Regime-Based Factor Investing Strategy

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Introduction

Traditional vs. Ours

Introduction #1

- **Novel Regime-Aware Strategy**
  - Dynamically adjusts long-short factor exposures based on macroeconomic regimes
  - Focuses on traditional anomalies: momentum, value, quality, etc.

- **Macroeconomic Regime Identification**
  - Uses term spread (long-term vs. short-term interest rates) to classify regimes
  - Conditions factor tilts on prevailing regime

Introduction #2

- **Objective & Performance**
  - Capitalize on time-varying efficacy of anomalies
  - Delivers strong risk-adjusted returns and significant alpha
  - Outperforms equal- and value-weighted benchmarks

- **Motivation & Hypothesis**
  - Traditional factor strategies assume stationarity across all markets
  - Proposed approach varies factor set by regime instead
  - Hypothesis: momentum, value, quality, etc., perform differently across regimes due to shifts in investor sentiment, risk appetite, and economic fundamentals

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Strategy Overview & Methodology

Data Source

Center for Research in Security Prices (CRSP) accessed through the Wharton Research Data Services (WRDS) platform.

Timeframe: January 1990 to December 2023, encompassing multiple market regimes including bull markets, bear markets, and periods of market stress.

After accounting for delisting returns, we have about 3000-7000 stocks per month

Data Source

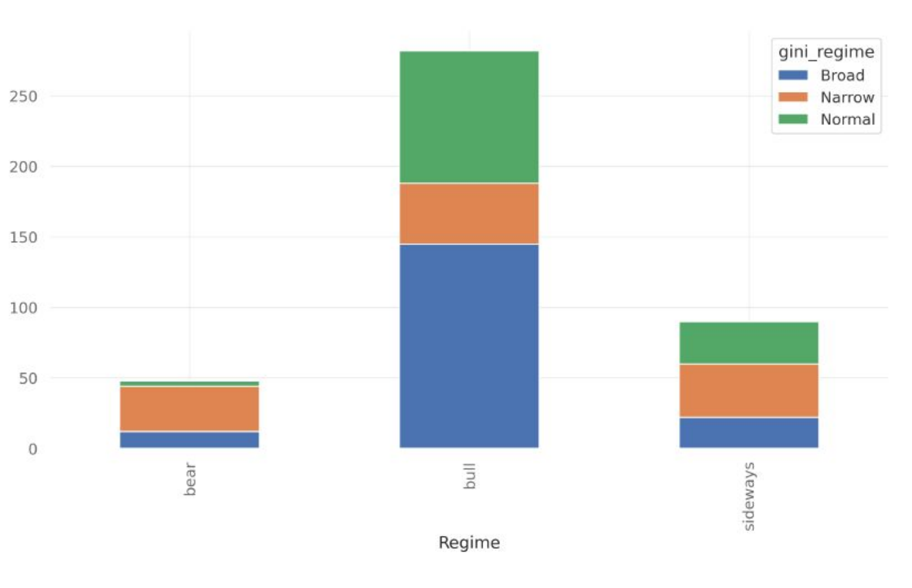
1. **Stock Return Data**: Monthly stock returns from CRSP for all common stocks (share codes 10 and 11) listed on NYSE, AMEX, and NASDAQ (exchange codes 1, 2, and 3).
2. **Risk-Free Rate**: Treasury bill returns from CRSP's monthly Treasury indices.
3. **Fama-French Factors**: Monthly returns for the Market (Mkt-RF), Size (SMB), and Value (HML) factors.
4. **Macroeconomic Indicators**: 10-Year Treasury Rate (GS10) and 3-Month T-Bill Rate (DTB3) from the Federal Reserve Economic Data (FRED) database.

Market Regime Identification

- **Macroeconomic Regimes** (Based on the term spread between 10-Year Treasury Rate and 3-Month T-Bill Rate)
  - Bull: Term Spread > 1%
  - Bear: Term Spread < 0%
  - Sideways: Otherwise
- **Market Concentration Regimes** (Based on Gini coefficient and Herfindahl-Hirschman Index (HHI))
  - Narrow: Concentration metrics > historical averages
  - Broad: Concentration metrics < historical averages
  - Normal: Concentration metrics within normal ranges

Market Regime Identification

The combination of these two dimensions creates a 3×3 matrix of nine possible market regimes, each with distinct factor performance characteristics.



