Winners & Losers in Motion: A Market-State Signal that Reverses Roles for Robust Returns (1940-2024)

Arnau Rodon Comas*
Universitat Pompeu Fabra, Barcelona, Spain
University of Essex, Colchester, United Kingdom

We solve momentum's Achilles' heel—catastrophic crashes that have plagued the strategy for decades. Traditional momentum strategies generate Sharpe ratios near zero after transaction costs and suffer drawdowns exceeding 60% during market turmoil. We develop a market state-dependent framework that dynamically switches between momentum during bull markets and contrarian positions during bear markets. Using comprehensive U.S. equity data from 1940-2024 and incorporating realistic transaction costs including historical brokerage commissions and bid-ask spreads, we document remarkable improvements: state-dependent strategies achieve post-cost Sharpe ratios of 0.40-0.50 (versus 0.05-0.10 for traditional momentum), constrain maximum drawdowns to 20-25% (versus 60%+), and generate monthly returns of 50-80 basis points. The strategy successfully navigates every major crash including 1987, 2008, and 2020. Our results are robust across formation and holding periods (3-6-9-12 months), market state definitions (12-24-36 months), and sub-periods. With the recent elimination of retail commissions, net returns have converged to gross returns, suggesting enhanced future viability. Rather than momentum being dead, we show it requires intelligent, state-aware implementation. The findings reconcile behavioral and risk-based theories while offering practitioners a robust solution to momentum's historic fragility.

Keywords: Momentum crashes, Market states, Transaction costs, Conditional strategies, Behavioral finance

Paper Under Review

*Undergraduate Student, Universitat Pompeu Fabra, Exchange Student at University of Essex. Email: rodonarnau@gmail.com. All errors remain my own. Code and data available at: `https://github.com/arnaurodondev/market-state-cross-sectional-momentum`

I. Introduction

The momentum anomaly—the tendency of past winners to outperform past losers—has captivated financial researchers since its formal documentation by Jegadeesh and Titman (1993) [1]. For decades, this simple yet powerful strategy of buying recent winners and selling recent losers generated remarkable returns across diverse markets and time periods, challenging traditional notions of market efficiency. However, recent years have witnessed growing concern about momentum's viability, with several studies documenting declining profitability and spectacular crashes during market turbulence. This paper addresses a fundamental question: has momentum truly lost its efficacy, or does its successful implementation now require more sophisticated, state-aware approaches?

We develop and test market state-dependent momentum strategies that dynamically switch between momentum and contrarian positions based on aggregate market conditions. Our central innovation lies in recognizing that momentum is not a static phenomenon but rather exhibits profound variation across different market environments. During bull markets characterized by positive trailing returns, traditional momentum strategies thrive as investor optimism and trend-following behavior create self-reinforcing price patterns. Conversely, bear markets often witness violent momentum reversals as correlations spike, liquidity evaporates, and previous winners experience catastrophic declines. By conditioning strategy implementation on these market states, we demonstrate that investors can capture momentum's upside while avoiding its periodic disasters.

A. Research Design and Methodology

Our empirical analysis spans 1940 to 2024, encompassing nearly a century of U.S. equity market data and multiple market cycles. We employ a comprehensive approach that examines both gross returns and net returns after realistic transaction costs, addressing a critical gap in the momentum literature that often ignores implementation frictions. The research design proceeds in several stages.

First, we replicate traditional momentum strategies using standard methodology, forming portfolios based on past 3-, 6-, 9- and 12-month returns and also holding for 3-, 6-, 9- and 12-month periods. This replication confirms the well-documented decline in momentum profitability, particularly after accounting for transaction costs. Second, we introduce market state classification based on trailing 12-, 24- and 36-month market returns, categorizing periods as UP or DOWN markets using a symmetric threshold approach. Third, we construct state-dependent strategies that follow momentum during UP markets but switch to contrarian positions during DOWN markets.

To ensure practical relevance, we develop a detailed historical reconstruction of transaction costs from 1926 to 2024, incorporating both brokerage commissions and bid-ask spreads. This analysis reveals a dramatic secular decline in trading costs, from over 200 basis points per round-trip transaction before the 1990s to near near 30 basis points following the 2019-2020 elimination of retail commissions. By applying period-appropriate costs, we assess the economic viability of momentum strategies across different market eras.

B. Preview of Main Results

Our findings fundamentally challenge the narrative of momentum's demise while revealing the critical importance of market state awareness. Traditional momentum strategies indeed show deteriorating performance over recent decades, generating average monthly returns of only 0.10-0.15% after transaction costs during 1993-2024, with catastrophic drawdowns exceeding 60% during the 2008-2009 financial crisis. These results corroborate concerns about momentum's continued viability as a standalone strategy.

However, market state-dependent strategies paint a dramatically different picture. By conditioning on aggregate market states, these adaptive approaches generate average monthly returns of 0.50-0.80% after full transaction costs—a four to eight-fold improvement over traditional momentum. More impressively, maximum drawdowns are constrained to approximately 20-30%, transforming momentum from a crash-prone strategy to a more stable source of returns. Sharpe ratios improve from near zero to 0.40-0.50, representing economically meaningful risk-adjusted performance even after accounting for implementation frictions.

The robustness of these results across multiple specifications strengthens our conclusions. Whether using 3-, 6-, 9- or 12-month formation and holding periods, 12-, 24- or 36-month market state lookbacks, or different sub-periods, the pattern remains consistent: state-dependent implementation dramatically improves momentum's risk-return profile. The strategy successfully navigates major market disruptions including the Black Monday, the dot-com crash, the global financial crisis, and the COVID-19 pandemic.

C. Contributions and Implications

This paper makes several contributions to the momentum literature and broader understanding of market anomalies. First, we provide the most comprehensive analysis to date of momentum strategies incorporating realistic transaction costs across nearly 30 years of data. The detailed reconstruction of historical trading costs enables assessment of strategy viability across different market eras and regulatory regimes.

Second, we demonstrate that momentum's apparent decline reflects not market efficiency eliminating the anomaly but rather the need for evolved implementation approaches. The success of state-dependent strategies suggests that too simple mechanical trading rules become less effective as markets develop, but simple improvements as conditional strategies can restore profitability.

Third, our results contribute to the theoretical debate between behavioral and risk-based explanations for momentum. The state-dependent nature of momentum profits aligns with behavioral models of varying investor confidence while also being consistent with rational frameworks of time-varying risk premia. This convergence suggests that integrated models combining both perspectives may best explain momentum phenomena.

For practitioners, our findings offer actionable insights for portfolio construction. Rather than abandoning momentum following recent poor performance, investors should consider state-aware implementations that adapt to changing market conditions. The documented importance of transaction costs also highlights how recent market structure changes, particularly commission-free trading, may herald a new era for systematic strategies.

D. Reproducibility and Extended Analysis

In the spirit of open science and to facilitate further research, we make our complete analysis publicly available through a comprehensive GitHub repository at `https://github.com/arnaurodondev/market-state-cross-sectional-momentum`. This repository contains all data processing code, strategy implementations, and visualization tools necessary to replicate our results. Researchers can easily modify parameters including formation periods, holding periods, market state definitions, and transaction cost assumptions to test alternative specifications or extend our analysis in new directions.

The modular structure of our code enables investigation of questions beyond those addressed in this paper. Users can explore different market state detection algorithms, test alternative portfolio construction methods, or apply the state-dependent framework to other anomalies. We encourage the research community to build upon this foundation, whether by testing our approach in international markets, incorporating machine learning techniques, or developing theoretical models that explain the documented patterns.

E. Paper Organization

The remainder of this paper proceeds as follows. Section II reviews the relevant literature on momentum strategies, market states, and transaction costs. Section III describes our data sources and the descriptive statistics used in the analysis. Section IV outlines our methodology, including the construction of momentum portfolios and the classification of market states. Section V analyzes the gross performance of both traditional momentum strategies and the proposed market state-dependent approach, without accounting for transaction costs, highlighting return dynamics across different market environments. Section VI incorporates transaction costs into the analysis to evaluate the net profitability of both strategies, emphasizing the impact of realistic trading frictions. Section VII provides a direct comparison between traditional and market state-dependent strategies, evaluating their relative performance in terms of returns, risk-adjusted metrics, and drawdown characteristics. Section VIII explores the economic mechanisms and theoretical underpinnings behind our empirical findings. Section IX concludes with implications for research and practice, and outlines promising directions for future investigation.

Through this comprehensive analysis, we aim to revitalize understanding of momentum phenomena and demonstrate how classical anomalies can maintain relevance through adaptive implementation. In an era of increasing market efficiency and technological advancement, success in active management requires not abandoning time-tested insights but rather implementing them with and contextual awareness.

II. Related Literature

A. Momentum Anomalies and Their Evolution

The momentum anomaly represents one of the most pervasive and economically significant challenges to market efficiency. Jegadeesh and Titman (1993) [1] provided seminal evidence that portfolios of past winners systematically outperform past losers over intermediate horizons of three to twelve months. Their analysis of NYSE and AMEX stocks from 1965 to 1989 demonstrated that zero-cost portfolios—long in the top decile of past performers and short in the bottom decile—generate statistically significant returns averaging 1% per month. This finding directly contradicts the weak-form efficient market hypothesis articulated by Fama (1970) [2], which posits that historical prices contain no information about future returns.

The robustness and pervasiveness of momentum effects have been extensively documented across diverse settings. Moskowitz, Ooi, and Pedersen (2012) [3] extended the momentum paradigm by introducing time-series momentum, demonstrating that an asset's own past returns predict its future performance across equities, currencies, commodities, and bond futures. This finding suggests momentum reflects fundamental aspects of price dynamics rather than equity-specific microstructure effects. Asness, Moskowitz, and Pedersen (2013) [4] provided comprehensive international evidence, documenting momentum profits in equity markets across North America, Europe, and Asia, as well as in currencies and commodities. Their work also revealed the negative correlation between value and momentum strategies, suggesting potential diversification benefits from combining these approaches.

Despite this extensive documentation, recent evidence points to a concerning secular decline in momentum profitability. Hwang and Rubesam (2015) [5] systematically document the weakening of momentum effects since the 1990s, particularly in developed markets. They report that traditional momentum strategies have generated insignificant or negative returns in many markets since 2000, raising fundamental questions about whether increased market efficiency, structural changes, or implementation challenges drive this deterioration. This "disappearance" of momentum has profound implications for both academic understanding of market efficiency and practical investment management.

B. Reversal Anomalies and Long-Term Mean Reversion

Complementing intermediate-term momentum, the literature has identified robust reversal patterns at both short and long horizons. De Bondt and Thaler (1985) [6] documented that portfolios of stocks with the worst performance over the prior three to five years subsequently outperform prior winners by approximately 25% over the following three years. They interpret this pattern as evidence of investor overreaction to information, whereby extreme price movements lead to predictable reversals as prices revert to fundamental values.

Chopra, Lakonishok, and Ritter (1992) [7] refined these findings by demonstrating that reversal effects are most pronounced for smaller stocks and during January, suggesting interactions with other known anomalies. Their work also documented short-term reversals at the one-month horizon, which Jegadeesh (1990) [8] had previously identified. These multiple reversal horizons suggest complex dynamics in price formation that cannot be captured by simple random walk models.

The coexistence of momentum at intermediate horizons and reversals at short and long horizons presents a puzzle for unified theories of price dynamics. This term structure of return predictability implies that similar economic forces may manifest differently across time scales, necessitating theoretical frameworks that can accommodate these seemingly contradictory patterns.

C. Market-State Dependency and Conditional Strategies

A crucial advancement in understanding momentum dynamics came from recognizing their state-dependent nature. Cooper, Gutierrez, and Hameed (2004) [9] demonstrated that momentum profits occur almost exclusively following UP market states, defined as periods when the trailing market return is positive. Following DOWN markets, momentum strategies generate negative returns, with the winner-loser spread actually reversing sign. Their analysis of U.S. data from 1929-1995 shows that the average monthly momentum profit is 0.93% following UP markets but -0.37% following DOWN markets.

Daniel, Hirshleifer, and Subrahmanyam (1998) [10] provide theoretical foundations for state-dependent momentum through a behavioral model incorporating investor overconfidence and biased self-attribution. Their framework predicts that momentum should be strongest when investor confidence is high—typically during bull markets—and weakest or reversed when confidence wanes during bear markets. This psychological mechanism offers compelling explanations for the empirical patterns documented by Cooper, Gutierrez, and Hameed (2004) [9].

Despite these insights, the literature has not fully exploited the implications of state-dependency for practical strategy construction. Most studies document conditional performance without developing complete switching frameworks that actively alternate between momentum and contrarian positions based on market conditions. This gap between theoretical understanding and practical implementation motivates our comprehensive approach to conditional momentum strategies.

D. Transaction Costs and Implementation Challenges

The gulf between theoretical momentum profits and practical implementation has been a persistent concern in the literature. Lesmond, Schill, and Zhou (2004) [11] argue that momentum profits are largely illusory once realistic trading costs are incorporated. They demonstrate that momentum strategies disproportionately select securities with high bid-ask spreads and price impact costs, particularly in the loser portfolio. Their estimates suggest that round-trip trading costs can exceed 5% for extreme momentum portfolios, eliminating most theoretical profits.

Frazzini, Israel, and Moskowitz (2012) [12] provide more nuanced evidence using proprietary trading data from a large institutional investor. While confirming that transaction costs significantly reduce momentum profits, they show that sophisticated implementation—including patient trading, portfolio optimization, and careful security selection—can preserve meaningful net returns. Their work emphasizes that implementation details matter as much as the underlying signal for anomaly-based strategies.

The evolution of market microstructure has dramatically altered the implementation landscape. Jones (2002) [13] documents the secular decline in trading costs over the twentieth century, with explicit brokerage commissions falling from near 100 basis points in the 1970s to under 20 basis points by 2000. Angel, Harris, and Spatt (2015) [14] extend this analysis to the electronic era, showing further compression in both explicit costs and bid-ask spreads. These structural changes fundamentally alter the feasibility of strategies requiring frequent rebalancing, yet much academic research continues to ignore implementation frictions.

E. Risk-Based and Behavioral Explanations

The theoretical interpretation of momentum has evolved from early behavioral models toward more sophisticated frameworks incorporating both psychological biases and rational risk considerations. Hong and Stein (1999) [15] develop a model where gradual information diffusion among heterogeneous investors creates initial underreaction (momentum) followed by eventual overreaction (reversals). Their framework unifies momentum and reversal within a single mechanism of information processing.

From a risk-based perspective, Chordia and Shivakumar (2002) [16] argue that momentum profits represent compensation for systematic risk exposure that varies with business cycle conditions. They show that controlling for macroeconomic variables substantially reduces momentum profitability, suggesting rational risk pricing rather than behavioral biases.

More recent work integrates these perspectives. Daniel and Moskowitz (2016) [17] document "momentum crashes"—periods when momentum strategies experience extreme negative returns, often during market recoveries from major declines. They show these crashes are predictable based on market volatility and past market returns, consistent with momentum strategies embedding significant tail risk. Barroso and Santa-Clara (2015) [18] demonstrate that managing this risk through volatility scaling can substantially improve momentum strategy performance.

F. Positioning of This Study

This study contributes to the momentum literature by developing and rigorously testing a comprehensive conditional strategy framework that addresses key limitations of existing approaches. We extend Cooper, Gutierrez, and Hameed (2004) [9] by implementing complete switching strategies that alternate between momentum and contrarian positions based on market states, rather than merely documenting conditional performance.

Our work bridges the gap between theoretical insights and practical implementation by incorporating realistic transaction costs throughout the analysis. We develop time-varying cost estimates, enabling assessment of strategy viability across different market regimes. This approach addresses criticisms from Lesmond, Schill, and Zhou (2004)

[11] while building on the implementation insights of Frazzini, Israel, and Moskowitz (2012) [12].

Methodologically, we employ robust statistical inference procedures using HAC-corrected standard errors and multiple testing adjustments, addressing concerns raised by Harvey, Liu, and Zhu (2016) [19] about data mining in anomaly research. Our comprehensive sample from 1940-2024 encompasses multiple market cycles and structural regime changes, providing powerful tests of strategy robustness.

Finally, we contribute to theoretical understanding by demonstrating how behavioral and risk-based explanations can be integrated within a unified implementation framework. Our results suggest that market inefficiencies persist but require increasingly sophisticated approaches for successful exploitation, with implications for both academic asset pricing theory and practical investment management.

III. Data and Descriptive Statistics

A. Data Sources and Sample Construction

This study employs comprehensive daily and monthly datasets from the Center for Research in Security Prices (CRSP) version 2, spanning from 1935 to 2024. The CRSP v2 dataset provides significant improvements over standard CRSP data through enhanced data quality controls and comprehensive inclusion of delisted returns, thereby addressing survivorship bias concerns that have plagued previous momentum studies. Our universe encompasses all common stocks (share codes 10 and 11) listed on NYSE, AMEX, and NASDAQ exchanges, ensuring comprehensive market coverage throughout the sample period.

Following the methodology established by Jegadeesh and Titman (1993) [1], we apply standard filters to construct our analysis sample. We restrict the universe to ordinary common shares while excluding American Depositary Receipts (ADRs), Real Estate Investment Trusts (REITs), and specialized securities that may exhibit fundamentally different return dynamics. Our dataset retains all delisted securities and incorporates delisting returns when available, addressing survivorship bias that is particularly problematic for momentum strategies given their potential concentration in distressed securities within loser portfolios.

The analysis employs different sample periods depending on data availability constraints. For gross return analysis without transaction costs, we utilize the complete sample period from 1940 to 2024, maximizing statistical power and capturing long-term momentum patterns across multiple market cycles. However, transaction cost analysis is necessarily constrained to the period from January 1993 to December 2024, as reliable daily bid-ask spread data becomes available only from this date forward. We additionally exclude the months from October 2000 to April 2001 from our transaction cost analysis, as fewer than 30% of universe securities have available daily bid and ask quotes during this period—likely due to data collection issues during the transition to decimal pricing. In contrast, coverage typically ranges between 90% and 95% in other sample months, ensuring robust cost estimation.

B. Transaction Cost Framework

We develop a comprehensive transaction cost framework incorporating both explicit brokerage commissions and implicit bid-ask spread costs. The evolution of these costs over time fundamentally shapes the economic viability of momentum strategies, as illustrated in Figure 1.

