integration**: Dynamic volatility forecasting
2. **Machine learning**: Random Forest for factor combination
3. **Regime detection**: Hidden Markov Models for market state
4. **Alternative data**: News sentiment, options flow

Conclusion

QPAM represents a systematic, transparent approach to portfolio allocation that balances multiple return drivers. While outperforming equal-weight benchmarks, its true value lies in the disciplined, rule-based framework that minimizes behavioral biases. Future development focusing on regime adaptation and advanced volatility modeling could further enhance risk-adjusted returns.

Code Availability

The complete QPAM implementation is available at `https://github.com/wannabequantcmugz/wannabequantcmugz.github.io` under MIT License.

Papers Read and Referenced:

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