Aalto University
School of Business

Bachelor's Programme in Economics and Business Administration

# Revisiting (Revitalizing) Momentum

**Pyry Pohjantähti**

Bachelor's Thesis
2024

**Aalto University**
**School of Business**

**Author** Pyry Pohjantähti

**Title** Revisiting (Revitalizing) Momentum

**Degree programme** Economics and Business Administration

**Major** Finance

**Teacher in charge and advisor** Prof. Matti Keloharju

**Date** 18 April 2024 **Number of pages** 26+3 **Language** English

**Abstract**

In this thesis, I investigate the impact of varying definitions of cross-sectional momentum on the performance of long-short momentum strategies under different market conditions. A long-short momentum portfolio takes a long position in stocks that have shown strong previous performance and shorts those with poor past performance. Over recent decades, the returns from standard long-short momentum portfolios have declined, prompting both academics and practitioners to explore numerous approaches to diagnose and remedy the issues inherent in these strategies.

I construct classical long-short momentum portfolios and investigate simple methods to counteract the diminished returns of these strategies. A notable challenge within momentum strategies is their tendency to "crash"—that is, after a period of significant gains, these portfolios often suffer abrupt, substantial losses. I propose a specific solution to manage these crash risks effectively, conditional on market states.

The asset pricing and portfolio management literature offers various complex methods to construct long-short portfolios. However, my objective is to demonstrate that relatively minor improvements can significantly rejuvenate the long-short momentum strategy, also known as the premium anomaly.

I discover that techniques such as volatility scaling and adjusting long and short positions based on the market state can significantly enhance the efficacy of the momentum strategy, restoring its former robustness.

**Keywords** asset pricing, momentum, anomaly, portfolio management

**Aalto-yliopisto**
**Kauppakorkeakoulu**

**Tekijä** Pyry Pohjantähti

**Työn nimi** Opinnäyteen otsikko — Opinnäytteen mahdollinen alaotsikko

**Koulutusohjelma** Kauppatiede

**Pääaine** Rahoitus

**Vastuuopettaja ja ohjaaja** Prof. Matti Keloharju

**Päivämäärä** 18.4.2024 **Sivumäärä** 26+3 **Kieli** englanti


**Tiivistelmä**

Tässä tutkielmassa tutkin erilaisten cross-sectional-momentumien määritelmien vaikutusta long-short -momentumstrategioiden tuottoihin erilaisissa markkinaolosuhteissa. Long-short -momentumstrategia tarkoittaa sitä, että asetetaan pitkä (long) positio osakkeissa, jotka ovat tuottaneet hyvin menneisyydessä ja lyhyt (short) positio osakkeissa, joiden menneet tuotot ovat olleet heikkoja. Viime vuosikymmenten aikana perinteisten long-short -momentumstrategioiden tuotot ovat laskeneet, mikä on saanut sekä akateemikot että sijoitusammattilaiset tutkimaan lukuisia lähestymistapoja näiden strategioiden ongelmien tunnistamiseksi ja korjaamikseksi.

Rakennan perinteisiä long-short-momentumportfolioita ja tutkin suoraviivaisia menetelmiä näiden strategioiden tuottojen heikkenemisen ehkäisemiseksi. Huomattava haaste long-short-momentumstrategioissa on niiden taipumus "romahdukseen" – toisin sanoen merkittävien voittojen jakson jälkeen nämä salkut kärsivät usein äkillisistä, merkittävistä tappioista. Näytän, että yksinkertainen ratkaisu ehdollistettuna markkinatilanteelle pystyy vähentämään romahdusriskin vaikutusta.

Arvopaperien hinnoiteluun ja salkunhallintaan liittyvä kirjallisuus tarjoaa erikoistuneita menetelmiä long-short-momentumportfolioitten rakentamiseen. Kuitenkin tavoitteenani on osoittaa, että suhteellisen pienet parannukset voivat merkittävästi elvyttää long-short -momentumstrategiaa, jota on myös aiemmin kutsuttu premium-anomaliaksi.

Huomaan, että metodit, kuten volatiliteetillä skaalaus ja pitkien ja lyhyiden positioitten säätäminen markkinatilanteen mukaan, voivat merkittävästi parantaa momentumstrategian tehokkuutta palauttaen sen tuotot aiemmalle tasolle ennen viimeisimpiä vuosikymmeniä.