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Factor Signal Construction

Momentum: Past 11-month log return, excluding the most recent month.

Growth: 6-month average price relative to 1-month lagged price.

Quality: Inverse of trailing 12-month volatility.

Volatility: Standard deviation of past 12 monthly returns.

Value: Inverse of lagged market capitalization.

Profitability: 12-month log return.

Regime-Based Portfolio Formation

For each market regime, we identify the optimal combination of factors based on historical performance patterns:

```
regime_factors = {
    'bull - Narrow': ['momentum', 'value'],
    'bull - Normal': ['momentum', 'growth'],
    'bull - Broad': ['momentum', 'growth'],
    'bear - Narrow': ['momentum', 'volatility'],
    'bear - Normal': ['quality', 'volatility'],
    'bear - Broad': ['quality', 'growth'],
    'sideways - Narrow': ['value', 'momentum'],
    'sideways - Normal': ['value', 'profitability'],
    'sideways - Broad': ['value', 'profitability']
```

Empirical Procedure

1. Load CRSP stock return and delisting data from WRDS

2. Compute firm-level factor signals monthly and merge with macroeconomic regime labels

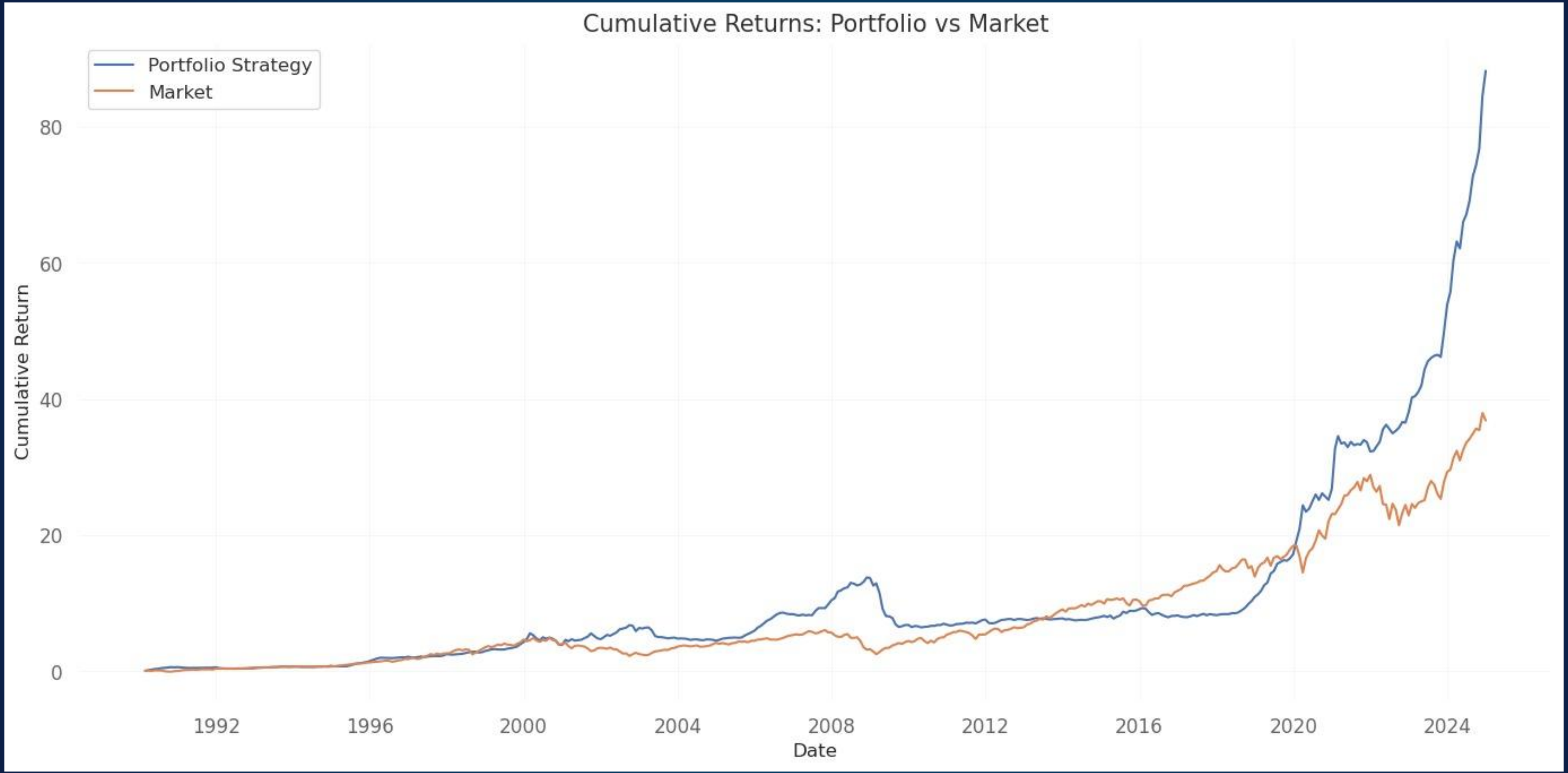
3. Select regime-specific factors and compute composite Z-score

