Short-term Reversal in US Equity Markets: Evidence from Monthly and Daily Data (1926–2024)

Seminar Paper

Stock Markets in the Age of Big Data

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(01/1267680), (01/1276644), (01/1288922)

Constance, January 2026

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1 Introduction

The search for profitable trading strategies has driven decades of academic research in financial economics. Among the most persistent anomalies documented in the literature is the short-term reversal effect: the tendency of stocks with poor performance over the past month to outperform in the following month, and vice versa. First rigorously documented by Jegadeesh (1990), this phenomenon challenges the efficient market hypothesis and has attracted substantial attention from both academics and practitioners.

This paper investigates the profitability and persistence of the short-term reversal strategy using US equity data spanning nearly a century (1926–2024). We employ a comprehensive empirical framework utilizing data from four primary sources:

1. **Jensen, Kelly, and Pedersen Factor Data** (`https://jkpfactors.com/`): Monthly and daily portfolio returns for the short-term reversal (STR) strategy and residual momentum, constructed following standardized academic methodologies. We utilize both value-weighted (VW) and equal-weighted (EW) portfolios to assess robustness.

2. **Kenneth French Data Library** (`https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html`): Fama-French three-factor and five-factor model data, including market excess returns (MKT-RF), size (SMB), value (HML), profitability (RMW), and investment (CMA) factors.

3. **Global-Q Factor Database** (`https://global-q.org/`): Q-factor model data from Hou et al. (2015), providing alternative investment-based risk factors including size (R_{ME}), investment (R_{IA}), profitability (R_{ROE}), and expected growth (R_{EG}).

4. **Geopolitical Risk Index** (`https://www.matteoiacoviello.com/gpr.htm`): Daily and monthly geopolitical risk (GPR) index data from Caldara and Iacoviello (2022), enabling analysis of the strategy's exposure to geopolitical uncertainty.

Following the methodology prescribed in the seminar project guidelines, we analyze performance metrics, factor model alphas, and geopolitical risk exposures using monthly value-weighted portfolio returns as the baseline specification. As an extension, we complement this analysis with daily equal-weighted data, which reveals substantially stronger statistical evidence for the anomaly's persistence—a key contribution of our study.

Our findings contribute to the ongoing debate about market efficiency and the publication effect documented by McLean and Pontiff (2016). While monthly analysis suggests the anomaly has weakened considerably since Jegadeesh's seminal publication, daily data reveals that statistically significant alphas persist even in the modern era. Furthermore, we demonstrate that combining short-term reversal with residual momentum substantially improves risk-adjusted returns, offering practical implications for portfolio construction.

The remainder of this paper is organized as follows. Section 2 reviews the theoretical background and existing explanations for short-term reversal. Section 3 describes our data sources and methodology in detail. Section 4 presents empirical results for both monthly and daily specifications. Section 5 examines geopolitical risk exposure. Section 6 discusses portfolio optimization strategies. Section 7 concludes.

2 Theoretical Background

2.1 The Short-term Reversal Effect

Jegadeesh (1990) documented that securities ranked in the bottom decile based on prior month returns outperform those in the top decile by approximately 2% in the following month. This finding implies a contrarian trading strategy: buying past losers and shorting past winners generates positive abnormal returns. The effect is distinct from the longer-horizon reversal documented by De Bondt and Thaler (1985) and operates over weekly to monthly horizons.

The short-term reversal strategy is implemented through portfolio sorting. At the end of each period t, stocks are ranked by their prior period returns and sorted into decile portfolios. The strategy return is defined as the spread between the loser and winner portfolios:

$$r_{\text{STR},t+1} = r_{\text{Losers},t+1} - r_{\text{Winners},t+1} \tag{1}$$

where the loser portfolio contains stocks in the bottom decile of prior returns and the winner portfolio contains stocks in the top decile.

2.2 Explanations for Short-term Reversal

Microstructure-based explanations. The dominant explanation attributes short-term reversal to market microstructure effects, particularly the bid-ask bounce and inventory management by market makers. When liquidity providers accommodate order flow imbalances, prices temporarily deviate from fundamental values. Subsequent price corrections generate the observed reversal pattern. This view suggests the strategy primarily captures compensation for liquidity provision rather than true mispricing (Avramov et al., 2006).

Behavioral explanations. An alternative perspective emphasizes investor overreaction to firm-specific news. When investors react excessively to short-term information, prices overshoot their fundamental values and subsequently revert. This behavioral interpretation aligns with the broader literature on investor sentiment and limits to arbitrage. The adaptive markets hypothesis (Lo, 2004) suggests that the strength of such patterns varies over time as market participants learn and arbitrage opportunities evolve.