For brokerage commissions, we construct a continuous time series of average percentage costs per one-way transaction from 1926 to 2024. This historical reconstruction draws on multiple sources to ensure accuracy across different market regimes. For the period 1926-2000, we utilize the commission rates meticulously documented by Jones (2002) [13], who found average one-way commissions declining from approximately 90 basis points in 1970s to 12 basis points by 2000. This secular decline reflects technological advances, increased competition, and regulatory changes including the abolition of fixed commissions on "May Day" 1975, clearly visible in Figure 1.

For the period 2000-2019, we compile data from multiple industry sources and regulatory filings, documenting continued commission compression with rates declining to 5-6 basis points by 2015-2016. The final phase of this evolution occurs in 2019-2020, when major brokers eliminated retail equity commissions entirely. This dramatic cost reduction has profound implications for the implementability of quantitative strategies that require frequent rebalancing.

Bid-ask spread costs are calculated as half-spreads using end-of-month quotes from the CRSP Daily Stock File v2:

$$\text{Half-Spread}_{i,t} = \frac{\text{Ask}_{i,t} - \text{Bid}_{i,t}}{2 \times \text{Midpoint}_{i,t}} \tag{1}$$

where the midpoint is defined as $(\text{Ask}_{i,t} + \text{Bid}_{i,t})/2$. Figure 2 illustrates the evolution of bid-ask spreads over time using three estimation methods: raw mean, capped mean (95th percentile), and median. The substantial difference between raw and capped means, particularly during crisis periods, highlights the importance of robust estimation procedures that account for outliers and market microstructure noise.

C. Liquidity and Size Constraints

To assess strategy robustness across market segments and examine capacity constraints, we implement both liquidity and size-based filters reflecting realistic implementation considerations raised by Frazzini, Israel, and Moskowitz (2012) [12]. These constraints serve dual purposes: reducing transaction costs and ensuring practical tradability for investors.

Liquidity constraints rank securities by their half-spreads at each portfolio formation date, retaining only the top X% most liquid securities. This ranking occurs independently at each formation date based on contemporaneous market conditions, ensuring no look-ahead bias. Once portfolios are formed, their composition remains fixed throughout the holding period regardless of subsequent liquidity changes, reflecting realistic trading constraints where portfolio managers cannot costlessly adjust positions based on changing market conditions.

Size constraints utilize market capitalization rankings from the previous month, following standard practice in the asset pricing literature.

D. Market State Classification

Following Cooper, Gutierrez, and Hameed (2004) [9], we define market states based on the cumulative return of the CRSP value-weighted index over prior periods. We examine three alternative lookback windows—12, 24, and 36 months—to assess sensitivity to the market state definition:

$$\text{Market State}_t = \begin{cases} \text{UP} & \text{if } \prod_{j=1}^{L}(1 + R_{m,t-j}) - 1 > 0 \\ \text{DOWN} & \text{otherwise} \end{cases} \tag{2}$$

where $L \in \{12, 24, 36\}$ represents the lookback period in months, and $R_{m,t}$ denotes the CRSP value-weighted market return in month t. This classification captures persistent market trends while remaining simple enough for practical implementation.

E. Performance Evaluation Framework

We employ a rolling 20-year window approach for computing performance metrics to reduce the influence of short-term noise while providing continuous perspective on strategy evolution. Each reported metric reflects average performance over a complete 20-year period, with windows advancing monthly throughout the sample. This methodology captures persistent effects of market structure changes and regime shifts while maintaining statistical reliability.

Standard performance metrics include average monthly returns, volatility, HAC-adjusted t-statistics, Sharpe ratios, and maximum drawdowns. Given our zero-cost portfolio design, Sharpe ratios focus purely on risk-return trade-offs without risk-free rate adjustments, calculated as:

$$\text{Sharpe Ratio} = \frac{\bar{R}_p}{\sigma_p} \tag{3}$$

where $\bar{R}_p$ and σ_p represent the mean and standard deviation of portfolio returns, respectively.

Statistical inference employs Heteroskedasticity and Autocorrelation Consistent (HAC) standard errors using Newey-West estimation. The lag selection equals the holding period length plus the market state lookback period minus one (i.e., $K + L - 1$), addressing serial correlation arising from overlapping portfolio structures and market state persistence. This conservative approach ensures robust inference in the presence of complex dependence structures inherent in momentum strategies.

IV. Methodology

A. Momentum Strategy Construction and Market-State Switching

Following the seminal methodology of Jegadeesh and Titman (1993) [1], we construct momentum portfolios using a standard J-month formation and K-month holding period framework. At each month-end t, eligible securities are ranked based on cumulative returns over months $t - J$ to t. Securities are sorted into deciles, with the top decile designated as winners (W) and the bottom decile as losers (L).

The return of the traditional momentum strategy in month t is:

$$R_{MOM,t} = \frac{1}{K} \sum_{k=1}^{K} (R_{W,t-k+1,t} - R_{L,t-k+1,t}) \tag{4}$$

where $R_{W,t-k+1,t}$ and $R_{L,t-k+1,t}$ represent returns of winner and loser portfolios formed in month $t - k + 1$ and held through month t. This overlapping structure ensures K cohorts contribute equally to strategy performance at any given time. In our analysis, we assume trading occurs on the last trading day of each month, utilizing bid-ask quotes from that day to ensure realistic transaction cost estimation.

Building on Cooper, Gutierrez, and Hameed (2004) [9], we implement a market-state dependent switching mechanism that dynamically alternates between momentum and contrarian strategies. The market state in month t depends on the cumulative market return over a lookback period L:

$$MS_t = \begin{cases} UP & \text{if } \prod_{j=1}^{L} (1 + R_{m,t-j}) - 1 > 0 \\ DOWN & \text{otherwise} \end{cases} \tag{5}$$

During UP states, we implement traditional momentum (long winners, short losers); during DOWN states, we implement contrarian reversal (long losers, short winners).

We incorporate sophisticated portfolio management logic to handle market state transitions during holding periods. When a portfolio formed under one market state experiences a regime switch while positions remain open, three alternatives exist: (1) maintain existing positions, (2) close positions entirely, or (3) reverse positions. For instance, a portfolio initiated with long winners and short losers during an UP state may face a transition to a DOWN state before the holding period expires. Our framework allows closing these positions or converting them to short winners and long losers, with appropriate transaction costs applied for both closing existing positions and opening reversed positions.

The market-state dependent strategy return incorporating early closure logic is:

$$R_{MS,t} = \frac{1}{K} \sum_{k=1}^{K} \alpha_{t-k+1,t} \cdot R_{t-k+1,t} \tag{6}$$

where $\alpha_{t-k+1,t}$ represents the position indicator accounting for potential early closures or reversals due to state transitions. In this analysis, we implement the early closure approach when market states switch, though unreported results confirm that maintaining positions or implementing reversals yields qualitatively similar outcomes across all scenarios. Complete implementation details and alternative specifications are available in the GitHub repository.

Unless otherwise stated, our baseline analysis uses a 24-month lookback window to define market states. This choice is grounded in both theoretical and empirical considerations. Cooper, Gutierrez, and Hameed (2004) [9] demonstrated that momentum profitability is sensitive to the horizon used for market-state classification—shorter windows capture transient trends, while longer windows reflect structural economic cycles. Over the 1940–2023 sample, a 12-month lookback produces 77 market state changes, suggesting excessive responsiveness to short-term noise. In contrast, a 36-month lookback yields only 18 state changes, indicating a sluggish response that may miss timely market shifts. The 24-month window strikes a balance between reactivity and smoothness, generating 47 market state transitions—enough to capture intermediate-term dynamics without being overwhelmed by noise. This balance enhances the adaptive switching mechanism of the strategy. Robustness checks using alternative lookback periods (12 and 36 months) confirm that the strategy's performance remains qualitatively stable across specifications.

B. Statistical Inference and Transaction Cost Implementation

The overlapping portfolio structure and market state persistence induce serial correlation in strategy returns, potentially biasing standard statistical tests. Following Newey and West (1987), we employ Heteroskedasticity and Autocorrelation Consistent (HAC) standard errors with lag selection equal to $K + L - 1$, where K represents the holding period and L the market state lookback period. This specification accounts for both sources of temporal dependence: overlapping portfolio returns and autocorrelation in market state classifications.

The HAC-corrected t-statistic for testing zero average returns is:

$$t_{HAC} = \frac{\bar{R}}{\sqrt{\hat{\Omega}/T}} \tag{7}$$

where $\bar{R}$ is the sample mean return, T is the number of observations, and $\hat{\Omega}$ is the HAC-consistent long-run variance estimator. This correction ensures statistical inferences properly account for temporal dependence inherent in our strategy construction.

Our comprehensive transaction cost framework incorporates both explicit commissions and implicit bid-ask spreads, building on the implementation cost analysis of Frazzini, Israel, and Moskowitz (2012) [12]. We apply time-varying commission rates c_t based on historical data from Jones (2002) [13] and contemporary industry sources documented by Angel, Harris, and Spatt (2015) [14]. Market impact costs utilize half-spreads calculated as:

$$\text{Half-Spread}_{i,t} = \frac{\text{Ask}_{i,t} - \text{Bid}_{i,t}}{2 \times \text{Midpoint}_{i,t}} \tag{8}$$

for each security i at time t.

Transaction costs are applied comprehensively across all trading activities. At portfolio formation and liquidation, we apply commission rates and half-spreads to the entire portfolio value. Additionally, monthly rebalancing costs are calculated at the individual security level to maintain equal-weighted portfolios with 50% long and 50% short exposure. The rebalancing percentage for each asset is computed as:

$$\text{Rebalance}_{i,t} = \text{Target Weight}_{i,t} - \text{Current Weight}_{i,t} \tag{9}$$

where target weights ensure equal allocation across all positions within long and short legs. We trade the required percentage to restore target allocations, incurring transaction costs proportional to the rebalancing magnitude. This framework captures costs as percentages of traded value, making them theoretically independent of trading volume, though we acknowledge that large-scale implementations would face additional market impact costs not captured in our analysis.

C. Liquidity and Size Constraints

To address implementability concerns raised by Lesmond, Schill, and Zhou (2004) [11], we implement comprehensive liquidity and size constraints. Liquidity constraints rank securities by half-spread on portfolio formation dates (last trading day of each month), retaining only the top X% most liquid securities. This approach eliminates securities with prohibitive transaction costs while maintaining sufficient breadth for anomaly exploitation.

Importantly, portfolio composition remains fixed throughout the holding period regardless of subsequent liquidity changes. Securities may migrate outside the liquidity threshold during the holding period, but we maintain positions to avoid look-ahead bias and reflect realistic portfolio management constraints. This methodology ensures that backtested results accurately represent achievable implementation strategies.

Market capitalization constraints follow similar logic, ranking securities by market value and selecting the top Y% largest firms. These constraints are applied sequentially: first filtering by size or liquidity, then constructing momentum portfolios within the constrained universe. This nested approach mirrors institutional investment processes where universe definition precedes strategy implementation.

D. Robustness Testing Framework

Our comprehensive robustness analysis encompasses multiple dimensions to ensure finding stability and practical relevance:

Parameter Sensitivity: We examine 16 formation-holding period combinations (3, 6, 9, 12 months each) across three market state definitions (12-, 24-, 36-month lookbacks), yielding 48 distinct specifications. Performance is evaluated across both the full sample (1940–2024) and restricted sample (1993–2024) to assess temporal stability.

Market State Definitions: In this study, we use the *value-weighted market index* to define market states, as it is the academically accepted benchmark and aligns with prior literature. Accordingly, all reported results are based on value-weighted index returns over the designated lookback horizons. However, we also replicate the analysis using the *equal-weighted index* as an alternative state signal. Interestingly, results under this specification are slightly stronger, suggesting that equal-weighted returns may better capture the broader market environment by incorporating performance from smaller-cap stocks.

Constraint Analysis: Grid searches across liquidity thresholds (20%-100% in 5% increments) and size constraints (30%-100% in 10% increments) identify optimal implementation parameters. This analysis reveals the trade-off between universe restriction and strategy performance.

Rolling Window Analysis: Twenty-year rolling windows provide dynamic perspective on strategy evolution, capturing regime changes and structural breaks while maintaining sufficient observations for reliable inference within each window.

Multiple Testing Corrections: Given the extensive parameter search, we implement Bonferroni corrections following Harvey, Liu, and Zhu (2016) [19] to ensure reported significance levels appropriately account for data mining concerns.

This methodology integrates theoretical insights from behavioral finance and risk-based asset pricing with practical implementation considerations, ensuring our findings provide actionable guidance for both academic researchers and investment practitioners.

V. Empirical Results: Gross Strategy Performance

A. Traditional Momentum Strategy Performance and Decline

We begin our empirical analysis by replicating traditional momentum strategies to establish baseline performance and validate our methodology. Figure 3 presents cumulative log returns of the traditional momentum strategy over our full 1940-2024 sample period, with market state periods clearly delineated. Our results confirm the seminal findings of Jegadeesh and Titman (1993) [1] for their original 1965-1989 sample period, during which momentum strategies generated substantial positive returns with consistent upward trajectory.

However, extending analysis beyond their sample period reveals pronounced temporal variation with significant implications for both theory and practice. The most striking feature is the dramatic decline in momentum profitability beginning around 2000, aligning with the “disappearance” documented by Hwang and Rubesam (2015) [5]. Figure 4 illustrates how from 1940 to 2000 the strategy witnessed only five years of severe losses, while the subsequent 25 years have experienced an equivalent number of catastrophic drawdowns, fundamentally altering the risk-return profile of traditional momentum strategies. The strategy experiences particularly severe losses during the 2000-2002 dot-com crash and 2008-2009 financial crisis, followed by extended poor performance through the subsequent decade.

The market state overlay in Figure 3 reveals that severe losses occur predominantly during bear market periods, providing initial evidence for conditional momentum profitability that motivates our state-dependent approach. This pattern aligns with theoretical predictions from Daniel, Hirshleifer, and Subrahmanyam (1998) [10] regarding state-dependent investor overconfidence effects.

Figure 6 illustrates the secular decline through 20-year rolling averages, showing momentum profitability peaks at approximately 1.5% monthly during the 1990s before declining to near-zero levels by 2010. This deterioration accompanies corresponding statistical significance losses, as demonstrated in Figure 5, where t-statistics fall below 5% significance thresholds around 2005 and remain largely insignificant thereafter. The risk-adjusted performance evolution in 7 shows Sharpe ratios declining from peaks above 1.0 in the 1970s to negative values during the 2010s, highlighting the strategy's increasing unsuitability for institutional implementation .

B. Market-State Dependent Strategy: Superior Performance and Stability

In stark contrast to deteriorating traditional momentum performance, our market-state dependent approach demonstrates remarkably stable and superior results throughout the sample period. Figure 8 shows cumulative log returns of the conditional strategy, exhibiting consistent upward trajectory without severe drawdowns characterizing traditional approaches.

The conditional strategy's performance excels particularly when traditional momentum struggles. Rather than experiencing catastrophic losses during bear markets, our approach adapts by switching to contrarian reversal positions, effectively capitalizing on mean-reversion during market stress periods. This adaptive mechanism produces smoother return paths and eliminates major drawdowns during the 2000–2002 and 2008–2009 crisis periods, validating the theoretical framework of Cooper, Gutierrez, and Hameed (2004) [9].

Figure 9 demonstrates improved distributional characteristics, with fewer extreme negative returns and more consistent positive performance across market environments. The reduced frequency of large negative returns substantially improves risk profiles while maintaining strong upside potential.

Superior risk-adjusted performance appears in Figure 10, where HAC-adjusted t-statistics remain consistently above 5% significance thresholds throughout most periods, frequently exceeding 1% significance levels. This statistical stability contrasts markedly with deteriorating traditional momentum significance in recent decades. Figure 11 shows 20-year rolling average returns consistently exceeding 1% monthly across the entire sample period, with 95% confidence intervals remaining predominantly positive, indicating robust performance even during shorter sub-periods. Figure 12 illustrates the rolling 20-year Sharpe ratio of the market-state dependent strategy, which remains consistently elevated—often exceeding 1.0—demonstrating strong and stable risk-adjusted performance over time. This underscores the strategy's ability to deliver high returns without proportionate increases in volatility, even in challenging market regimes.

C. Comprehensive Parameter Robustness Analysis

To demonstrate our conditional approach's fundamental robustness, we conduct systematic sensitivity analysis across diverse parameter combinations. Figure 13 presents examination across 16 formation-holding period combinations (3, 6, 9, 12 months each) and three market state definitions (12-, 24-, 36-month lookbacks), encompassing 48 total specifications.

Results provide compelling robustness evidence across parameter specifications. All 48 combinations generate positive average monthly returns ranging from 0.43% to 1.42%, contrasting sharply with traditional momentum's frequent negative returns in recent decades. This universal positive performance suggests our approach captures fundamental market features rather than parameter-dependent statistical artifacts.

The 24-month market state specification demonstrates superior performance across most formation-holding combinations, generating highest returns while maintaining statistical robustness. Strongest performance occurs for shorter formation periods (3-9 months) combined with shorter holding periods (3-6 months), extending Jegadeesh and Titman (1993) [1] insights to conditional strategies while providing protection during traditional momentum failure periods.

Figure 14 reinforces findings from statistical significance perspectives. The overwhelming majority of combinations achieve t-statistics above 2.0, indicating 5% significance or better. To address multiple testing concerns, we apply the Bonferroni correction methodology from Harvey, Liu, and Zhu (2016) [19], determining the effective number of independent tests such that they accumulate 99% of total variance (K=10 out of 48 combinations). This yields a Bonferroni critical value of 2.81 at 95% confidence, which 48 out of 48 strategies achieve, proving robust statistical significance of the conditional approach.

D. Portfolio Granularity and Implementation Optimization

While traditional momentum studies, including Jegadeesh and Titman (1993) [1], classify assets into 10 deciles, we examine the impact of portfolio granularity on strategy performance. Figure 17 presents comprehensive analysis varying the number of momentum groups from 4 to 36.

Our results reveal that average monthly returns increase at a logarithmic rate as portfolio granularity increases (becoming more selective in extreme momentum positions). However, volatility increases linearly with the number of groups, leading to deteriorating t-statistics, risk-adjusted returns, and increased downside risk for highly granular portfolios. As shown in Figure 18, optimal performance metrics are achieved with approximately 10 groups—precisely the specification employed in the original momentum literature—suggesting this choice reflects an optimal balance between return enhancement and risk management rather than arbitrary convention.

The analysis demonstrates that while finer portfolio granularity can marginally increase gross returns through more precise momentum sorting, the accompanying increase in portfolio concentration and reduced diversification benefits ultimately deteriorates risk-adjusted performance.

