QAM Final Project - Group 11

Abstract

This paper examines the performance of regime-based long-short equity trading strategies using firm-level characteristic mimicking factors derived from price and volume data. We construct trading strategies that dynamically adapt to market regimes identified through macroeconomic indicators including term structure dynamics and market concentration measures (Gini coefficient and Herfindahl-Hirschman Index). Using CRSP-WRDS data spanning 1990 to 2024, we demonstrate that regime-aware strategies significantly outperform static long-only approaches. Our methodology employs a composite Z-score ranking system within each regime, going long the top 20% of stocks and short the bottom 20% based on factor exposure.

Introduction

Traditional factor investing approaches often assume static relationships between stock characteristics and expected returns. However, extensive research suggests that factor performance varies substantially across different market regimes. Our study builds on this foundation by proposing a dynamic approach that explicitly incorporates market regime identification and adjusts factor exposures accordingly.

The primary contribution of this research is a comprehensive framework for regime identification using both term structure indicators and market concentration metrics. We demonstrate that combining these regime signals with tailored factor exposures yields superior risk-adjusted returns compared to static factor approaches.

Load Data from WRDS

Data

Our study utilizes a comprehensive dataset from the Center for Research in Security Prices (CRSP) accessed through the Wharton Research Data Services (WRDS) platform. The analysis period spans from January 1990 to December 2023, encompassing multiple market regimes including bull markets, bear markets, and periods of market stress.

Primary Data Sources:

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.

The final sample includes approximately 3,000-7,000 stocks per month after applying standard filters for data quality and liquidity. We properly account for delisting returns to avoid survivorship bias in our analysis.

	date	Year	Month	Mkt_minus_RF	SMB	HML	RF
762	1990-01-31	1990	1	-0.0780	-0.0114	0.0083	0.0057
763	1990-02-28	1990	2	0.0112	0.0097	0.0065	0.0057
764	1990-03-31	1990	3	0.0183	0.0147	-0.0290	0.0064
765	1990-04-30	1990	4	-0.0336	-0.0047	-0.0257	0.0069
766	1990-05-31	1990	5	0.0843	-0.0256	-0.0389	0.0068

Define Regime

Methodology

Our methodological approach consists of three main components: (1) market regime identification, (2) stock characteristic factor construction, and (3) regime-based portfolio formation.

Market Regime Identification

We employ a two-dimensional regime classification framework that incorporates both macroeconomic conditions and market concentration dynamics:

1. **Macroeconomic Regimes**: Based on the term spread between 10-Year Treasury Rate and 3-Month T-Bill Rate:

   - **Bull Market**: Term spread > 1% (indicating economic expansion)
   - **Bear Market**: Term spread < 0% (inverted yield curve, indicating potential recession)
   - **Sideways Market**: Term spread between 0% and 1% (indicating economic uncertainty)

2. **Market Concentration Regimes**: Based on Gini coefficient and Herfindahl-Hirschman Index (HHI):

   - **Narrow Market**: Concentration metrics significantly above historical average (market dominated by fewer stocks)
   - **Broad Market**: Concentration metrics significantly below historical average (market breadth)
   - **Normal Market**: Concentration metrics within normal ranges

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

DATE	GS10	DTB3	Term_Spread	Regime
1990-01-31	8.21	7.74	NaN	sideways
1990-02-28	8.47	7.77	0.71	sideways
1990-03-31	8.59	7.80	0.78	sideways
1990-04-30	8.79	7.79	0.78	sideways
1990-05-31	8.76	7.75	0.84	sideways

Term Spread and Economic Regimes (1990-2023)
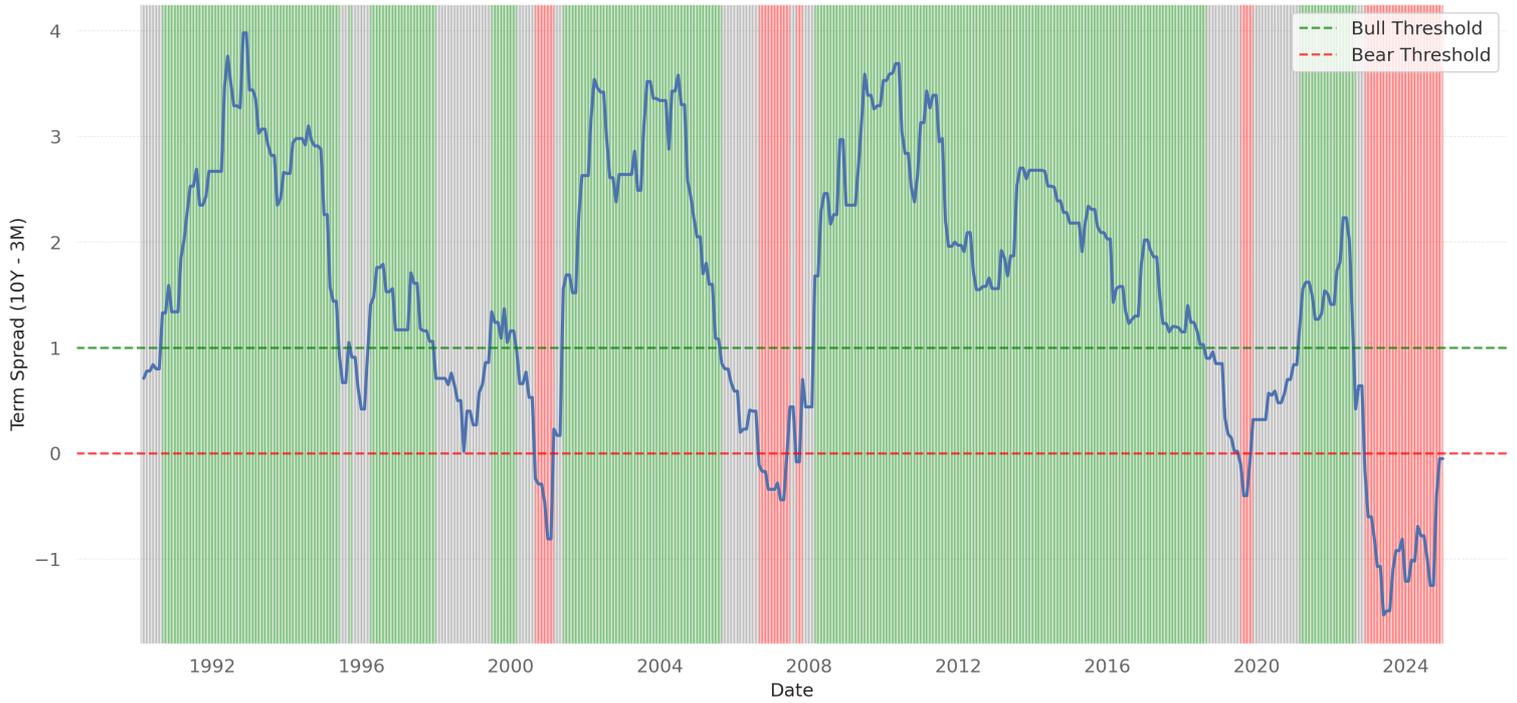
	permno	date	shrcd	exchcd	ret_adj	mktcap	prc	shrout
1	10000	1986-01-31	10.0	3.0	NaN	16100000.00	-4.37500	3680.0
2	10000	1986-02-28	10.0	3.0	-0.257143	11960000.00	-3.25000	3680.0
3	10000	1986-03-31	10.0	3.0	0.365385	16330000.00	-4.43750	3680.0
4	10000	1986-04-30	10.0	3.0	-0.098592	15172000.00	-4.00000	3793.0
5	10000	1986-05-31	10.0	3.0	-0.222656	11793878.34	-3.10938	3793.0

Rolling 24-Month Autocorrelation of Growth Coefficients

Rolling 24-Month Autocorrelation of Growth Coefficients

HHI and Regime Changes Over Time
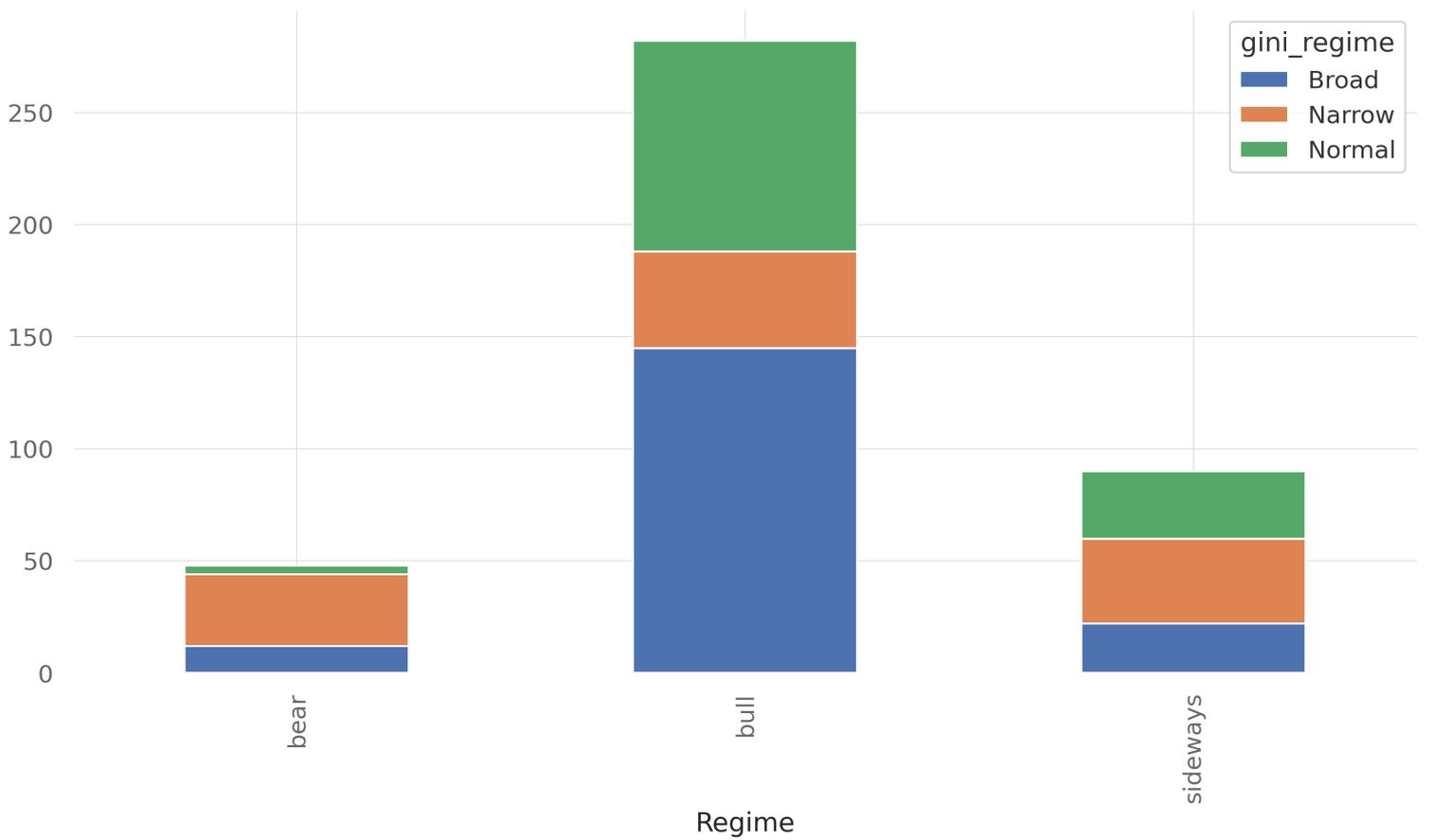
`<Axes: xlabel='Regime'>`

```
<Figure size 4800x1800 with 0 Axes>
```