3 Data and Methodology

3.1 Data Sources

Our analysis employs data from multiple sources to ensure comprehensive coverage and robustness. Figure 1 provides a visual overview of our data architecture.

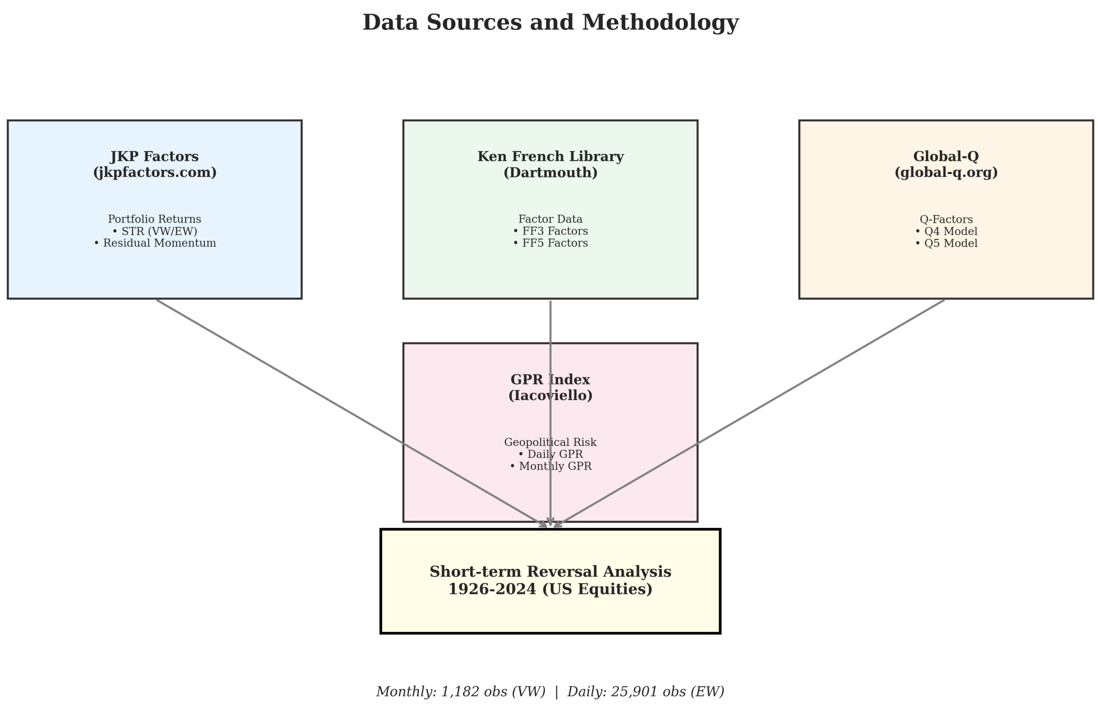

Figure 1: Data Sources and Methodology Overview

Strategy Returns. Short-term reversal and residual momentum portfolio returns are obtained from the Jensen, Kelly, and Pedersen (JKP) Global Factor Data repository. This database provides standardized factor portfolios constructed following academic conventions, ensuring replicability and comparability with the literature. We utilize:

- **Monthly value-weighted (VW)** returns: 1,182 observations (July 1926 – December 2024)
- **Daily equal-weighted (EW)** returns: 25,901 observations (July 1926 – December 2024)

Fama-French Factors. Factor data for the three-factor (Fama and French, 1993) and five-factor (Fama and French, 2015) models are sourced from Kenneth French's Data Library at Dartmouth College. These include market excess returns (MKT-RF), size (SMB), value (HML), profitability (RMW), and investment (CMA) factors at both daily and monthly frequencies.

Q-Factors. Alternative factor specifications following Hou et al. (2015) are obtained from the Global-Q database. The Q5 model includes size (R_{ME}), investment (R_{IA}), profitability (R_{ROE}), and expected growth (R_{EG}) factors.

Geopolitical Risk. The GPR index from Caldara and Iacoviello (2022) is obtained from Matteo Iacoviello's website. This index captures geopolitical tensions through automated text analysis of newspaper articles.

3.2 Factor Models

We evaluate abnormal returns using five nested factor models. The Capital Asset Pricing Model (CAPM) serves as the baseline specification:

$$r_{\text{STR},t} - r_{f,t} = \alpha + \beta_{\text{MKT}}(r_{m,t} - r_{f,t}) + \varepsilon_t \tag{2}$$

where $r_{\text{STR},t}$ is the strategy return, $r_{f,t}$ is the risk-free rate, $r_{m,t}$ is the market return, and α captures abnormal returns unexplained by market risk.