VI. Empirical Results: Net Performance under Transaction Cost Framework

A. Transaction Cost Environment and Sample Period Constraints

The implementation of momentum strategies in practice necessitates careful consideration of transaction costs, which can substantially erode theoretical returns. Our comprehensive transaction cost framework incorporates multiple parameters to assess the viability of the market-state dependent strategy under realistic trading conditions. The primary parameter is the liquidity cutoff, which selects the top x% of assets with the lowest bid-ask spreads at the time of position initiation, thereby excluding securities with prohibitively high transaction costs from portfolio formation.

We examine liquidity cutoff values ranging from 100% (retaining all assets) to 20% (retaining only the most liquid quintile) in 5% increments to evaluate the parameter's impact on net performance. Following the gross return analysis, we employ a 9-month formation period but extend the holding period to 6 months, as this configuration provides enhanced stability through reduced monthly transaction costs. The extended holding period is particularly advantageous in the presence of transaction costs, as it minimizes portfolio turnover while maintaining exposure to the momentum effect documented by Jegadeesh and Titman (1993) [1].

B. Liquidity Constraints and Implementation Optimization

Figure 19 presents the cumulative log returns of the market-state dependent strategy across varying liquidity constraints. When no liquidity filter is applied (100% inclusion), the impact of bid-ask spreads on position initiation and monthly rebalancing substantially reduces net returns. Conversely, excessively restrictive cutoffs (e.g., 20%) diminish returns by constraining the investment universe based solely on liquidity considerations, potentially excluding securities with strong momentum characteristics.

The performance metrics across liquidity constraints, illustrated in Figure 20, reveal a nuanced relationship between liquidity filtering and risk-adjusted returns. Panel (a) demonstrates that average monthly returns exhibit an inverted U-shape pattern, peaking at approximately 80% liquidity cutoff before declining with more stringent constraints. This non-monotonic relationship suggests an optimal balance between transaction cost mitigation and universe breadth.

Notably, the Sharpe ratio remains remarkably stable across different cutoff values, as shown in Panel (b). This stability arises from the proportional decrease in both portfolio returns and volatility as liquidity constraints tighten, evidenced in Panel (d). The HAC-adjusted t-statistics, computed with $(L + K - 1)$ lags where L represents the market-state formation period and K the holding period, maintain statistical significance across most specifications, confirming the strategy's robustness to liquidity-based implementation constraints.

C. Comparative Transaction Cost Impact and Strategy Resilience

To comprehensively assess implementation viability, we conduct a two-dimensional analysis incorporating both liquidity and market capitalization constraints. Figure 21 presents a grid search across combinations of liquidity cutoffs (30% to 100%) and market capitalization cutoffs (30% to 100%), maintaining the 9-month formation and 6-month holding configuration.

All parameter combinations yield positive average monthly returns, ranging from 0.40% to 0.75%, demonstrating the strategy's resilience to implementation constraints. Less restrictive cutoffs generate higher absolute returns but correspondingly higher volatility, maintaining relatively constant Sharpe ratios across the parameter space. This finding echoes the liquidity-only analysis and suggests that the risk-return tradeoff remains favorable even under stringent implementation constraints.

The t-statistics in Panel (c) confirm statistical significance across nearly all combinations, with values consistently exceeding the 5% significance threshold. The maintenance of statistical significance under transaction costs provides strong evidence for the economic viability of the conditional momentum strategy, addressing concerns raised by Lesmond, Schill, and Zhou (2004) [11] regarding the illusory nature of momentum profits after implementation costs.

Importantly, the strategy's resilience under these conditions highlights its potential for real-world application using only the most liquid and investable segments of the market. By restricting implementation to high-volume, large-cap assets with low bid-ask spreads, practitioners can still capture meaningful abnormal returns while minimizing slippage and execution costs. This enhances the practical relevance of the approach for institutional investors operating under realistic trading constraints.

D. Statistical and Economic Significance under Implementation Constraints

Following the gross return analysis, we examine portfolio granularity effects under transaction costs using 80% cutoffs for both liquidity and market capitalization constraints. These moderately restrictive filters eliminate assets with excessive bid-ask spreads while excluding penny stocks that exhibit higher price fluctuations and pose execution challenges in realistic trading environments.

Figure 22 demonstrates that stable risk-adjusted returns emerge with 10 to 15 momentum groups, consistent with the gross return findings. However, downside risk increases monotonically with portfolio granularity, as shown in Figure 23, reflecting the reduced diversification inherent in more concentrated portfolios. The optimal configuration balances momentum signal strength against diversification benefits, with the traditional decile approach proving remarkably robust.

E. Implementation Implications and Practitioner Guidelines

The comprehensive parameter grid analysis, presented in Figures 24 through 26, evaluates various formation-holding period combinations under 80% liquidity and market capitalization constraints using 12 momentum groups. Consistent with established practice, we apply HAC standard errors and conduct Bonferroni correction analysis at 95% confidence. The eigenvalue decomposition reveals that 12 factors explain 99% of return variance, yielding a Bonferroni critical value of 2.87.

Remarkably, the strategy maintains statistical significance after accounting for brokerage commissions, bid-ask spreads on position initiation and liquidation, and monthly rebalancing costs. Figure 25 shows that 85% of parameter combinations exceed the Bonferroni-adjusted significance threshold, with the 24-month market state specification demonstrating superior performance across most formation-holding configurations.

These results provide compelling evidence that the market-state dependent momentum strategy remains economically viable under realistic implementation constraints. The robustness to transaction costs, combined with the strategy's adaptive nature, offers institutional investors a practical framework for capturing momentum and reversal effects while managing implementation challenges. The findings directly address the critique that momentum profits disappear after accounting for trading costs, demonstrating that conditional strategies can preserve economic significance through reduced turnover and enhanced timing of regime switches.

VII. Comparative Analysis of Traditional and Market State-Dependent Strategies

A. Strategy Performance Overview

This section presents a comparative analysis of traditional momentum strategies and market state-dependent approaches across a subset of parameter configurations over the period 1993–2024. We evaluate four representative setups that vary in formation periods (6 and 9 months), holding period (6 months), and market state lookback windows (12 and 24 months). Each configuration is assessed both with and without transaction costs to illustrate the impact of implementation frictions on performance. While these specifications are selected to provide a clear and concise view of cost sensitivity, any other combination of parameters can be tested using the code and data available in the accompanying GitHub repository. This selection is intended as a practical illustration.

Figure 28 illustrates the cumulative log returns for strategies employing a 9-month formation period, 6-month holding period, and 24-month market state lookback window. The comparison reveals stark differences in risk-adjusted performance between traditional and state-dependent approaches. Traditional momentum strategies, represented by the light gray line (without costs) and dark gray line (with costs), exhibit strong performance during extended bull markets but suffer catastrophic drawdowns during market reversals. Most notably, the strategy experiences severe losses during the 2001 technology crash, the 2008-2009 financial crisis, and the 2020 COVID-19 market disruption.

In contrast, the market state-dependent strategy, shown in black, demonstrates remarkable resilience during these turbulent periods. By switching from momentum to contrarian positions following DOWN market states (indicated by dark shaded regions), the strategy successfully avoids—and often profits from—the momentum crashes that plague traditional approaches. The visual evidence strongly supports the theoretical framework suggesting that momentum profits are fundamentally state-dependent phenomena.

B. Impact of Market State Lookback Period

Figure 29 presents results using a shorter 12-month market state lookback window while maintaining the 9-month formation and 6-month holding periods. The reduced lookback period leads to more frequent state transitions, as evidenced by the increased number of shaded regions representing market state changes. Despite these more frequent switches, the state-dependent strategy continues to outperform traditional momentum, suggesting robustness to the specific market state definition.

The performance patterns remain qualitatively similar to those observed with the 24-month lookback, with the state-dependent strategy avoiding major drawdowns while capturing upside during favorable momentum regimes. However, the shorter lookback period results in slightly higher turnover due to more frequent state changes, marginally increasing transaction costs but not eliminating the strategy's advantage.

C. Sensitivity to Formation Period Length

Figures 30 and 31 examine strategies using 6-month formation periods paired with 6-month holding periods, representing the classic "6-6" momentum configuration widely studied in the academic literature. These specifications test whether the benefits of state-dependent implementation persist across different momentum definitions.

The results demonstrate remarkable consistency with the 9-6 specifications. Traditional momentum strategies continue to exhibit vulnerability to market reversals, while state-dependent approaches maintain their defensive characteristics. The 6-6 configuration shows slightly lower gross returns compared to the 9-6 specification, consistent with prior literature documenting that intermediate formation periods (9-12 months) often generate stronger momentum effects. Nevertheless, the relative advantage of state-dependent strategies remains pronounced.

D. Transaction Cost Analysis

A critical finding across all specifications is the substantial but manageable impact of transaction costs on strategy performance. The analysis incorporates comprehensive cost estimates including both brokerage commissions and bid-ask spreads, as detailed in Section III. Across all parameter combinations, transaction costs reduce average monthly returns by approximately 50-80 basis points, representing a significant performance drag that cannot be ignored in practical implementation.

For traditional momentum strategies, these costs prove particularly burdensome during market transitions when portfolios require wholesale restructuring. The summary statistics in Figure 28 indicate that traditional momentum generates average monthly returns of 0.44% without costs but only 0.10% after costs—a reduction of 77%. This dramatic cost impact aligns with the findings of Lesmond, Schill, and Zhou (2004) [11] regarding the fragility of momentum profits to implementation frictions.

State-dependent strategies, while also affected by transaction costs, maintain economically significant returns. The 9-6-24 specification generates average monthly returns of 1.41% before costs and 0.65% after costs—a reduction of 54%. The lower proportional cost impact reflects the strategy's ability to maintain positions during favorable regimes while switching only when market states change, reducing unnecessary turnover.

E. Risk-Adjusted Performance Metrics

Beyond raw returns, the risk characteristics of state-dependent strategies prove substantially superior to traditional approaches. Maximum drawdowns for traditional momentum strategies exceed 60% during the 2008-2009 financial crisis across all specifications, while state-dependent strategies limit maximum drawdowns to approximately 20-30%. This dramatic risk reduction occurs without sacrificing long-term returns, resulting in substantially improved Sharpe ratios.

The cost impact differential between strategies also manifests in risk-adjusted terms. Traditional momentum strategies see their Sharpe ratios decline from approximately 0.30-0.35 before costs to 0.05-0.10 after costs, rendering them marginally attractive at best. State-dependent strategies maintain Sharpe ratios of 0.40-0.50 even after full transaction costs, representing economically meaningful risk-adjusted returns.

F. Temporal Stability and Recent Performance

An encouraging aspect of the results is the continued effectiveness of state-dependent strategies in recent years, particularly following the elimination of retail brokerage commissions in 2019-2020. The rightmost portions of all figures show strong performance acceleration as transaction costs approach zero, suggesting that structural market changes have enhanced rather than diminished the viability of systematic momentum strategies.

The strategies also demonstrate resilience during the 2020 COVID-19 crisis, a period that proved particularly challenging for traditional momentum approaches. The rapid market decline in March 2020 followed by an equally rapid recovery created a classic momentum crash scenario. State-dependent strategies successfully navigated this period by maintaining contrarian positions during the DOWN state and quickly reverting to momentum as market conditions improved.

G. Implementation Considerations

The consistent outperformance of state-dependent strategies across various parameter specifications suggests that the core insight—momentum's fundamental dependence on market states—is robust to implementation details. Whether using different parameter combinations, the pattern remains clear: conditioning momentum exposure on aggregate market conditions substantially improves risk-adjusted returns while reducing vulnerability to momentum crashes.

The analysis also reveals that transaction costs, while significant, do not eliminate the economic viability of well-designed momentum strategies. The secular decline in trading costs documented in Section III has progressively improved net returns, with the recent elimination of retail commissions marking a potential regime change for systematic strategy implementation. Even during periods of higher costs, state-dependent approaches generated positive risk-adjusted returns, suggesting historical viability despite implementation frictions.

These findings have important implications for both academic understanding and practical investment management. They suggest that the "death of momentum" proclaimed by some researchers may be premature, with the apparent decline in traditional momentum profits reflecting not market efficiency but rather the need for more sophisticated, state-aware implementation approaches.

VIII. Economic Mechanisms and Theoretical Foundation

A. Behavioral Foundations of State-Dependent Momentum

The superior performance of market state-dependent momentum strategies documented in this study requires theoretical grounding to distinguish genuine economic phenomena from statistical artifacts. The behavioral finance literature provides compelling explanations for why momentum effects should vary systematically with aggregate market conditions, rooted in fundamental aspects of investor psychology and information processing.

Daniel, Hirshleifer, and Subrahmanyam (1998) [10] develop a model where investor overconfidence and biased self-attribution generate momentum in security prices. Their framework predicts that momentum should be strongest when investor confidence is high—typically during bull markets characterized by positive past returns. During such periods, investors attribute success to their own skill, becoming increasingly overconfident and pushing prices further from fundamental values. This overreaction creates predictable continuation patterns as confidence-driven mispricing persists before eventual correction.

Conversely, bear markets puncture investor overconfidence, leading to more conservative behavior and reduced momentum effects. The model predicts that following market declines, investors become more attentive to fundamental information and less prone to extrapolating past trends. This psychological shift can reverse the typical momentum pattern, as previously overvalued winners experience sharp corrections while oversold losers benefit from mean reversion—precisely the pattern our empirical results document.

Hong and Stein (1999) [15] provide complementary insights through their model of gradual information diffusion. They argue that momentum arises from the slow incorporation of firm-specific information across heterogeneous investor groups. During favorable market conditions, positive information diffuses gradually, creating underreaction and subsequent momentum. However, their framework also predicts that during market stress, the arrival of negative systematic information can overwhelm firm-specific signals, causing coordinated selling that disrupts normal momentum patterns.

B. Risk-Based Explanations and Time-Varying Risk Premia

While behavioral models provide intuitive explanations, risk-based theories offer alternative interpretations grounded in rational asset pricing. These frameworks suggest that momentum profits represent compensation for bearing systematic risks that vary with market conditions.

Johnson (2002) [20] demonstrates that momentum can arise rationally when expected growth rates are persistent and priced. In his model, winner stocks have persistently higher expected growth rates, justifying their continued outperformance. Crucially, the model predicts that this relationship breaks down during market downturns when growth expectations are revised downward across the board, eliminating the cross-sectional dispersion that drives momentum profits.

Stivers and Sun (2010) [21] provide empirical support for time-varying risk explanations by documenting that momentum profits are significantly lower during periods of high cross-sectional return dispersion—often coinciding with bear markets. They argue that increased dispersion reflects higher systematic risk and uncertainty, leading investors to demand higher returns for holding any risky assets rather than betting on relative performance. This "flight to quality" during turbulent periods naturally disrupts momentum strategies that rely on stable relative performance rankings.

Chordia and Shivakumar (2002) [16] argue that momentum profits arise from systematic variations in expected returns related to business cycle variables. Their evidence suggests that controlling for macroeconomic risk factors substantially reduces momentum profitability, implying that apparent momentum may simply reflect omitted risk factors. Our state-dependent approach can be interpreted as a practical implementation of their insight, using market states as a parsimonious proxy for complex macroeconomic conditions.

C. Market Microstructure and Limits to Arbitrage

The persistence of momentum effects despite widespread knowledge suggests important limits to arbitrage that prevent immediate price correction. Our analysis incorporates explicit transaction costs through brokerage commissions and bid-ask spreads, but several additional implementation frictions merit discussion.

Market impact costs, not captured in our framework, represent a potentially significant additional burden for momentum strategies. Winners often exhibit positive price pressure from momentum traders, while losers face selling pressure, creating adverse price impact for strategies attempting to establish positions. Korajczyk and Sadka (2004) [22] estimate that price impact costs can consume a portion of momentum profits, particularly for larger fund sizes. These costs likely vary with market states, potentially being highest during volatile DOWN markets when liquidity provision is most costly.

Short-sale constraints present another implementation challenge not fully captured in our analysis. During market downturns, short-selling often becomes more difficult and expensive due to increased borrow costs, reduced share availability, and regulatory restrictions. D'Avolio (2002) [23] documents that short-selling costs rise dramatically for stocks with high disagreement and during volatile markets—precisely when our state-dependent strategy would attempt to short previous winners. These constraints could limit the practical implementation of contrarian positions during DOWN states, though they would affect traditional momentum strategies equally.

The assumption of equal capital allocation to long and short positions also warrants scrutiny. In practice, margin requirements, risk management constraints, and prime broker limitations often prevent perfect symmetric implementation. Futures-based implementations might partially address these concerns but introduce basis risk and roll costs not considered in our equity-based analysis.

D. Information Theory and Adaptive Markets

Lo's (2004) [24] Adaptive Markets Hypothesis provides a unifying framework for understanding the time-varying nature of momentum profits. This perspective views financial markets as evolutionary systems where strategies compete for profits, with successful approaches attracting capital until profitability erodes. The decline in traditional momentum profits documented by Hwang and Rubesam (2015) [5] fits this narrative—as momentum became widely known and implemented, its effectiveness diminished.

Our state-dependent approach represents an evolutionary adaptation to this changed environment. By incorporating market state information, the strategy adds a layer of complexity that may restore profitability even as simple momentum fails. This interpretation suggests an ongoing arms race between increasingly sophisticated strategies and market efficiency, with conditional approaches representing the current frontier.

The information-theoretic perspective also explains why market states provide valuable conditioning information. Aggregate market movements contain information about systematic factors, risk aversion, and investor sentiment that individual stock returns cannot capture. By conditioning on this macro-information, state-dependent strategies effectively increase their information ratio relative to simple momentum approaches.

E. Reconciling Behavioral and Rational Explanations

The behavioral and risk-based explanations for state-dependent momentum need not be mutually exclusive. Indeed, the most compelling theoretical frameworks incorporate elements of both perspectives. Investors may exhibit behavioral biases that create momentum patterns, while simultaneously demanding rational risk compensation that varies with market conditions.

Vayanos and Woolley (2013) [25] develop a unified model where institutional frictions interact with investor behavior to generate both momentum and reversals. In their framework, fund flows create price pressure that generates momentum in the short run but reversals in the long run. Crucially, these effects are amplified during periods of high volatility and poor market performance—consistent with our empirical findings of state-dependent momentum profits.

The practical success of state-dependent strategies suggests that whether driven by behavioral biases, risk compensation, or institutional frictions, the underlying economic mechanisms are sufficiently persistent to support profitable trading strategies. The key insight is that momentum represents a conditional phenomenon requiring dynamic implementation rather than a static anomaly that can be arbitraged away through simple mechanical trading.