4. Form top-quintile and lower-quintile portfolios and compute return

5. Hold for one month and then rebalance

6. Evaluate performance, factor exposures, and robustness

Analysis



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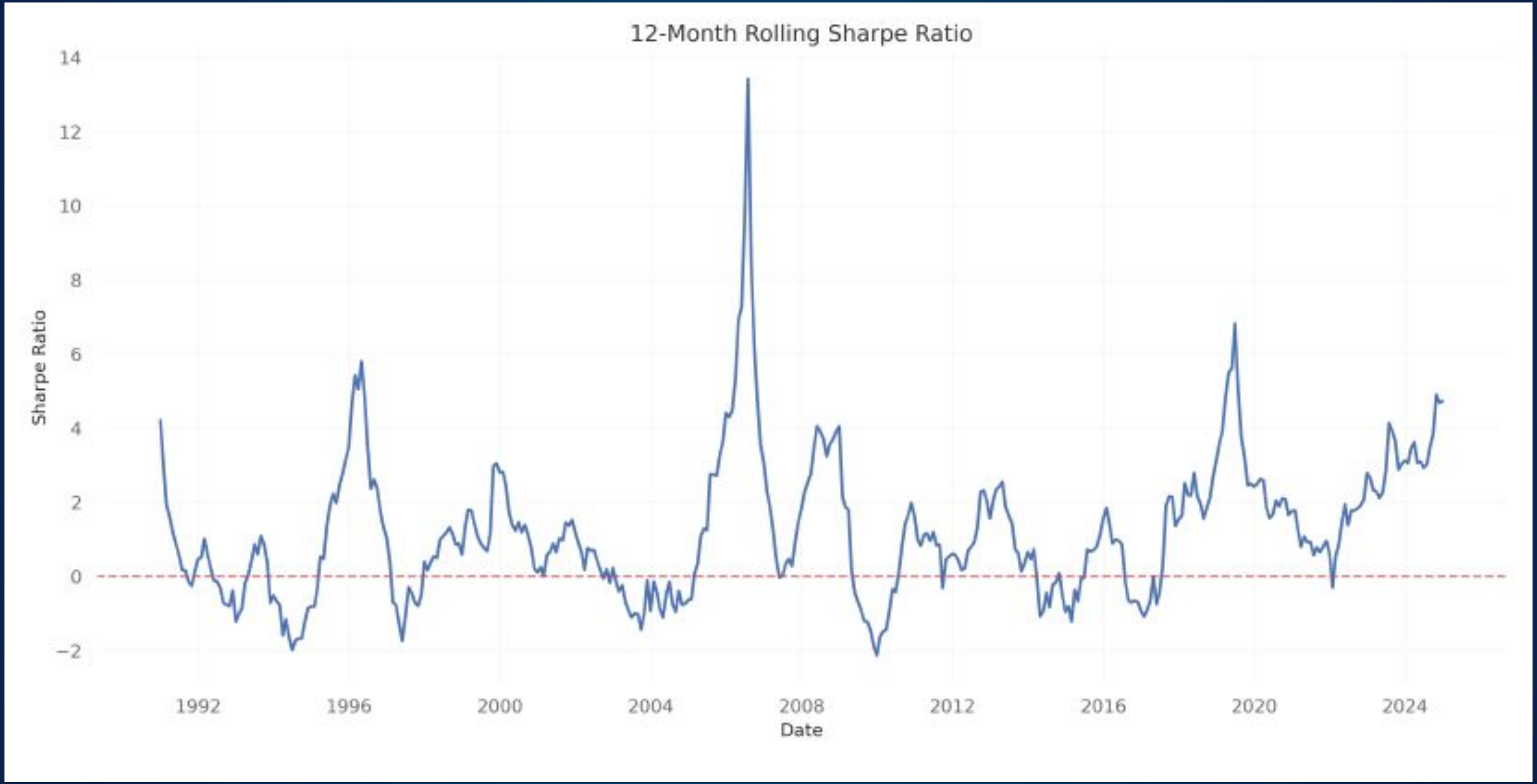