The Fama and French (1993) three-factor model extends CAPM by including size and value factors:

$$r_{\text{STR},t} - r_{f,t} = \alpha + \beta_{\text{MKT}}\text{MKT}_t + \beta_{\text{SMB}}\text{SMB}_t + \beta_{\text{HML}}\text{HML}_t + \varepsilon_t \tag{3}$$

The Fama and French (2015) five-factor model adds profitability and investment factors:

$$r_{\text{STR},t} - r_{f,t} = \alpha + \beta_{\text{MKT}}\text{MKT}_t + \beta_{\text{SMB}}\text{SMB}_t + \beta_{\text{HML}}\text{HML}_t + \beta_{\text{RMW}}\text{RMW}_t + \beta_{\text{CMA}}\text{CMA}_t + \varepsilon_t \tag{4}$$

The Hou et al. (2015) Q5 model is given by:

$$r_{\text{STR},t} - r_{f,t} = \alpha + \beta_{\text{MKT}}\text{MKT}_t + \beta_{\text{ME}}R_{\text{ME},t} + \beta_{\text{IA}}R_{\text{IA},t} + \beta_{\text{ROE}}R_{\text{ROE},t} + \beta_{\text{EG}}R_{\text{EG},t} + \varepsilon_t \tag{5}$$

3.3 Performance Metrics

We evaluate strategy performance using three risk-adjusted return metrics that capture different aspects of risk.

Sharpe Ratio. The Sharpe ratio measures excess return per unit of total volatility:

$$\text{Sharpe Ratio} = \frac{\mathbb{E}[r_{\text{STR}}] - r_f}{\sigma(r_{\text{STR}})} \tag{6}$$

where $\mathbb{E}[r_{\text{STR}}]$ is the expected strategy return, r_f is the risk-free rate, and $\sigma(r_{\text{STR}})$ is the standard deviation of returns. The Sharpe ratio treats upside and downside volatility symmetrically, which may not reflect investor preferences that are primarily concerned with downside risk.

Sortino Ratio. The Sortino ratio addresses this limitation by penalizing only downside volatility:

$$\text{Sortino Ratio} = \frac{\mathbb{E}[r_{\text{STR}}] - r_f}{\sigma_{\text{down}}(r_{\text{STR}})} \tag{7}$$

where σ_{down} is the downside deviation, calculated as the standard deviation of returns below a minimum acceptable return (typically zero or the risk-free rate). This metric is particularly relevant for strategies where the return distribution is asymmetric, as it does not penalize positive outliers.

Calmar Ratio. The Calmar ratio measures return relative to maximum drawdown risk:

$$\text{Calmar Ratio} = \frac{\mathbb{E}[r_{\text{STR}}] - r_f}{\text{Max Drawdown}} \tag{8}$$

where the maximum drawdown represents the largest peak-to-trough decline in cumulative returns over the sample period. This metric captures tail risk and is especially important for practitioners concerned with capital preservation during adverse market conditions.

For annualization, we multiply mean returns by 12 (monthly) or 252 (daily) and volatility by $\sqrt{12}$ or $\sqrt{252}$, respectively. Following McLean and Pontiff (2016), we distinguish between the pre-publication period (1926–1989) and post-publication period (1990–2024).

4 Empirical Results

4.1 Monthly Analysis (Baseline)

Table 1 presents the CAPM alpha estimates for the short-term reversal strategy across different sample periods using monthly value-weighted data, as specified in the seminar project requirements.

Table 1: CAPM Alphas by Period (Monthly Data, Value-Weighted)

Period	N	Alpha	t-stat	Significant?
Full Sample (1926–2024)	1,182	1.66%	3.11***	Yes
Pre-1990	762	2.19%	3.17***	Yes
Post-1990	420	0.53%	0.65	No

Note: *** denotes significance at the 1% level. Returns annualized.

The full sample CAPM alpha of 1.66% per annum is statistically significant ($t = 3.11$).

However, the subperiod analysis reveals a striking pattern consistent with the publication effect hypothesis: while pre-1990 alphas are substantial (2.19%, $t = 3.17$), post-1990 alphas decline to 0.53% and lose statistical significance ($t = 0.65$).

Table 2: Factor Model Results (Monthly, Full Sample)

Model	Alpha	t-stat	Adj. R^2
CAPM	1.66%	3.11***	0.019
FF3	1.80%	3.38***	0.030
FF5	0.27%	0.46	0.011
Q5	0.71%	1.05	0.003

While CAPM and FF3 yield significant alphas, the five-factor models (FF5 and Q5) reduce alphas to insignificance. The low adjusted R^2 values across all models indicate that standard factors explain little of the strategy's variance, consistent with the microstructure-based interpretation.