F. Limitations and Future Theoretical Development

While our empirical results strongly support state-dependent momentum implementation, several theoretical questions remain unresolved. First, the optimal conditioning variables for momentum strategies remain an open question. Market states based on past returns represent a simple and intuitive approach, but other macroeconomic or sentiment indicators might provide superior conditioning information.

Second, the welfare implications of momentum trading deserve further consideration. If momentum profits represent risk compensation, then momentum traders provide valuable liquidity and risk-bearing services. However, if profits arise from behavioral biases, momentum trading may reduce market efficiency by amplifying price deviations from fundamental values. The state-dependent nature of the phenomenon complicates welfare analysis, as the strategy's impact may vary with market conditions.

Finally, the interaction between momentum strategies and other known anomalies in a state-dependent context warrants investigation. Value, quality, and low-volatility strategies may exhibit their own state dependencies that could be exploited in integrated multi-factor frameworks. Understanding these interactions could lead to more robust and efficient portfolio construction methodologies.

The theoretical foundations explored in this section suggest that state-dependent momentum strategies exploit genuine economic phenomena rather than statistical flukes. Whether interpreted through behavioral or risk-based lenses, the evidence points to fundamental variation in momentum profits across market states that sophisticated investors can potentially exploit. As markets continue to evolve, theoretical understanding must likewise adapt to explain new empirical patterns and guide practical implementation.

IX. Conclusion

This study provides comprehensive evidence that the apparent decline of momentum profitability reflects not the elimination of market inefficiencies but rather the need for more sophisticated, state-aware implementation approaches. By developing and testing market state-dependent momentum strategies across nearly a century of data, we demonstrate that conditioning momentum exposure on aggregate market conditions dramatically improves risk-adjusted returns while mitigating vulnerability to momentum crashes.

A. Summary of Key Findings

Our analysis yields several crucial insights for understanding momentum phenomena. First, we document that traditional momentum strategies have indeed experienced declining profitability since the 1990s, with particularly poor performance during major market disruptions. This decline accelerates when realistic transaction costs are incorporated, with bid-ask spreads and brokerage commissions consuming 50-80 basis points of monthly returns across various specifications.

Second, and more importantly, we show that market state-dependent strategies that switch between momentum and contrarian positions based on trailing market returns achieve remarkable improvements in risk-adjusted performance. These conditional strategies generate average monthly returns of 0.50-0.80% after transaction costs, compared to just 0.10-0.15% for traditional momentum approaches. Maximum drawdowns are reduced from over 60% to approximately 20-30%, while Sharpe ratios improve by factors of 4-8x after accounting for implementation costs.

Third, we demonstrate that these results are robust across multiple specifications of formation and holding periods periods (3, 6, 9 and 12 months), and market state lookback windows (12, 24 and 36 months). The consistency of findings suggests that market state dependence represents a fundamental characteristic of momentum rather than a parameter-specific anomaly.

Fourth, our historical analysis of transaction costs reveals a secular decline from over 200 basis points in the 1970s on round-trip basis to near 30 basis points following the 2019-2020 elimination of retail brokerage commissions. This structural evolution has progressively enhanced the feasibility of systematic trading strategies, with recent changes potentially marking a regime shift in implementation economics.

B. Theoretical and Practical Implications

The success of state-dependent momentum strategies carries important implications for both academic theory and investment practice. From a theoretical perspective, our results support integrated models that combine behavioral and risk-based explanations for momentum phenomena. The state-dependent nature of momentum profits aligns with psychological theories of investor overconfidence that varies with market conditions, while also being consistent with rational models of time-varying risk premia.

For practitioners, our findings suggest that reports of momentum's death have been greatly exaggerated. Rather than abandoning momentum strategies, investors should adopt more nuanced approaches that account for market regime changes. The dramatic improvement in risk-adjusted returns achieved through simple market state conditioning indicates substantial room for enhancement in factor-based investment strategies.

The documented importance of transaction costs also highlights the critical role of implementation efficiency in translating theoretical insights into practical returns. The recent elimination of retail brokerage commissions, combined with continued compression in bid-ask spreads, suggests that systematic strategies may become increasingly viable for a broader range of investors.

C. Limitations and Future Research Directions

While our analysis provides robust evidence for state-dependent momentum strategies, several limitations point toward productive avenues for future research. Our transaction cost framework, though comprehensive in incorporating brokerage commissions and bid-ask spreads, does not account for market impact costs that may be substantial for large-scale implementations. Future work should examine how price impact varies across market states and develop optimal execution strategies that minimize total implementation costs.

The extension of our analysis to international markets represents a particularly promising research direction. While momentum effects have been documented globally, the interaction between momentum and market states may vary across countries due to differences in market structure, investor composition, and regulatory environments. A comprehensive international study could reveal whether state-dependent momentum represents a universal phenomenon or exhibits important cross-country variations.

Perhaps most intriguingly, advances in machine learning offer opportunities to develop more sophisticated market state detection mechanisms. While our simple approach based on trailing market returns proves remarkably effective, modern techniques such as Long Short-Term Memory (LSTM) networks could potentially identify complex patterns in market dynamics that better predict regime changes. These neural network architectures excel at capturing temporal dependencies and non-linear relationships that traditional econometric methods might miss.

Future research should also explore alternative momentum constructions beyond the traditional price-based measures examined here. Fundamental momentum based on earnings revisions, analyst forecast changes, or other accounting variables may exhibit different state dependencies. Similarly, cross-asset momentum strategies involving currencies, commodities, and fixed income securities could benefit from state-dependent implementation, potentially offering diversification benefits in multi-asset portfolios.

The integration of momentum with other documented factors in a state-dependent framework presents another fertile area for investigation. Value, quality, and low-volatility strategies may exhibit their own regime dependencies that could be exploited in conjunction with momentum. Machine learning approaches could prove particularly valuable in identifying optimal factor combinations conditional on market states.

D. Final Remarks

The evolution of financial markets demands corresponding evolution in investment strategies. This study demonstrates that classical anomalies like momentum can maintain relevance through adaptive implementation that accounts for changing market conditions. As markets become increasingly efficient in eliminating simple inefficiencies, the frontier of active management shifts toward more sophisticated approaches that combine multiple sources of information with dynamic strategy selection.

The success of market state-dependent momentum strategies illustrates a broader principle: market efficiency is not a binary state but rather a continuous process of adaptation between investors and markets. Strategies that worked in the past may fail in the present, but creative combinations of existing insights with new conditioning information can restore profitability. This evolutionary perspective suggests that reports of the death of active management, like those of momentum's demise, may prove premature.

Looking forward, the continued advancement of technology, data availability, and analytical methods promises to unlock new dimensions of market dynamics. Whether through machine learning algorithms that detect subtle regime changes, high-frequency data that reveals microstructure patterns, or alternative data sources that capture previously unobservable information, the toolkit for sophisticated investors continues to expand.

In conclusion, this study reaffirms the enduring relevance of momentum as a source of abnormal returns while highlighting the necessity of evolution in its implementation. By embracing market state dependence and carefully managing transaction costs, investors can continue to profit from one of the most studied phenomena in finance.

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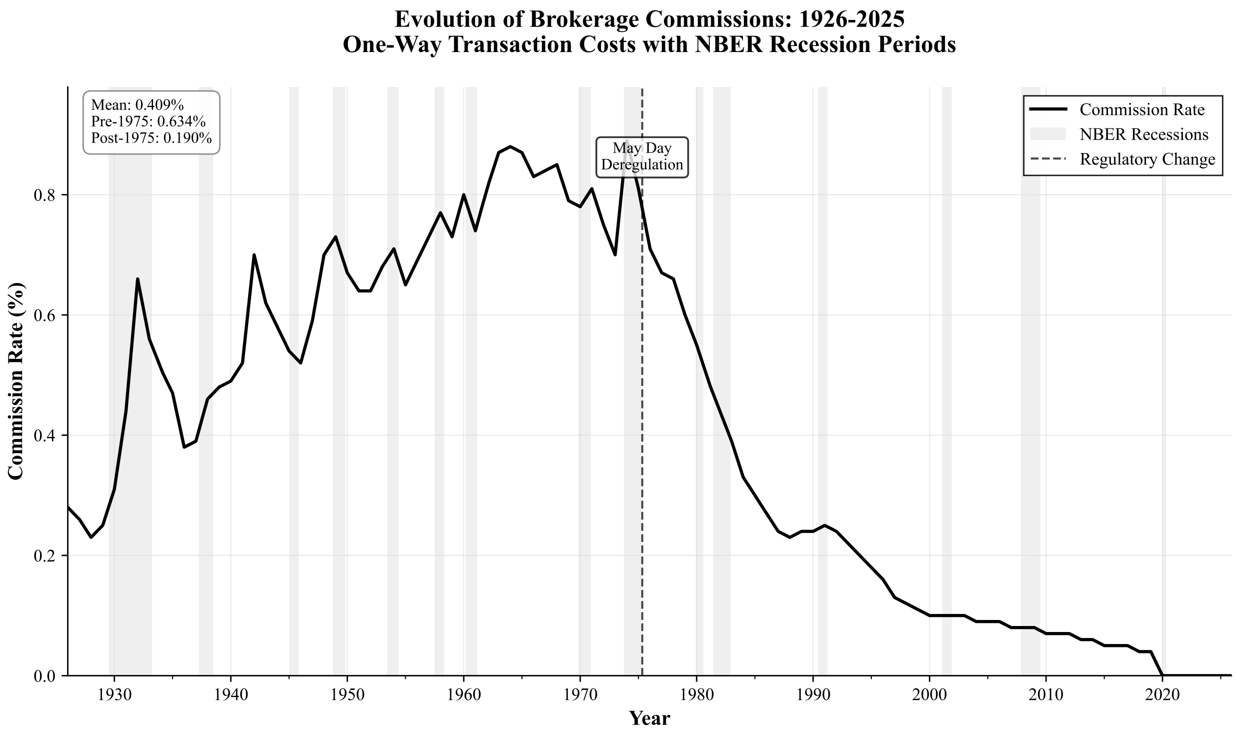

Fig. 1 Evolution of Brokerage Commissions: 1926-2024

One-Way Transaction Costs with NBER Recession Periods

This figure traces the historical evolution of average one-way brokerage commission rates from 1926 to 2024, expressed as a percentage of transaction value. The solid line represents commission rates compiled from Jones (2002) for 1926-2000 and industry sources for 2000-2024. Shaded areas indicate NBER-dated recession periods. The vertical dashed line marks May 1, 1975 ("May Day"), when fixed commission schedules were abolished.

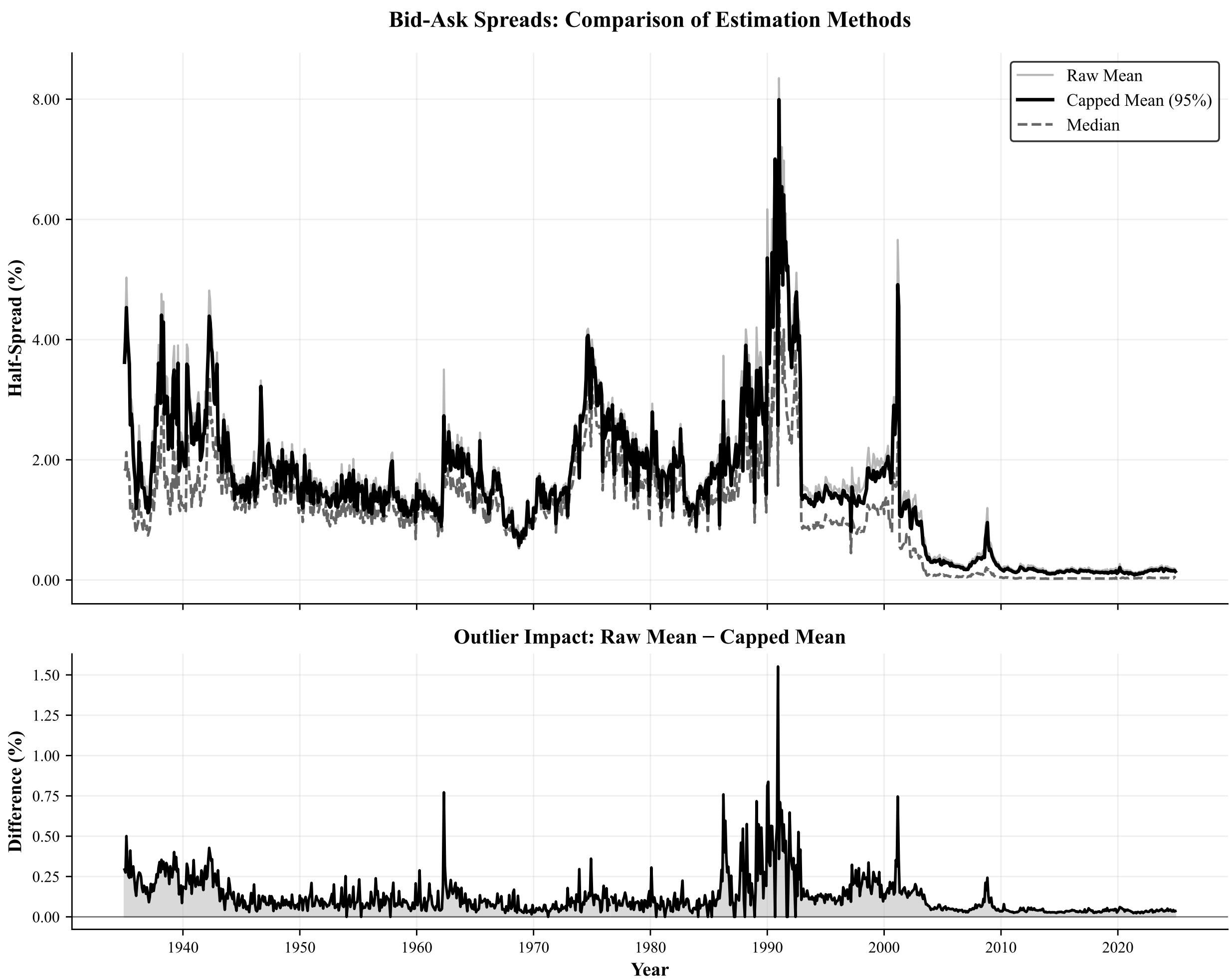

Fig. 2 Bid-Ask Spreads: Comparison of Estimation Methods

This figure presents the evolution of bid-ask half-spreads from 1935 to 2024 using three estimation methods. The gray line shows raw mean spreads, the solid black line displays capped means (95th percentile), and the dashed line represents median spreads. All spreads are expressed as percentages of the midpoint price. The lower panel illustrates the difference between raw and capped means, highlighting the impact of outliers particularly during crisis periods. Notable spikes occur during the 1987 crash, the 2000-2001 dot-com bust, and the 2008 financial crisis. The secular decline in spreads after 2000 reflects decimalization and improved market liquidity, with median spreads falling below 10 basis points by 2024.

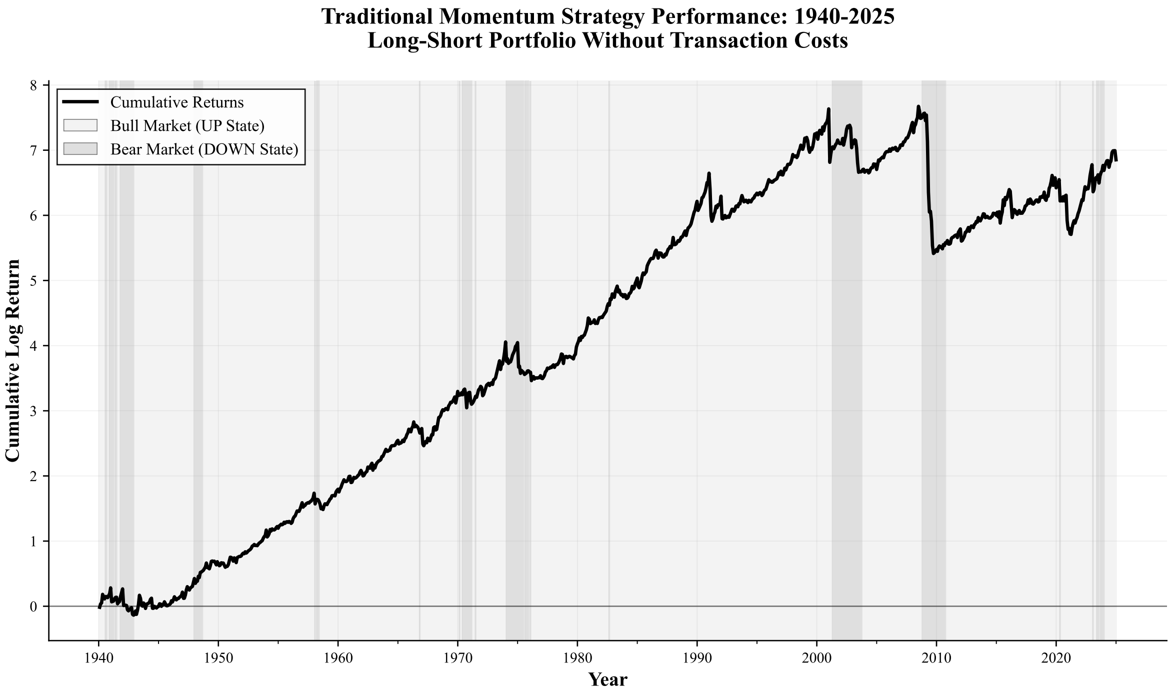

Fig. 3 Traditional Momentum Strategy Performance (1940-2024).
The figure shows cumulative log returns of the traditional momentum strategy over the full sample period, with bull market (State = 1) and bear market (State = -1) periods highlighted in different shades. The strategy exhibits strong performance through the 1990s followed by significant deterioration after 2000, with major drawdowns during the dot-com crash, 2008 financial crisis, and other market stress periods.