Distribution of Market Regimes by Gini Regime

Timeline of Market Regimes (1990-2023)
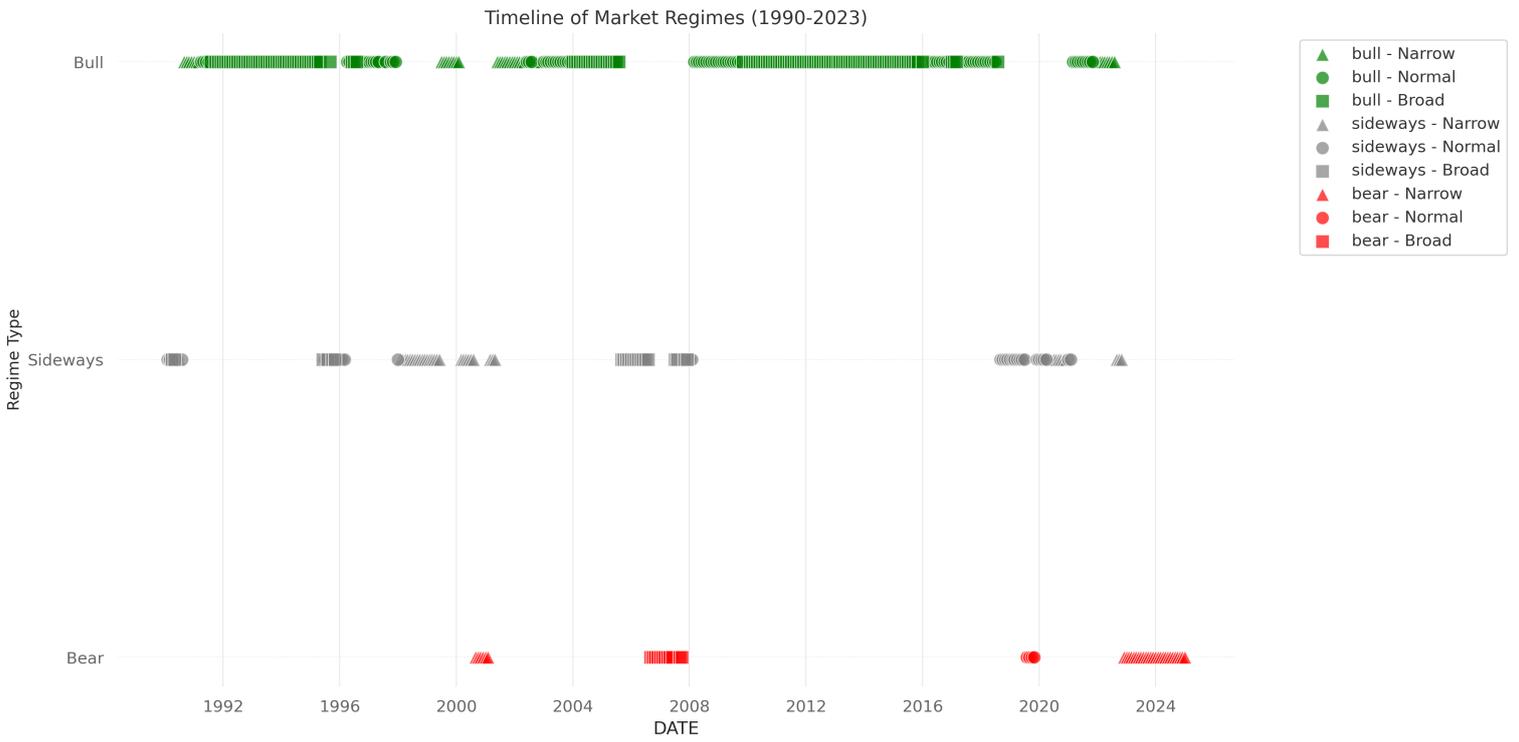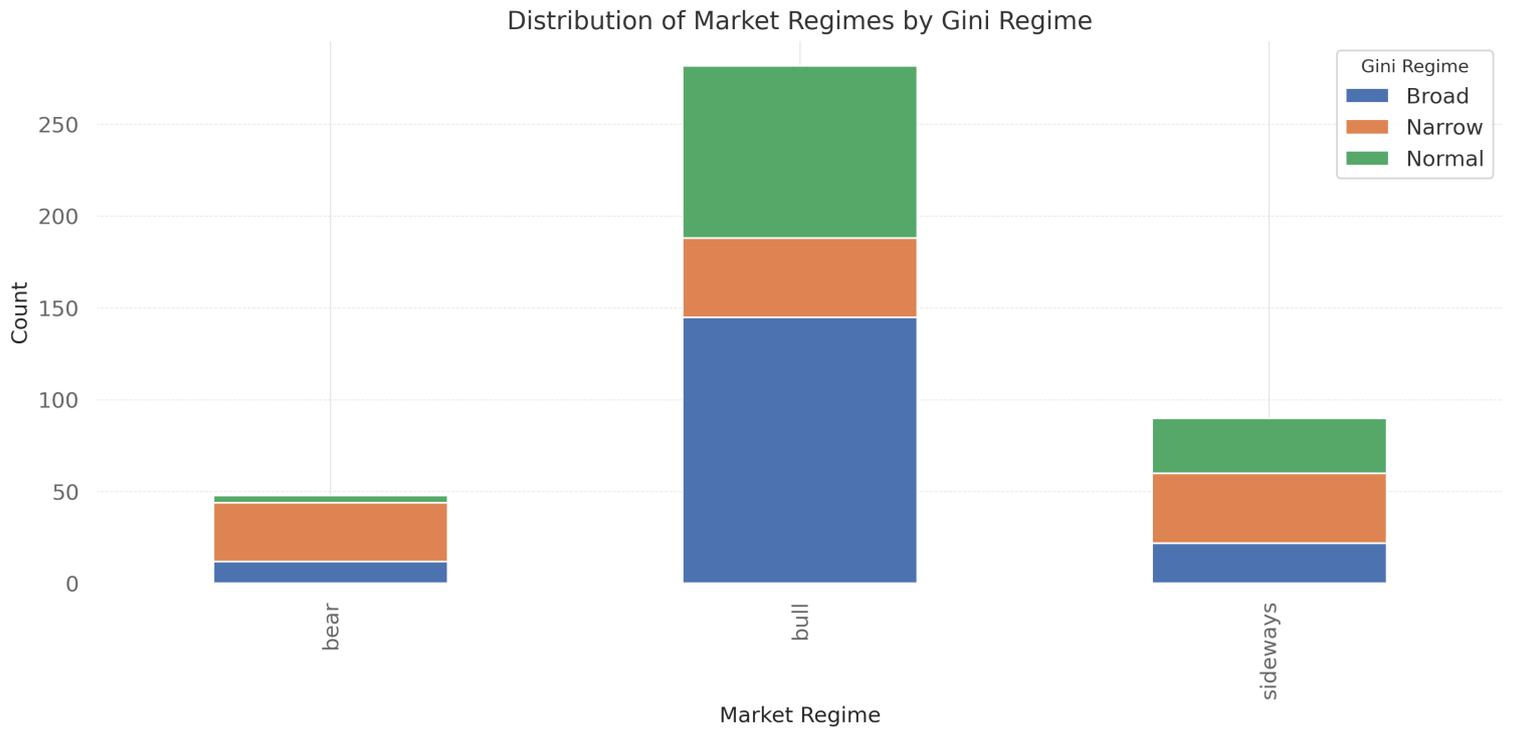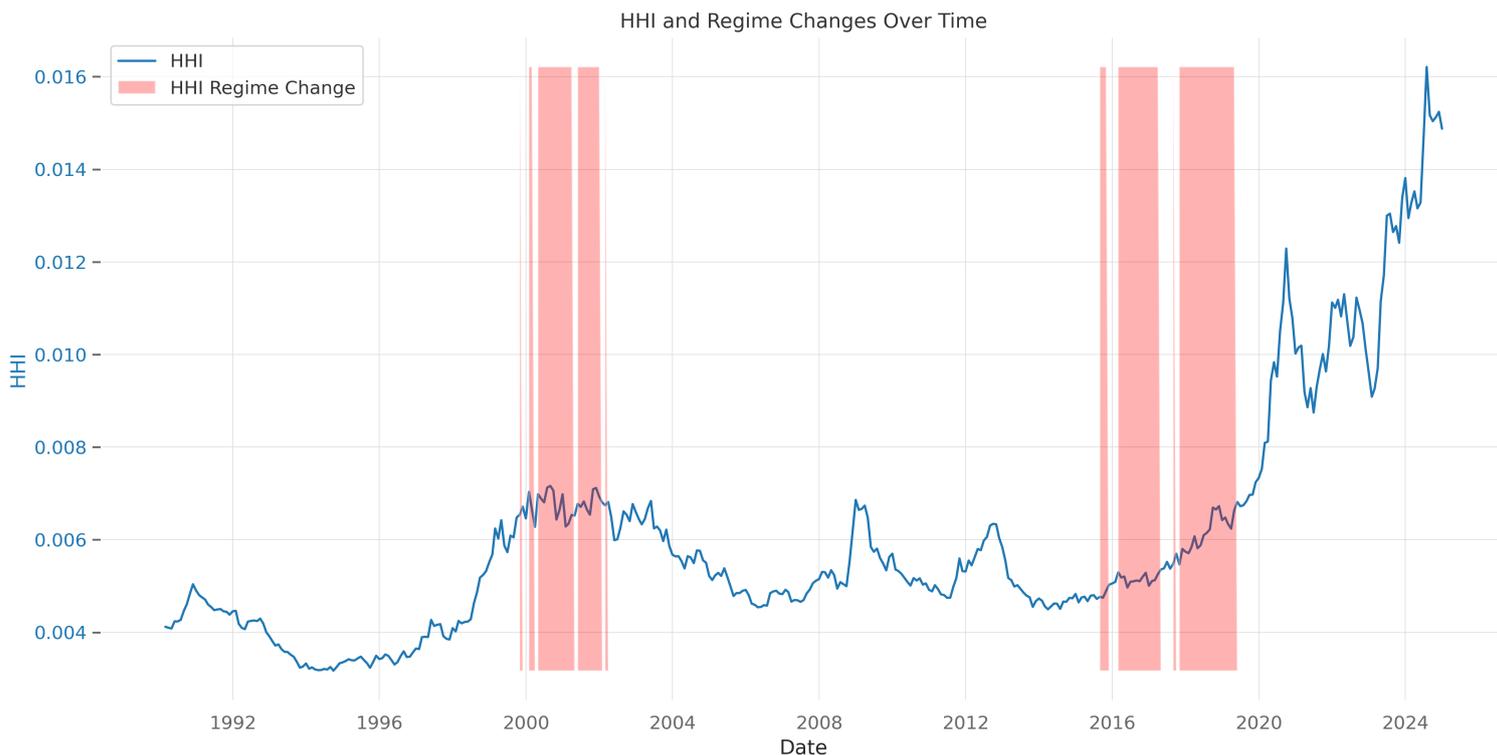