**Avainsanat** momentum, salkunhoito, arvopaperien hinnoittelu, anomalia

# Contents

# 1 Introduction

In the realm of quantitative investment strategies, the momentum strategy capitalizes on the momentum anomaly. An anomaly, in this context, refers to a persistent deviation from the typical market efficiency, where certain patterns of returns can be predicted based on historical data. This particular anomaly has been robustly documented since the seminal work of Jegadeesh and Titman in 1993, which demonstrated that stocks exhibiting strong past performance tend to continue outperforming, while those with poor historical returns tend to continue underperforming.

When implementing the momentum strategy, it is crucial to consider several key aspects. One must decide between employing cross-sectional momentum, time-series momentum, or a combination of both, as outlined by Moskowitz, Ooi, and Pedersen in 2012. Cross-sectional momentum involves ranking stocks at a given time $t$ into portfolios based on their returns over the past $j$ months, and then maintaining these positions for a set period $k$. Conversely, time-series momentum assesses the performance of individual assets—such as indices, stocks, funds, commodities, and currencies—at time $t$, initiating long or short positions based on their historical performance.

This thesis will concentrate on the cross-sectional momentum, often called as the "premium" anomaly by Fama and French in 2008. Despite its acclaim as a superior strategy, the returns from cross-sectional momentum have been waning over time.

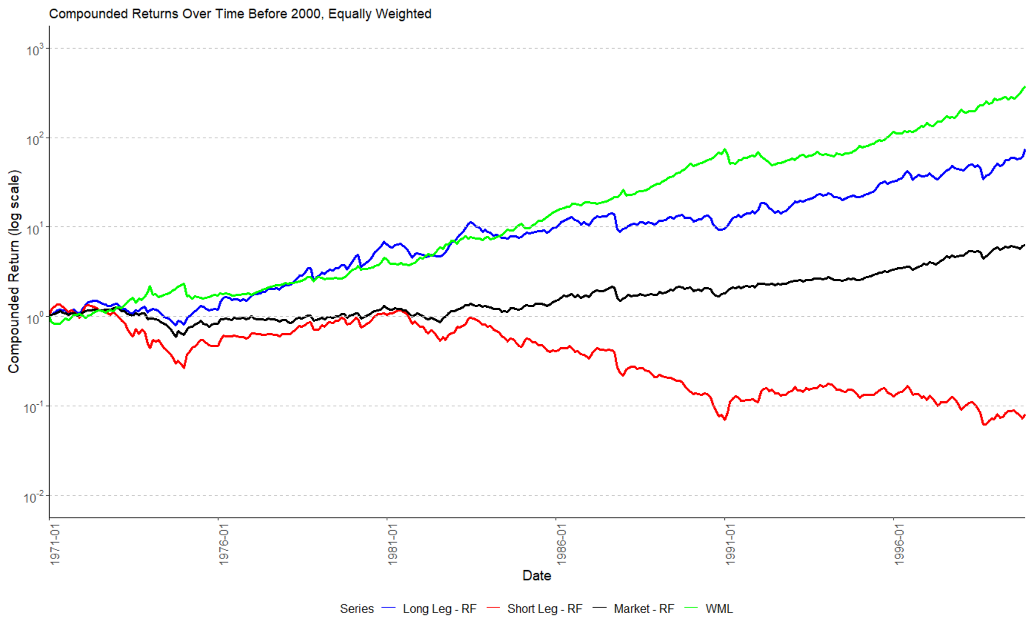


**Figure 1:** Equally weighted momentum portfolio dollar returns from 1971-01 to 1999-12


**Figure 2:** Equally weighted momentum portfolio dollar returns from 2000-01 to 2023-12

The implementation of cross-sectional momentum involves several considerations:

1. Investment universe: Determining which stocks, assets, or asset classes are eligible.

2. Lookback period, Establishing the duration, denoted as $j$, over which past returns are considered. Typically, the most recent month is excluded due to the reversal effect, where the previous month's top performers tend to underperform in the following month.

3. Holding Period: Setting the duration, denoted as $k$, for which positions are maintained after the formation period.

4. "Signal" measurement: Identifying which stocks performed well and which did poorly during the lookback period.

5. Portfolio construction: Considering the volatility of stock returns, diversification is necessary. This involves transforming the signal into long and short portfolios, which can be amalgamated to create a balanced long-short portfolio.