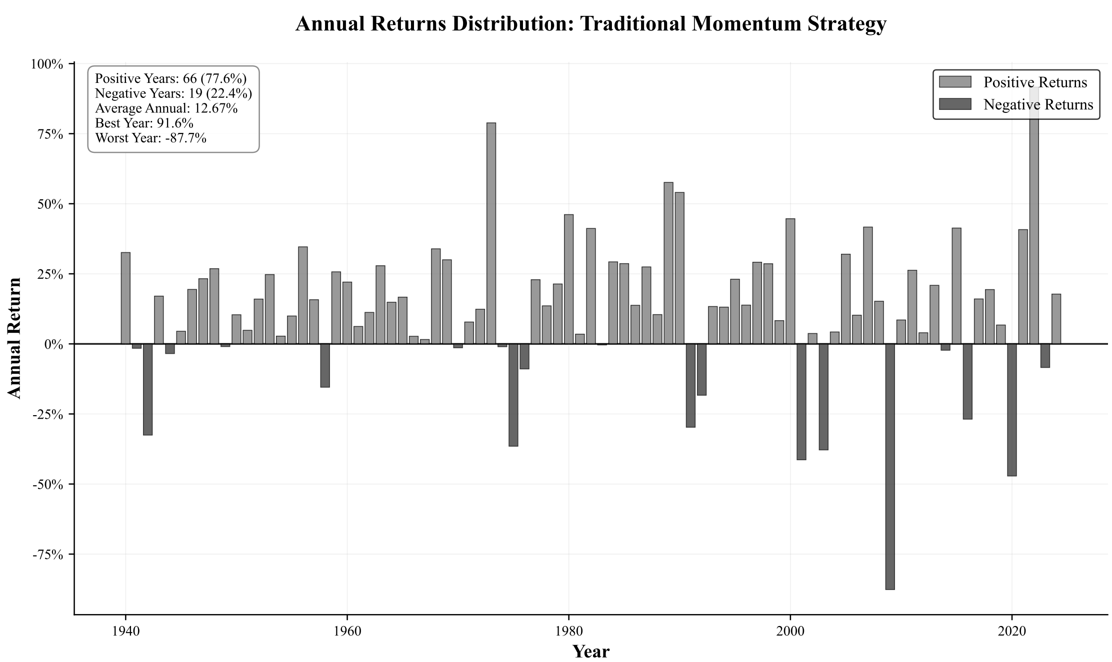

Fig. 4 Annual Returns Distribution - Traditional Momentum Strategy.
The distribution shows the frequency of positive and negative annual returns over the sample period, revealing the highly skewed nature of momentum returns with several years of extreme negative performance during market downturns.

Fig. 5 Rolling 20-Year t-Statistics Traditional Momentum Strategy.
The dashed line indicates the 5% significance threshold (t = 1.96), showing that traditional momentum strategies lose statistical significance around 2005 and remain largely insignificant thereafter.

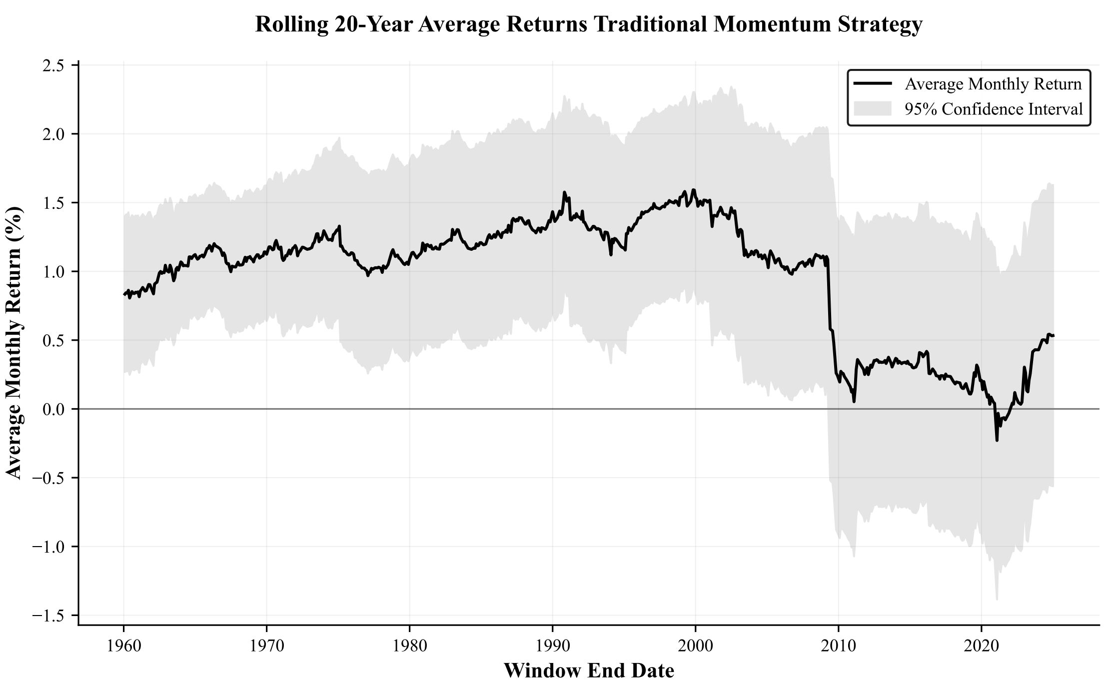

Fig. 6 Rolling 20-Year Average Returns Traditional Momentum Strategy.
Each data point represents the average monthly return calculated over a complete 20-year window, showing the secular decline in momentum profitability from peaks of approximately 1.5% in the 1990s to near-zero levels by 2010.

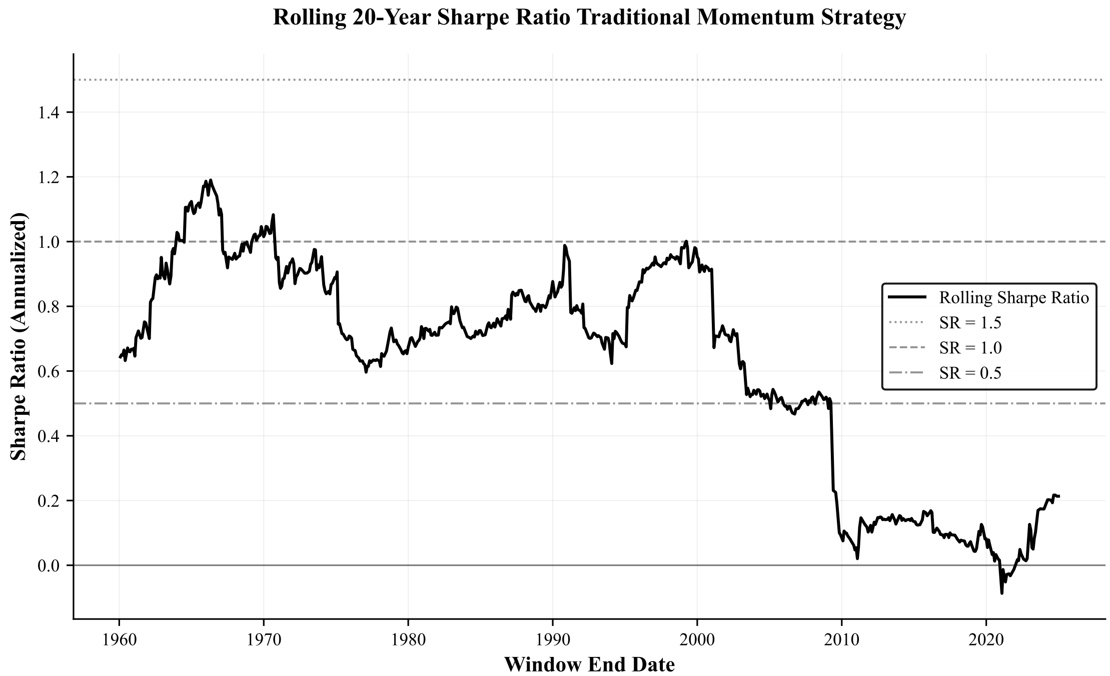

Fig. 7 Rolling 20-Year Sharpe Ratio – Traditional Momentum Strategy.
This figure displays the rolling 20-year annualized Sharpe ratio of the traditional momentum strategy from 1940 to 2024. The performance peaks above 1.2 in the 1990s but deteriorates significantly in the 2000s, with Sharpe ratios frequently falling below 0.5 in the last two decades, reflecting declining risk-adjusted returns.

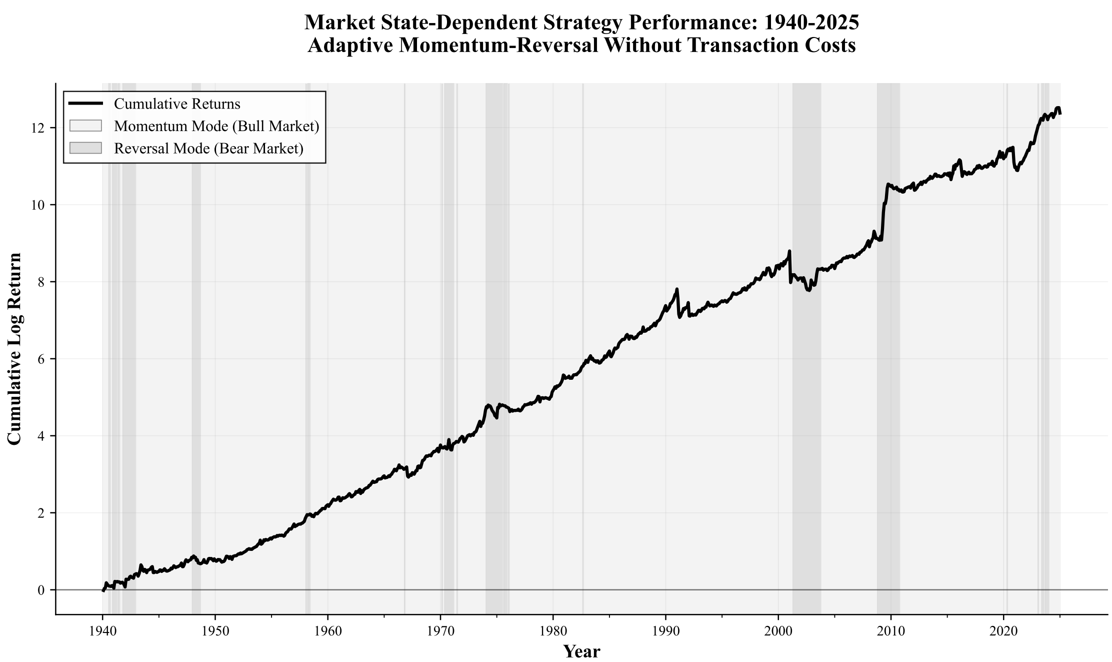

Fig. 8 Market State-Dependent Strategy Performance (1940-2024).
The figure displays cumulative log returns of the market-state dependent strategy, which exhibits consistent upward trajectory without the severe drawdowns that characterize traditional momentum approaches. The adaptive mechanism successfully navigates crisis periods by switching to contrarian positions during market stress.

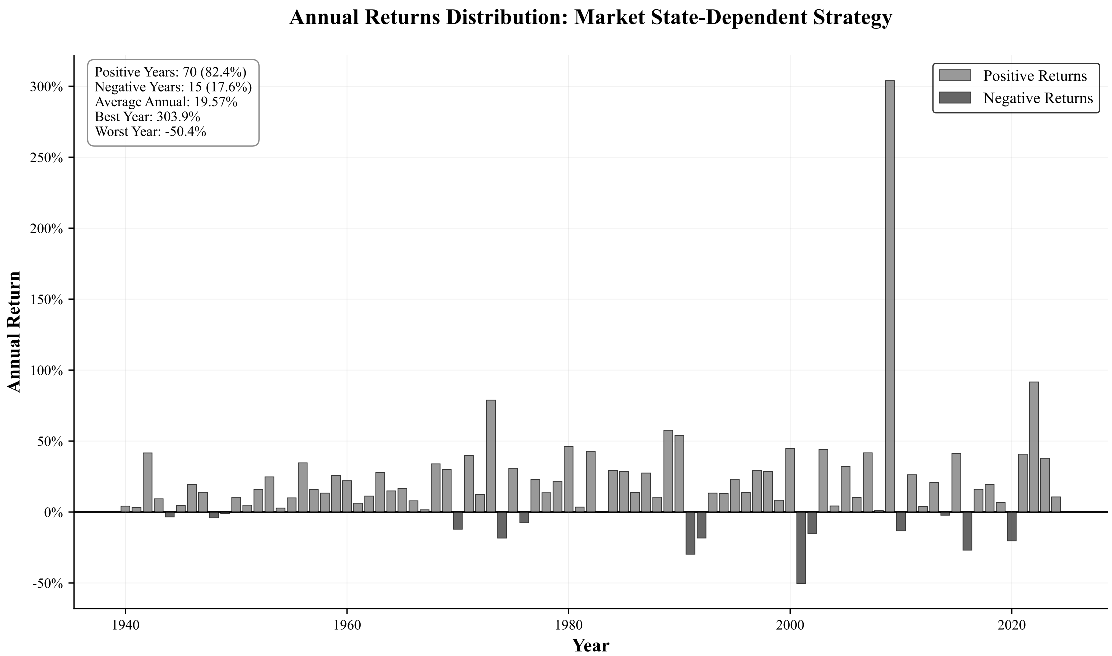

Fig. 9 Annual Returns Distribution - Market State-Dependent Strategy.
Compared to traditional momentum, the conditional strategy exhibits fewer extreme negative returns and more consistent positive performance across different market environments, demonstrating improved distributional characteristics.

Fig. 10 Rolling 20-Year t-Statistics Market State-Dependent Strategy.
The HAC-adjusted t-statistics remain consistently above the 5% significance threshold throughout most of the sample period, frequently exceeding the 1% significance level (t = 2.58), demonstrating robust statistical performance.

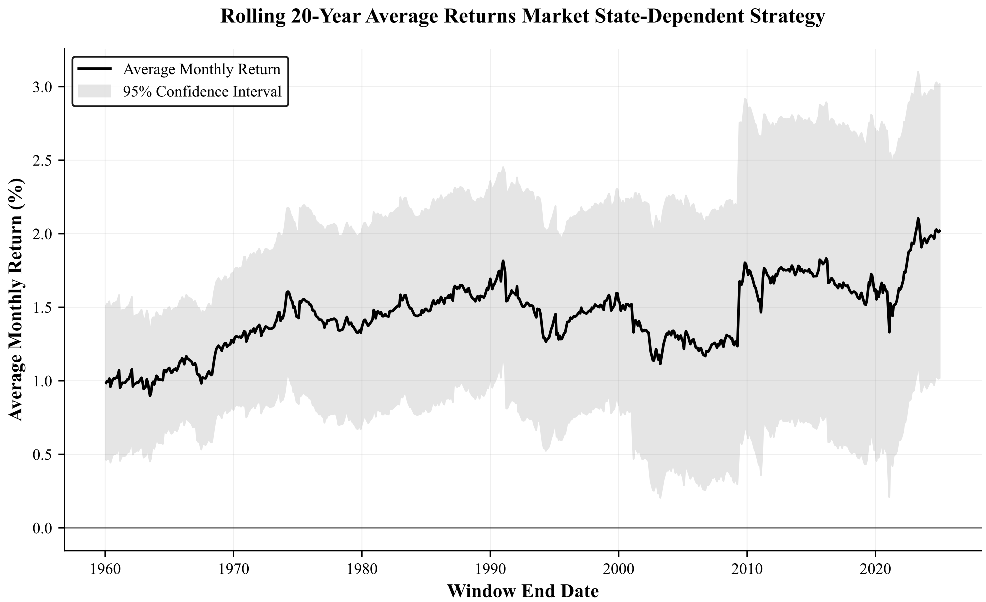

Fig. 11 Rolling 20-Year Average Returns Market State-Dependent Strategy.
The 95% confidence intervals around the rolling averages remain predominantly positive, indicating robust statistical significance even during shorter sub-periods. The strategy maintains positive expected returns across different market cycles.

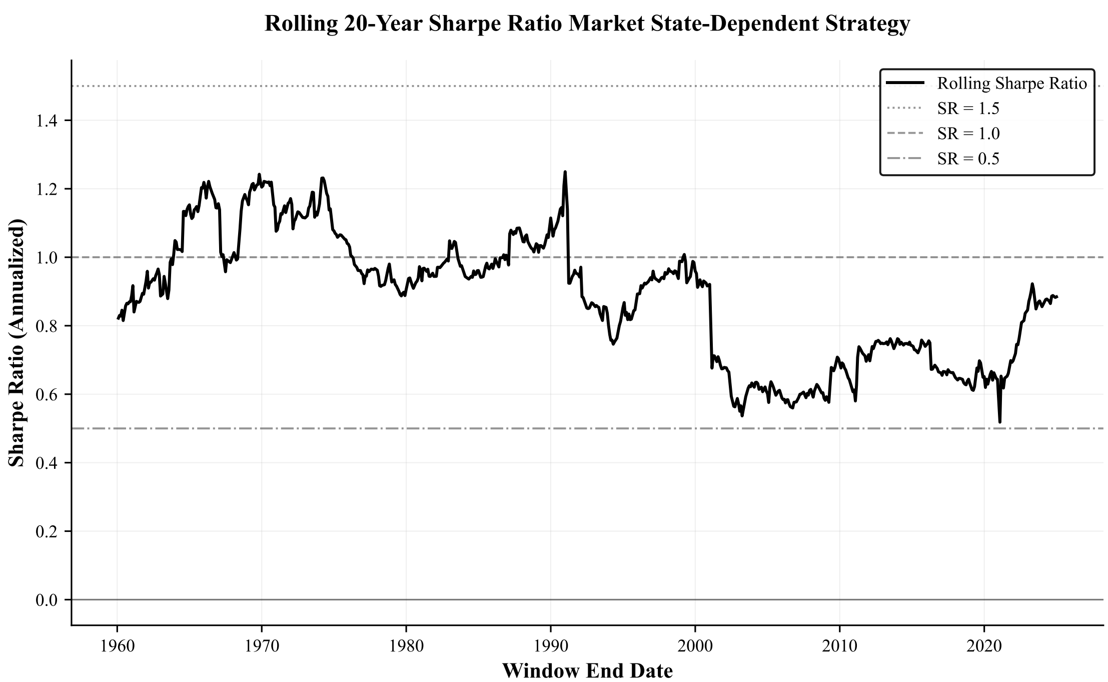

Fig. 12 Rolling 20-Year Sharpe Ratio – Market State-Dependent Strategy.
The figure illustrates the rolling 20-year annualized Sharpe ratio of the adaptive strategy. Unlike the traditional approach, the market state-dependent strategy maintains consistently high Sharpe ratios—often exceeding 1.0—throughout the sample period, with limited drawdowns even during turbulent market episodes. This indicates more stable and favorable risk-adjusted performance.