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Regression Analysis - CAPM & FF3

We assess the risk-adjusted performance of our regime-based strategy.

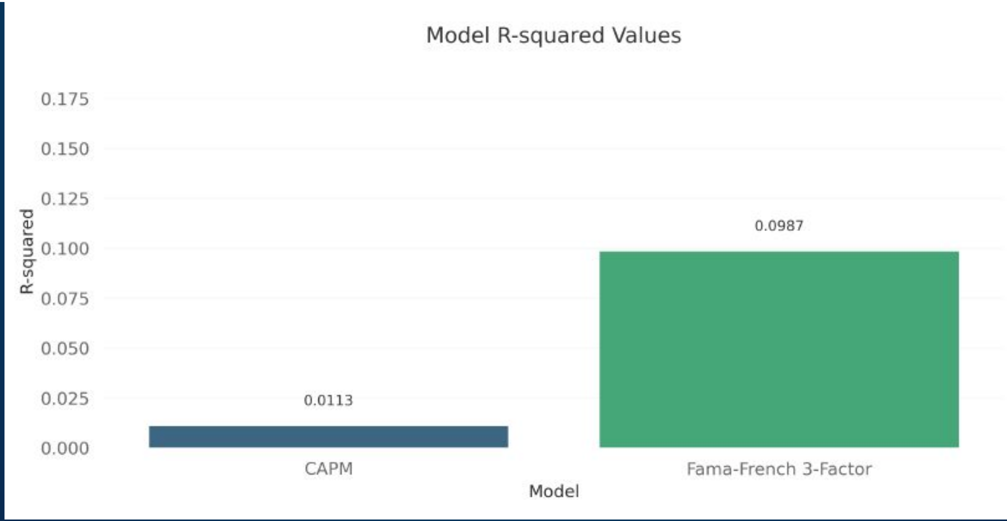
1. The strategy generates statistically significant alpha (excess return) after controlling for market risk

2. The strategy exhibits low exposure to the market factor, indicating effective market neutrality through the long-short construction

3. When controlling for size (SMB) and value (HML) factors, the strategy continues to deliver significant alpha, suggesting that our regime-based approach captures return drivers beyond traditional factor exposures

Regression Analysis - CAPM & FF3

	Alpha (CAPM)	Beta (Mkt-RF)	CAPM R-squared	Alpha (FF3)	Beta (SMB)	Beta (HMI
CAPM	0.023492	-0.168933	0.011296	NaN	NaN	NaN
Fama-French 3-Factor	NaN	-0.274378	NaN	0.024638	0.391634	-0.475453



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Performance Evaluation

1. Bull Market Performance:

• Narrow markets, momentum + value factors yield the strongest returns

• Normal and broad markets, momentum + growth -> positive performance

2. Bear Market Performance:

• Narrow breadth, momentum + volatility provide the most effective factor combination

• In normal bear markets, quality and volatility factors show defensive characteristics