In exploring these factors, I will focus particularly on signal measurement and portfolio construction. The aim is to determine whether different weighting strategies or methods of signal construction can mitigate the recent underperformance of the long-short momentum portfolio, inspired by the analysis of momentum strategy's crash proneness by Daniel and Moskowitz in 2016.

I will also show, that rather simple strategy to detect a small "momentum crash" does produce abnormal returns under most standard asset pricing tests (Fama & French, 1992).

# 2 Data

I utilize data from Wharton Research Data Services' Center for Research in Security Prices (WRDS CRSP) and from the Kenneth French Data Library (2024). From CRSP, I collected monthly stock returns spanning from January 1970 to December 2023. The selected stocks have share codes 10 (ordinary common shares) or 11 (ordinary common shares, unspecified), and are primarily listed on the NYSE (N), AMEX (A), or NASDAQ (Q).

The data include the following variables: CUSIP (security identifier), SIC Code (sector code), *prc* (price), *shrout* (shares outstanding), and *ret* (returns). Notably, *ret* accounts for all corporate actions, making it suitable for use as the holding period return, denoted as $r_{i,t}$ or referred to as simple returns.

For the analysis, I only include time series for each asset that have at least 15 consecutive prices and 14 consecutive returns. Entries with NAs are excluded. In cases where the implied market capitalization ($shrout \times prc$) is negative, I also exclude those values until 15 consecutive prices and 14 consecutive returns are available.

When filtering out stocks from the finance and banking sectors, I exclude those with SIC Codes ranging from 6000 to 6999.

From the French Data Library, I collect monthly Fama-French 3-factor returns (excess market return, small minus big, and high minus low) along with the risk-free rate. I use these excess market and risk-free rate values instead of the CRSP value-weighted or equally-weighted returns, which are commonly referenced in asset pricing literature.

# 3 Models and Methods

I will construct multiple long-short momentum portfolios. Each portfolio will adhere to the same lookback and holding periods, denoted as $j$ and $k$ respectively. The most typical configuration for these periods in momentum portfolio formation is $(j = 12, k = 1)$, which excludes the previous month's returns. For instance, to form the momentum portfolio for January, I will disregard December's returns and instead use the returns from January through November to calculate the signal for portfolio construction. In every case, $r_{i,t}$ denotes the simple holding period return, accounting for all corporate actions such as splits, dividends, and share repurchases. For detailed data specifications, refer to the previous section.

## 3.1 Equally weighted

For the momentum portfolio of time $t$, each stock $i$ gets its signal $r^s_{i,t}$ calculated as

$$r^s_{i,t} = e^{r^c_{i,t}} - 1, \text{ where } r^c_{i,t} = \sum_{t=-12}^{T=-2} \ln(1 + r_{i,t}). \tag{1}$$

Then these return signals $r^s_{i,t}$ get ranked into deciles. If the $r^s_{i,t}$ is in the lowest 10% in time $t$ across all the $r^s_{i,t}$, $\exists t$, the stock gets ranked in to the first decile, decile 1. Given these portfolio rankings for $n$ number of $r^s_{i,t}$, the portfolio returns per decile $d \in \{1, 2, 3, ..., 10\}$ are calculated in time $t$ as follows

$$r^p_{d,t} = \frac{1}{n} \sum_{i=1}^{n} r_{i,t}.$$

## 3.2 Value weighted

For the momentum portfolio of time $t$, each stock $i$ gets its signal $r^s_{i,t}$ calculated as in 1. Also, the ranking process is similar as described for the equally weighted portfolios. The total market cap for decile portfolio construction in time $t$ is calculated as follows:

$$w^p_{d,t} = \sum_{i=1}^{n} w_{i,t-2} \tag{2}$$

In other words, I will be summing the market capitalizations of individual assets from the end of the lookback period $t-2$, $w_{i,t-2}$, to find out the total market capitalization of the given decile portfolio to calculate the weights for each individual asset per the decile portfolio. The total decile portfolio return at time $t$ will thus be the sum weighted of returns, where the weights are per market capitalizations at the end of the lookback period, time $t - 2$.

$$r^p_{d,t} = \sum_{i=1}^{n} \frac{w_{i,t-2}}{w^p_{d,t}} r_{i,t}$$

## 3.3 Equally and value weighted models without finance and banking sector

In the literature, there are precedents for excluding the finance and banking sector when calculating long-short factor returns, as noted by Fama and French (1992). They argue that there are economic motivations for such exclusions, although it is not universally practiced. Specifically, Fama and French construct well-known size and value factors, recognized as anomalies, and deliberately exclude the finance and banking sector due to its inherent high leverage, which is atypical of other industries. In their study, they seek to identify reasons for the existence of the value anomaly beyond leverage, making the exclusion of a heavily debt-laden industry logical.