HHI and Regime Changes Over Time
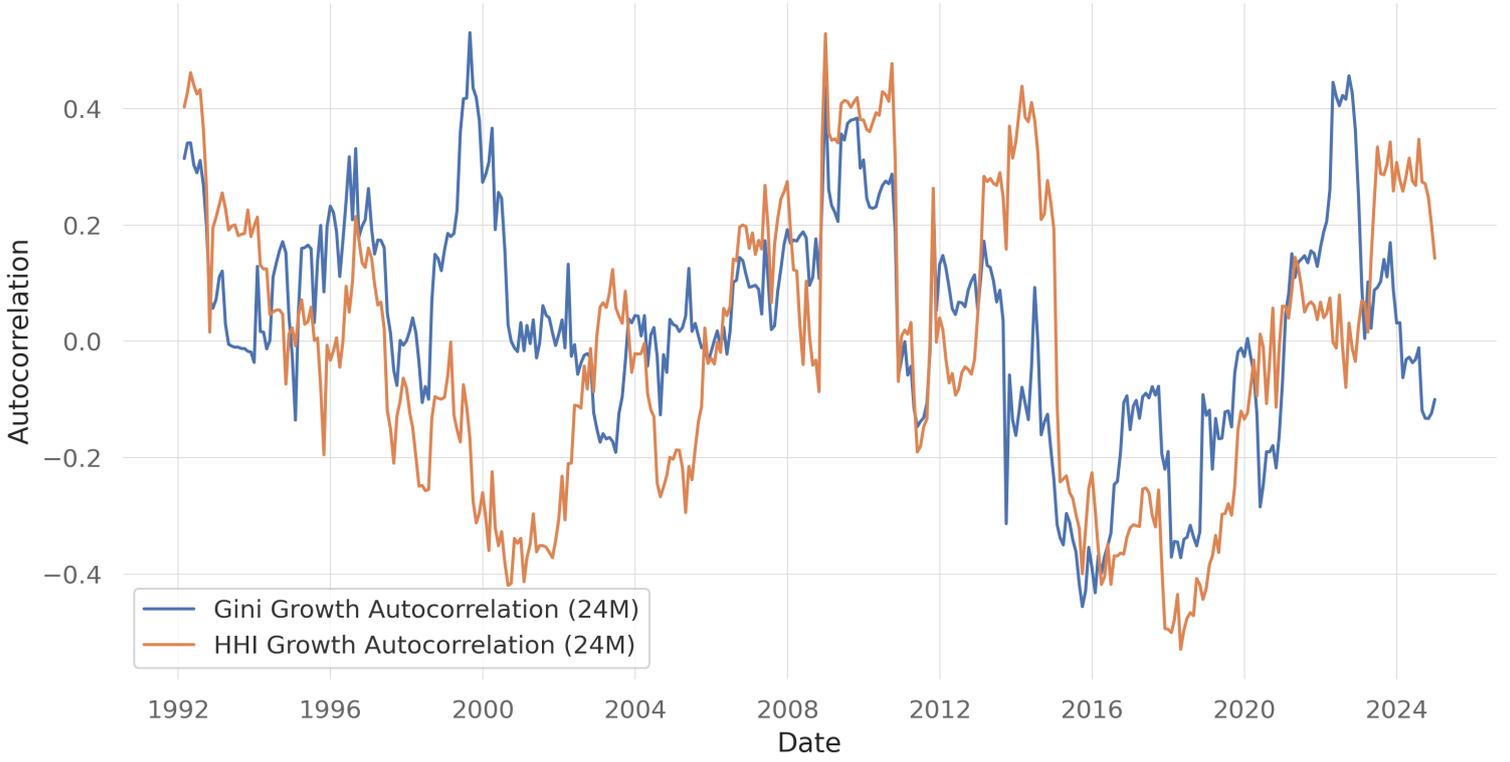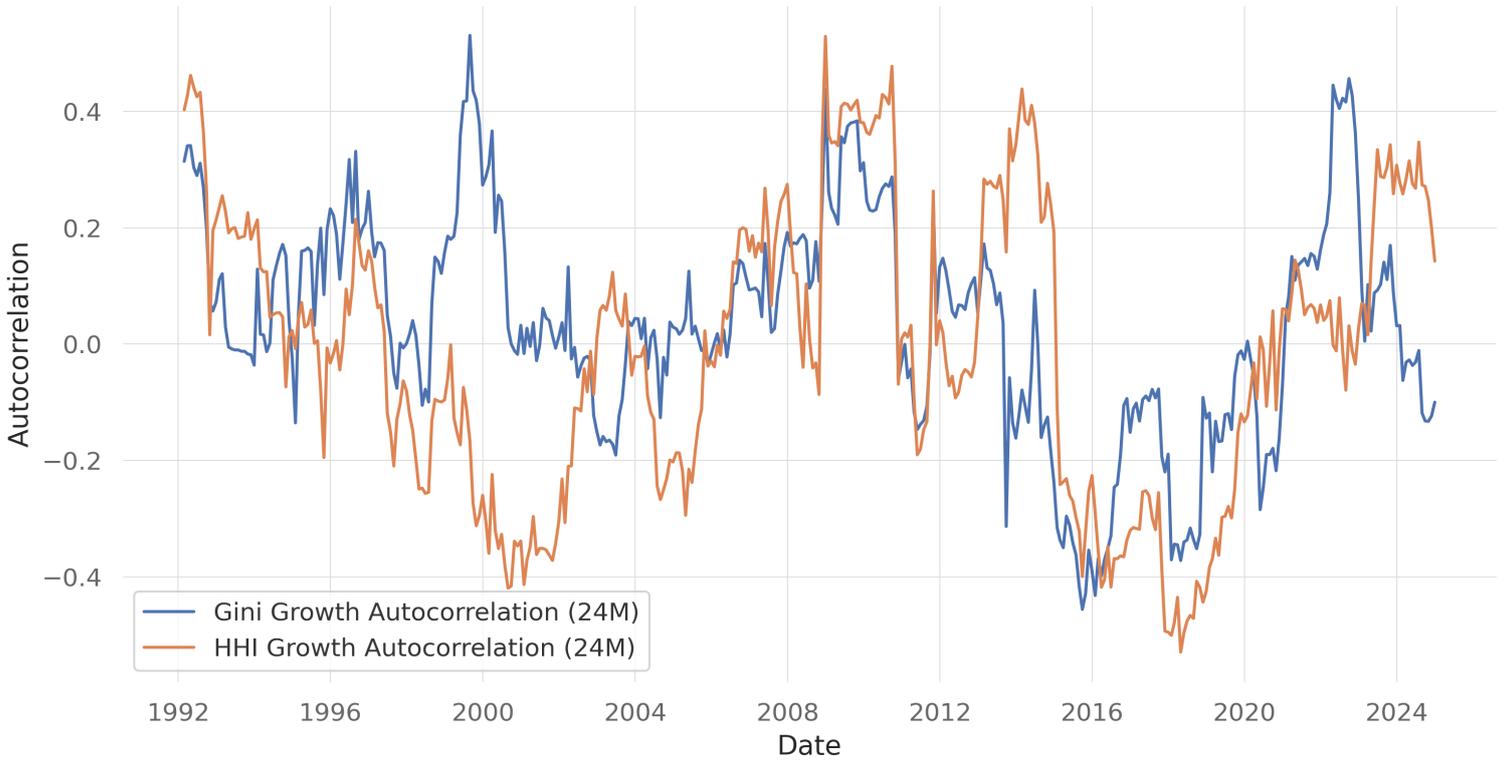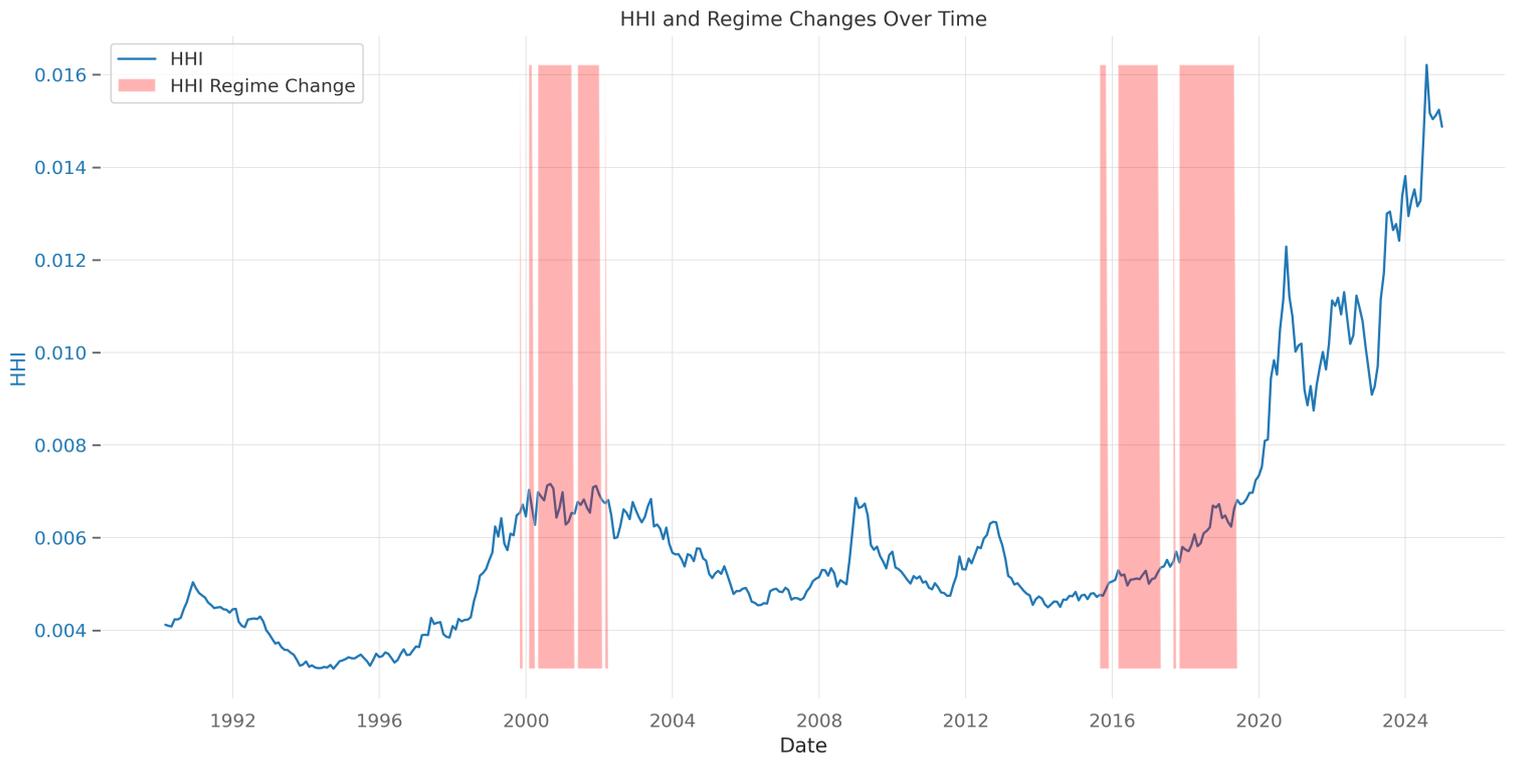
Factor Construction