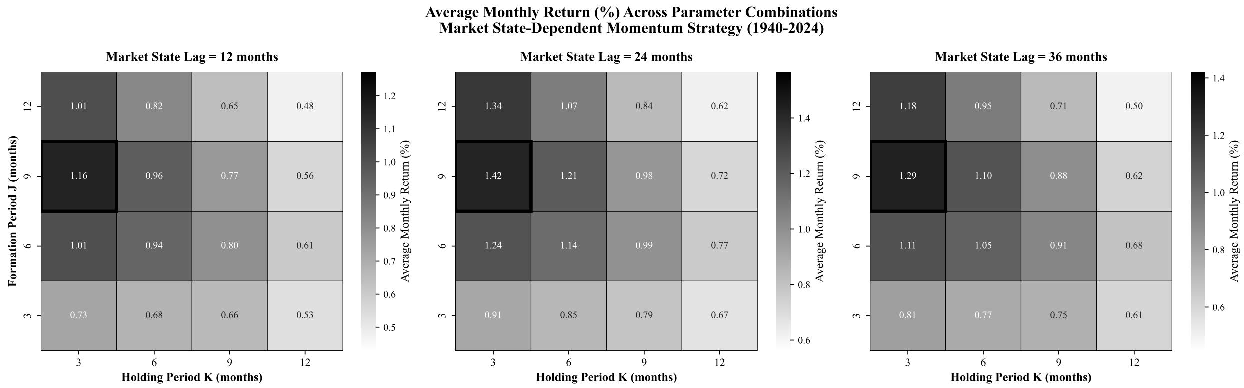

Fig. 13 Average Monthly Return (%) Across Different Parameters.
Heat map showing strategy performance across 16 formation-holding period combinations and three market state definitions (12-, 24-, and 36-month lookbacks). All 48 combinations generate positive returns, with the 24-month specification demonstrating superior performance across most parameter combinations.

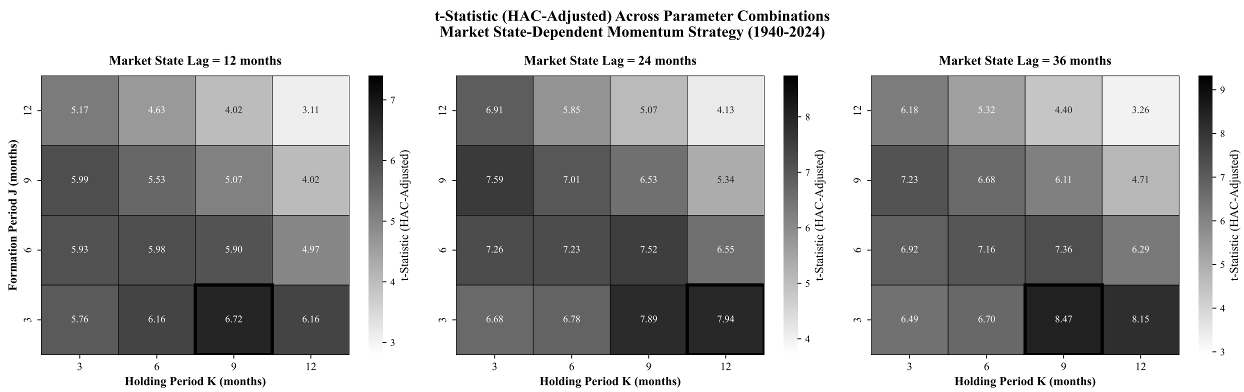

Fig. 14 t-Statistic (HAC-Adjusted) Across Different Parameters.
Heat map displaying HAC-adjusted t-statistics across parameter combinations, with 45 out of 48 specifications achieving statistical significance at the 5% level. The 24-month market state specification shows the most consistent statistical performance.

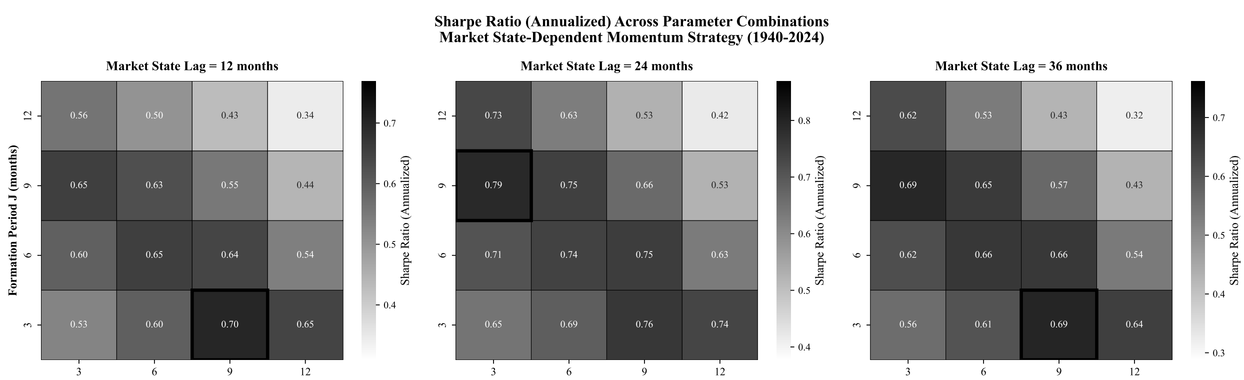

Fig. 15 Sharpe Ratio (Annualized) Across Different Parameters.
Risk-adjusted performance remains attractive across the parameter space, with Sharpe ratios ranging from 0.32 to 0.79, confirming economically meaningful returns across diverse specifications.

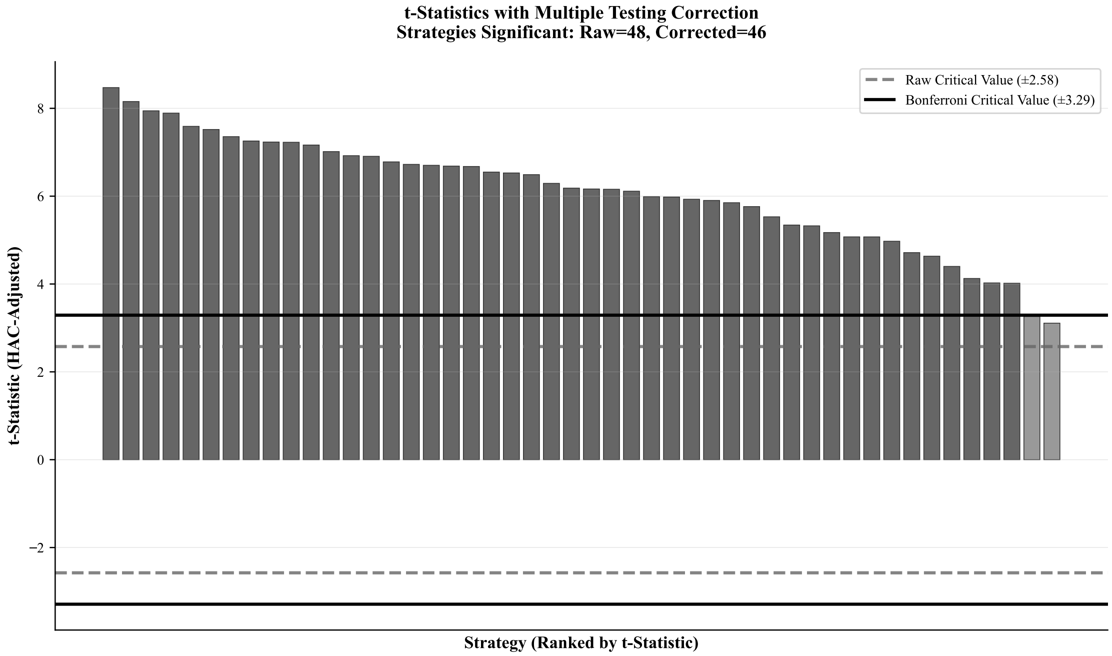

Fig. 16 t-Statistics with Multiple Testing Correction.
The figure shows all 48 strategy combinations ranked by t-statistic, with Bonferroni critical value (3.29) based on K=10 effective independent tests. 46 out of 48 strategies exceed this threshold, demonstrating robust statistical significance after controlling for multiple testing.

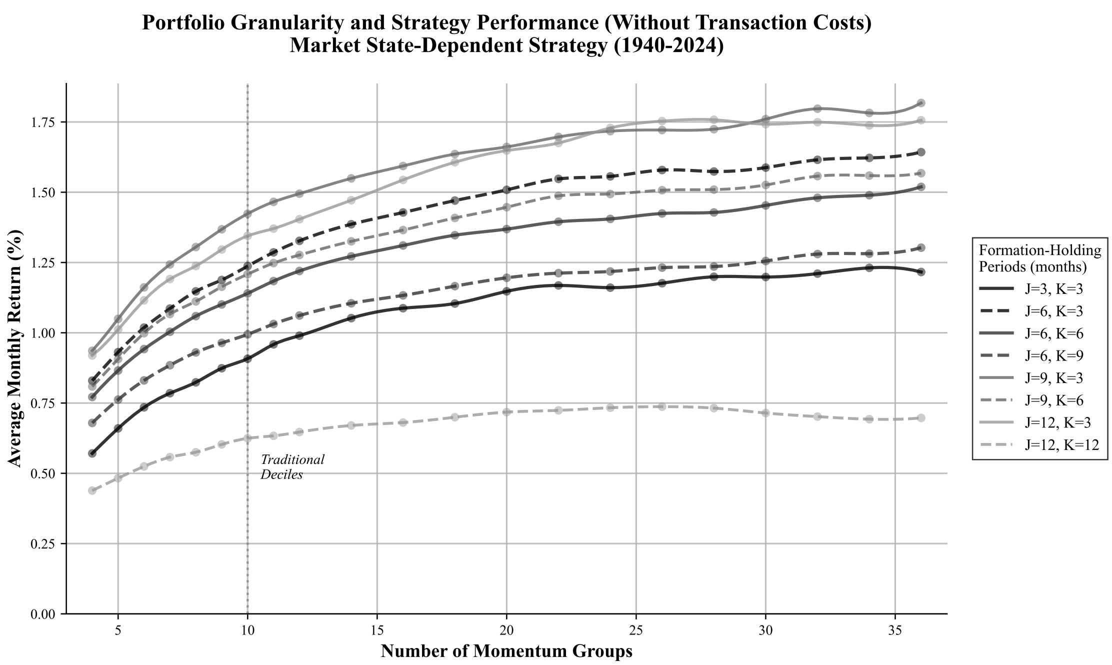

Fig. 17 Portfolio Granularity and Strategy Performance.
The relationship between the number of momentum groups (4-36) and average monthly returns for various formation-holding period combinations. Returns increase logarithmically with granularity while volatility increases linearly, suggesting optimal performance around 10 groups.

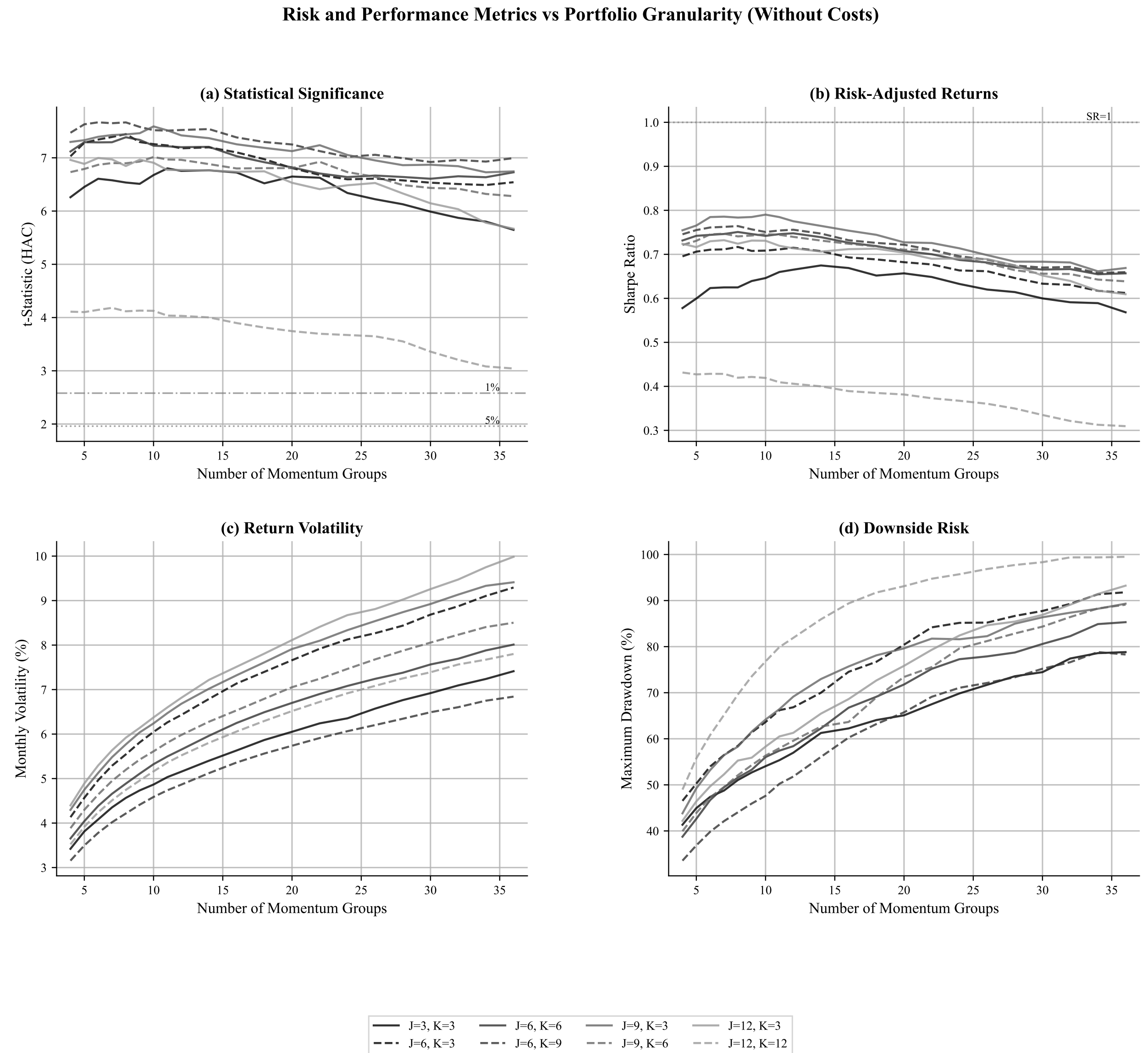

Fig. 18 Risk and Performance Metrics vs Portfolio Granularity.
(a) Statistical significance peaks around 10 groups; (b) Risk-adjusted returns deteriorate with excessive granularity; (c) Volatility increases linearly with portfolio divisions; (d) Maximum drawdown worsens substantially beyond 10-15 groups, confirming the optimality of decile portfolios.

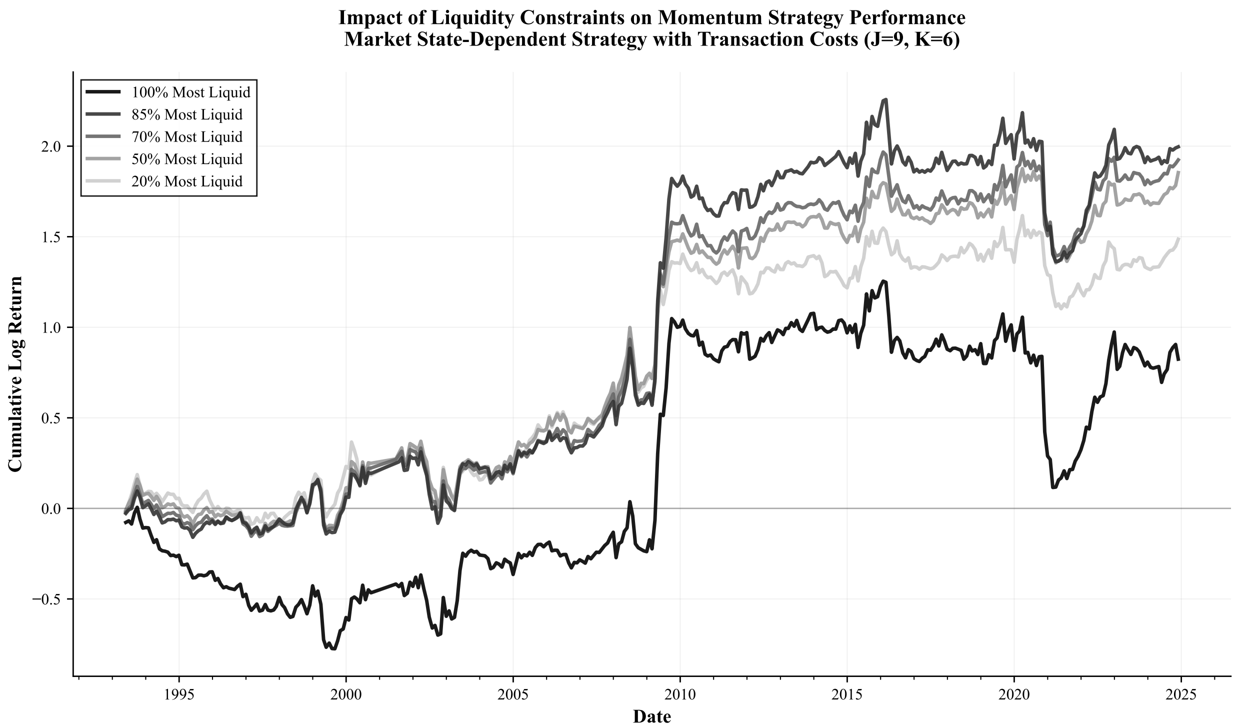

Fig. 19 Impact of Liquidity Constraints on Momentum Strategy Performance.
This figure presents cumulative log returns of the market-state dependent strategy (J=9, K=6) across different liquidity cutoff levels from 1993 to 2024. Each line represents a strategy variant that includes only the top x% most liquid stocks based on bid-ask spreads at portfolio formation. The 100% line includes all stocks, while more restrictive cutoffs (e.g., 20%) limit the investment universe to the most liquid securities. The convergence of returns across moderate liquidity constraints (50%-85%) suggests an optimal balance between transaction cost mitigation and investment opportunity set preservation.