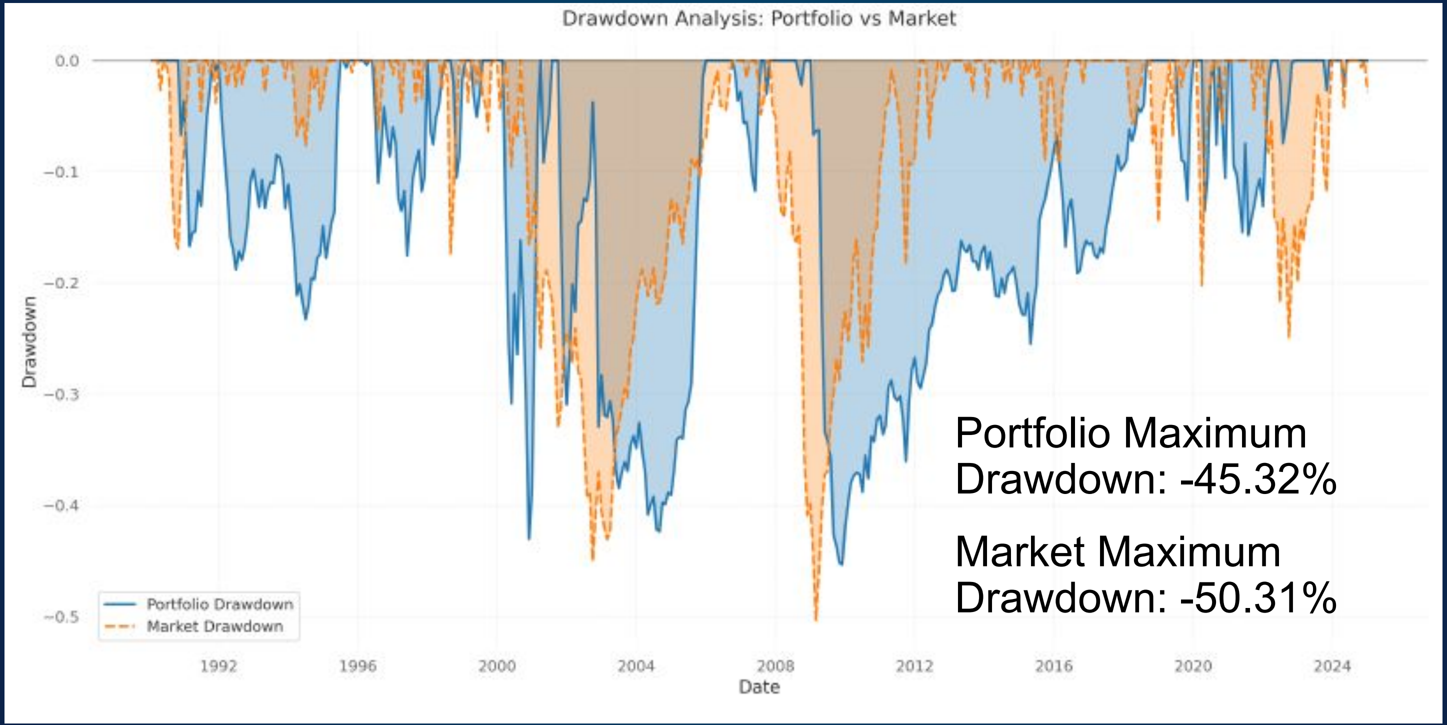
• In broad bear markets, quality combined with growth shows the best performance