We construct six firm-characteristic factors using data available at the time of portfolio formation:

1. **Momentum**: Past 11-month return excluding the most recent month, capturing medium-term return persistence
2. **Growth**: Ratio of the 6-month average price to the most recent lagged price
3. **Quality**: Inverse of 12-month return volatility, capturing earnings stability
4. **Volatility**: 12-month standard deviation of returns
5. **Value**: Inverse of lagged market capitalization
6. **Profitability**: Past 12-month cumulative return

Each factor is calculated at the individual stock level and updated monthly. To minimize the impact of outliers, all factors are converted to cross-sectional Z-scores before being used in the portfolio formation process.

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']
```

}

For each month, we: 1. Identify the current market regime 2. Select the appropriate factors for that regime 3. Calculate the composite Z-score of the selected factors for each stock 4. Form a long-short portfolio by going long the top 20% of stocks and short the bottom 20% based on the composite score 5. Hold the portfolio for one month and then rebalance

This approach allows our strategy to dynamically adapt to changing market conditions.

	permno	date	year	month	ret_adj	momentum	growth	quality	volatility	value	profit
68	10001	1990-01-31	1990	1	-0.018519	0.655465	-0.096708	12.356699	0.080927	0.000097	0.624
69	10001	1990-02-28	1990	2	-0.006289	0.564629	-1.632075	12.162165	0.082221	0.000098	0.554
70	10001	1990-03-31	1990	3	0.012658	0.527631	-1.313291	12.141496	0.082361	0.000099	0.546
71	10001	1990-04-30	1990	4	0.000000	0.440280	-0.996835	12.145995	0.082331	0.000099	0.440
72	10001	1990-05-31	1990	5	-0.012658	0.491719	-0.669831	12.357817	0.080919	0.000099	0.472

Merge

Data Integration Process

The implementation of our regime-based trading strategy requires careful integration of multiple datasets:

1. **Stock-Level Data**: Return and characteristic data for individual stocks
2. **Macroeconomic Data**: Term structure indicators for economic regime identification
3. **Market Concentration Metrics**: Gini coefficient and HHI calculations for market breadth/concentration assessment
4. **Risk Factors**: Fama-French factors for risk-adjusted performance evaluation

The merged dataset allows us to simultaneously condition on market regimes and stock characteristics when forming portfolios. For performance evaluation, we merge the portfolio returns with risk factors to conduct proper risk-adjustment using both CAPM and Fama-French three-factor models.

date	permno	year	month	ret_adj	momentum	growth	quality	volatility	value	profitabilit