Performance Metrics Across Liquidity Constraints

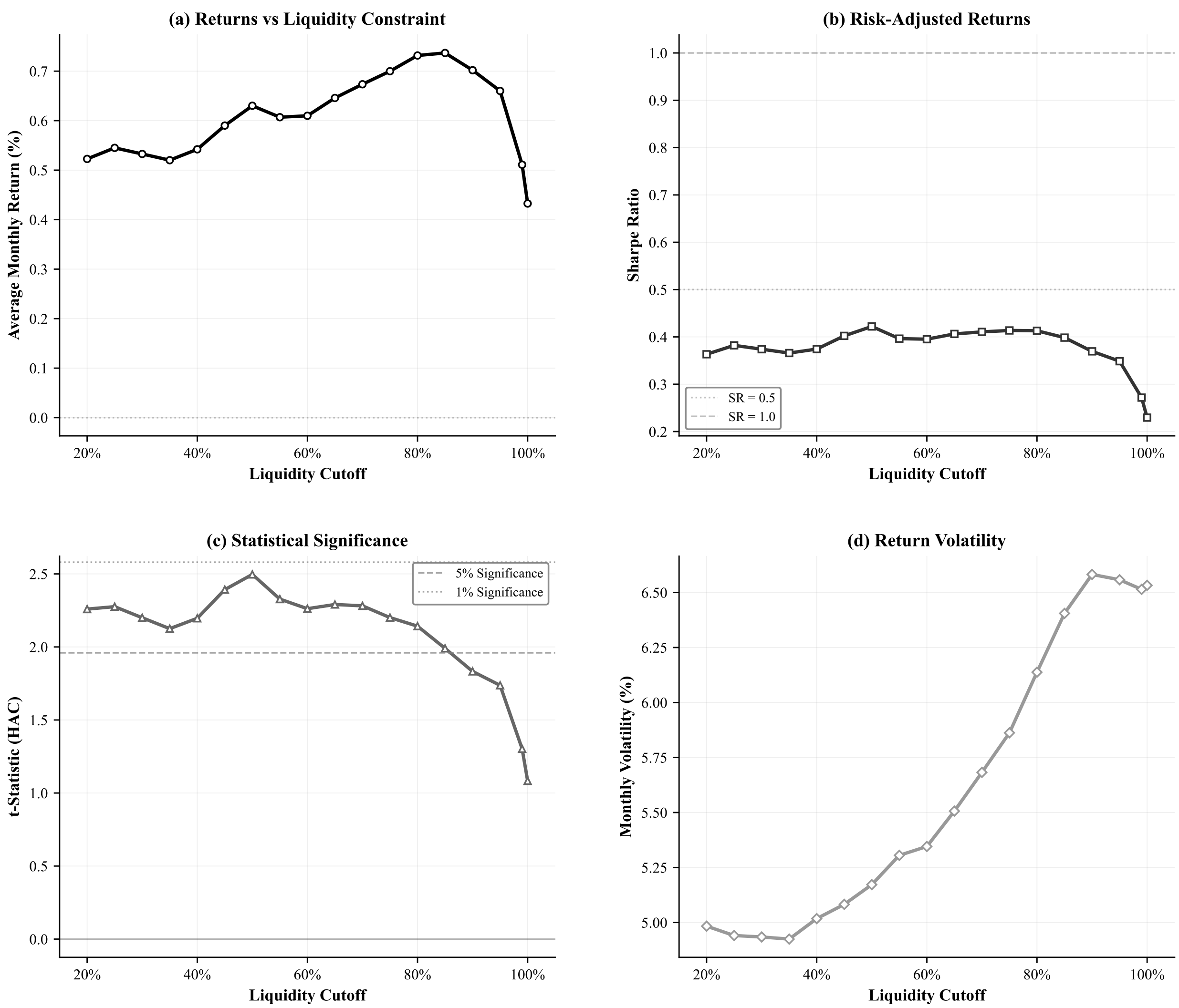

Fig. 20 Performance Metrics Across Liquidity Constraints.
This figure displays key performance metrics for the market-state dependent strategy as a function of liquidity cutoff levels. Panel (a) shows average monthly returns exhibiting an inverted U-shape, peaking around 75%-85% liquidity inclusion. Panel (b) presents Sharpe ratios (SR=0.5 and SR=1.0 benchmarks shown), demonstrating remarkable stability across liquidity constraints. Panel (c) reports HAC-adjusted t-statistics with 5% and 1% significance thresholds. Panel (d) illustrates monthly return volatility, which increases monotonically as liquidity constraints relax. The stability of risk-adjusted returns across moderate liquidity filters supports practical implementation.

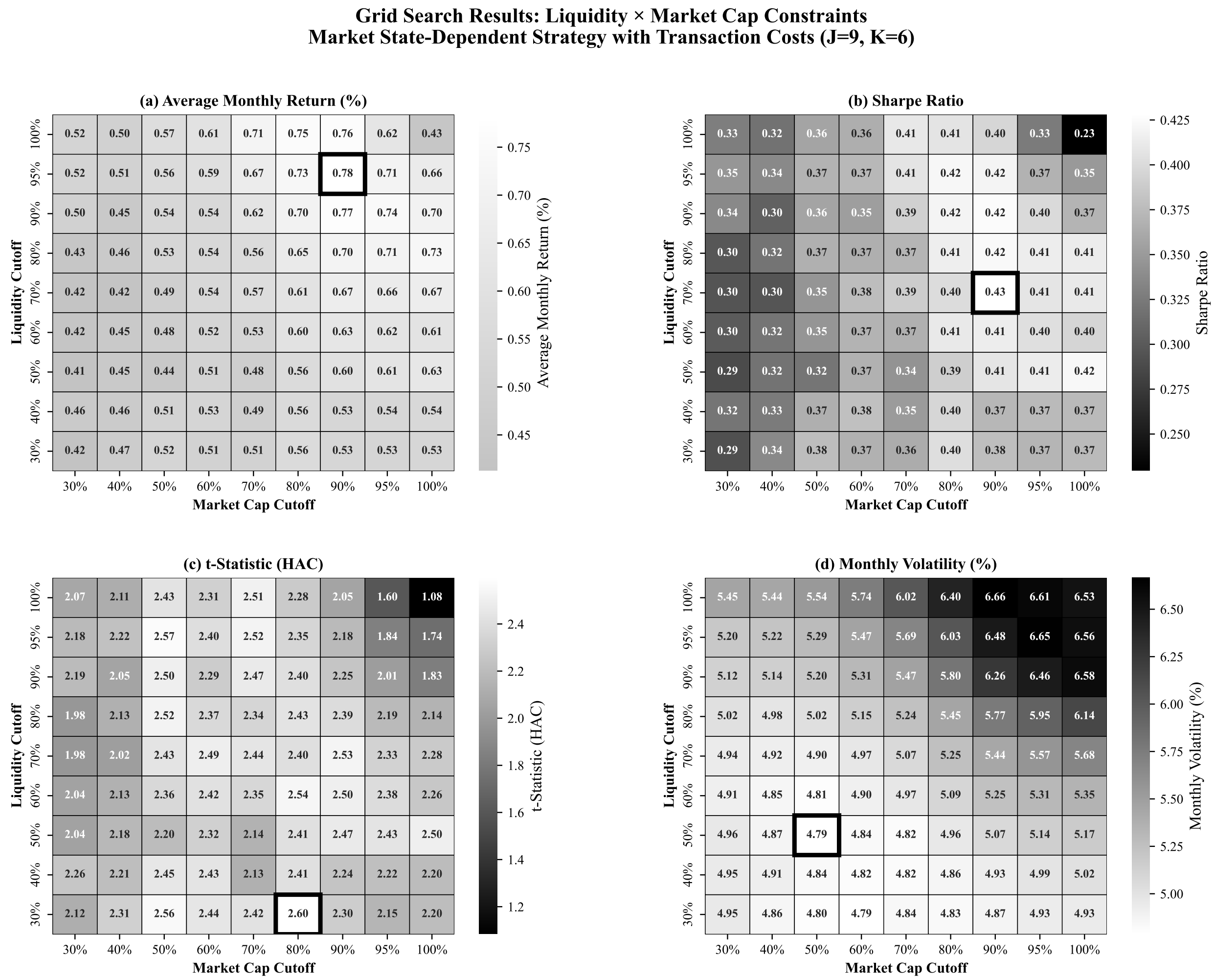

Fig. 21 Grid Search Results: Liquidity × Market Cap Constraints.
This figure presents a comprehensive analysis of the market-state dependent strategy (J=9, K=3) performance across two-dimensional implementation constraints. Panel (a) shows average monthly returns ranging from 0.41% to 0.74% across all combinations. Panel (b) displays Sharpe ratios maintaining values between 0.24 and 0.36. Panel (c) reports HAC-adjusted t-statistics, with darker shading indicating higher statistical significance. Panel (d) presents monthly volatility patterns. The consistency of positive returns and statistical significance across the parameter space demonstrates strategy robustness to joint liquidity and size constraints.

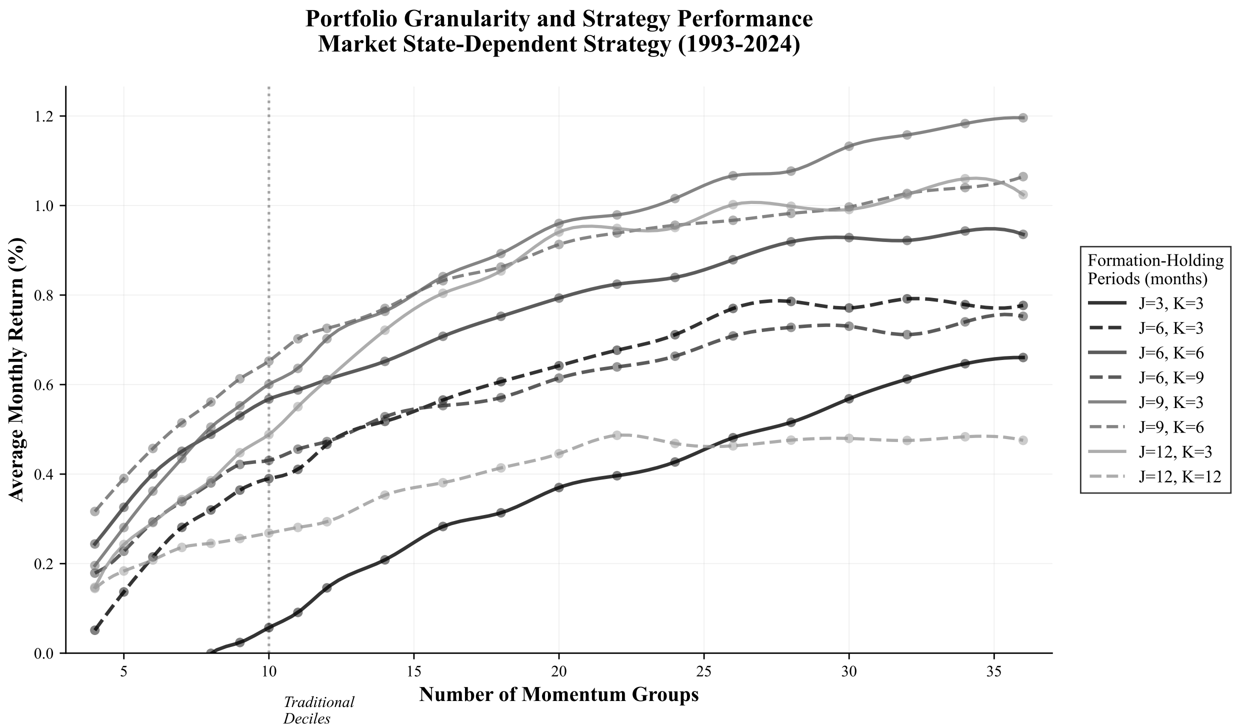

Fig. 22 Portfolio Granularity and Strategy Performance Under Transaction Costs.
This figure examines the impact of portfolio granularity on the market-state dependent strategy (1993-2024) with 80% liquidity and market cap constraints. Different lines represent various formation-holding period combinations. The vertical dashed line indicates the traditional 10-decile approach. Average monthly returns initially increase with finer momentum sorting but plateau beyond 15-20 groups. The diminishing marginal returns beyond the traditional decile specification, combined with increased implementation complexity, support the conventional portfolio construction approach.

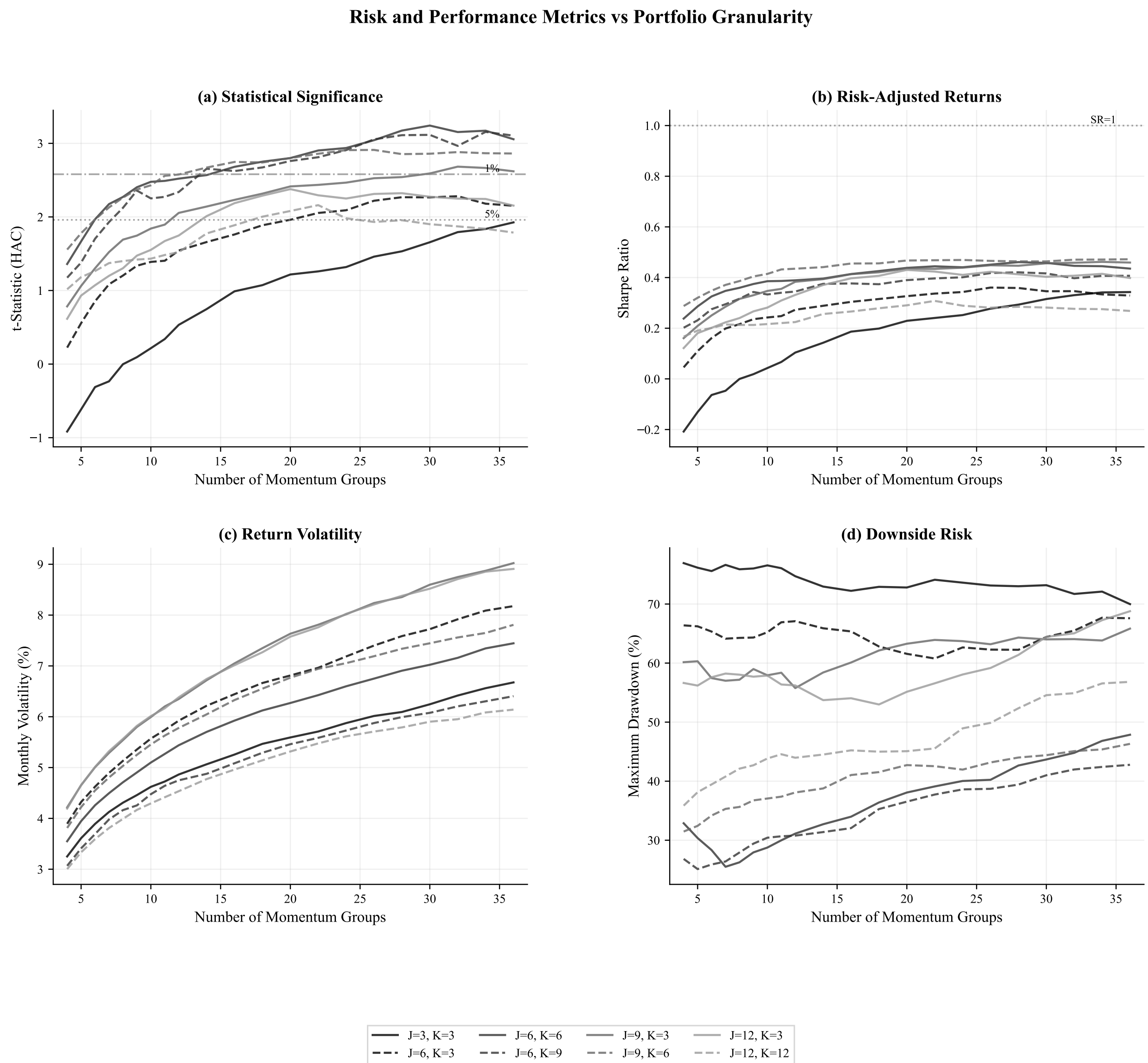

Fig. 23 Risk and Performance Metrics vs Portfolio Granularity Under Transaction Costs.
This figure presents the evolution of key risk and performance metrics as portfolio granularity increases. Panel (a) shows HAC-adjusted t-statistics peaking around 10-15 groups before declining. Panel (b) displays Sharpe ratios exhibiting similar patterns, with SR=1 benchmark indicated. Panel (c) demonstrates the linear increase in return volatility with granularity. Panel (d) reveals maximum drawdown percentages increasing substantially beyond 15 groups. The results indicate that moderate granularity (10-15 groups) optimally balances signal strength against implementation risks under transaction cost constraints.

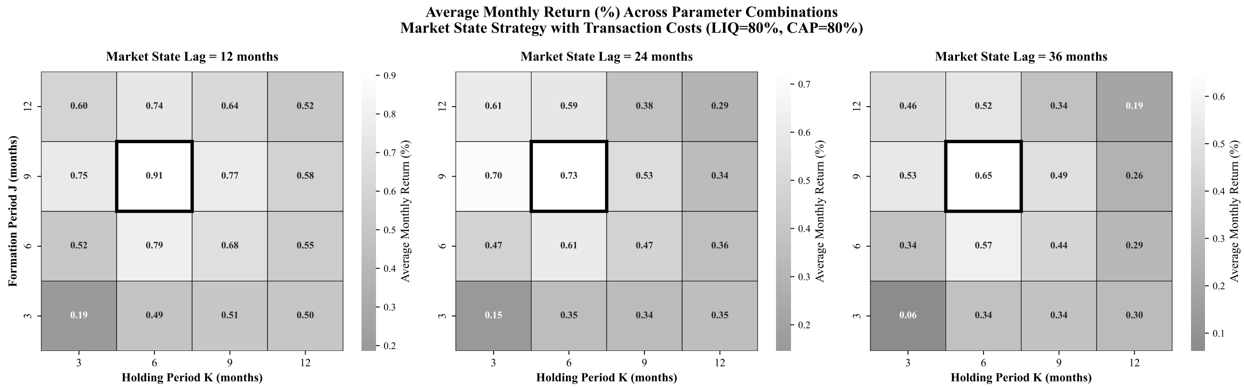

Fig. 24 Average Monthly Return (%) Across Parameter Combinations Under Transaction Costs.
This figure presents average monthly returns for the market-state dependent strategy across formation (J) and holding (K) period combinations with three market state lag specifications (12, 24, and 36 months). Implementation includes 80% liquidity and 80% market cap constraints. Darker shading indicates higher returns.