3. Sideways Market Performance:

• Value-based factors consistently outperform during sideways markets

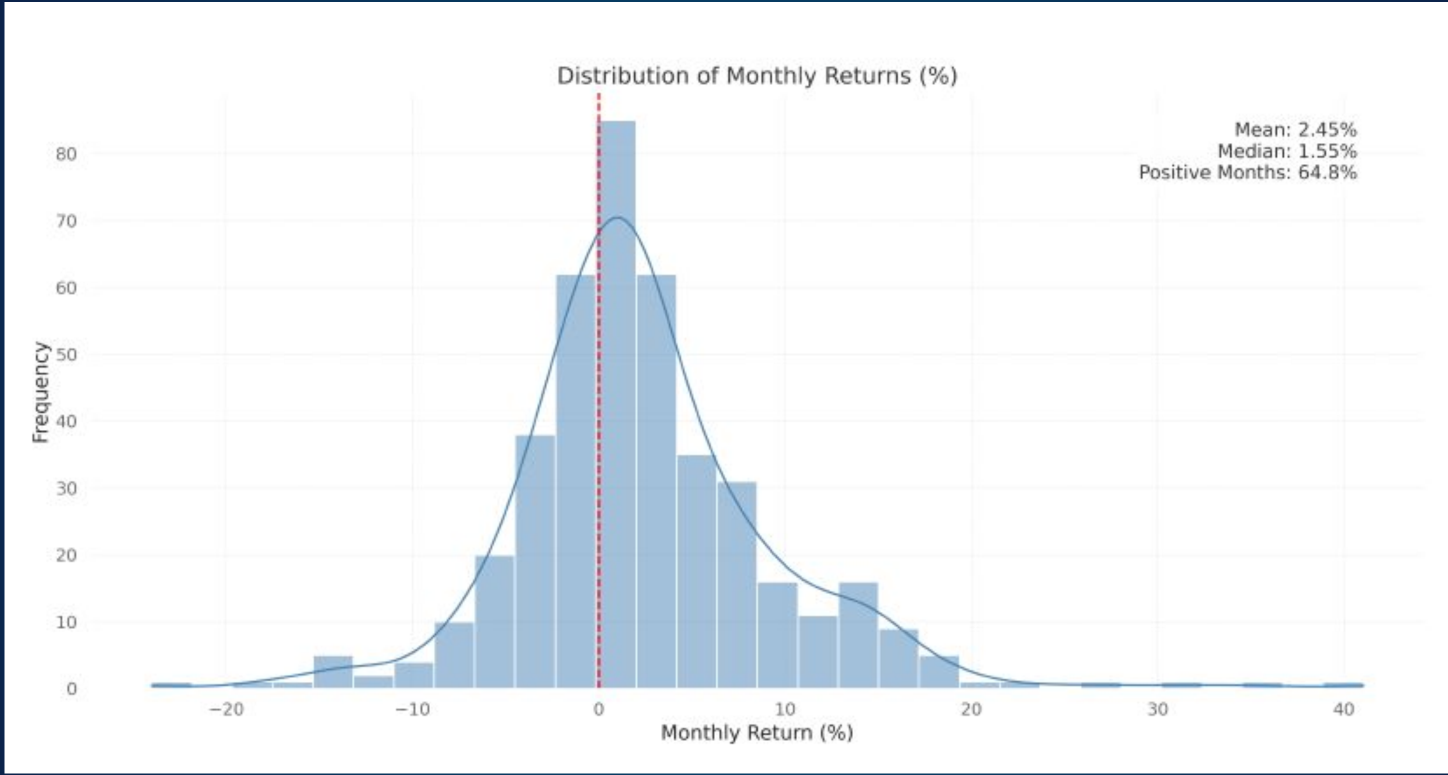
• The combination of value with momentum (narrow markets) or profitability (normal/broad markets) delivers robust returns

Performance During Transitions



Performance During Major Bear Markets

- Dot-com Bubble: 65.13% outperformance
- Global Financial Crisis: 151.51%
- COVID-19: 73.55%
- 2022 Bear Market: 54.72%



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Key Limitations

- **Transaction Costs & Market Impact**
  - Not fully accounted for; may reduce net returns, especially in less liquid regimes

- **Regime Identification Bias**
  - Relies on ex-post calculation of market concentration metrics
  - Potential look-ahead bias, even with lagged indicators

Future Directions

- **Additional Regime Indicators**
  - Incorporate volatility-based and monetary policy regimes
- **Alternative Factor Definitions**
  - Test different factor constructions and combinations for each regime
- **Machine Learning Applications**
  - Use ML methods for more robust regime classification and factor selection
- **Broader Market Scope**
  - Extend framework to international equity markets
  - Study regime-aware strategies in other asset classes (e.g., fixed income, commodities)

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Conclusion

Conclusion

1. Regime Identification

   - The combination of term structure indicators and market concentration measures provides a robust framework for identifying distinct market regimes with characteristic factor performance patterns.

2. Dynamic Factor Selection

   - Different factors exhibit varying effectiveness across market regimes, validating the need for dynamic allocation rather than static factor exposure.

Conclusion

3. Risk-Adjusted Performance

   - Our regime-based strategy generates statistically significant alpha after controlling for market, size, and value factors, indicating that it captures return drivers not explained by traditional risk factors.

4. Drawdown Mitigation

   - The strategy demonstrates enhanced downside protection during market stress periods, with lower maximum drawdowns and faster recovery times compared to the market benchmark.

5. Transition Performance

   - The strategy adapts effectively to regime transitions, capturing upside during recovery phases while offering protection during market deterioration.

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