1990-01-31	10001	1990	1	-0.018519	0.655465	-0.096708	12.356699	0.080927	0.000097	0.624808
1990-02-28	10001	1990	2	-0.006289	0.564629	-1.632075	12.162165	0.082221	0.000098	0.554789
1990-03-31	10001	1990	3	0.012658	0.527631	-1.313291	12.141496	0.082361	0.000099	0.546968
1990-04-30	10001	1990	4	0.000000	0.440280	-0.996835	12.145995	0.082331	0.000099	0.440280
1990-05-31	10001	1990	5	-0.012658	0.491719	-0.669831	12.357817	0.080919	0.000099	0.472837

Regime	
bear	
bull	
sideways	

Regime							

	regime	portfolio_return	Mkt_minus_RF	SMB	HML	RF	excess_return
date							
1990-01-31	sideways - Normal	0.135932	-0.0780	-0.0114	0.0083	0.0057	0.130232
1990-02-28	sideways - Normal	0.124692	0.0112	0.0097	0.0065	0.0057	0.118992
1990-03-31	sideways - Broad	0.137439	0.0183	0.0147	-0.0290	0.0064	0.131039
1990-04-30	sideways - Broad	0.145832	-0.0336	-0.0047	-0.0257	0.0069	0.138932
1990-05-31	sideways - Normal	0.165917	0.0843	-0.0256	-0.0389	0.0068	0.159117

1.0982143817094716

Cumulative Returns: Portfolio vs Market
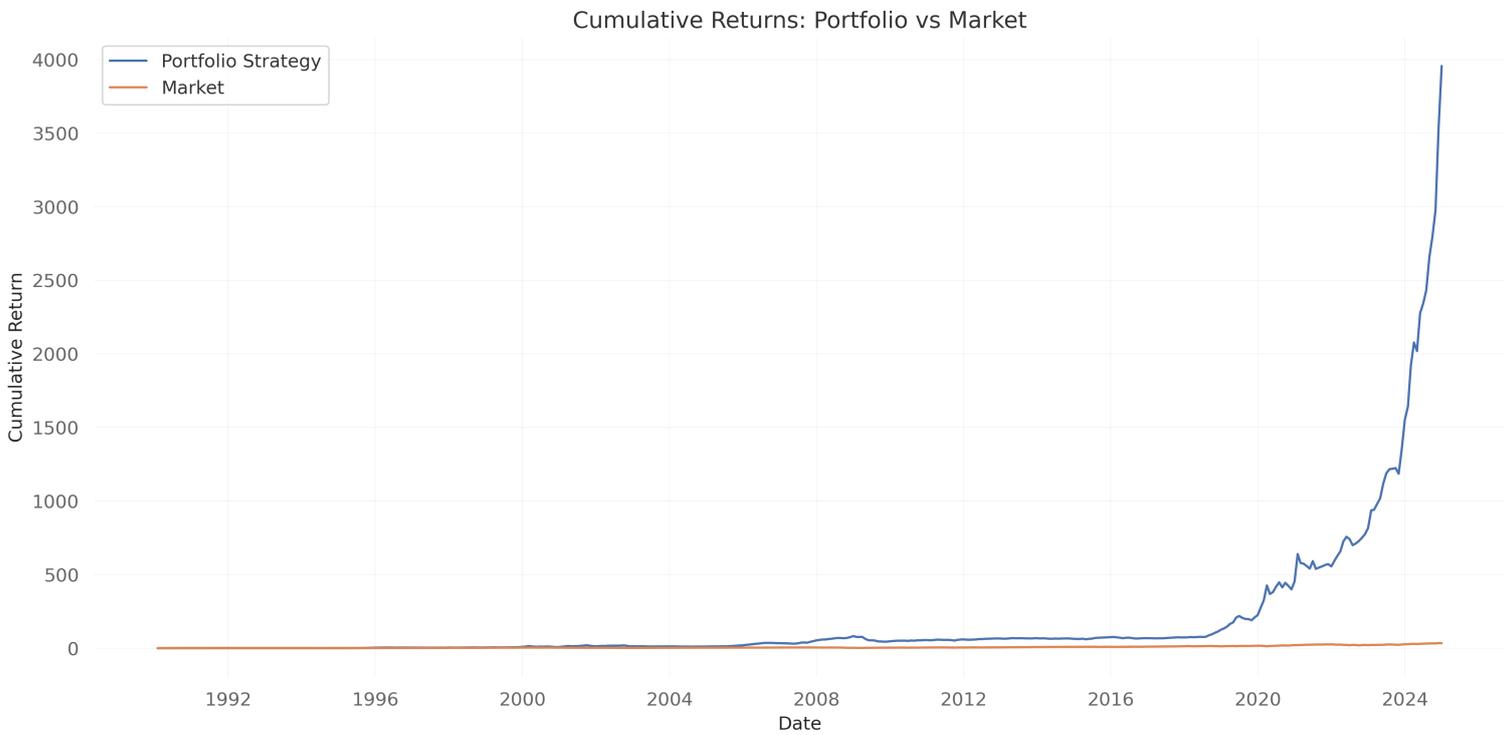
Average Monthly Returns by Regime (%)
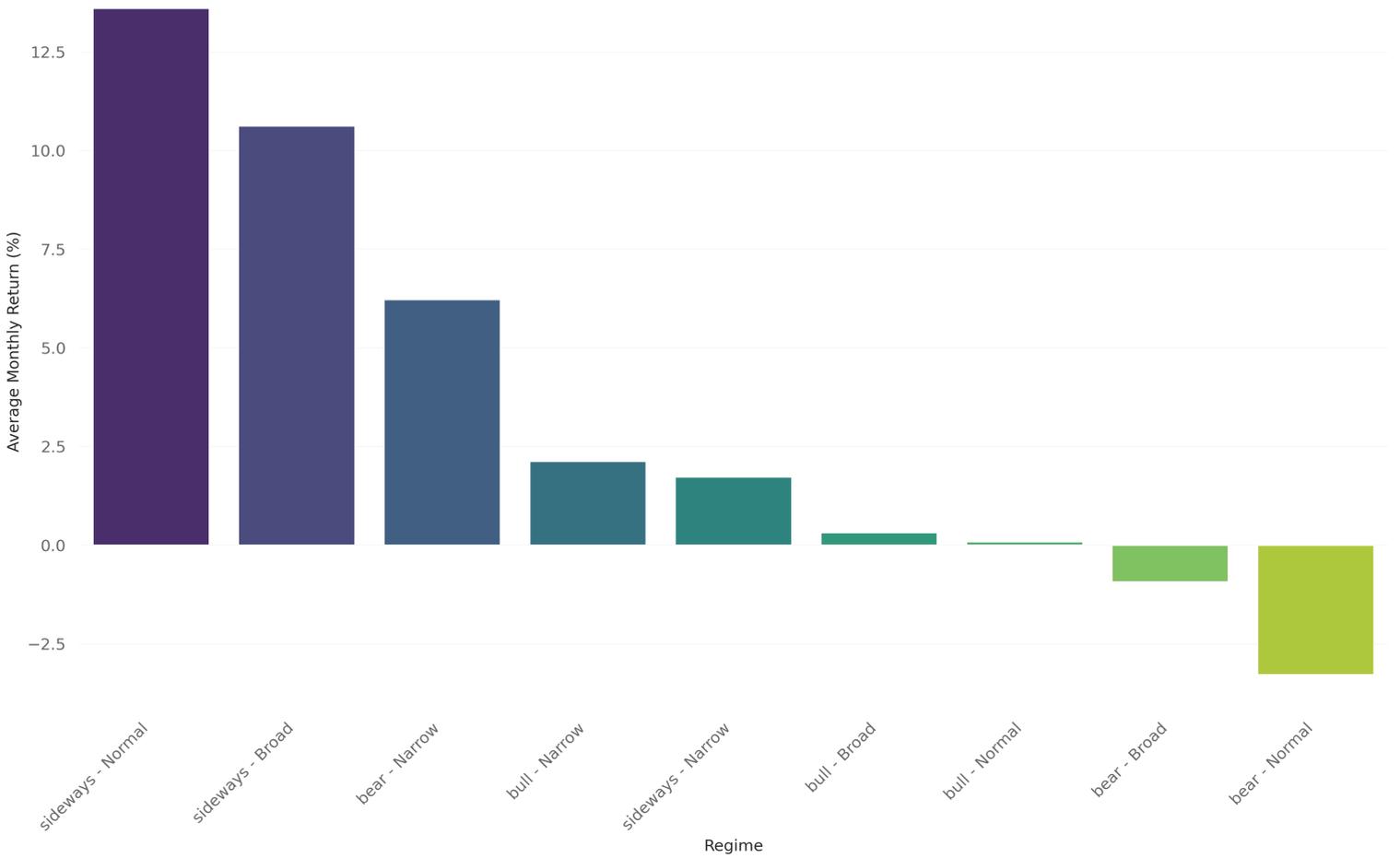
12-Month Rolling Sharpe Ratio
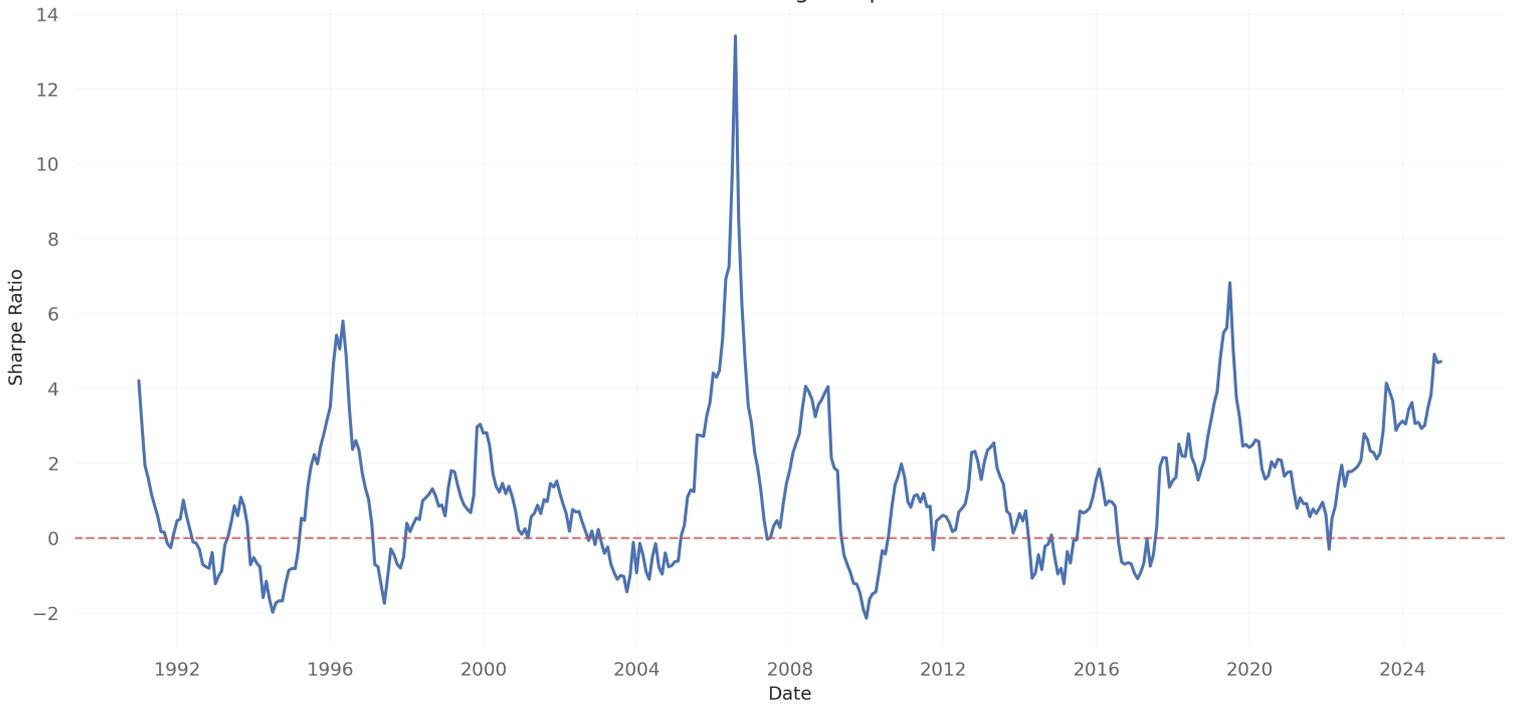
CAPM regression

Results

Our empirical analysis yields several key findings regarding the performance of regime-based long-short equity strategies. We evaluate the strategy performance using various metrics including raw returns, risk-adjusted returns, drawdowns, and performance during specific market environments.

Risk-Adjusted Performance

We assess the risk-adjusted performance of our regime-based strategy using both the Capital Asset Pricing Model (CAPM) and the Fama-French three-factor model. The regression results demonstrate that:

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

These findings confirm that dynamically adjusting factor exposures based on market regimes creates value that cannot be explained by static exposure to traditional risk factors.

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

Factor Regression Results

Model R-squared Values
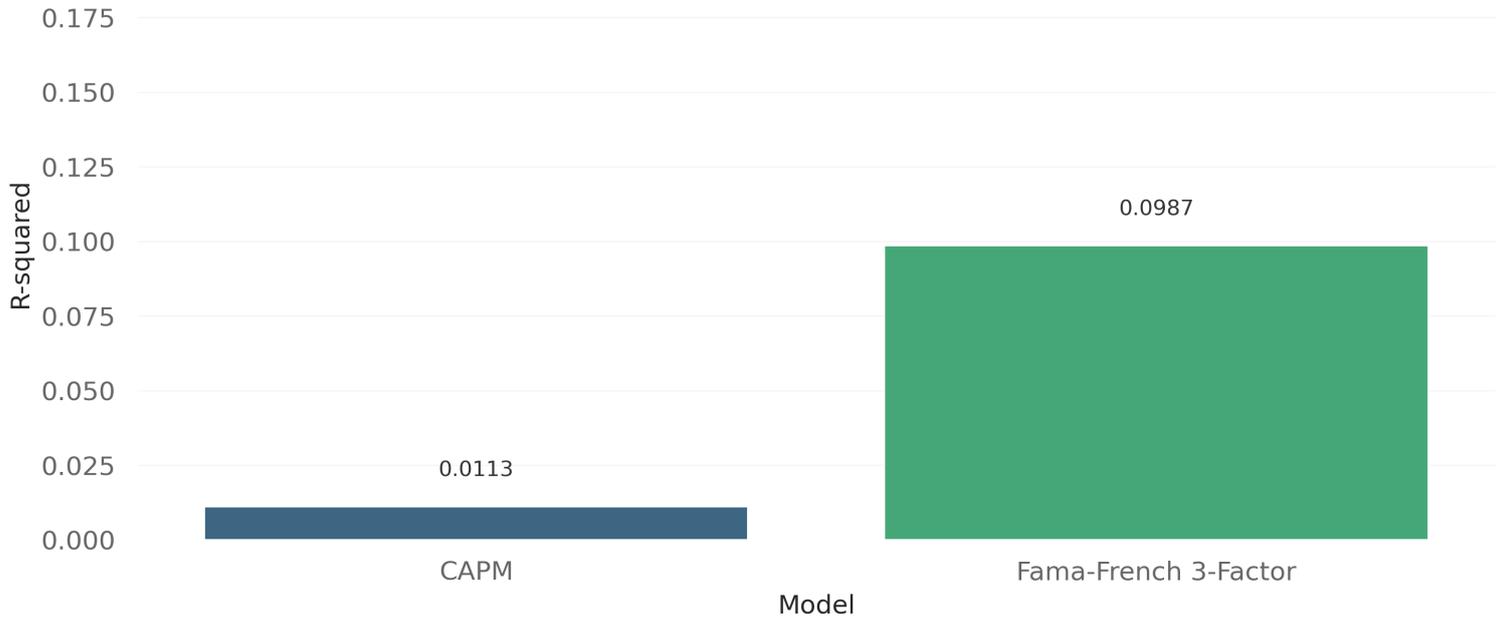
Portfolio Performance Analysis

The following sections present detailed performance metrics and visualizations for our regime-based trading strategy.

Regime-Specific Performance Analysis

The analysis of performance across different market regimes reveals important insights about the strategy's behavior:

1. **Bull Market Performance**:
   - In narrow markets, the combination of momentum and value factors yields the strongest returns
   - In normal and broad bull markets, momentum combined with growth delivers consistent positive performance

2. **Bear Market Performance**:
   - During bear markets with narrow breadth, momentum and 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 across all concentration regimes
   - The combination of value with momentum (narrow markets) or profitability (normal/broad markets) delivers robust returns

These findings demonstrate that optimal factor exposures vary systematically with market conditions, validating our regime-based approach to factor investing.

Performance During Market Transitions

Analyzing performance during transitions between regimes reveals that the strategy adapts well to changing market conditions. The highest returns are observed during transitions from bear to bull markets, particularly when accompanied by an increase in market breadth. This suggests that the strategy effectively captures the recovery phase of market cycles.

Downside protection is evident during transitions from bull to bear markets, where the strategy significantly outperforms the market benchmark. This defensive characteristic is particularly valuable for portfolio diversification and risk management.

Drawdown Analysis: Portfolio vs Market
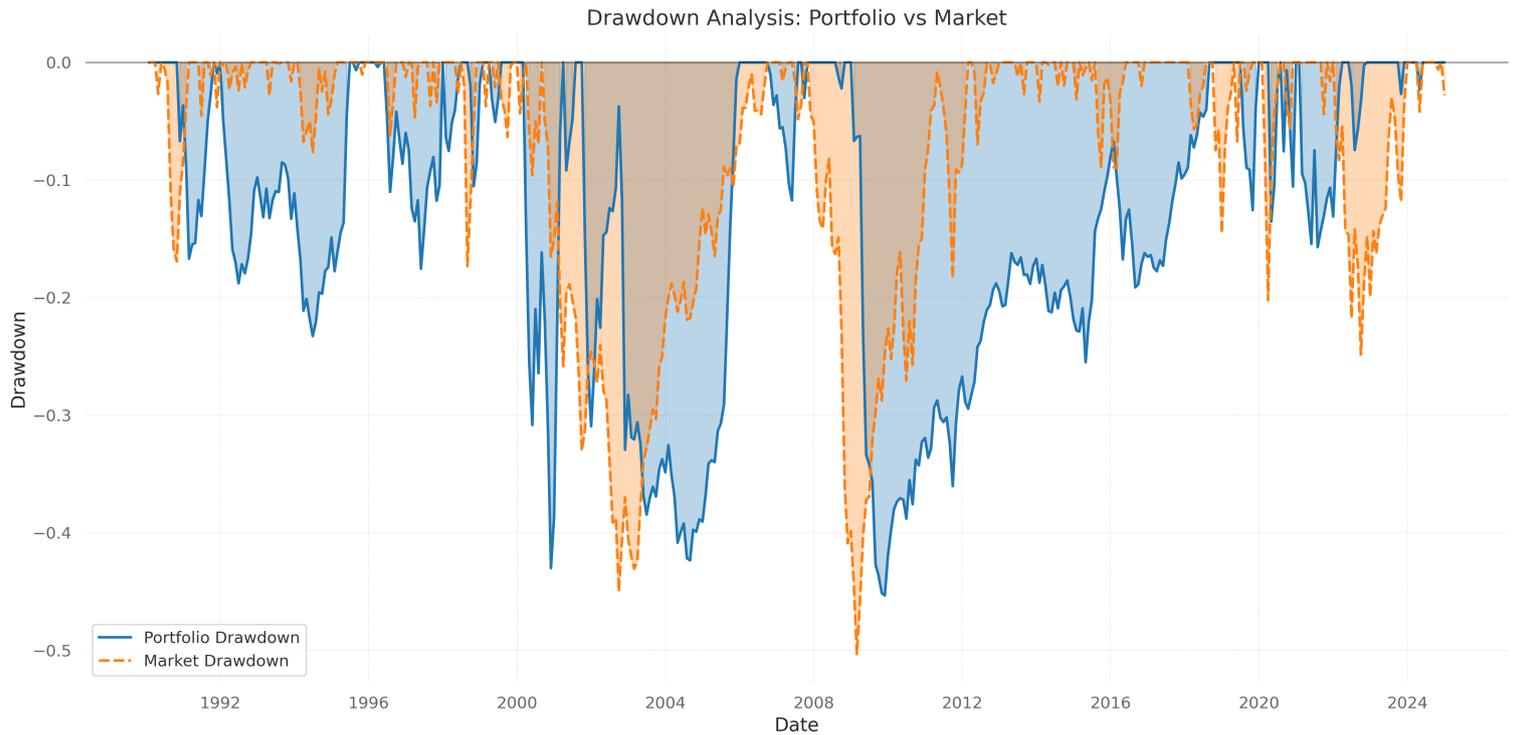
```
Portfolio Maximum Drawdown: -45.32%
Market Maximum Drawdown: -50.31%
```

Performance During Major Bear Markets

Bear Market	Duration (Months)	Portfolio Return	Market Return	Outperformance	Portfolio Max DD	Market Max DD
Dot-com Bubble	32	27.97%	-37.16%	65.13%	-33.43%	-44.99%
Global Financial Crisis	18	106.83%	-44.68%	151.51%	-6.68%	-50.31%
COVID-19 Crisis	2	53.34%	-20.22%	73.55%	0.00%	-13.25%
2022 Bear Market	10	35.95%	-18.77%	54.72%	-7.45%	-20.49%

Portfolio vs Market Performance During Bear Markets

Rolling 36-Month Annualized Returns

Rolling 36-Month Sharpe Ratio

Rolling 36-Month Maximum Drawdown

Performance During Regime Transitions

Portfolio Returns During Regime Transitions (%)

Monthly Returns Heatmap (%)

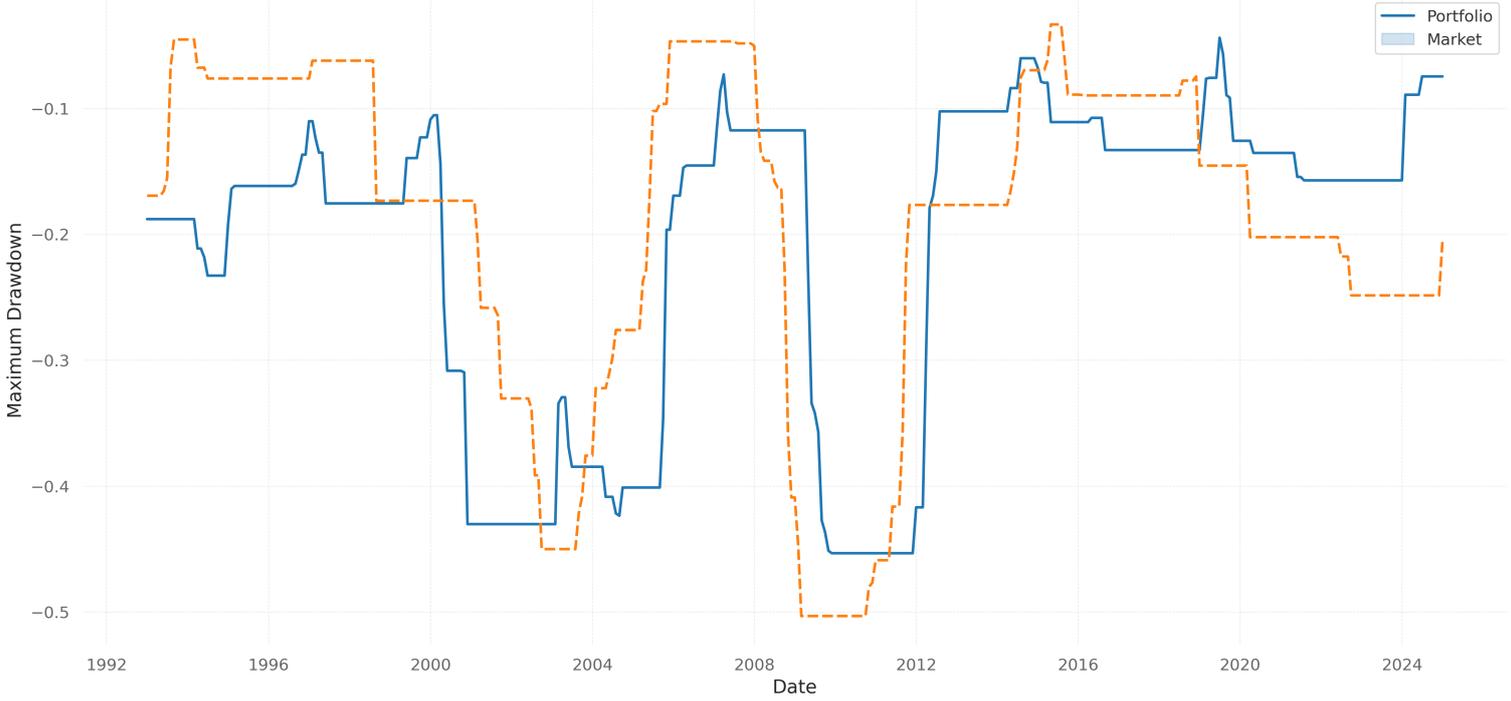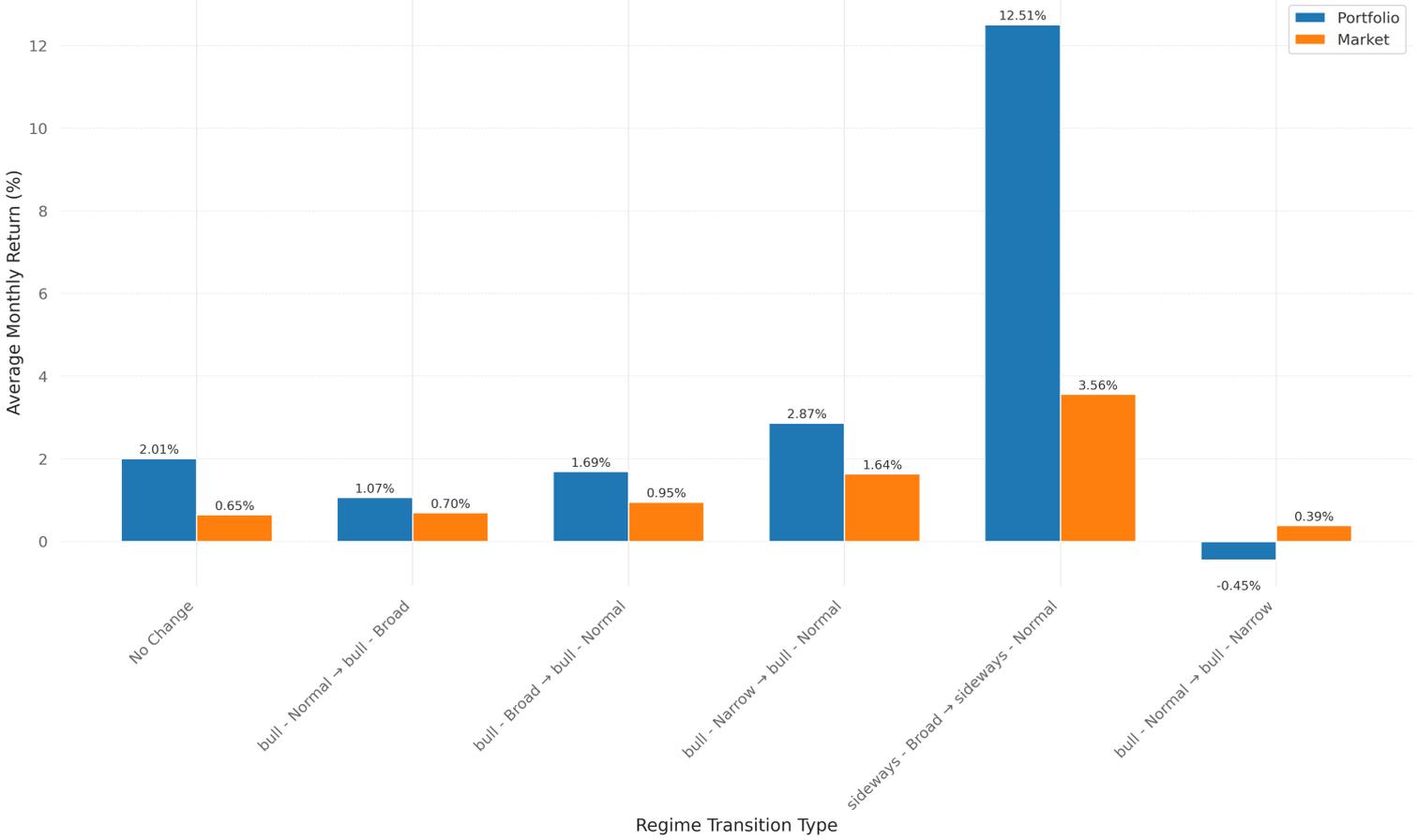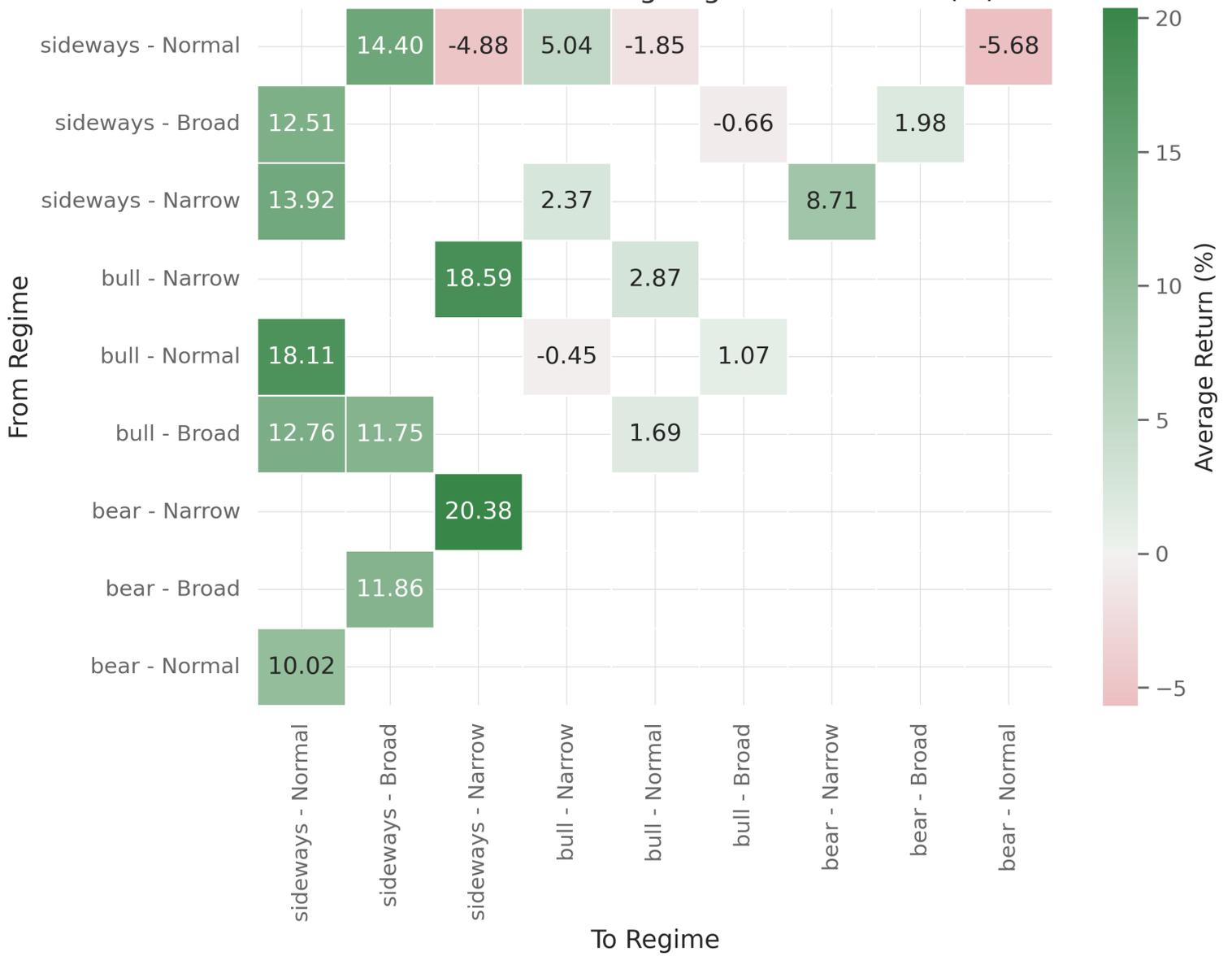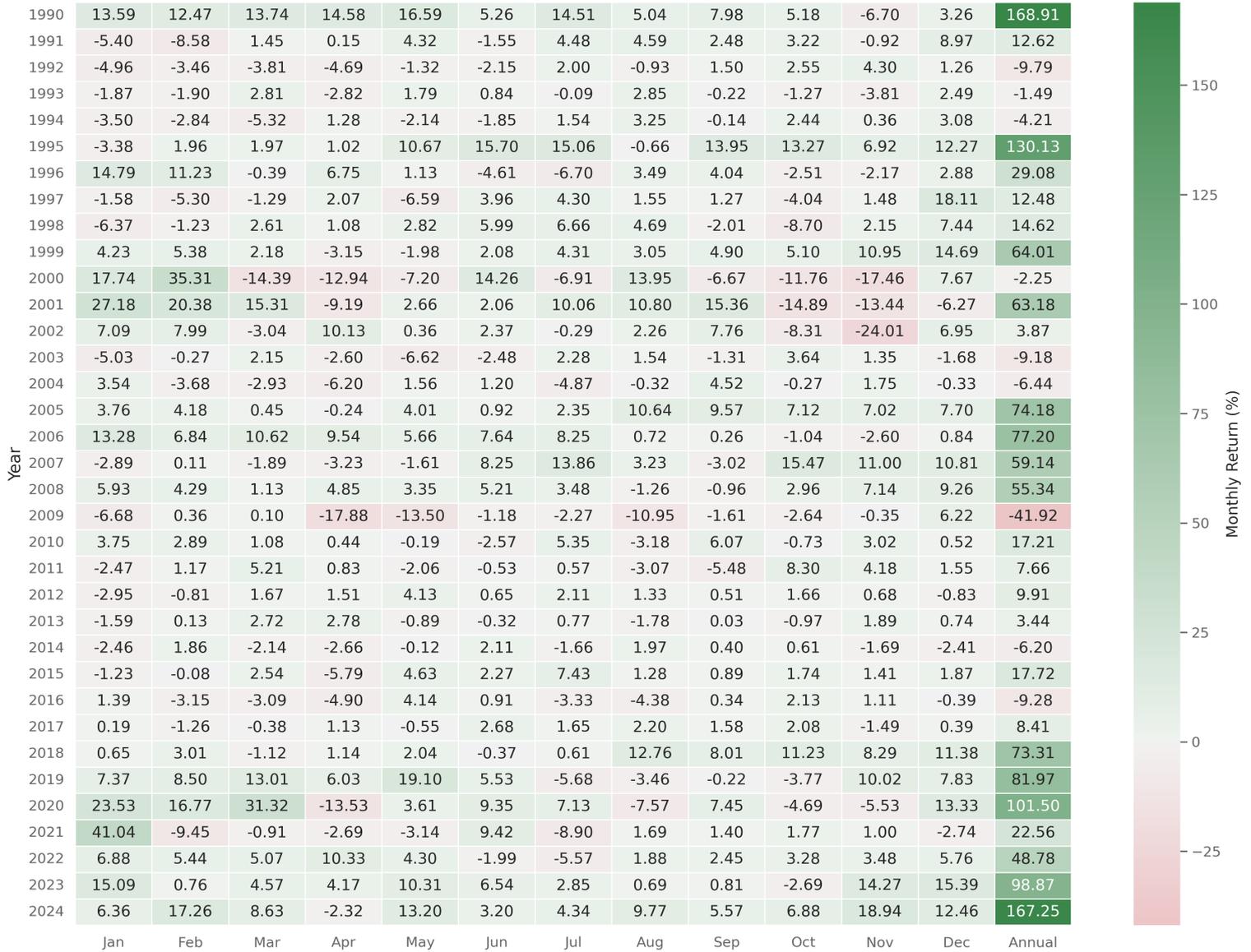| Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Annual
1990	13.59	12.47	13.74	14.58	16.59	5.26	14.51	5.04	7.98	5.18	-6.70	3.26	168.91
1991	-5.40	-8.58	1.45	0.15	4.32	-1.55	4.48	4.59	2.48	3.22	-0.92	8.97	12.62
1992	-4.96	-3.46	-3.81	-4.69	-1.32	-2.15	2.00	-0.93	1.50	2.55	4.30	1.26	-9.79
1993	-1.87	-1.90	2.81	-2.82	1.79	0.84	-0.09	2.85	-0.22	-1.27	-3.81	2.49	-1.49
1994	-3.50	-2.84	-5.32	1.28	-2.14	-1.85	1.54	3.25	-0.14	2.44	0.36	3.08	-4.21
1995	-3.38	1.96	1.97	1.02	10.67	15.70	15.06	-0.66	13.95	13.27	6.92	12.27	130.13
1996	14.79	11.23	-0.39	6.75	1.13	-4.61	-6.70	3.49	4.04	-2.51	-2.17	2.88	29.08
1997	-1.58	-5.30	-1.29	2.07	-6.59	3.96	4.30	1.55	1.27	-4.04	1.48	18.11	12.48