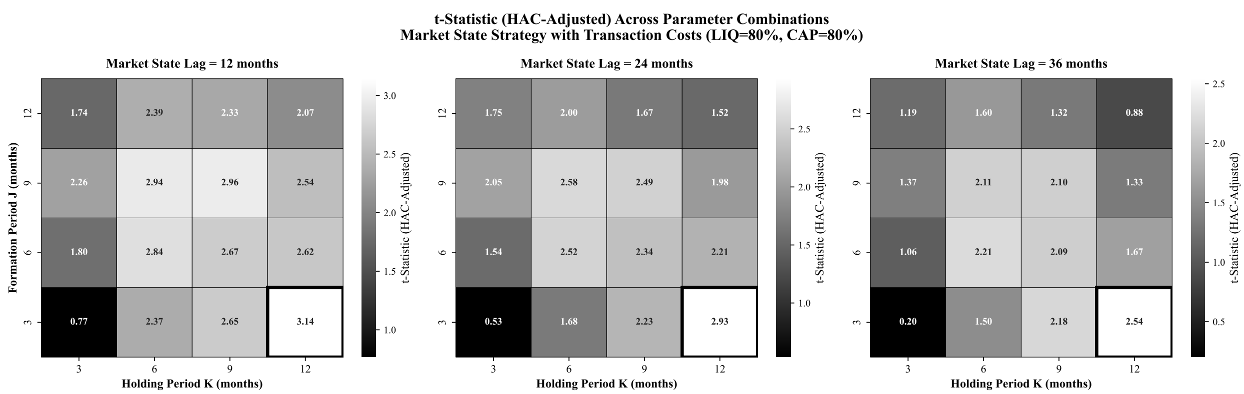

Fig. 25 HAC-Adjusted t-Statistics Across Parameter Combinations Under Transaction Costs.
This figure displays t-statistics for the market-state dependent strategy using heteroskedasticity and autocorrelation consistent (HAC) standard errors with optimal lag selection. Implementation includes 80% liquidity and 80% market cap constraints. Darker shading indicates higher statistical significance. The prevalence of t-statistics exceeding 2.0 across parameter specifications confirms robust statistical significance after accounting for transaction costs.

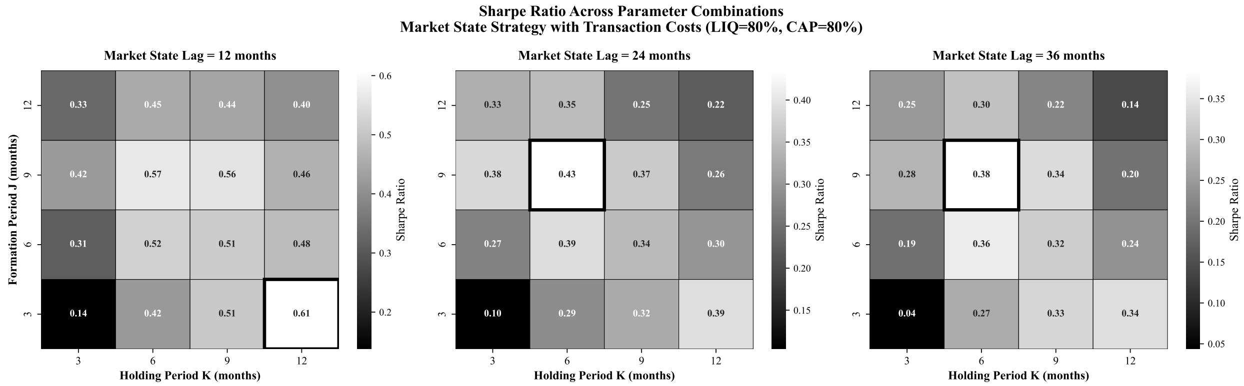

Fig. 26 Sharpe Ratio Across Parameter Combinations Under Transaction Costs.
This figure presents annualized Sharpe ratios for the market-state dependent strategy across different specifications with transaction costs. Implementation includes 80% liquidity and 80% market cap constraints. Darker shading indicates higher risk-adjusted returns. Sharpe ratios range from negative values to above 0.55, with the 24-month market state specification demonstrating superior risk-adjusted performance.

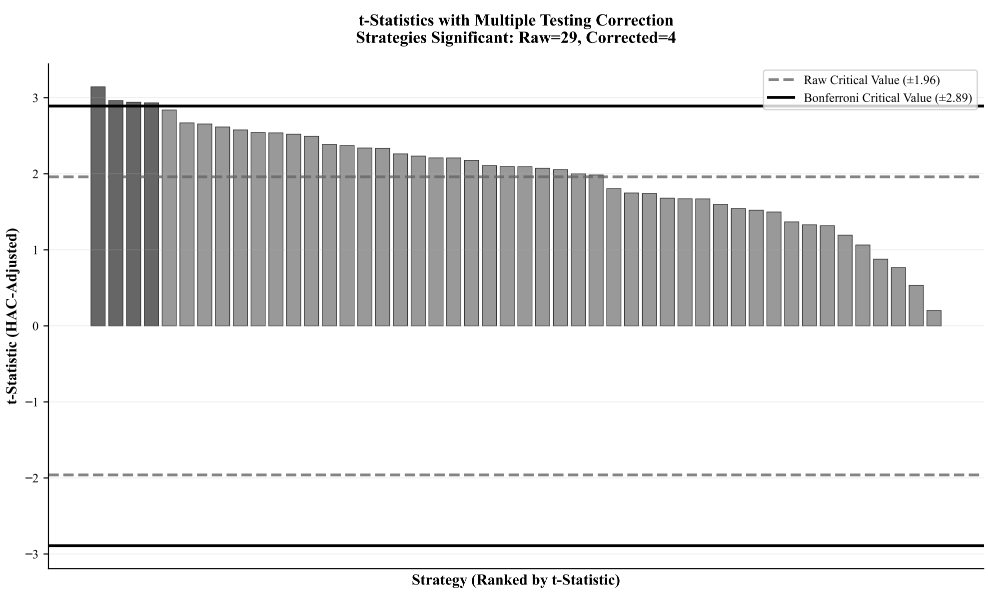

Fig. 27 t-Statistics with Multiple Testing Correction Under Transaction Costs.
This figure displays HAC-adjusted t-statistics for all 48 strategy variants, ranked by statistical significance. The dashed line indicates the standard 5% critical value (1.96), while the solid line shows the Bonferroni-corrected critical value (2.87) based on 12 effective independent tests explaining 99% of return variance.

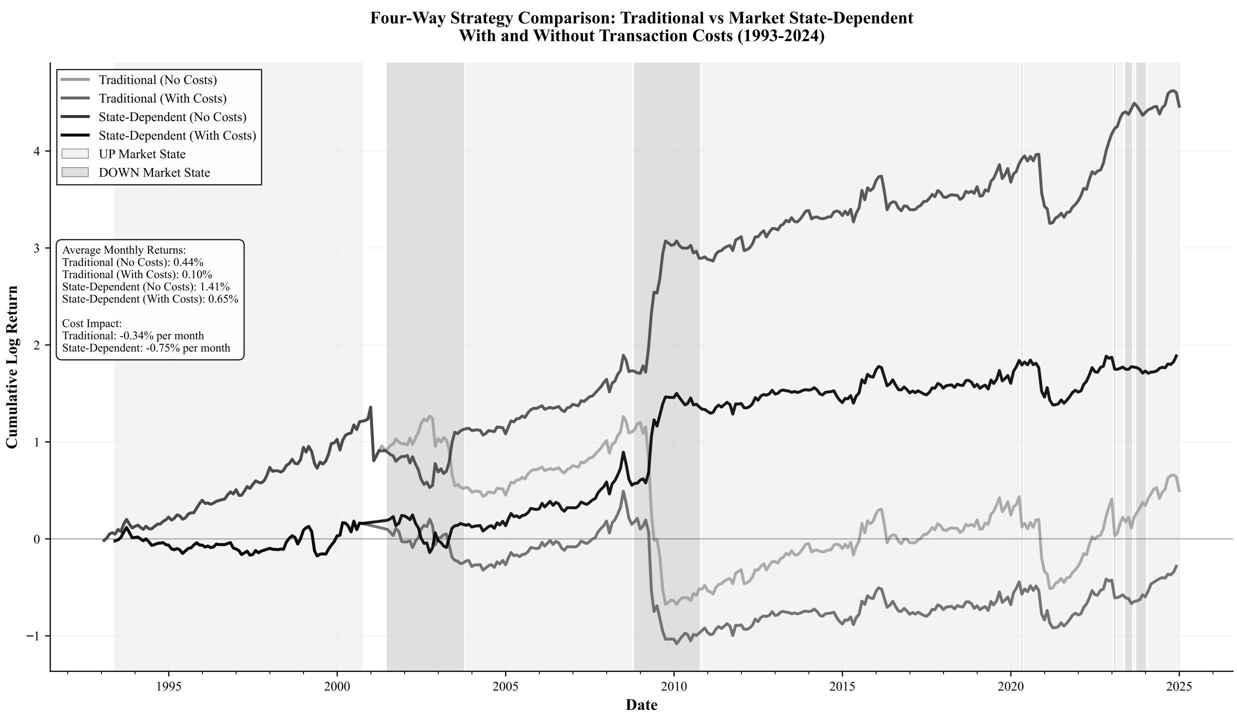

Fig. 28 **Four-Way Strategy Comparison: Traditional vs Market State-Dependent**
With and Without Transaction Costs (1993-2024)
Formation Period: 9 months, Holding Period: 6 months, Market State Lookback: 24 months
This figure compares cumulative log returns for traditional momentum and market state-dependent strategies from 1993 to 2024.

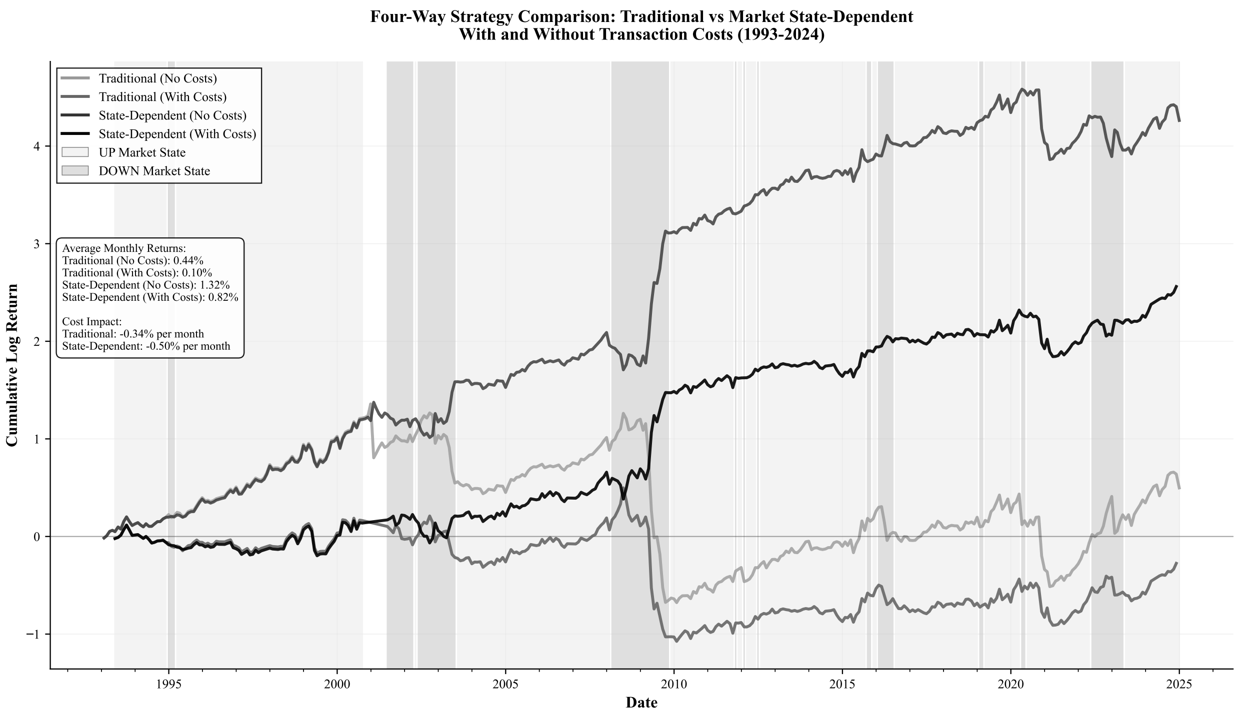

Fig. 29 Four-Way Strategy Comparison: Traditional vs Market State-Dependent
With and Without Transaction Costs (1993-2024)
Formation Period: 9 months, Holding Period: 6 months, Market State Lookback: 12 months
This figure presents strategy comparison using a 12-month market state lookback window. The shorter lookback period results in more frequent state transitions compared to the 24-month specification. Traditional momentum strategies continue to exhibit vulnerability during market reversals, while state-dependent approaches maintain defensive characteristics.

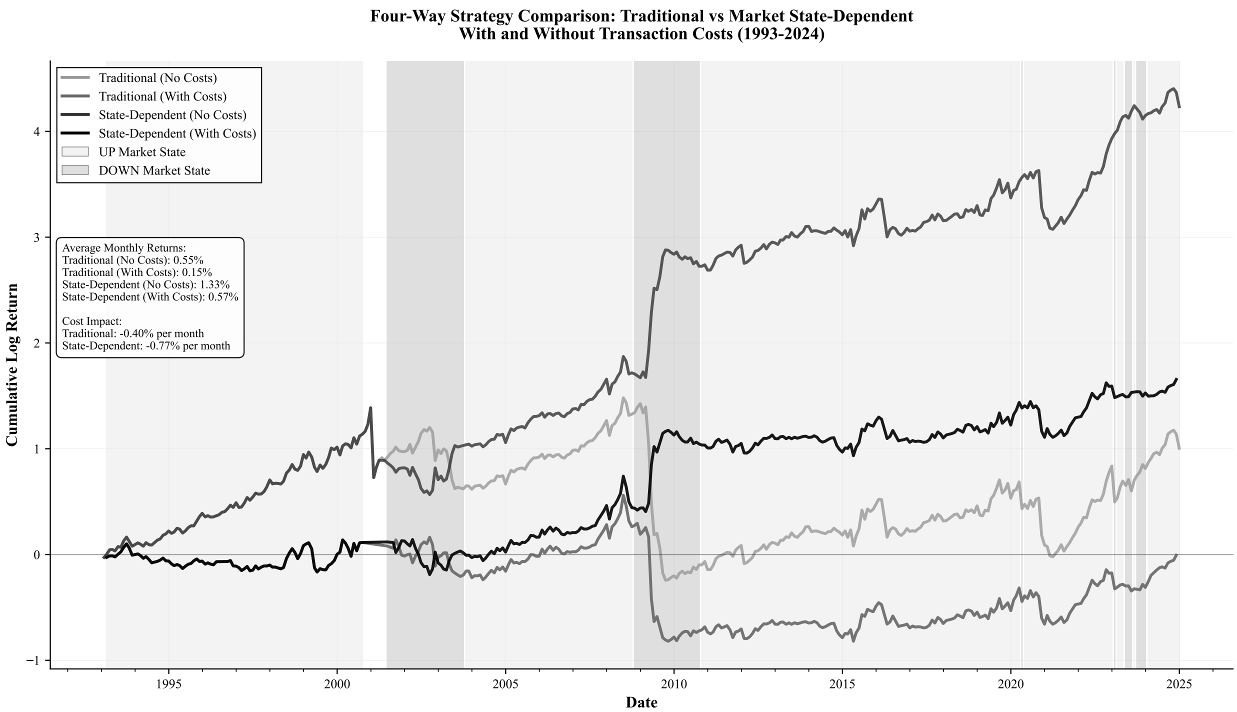

Fig. 30 Four-Way Strategy Comparison: Traditional vs Market State-Dependent
With and Without Transaction Costs (1993-2024)
Formation Period: 6 months, Holding Period: 6 months, Market State Lookback: 24 months
This figure examines the classic 6-6 momentum specification with 24-month market state determination. The symmetric formation and holding periods represent the configuration most commonly studied in academic literature.

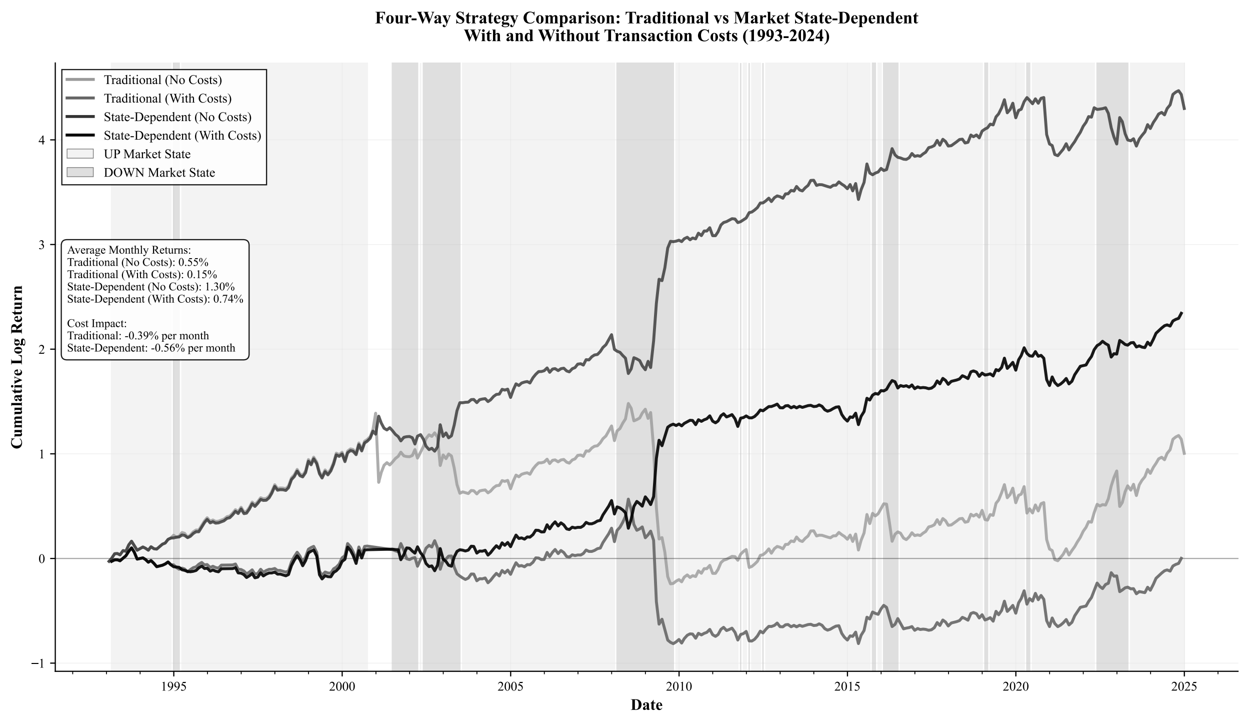

Fig. 31 Four-Way Strategy Comparison: Traditional vs Market State-Dependent
With and Without Transaction Costs (1993-2024)
Formation Period: 6 months, Holding Period: 6 months, Market State Lookback: 12 months
This figure combines 6-month formation/holding periods with 12-month market state lookback. This specification exhibits the highest switching frequency among tested configurations.