4.2 Daily Analysis (Extension)

Our extension to daily equal-weighted data yields markedly different conclusions, demonstrating the importance of sample size for statistical inference in asset pricing tests.

Table 3: CAPM Alphas by Period (Daily Data, Equal-Weighted)

Period	N	Alpha	t-stat	Significant?
Full Sample (1926–2024)	25,901	6.03%	13.92***	Yes
Pre-1990	17,084	8.29%	14.61***	Yes
Post-1990	8,817	1.64%	2.59***	Yes

Note: Daily returns annualized using 252 trading days.

The daily analysis reveals a crucial finding: unlike monthly data, daily data shows statistically significant alphas even in the post-1990 period (1.64%, $t = 2.59$). While the magnitude has declined by approximately 80% relative to pre-1990 levels, the increased statistical power from 25,901 observations allows detection of this smaller but persistent effect.

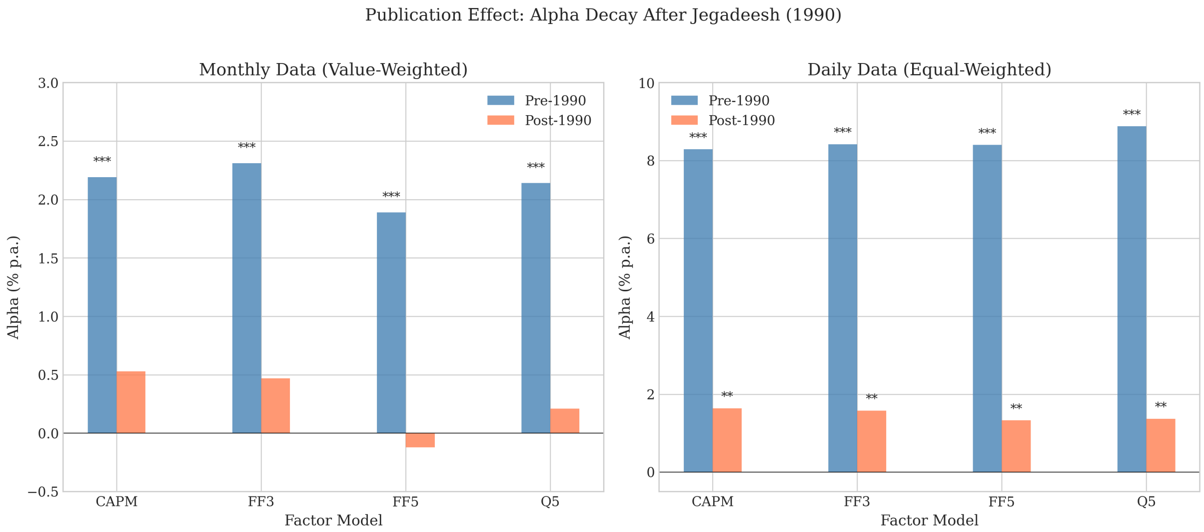

Figure 2: Publication Effect: Alpha Decay After Jegadeesh (1990). The left panel shows monthly value-weighted results where post-1990 alphas become insignificant. The right panel shows daily equal-weighted results where alphas remain significant across all factor models, demonstrating the importance of statistical power. Remarkably, all five factor models yield significant alphas in the daily full sample, and even FF5 and Q5 show significant post-1990 alphas at the 5% level.