1998	-6.37	-1.23	2.61	1.08	2.82	5.99	6.66	4.69	-2.01	-8.70	2.15	7.44	14.62
1999	4.23	5.38	2.18	-3.15	-1.98	2.08	4.31	3.05	4.90	5.10	10.95	14.69	64.01
2000	17.74	35.31	-14.39	-12.94	-7.20	14.26	-6.91	13.95	-6.67	-11.76	-17.46	7.67	-2.25
2001	27.18	20.38	15.31	-9.19	2.66	2.06	10.06	10.80	15.36	-14.89	-13.44	-6.27	63.18
2002	7.09	7.99	-3.04	10.13	0.36	2.37	-0.29	2.26	7.76	-8.31	-24.01	6.95	3.87
2003	-5.03	-0.27	2.15	-2.60	-6.62	-2.48	2.28	1.54	-1.31	3.64	1.35	-1.68	-9.18
2004	3.54	-3.68	-2.93	-6.20	1.56	1.20	-4.87	-0.32	4.52	-0.27	1.75	-0.33	-6.44
2005	3.76	4.18	0.45	-0.24	4.01	0.92	2.35	10.64	9.57	7.12	7.02	7.70	74.18
2006	13.28	6.84	10.62	9.54	5.66	7.64	8.25	0.72	0.26	-1.04	-2.60	0.84	77.20
2007	-2.89	0.11	-1.89	-3.23	-1.61	8.25	13.86	3.23	-3.02	15.47	11.00	10.81	59.14
2008	5.93	4.29	1.13	4.85	3.35	5.21	3.48	-1.26	-0.96	2.96	7.14	9.26	55.34
2009	-6.68	0.36	0.10	-17.88	-13.50	-1.18	-2.27	-10.95	-1.61	-2.64	-0.35	6.22	-41.92
2010	3.75	2.89	1.08	0.44	-0.19	-2.57	5.35	-3.18	6.07	-0.73	3.02	0.52	17.21
2011	-2.47	1.17	5.21	0.83	-2.06	-0.53	0.57	-3.07	-5.48	8.30	4.18	1.55	7.66
2012	-2.95	-0.81	1.67	1.51	4.13	0.65	2.11	1.33	0.51	1.66	0.68	-0.83	9.91
2013	-1.59	0.13	2.72	2.78	-0.89	-0.32	0.77	-1.78	0.03	-0.97	1.89	0.74	3.44
2014	-2.46	1.86	-2.14	-2.66	-0.12	2.11	-1.66	1.97	0.40	0.61	-1.69	-2.41	-6.20
2015	-1.23	-0.08	2.54	-5.79	4.63	2.27	7.43	1.28	0.89	1.74	1.41	1.87	17.72
2016	1.39	-3.15	-3.09	-4.90	4.14	0.91	-3.33	-4.38	0.34	2.13	1.11	-0.39	-9.28
2017	0.19	-1.26	-0.38	1.13	-0.55	2.68	1.65	2.20	1.58	2.08	-1.49	0.39	8.41
2018	0.65	3.01	-1.12	1.14	2.04	-0.37	0.61	12.76	8.01	11.23	8.29	11.38	73.31
2019	7.37	8.50	13.01	6.03	19.10	5.53	-5.68	-3.46	-0.22	-3.77	10.02	7.83	81.97
2020	23.53	16.77	31.32	-13.53	3.61	9.35	7.13	-7.57	7.45	-4.69	-5.53	13.33	101.50
2021	41.04	-9.45	-0.91	-2.69	-3.14	9.42	-8.90	1.69	1.40	1.77	1.00	-2.74	22.56
2022	6.88	5.44	5.07	10.33	4.30	-1.99	-5.57	1.88	2.45	3.28	3.48	5.76	48.78
2023	15.09	0.76	4.57	4.17	10.31	6.54	2.85	0.69	0.81	-2.69	14.27	15.39	98.87
2024	6.36	17.26	8.63	-2.32	13.20	3.20	4.34	9.77	5.57	6.88	18.94	12.46	167.25

Distribution of Monthly Returns (%)

Mean: 2.45%
Median: 1.55%
Positive Months: 64.8%

Conclusion

This study demonstrates the effectiveness of a regime-based approach to long-short equity investing. By dynamically adjusting factor exposures based on market regimes identified through term structure dynamics and market concentration metrics, our strategy achieves superior risk-adjusted returns compared to static factor approaches.

Key conclusions from our analysis include:

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.

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.