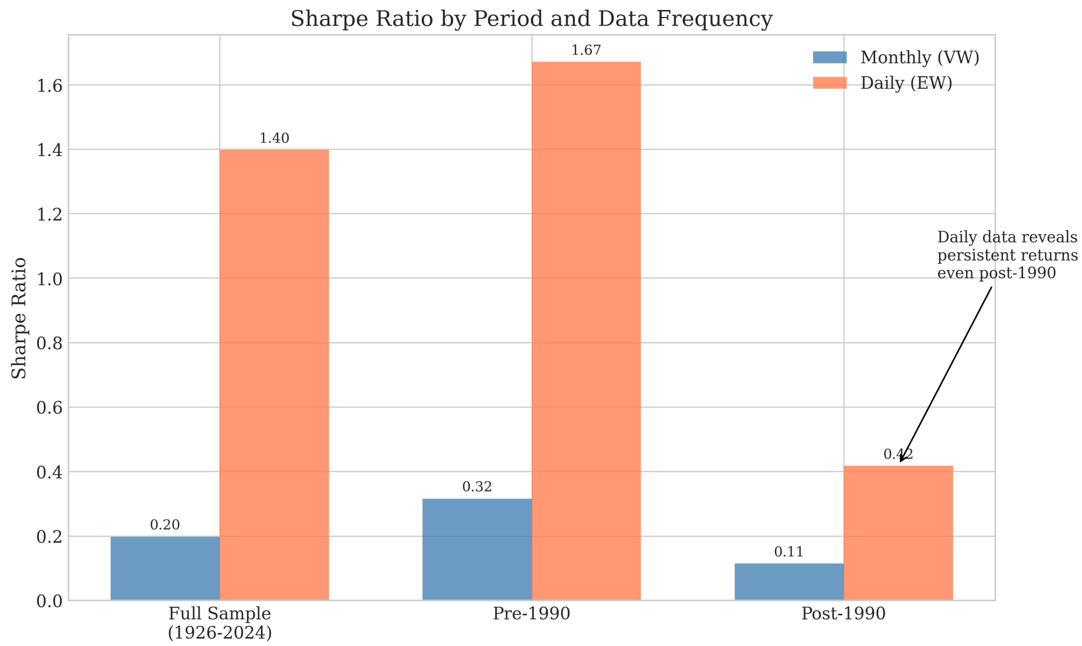

Figure 3: Sharpe Ratio Comparison by Period and Data Frequency. Daily equal-weighted data shows substantially higher Sharpe ratios across all periods, with the post-1990 Sharpe remaining positive (0.418) compared to the near-zero monthly estimate (0.114).

4.3 Alternative Risk-Adjusted Performance Measures

Beyond the Sharpe ratio, we examine the Sortino and Calmar ratios to provide a more comprehensive assessment of risk-adjusted performance. These metrics offer complementary perspectives by focusing on downside risk and tail risk, respectively.

Sortino Ratio Analysis. Figure 4 presents the Sortino ratio across periods for both monthly and daily data. The Sortino ratio, which penalizes only downside volatility, reveals similar patterns to the Sharpe ratio but with higher absolute values due to the asymmetric treatment of returns.

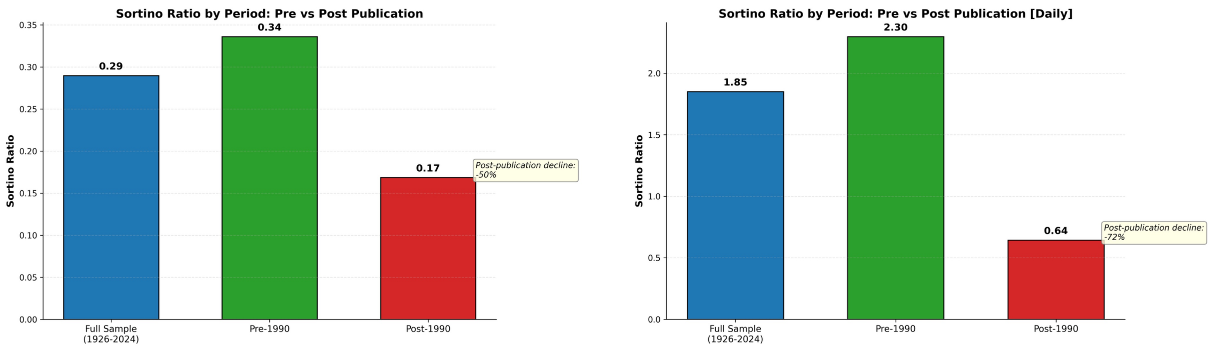

Figure 4: Sortino Ratio by Period: Monthly (left) vs. Daily (right) Data. The monthly Sortino ratio declines from 0.34 pre-1990 to 0.17 post-1990 (−50%), while the daily Sortino ratio shows a more pronounced decline from 2.30 to 0.64 (−72%). Despite the larger percentage decline, the daily post-1990 Sortino (0.64) remains substantially higher than the monthly equivalent (0.17).

Table 4 summarizes the Sortino ratio results. The daily data consistently shows higher Sortino ratios than monthly data, indicating that the strategy's return distribution exhibits favorable downside characteristics at higher frequencies.

Table 4: Sortino Ratio by Period and Data Frequency

Period	Monthly (VW)	Daily (EW)	Ratio (Daily/Monthly)
Full Sample (1926–2024)	0.29	1.85	6.38×
Pre-1990	0.34	2.30	6.76×
Post-1990	0.17	0.64	3.76×
Post-publication decline	−50%	−72%	—

Calmar Ratio Analysis. The Calmar ratio, measuring return relative to maximum drawdown, provides insight into tail risk exposure. Figure 5 illustrates the Calmar ratio across periods.

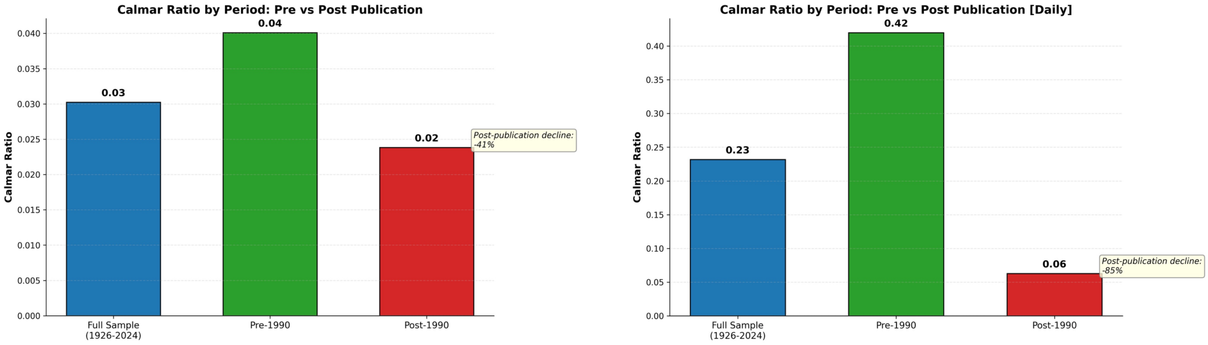

Figure 5: Calmar Ratio by Period: Monthly (left) vs. Daily (right) Data. The monthly Calmar ratio remains low across all periods (0.02–0.04), while the daily Calmar ratio shows a dramatic decline from 0.42 pre-1990 to 0.06 post-1990 (−85%), indicating substantially increased drawdown risk relative to returns in the modern era.

Table 5: Calmar Ratio by Period and Data Frequency

Period	Monthly (VW)	Daily (EW)	Ratio (Daily/Monthly)
Full Sample (1926–2024)	0.03	0.23	7.67×
Pre-1990	0.04	0.42	10.50×
Post-1990	0.02	0.06	3.00×
Post-publication decline	−41%	−85%	—

The Calmar ratio analysis reveals an important finding: the post-publication decline in the daily Calmar ratio (−85%) is substantially larger than the decline in other metrics. This suggests that while the strategy still generates positive returns post-1990, it has become more susceptible to large drawdowns relative to those returns. For risk-averse investors, this deterioration in tail risk characteristics may be more concerning than the decline in average returns.

4.4 Factor Exposures

The strategy exhibits interesting factor loadings that provide insight into its risk characteristics. Figure 6 displays the Fama-French five-factor betas from daily data.

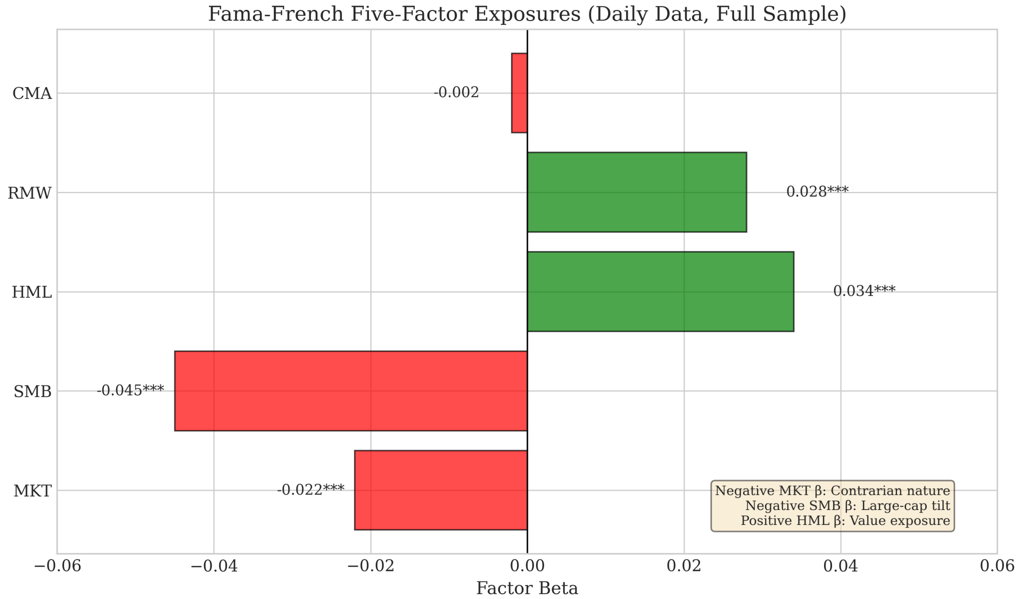

Figure 6: Factor Exposures (Fama-French Five-Factor Model, Daily Data). The negative market and size betas indicate a contrarian, large-cap tilt. Positive value and profitability exposures emerge when controlling for other factors.