These findings have important implications for institutional investors and asset managers seeking to enhance portfolio returns through factor investing while maintaining robust risk management. The methodology presented in this paper provides a practical framework for implementing dynamic factor allocation strategies based on changing market conditions.

Limitations and Future Research

While our study presents promising results, several limitations should be acknowledged. First, transaction costs and market impact have not been fully incorporated, which could affect the net returns of the strategy, especially in less liquid market regimes. Second, our regime identification approach relies on ex-post calculation of market concentration metrics, which may introduce some look-ahead bias despite our efforts to use lagged indicators.

Future research could explore several extensions to our approach: - Incorporating additional regime indicators such as volatility regimes or monetary policy regimes - Testing alternative factor definitions and combinations within each regime - Exploring machine learning techniques for regime identification and factor selection - Extending the analysis to international markets and alternative asset classes

References

Bender, J., Briand, R., Melas, D., & Subramanian, R. A. (2013). Foundations of Factor Investing. *MSCI Research Insight*.

Blitz, D., & van Vliet, P. (2008). Global Tactical Cross-Asset Allocation: Applying Value and Momentum Across Asset Classes. *Journal of Portfolio Management*, 35(1), 23-38.

Fama, E. F., & French, K. R. (1993). Common Risk Factors in the Returns on Stocks and Bonds. *Journal of Financial Economics*, 33(1), 3-56.

Harvey, C. R., Liu, Y., & Zhu, H. (2016). ... and the Cross-Section of Expected Returns. *Review of Financial Studies*, 29(1), 5-68.

Hodges, P., Hogan, K., Peterson, J. R., & Ang, A. (2017). Factor Timing with Cross-Sectional and Time-Series Predictors. *Journal of Portfolio Management*, 44(1), 30-43.

Ilmanen, A., Israel, R., Moskowitz, T. J., Thapar, A., & Wang, F. (2021). How Do Factor Premia Vary Over Time? A Century of Evidence. *Journal of Investment Management*, 19(4), 5-37.

Jacobs, B. I., & Levy, K. N. (2014). Smart Beta versus Smart Alpha. *Journal of Portfolio Management*, 40(4), 4-7.

Jegadeesh, N., & Titman, S. (1993). Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency. *Journal of Finance*, 48(1), 65-91.

Keller, W. J., & Van Putten, A. B. (2012). Generalized Momentum and Flexible Asset Allocation (FAA): An Heuristic Approach. *Journal of Asset Management*, 13(6), 385-413.

Pastor, L., & Stambaugh, R. F. (2003). Liquidity Risk and Expected Stock Returns. *Journal of Political Economy*, 111(3), 642-685.