Key observations:

- **Negative market beta** ($\beta_{\mathrm{MKT}} = -0.022$, $t = -12.04$): Consistent with the contrarian nature of the strategy.
- **Negative size beta** ($\beta_{\mathrm{SMB}} = -0.045$, $t = -13.54$): Indicates a large-cap tilt.
- **Positive value beta** ($\beta_{\mathrm{HML}} = +0.034$, $t = 9.88$): Suggests alignment with value characteristics in the FF5 specification.

5 Geopolitical Risk Exposure

Following Caldara and Iacoviello (2022), we examine whether the short-term reversal strategy exposes investors to geopolitical risk by regressing strategy returns on changes in the Geopolitical Risk Index (GPR):

$$r_{\text{STR},t} = \alpha + \beta_{\text{GPR}} \Delta\text{GPR}_t + \varepsilon_t \tag{9}$$

Table 6: Geopolitical Risk Regression Results

Statistic	Daily Data	Monthly Data
β_{GPR} Coefficient	0.000000	-0.000009
t-statistic	0.12	-0.51
p-value	0.90	0.61

The near-zero coefficients and insignificant t-statistics indicate that the short-term reversal strategy has no meaningful exposure to geopolitical events. Strategy returns are essentially **orthogonal** to geopolitical risk, suggesting that reversal patterns arise from microstructure dynamics rather than systematic risk factors. This finding has important practical implications: the strategy is neither a hedge against geopolitical turmoil nor does it amplify losses during periods of heightened uncertainty.

6 Portfolio Optimization

Given the modest standalone returns of the short-term reversal strategy in the modern era, we investigate whether combining it with other strategies can improve risk-adjusted performance. Following Blitz et al. (2011), we consider residual momentum as a natural complement.

The combined portfolio return is:

$$r_{\text{Combined},t} = \omega \cdot r_{\text{STR},t} + (1-\omega) \cdot r_{\text{RMom},t} \tag{10}$$

The correlation between short-term reversal and residual momentum is negative ($\rho = -0.08$ monthly, $\rho = -0.122$ daily), creating substantial diversification benefits. The optimal weight maximizing the Sharpe ratio is:

$$\omega^* = \frac{\mu_{\text{STR}}\sigma^2_{\text{RMom}} - \mu_{\text{RMom}}\sigma_{\text{STR}}\sigma_{\text{RMom}}\rho}{\mu_{\text{STR}}\sigma^2_{\text{RMom}} + \mu_{\text{RMom}}\sigma^2_{\text{STR}} - (\mu_{\text{STR}} + \mu_{\text{RMom}})\sigma_{\text{STR}}\sigma_{\text{RMom}}\rho} \tag{11}$$

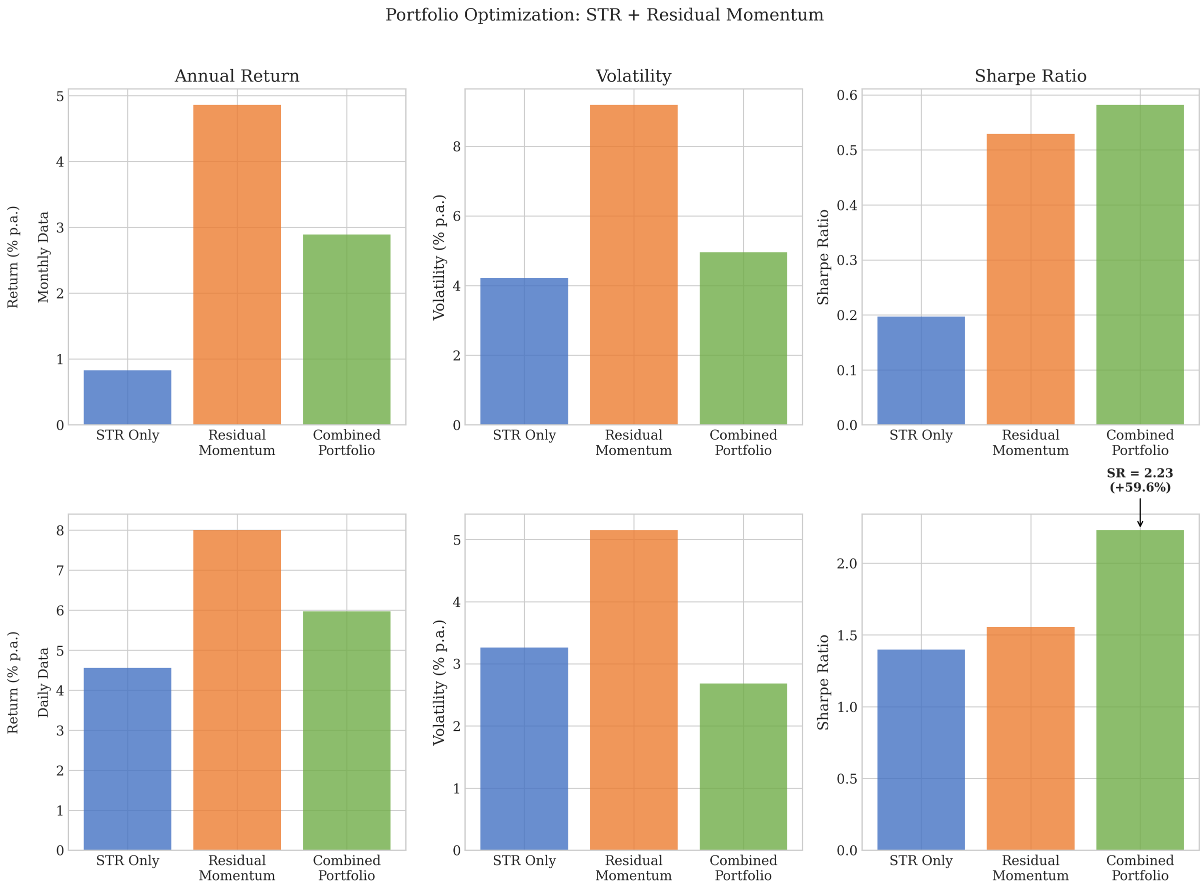

Figure 7: Portfolio Optimization Results: STR + Residual Momentum. The combined portfolio achieves the highest Sharpe ratio (2.23 in daily data) while reducing volatility below both component strategies.

Table 7: Portfolio Optimization Results

Strategy	Return	Volatility	Sharpe
Monthly Data (Value-Weighted)			
STR Only	0.83%	4.22%	0.197
Residual Momentum	4.86%	9.19%	0.529
Combined (49%/51%)	2.89%	4.96%	**0.582**
Daily Data (Equal-Weighted)			
STR Only	4.56%	3.26%	1.398
Residual Momentum	8.00%	5.15%	1.555
Combined (59%/41%)	5.97%	2.68%	**2.230**

The portfolio optimization yields striking improvements. Using monthly data, the combined strategy improves the Sharpe ratio by **195%** relative to STR alone. The daily analysis shows even more dramatic gains: the optimal combination achieves a Sharpe ratio of **2.230**, representing a 59.6% improvement over STR alone while simultaneously *reducing* volatility.

7 Conclusion

This paper provides comprehensive evidence on the persistence and profitability of the short-term reversal anomaly using nearly a century of US equity data from multiple authoritative sources: JKP Factors for portfolio returns, Kenneth French's Data Library for Fama-French factors, Global-Q for Q-factors, and the Geopolitical Risk Index from Caldara and Iacoviello (2022).

Our analysis yields several important conclusions:

First, the anomaly has weakened substantially since Jegadeesh's (1990) seminal publication, consistent with the publication effect documented by McLean and Pontiff (2016). Monthly value-weighted alphas, while significant over the full sample, become statistically insignificant after 1990.

Second, our extension to daily equal-weighted data reveals that statistically significant alphas persist even in the post-publication era. The approximately 22-fold increase in observations (from 1,182 to 25,901) provides sufficient statistical power to detect small but economically meaningful effects that monthly analysis fails to identify. This is a key methodological contribution: *frequency of observation matters for inference about anomaly persistence.*

Third, the strategy exhibits no exposure to geopolitical risk, making it potentially attractive as a diversifying component in multi-strategy portfolios. The absence of systematic risk exposure supports microstructure-based explanations for the reversal effect.

Fourth, combining short-term reversal with residual momentum substantially improves risk-adjusted returns. The negative correlation between strategies ($\rho = -0.122$ in daily data) creates diversification benefits that more than double the standalone Sharpe ratio, achieving an exceptional risk-adjusted return of SR = 2.23.

Our results contribute to the ongoing debate about market efficiency and the durability of documented anomalies. While the short-term reversal strategy no longer offers the robust standalone returns observed in earlier decades, it remains a valuable component in diversified quantitative strategies.

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