Similarly, the influence of leverage on momentum is also noteworthy. Goyal and Jegadeesh (2018) explored this in the context of time-series momentum, discovering that the performance can be significantly attributed to leverage. Following these insights, I will also exclude the finance and banking sector when calculating the returns for the cross-sectional momentum portfolios, as discussed in the previous sections.

## 3.4 Equally and value weighted models with volatility scaled past returns

With this iteration I will scale the past returns by the inverse of past volatility. The past volatility signal for asset $i$ for time $t$, $\sigma^s_{i,t}$, is calculated as sample standard deviation:

$$\sigma^s_{i,t} = \sqrt{\frac{1}{10}\sum_{t=-12}^{T=-2}(\ln(1+r_{i,t}) - \overline{r_{i,t}})^2} \tag{3}$$

where $\overline{r_{i,t}}$ is calculated as the mean return of the lookback period.

$$\overline{r_{i,t}} = \frac{1}{11}\sum_{t=-12}^{T=-2}\ln(1+r_{i,t})$$

Then, the signal $r^s_{i,t}$ is found by scaling the return given by equation 1, which is scaled by the inverse of 3. Analytically, under this model the signal for individual asset per time $t$ is given by:

$$r^s_{i,t} = \frac{1}{\sigma^s_{i,t}}\left(e^{r^c_{i,t}} - 1\right), \text{ where } r^c_{i,t} = \sum_{t=-12}^{T=-2}\ln(1+r_{i,t}) \tag{4}$$

This volatility scaled signal is then used to do the same process as already described in sections 3.1 and 3.2. The idea is analogous to the one of Fan, Kearney, Li & Liu (2022), as they generate volatility scaled method to account for the fact that stocks with high realised volatility during the lookback period have weaker momentum effect. Instead of using daily returns, I use monthly returns for convenience.

### 3.5 Equally and value weighted models with crash measure

Finally, I will develop an ad-hoc strategy to account for the crashiness of the WML momentum portfolio, as discussed in Daniel & Moskowitz (2016) and the appendix. I will first introduce the model and then explain the economic motivation behind it. The strategy alternates between the standard WML zero-investment portfolio (see 3.1 and 3.2) and, during market downturns, switches to going long on both the loser and winner portfolios. This can be analytically described as follows.

Firstly, the panic state indicator is derived as $I_t^p$ for period $t$ on which the portfolio will be constructed, portfolio construction will follow the methods of 3.1. $SR$ refers to short run and $LR$ refers to long run

$$
\begin{aligned}
I_t^p(\delta) &= \begin{cases} 1, r_{m,t}^{SR} < r_{m,t}^{LR} - \delta\sigma_{m,t}^{LR} \\ 0, r_{m,t}^{SR} \geq r_{m,t}^{LR} - \delta\sigma_{m,t}^{LR} \end{cases} \\
r_{m,t}^{SR} &= \frac{1}{3}\sum_{t=-4}^{T=-2} r_{m,t} \\
r_{m,t}^{LR} &= \overline{r_t} = \frac{1}{120}\sum_{t-121}^{t-2} r_{m,t} \\
\sigma_{m,t}^{LR} &= \sqrt{\frac{1}{119}\sum_{t-121}^{t-2}(r_{m,t}-\overline{r_t})^2} \\
\delta &\in \mathbb{R}_+
\end{aligned}
\tag{5}
$$

When $I_t^p = 0$, the market is stable, as the short run average return closely aligns with the long run average return and its negative standard deviation, which is adjusted by a parameter $\delta$. Conversely, when $I_t^p = 1$, the market is in a state of panic, indicated by a significant deviation of the short run average from the long run expected return and its standard deviation, also dependent on the scalar $\delta$.

The evaluation period comprises 120 months. The most recent period, $t = -1$, is excluded to avoid including the reversal effect, thereby matching the information set used in the portfolio formation described in previous sections. Including the $r_{t-1}$ would cause the rolling mean $\frac{1}{3}\sum_{t=-4}^{t=-2} r_{m,t}$ to incorporate the reversal effect, thus not accurately capturing the short run trend.

The idea is to use the fact that the short leg of the momentum portfolio has very high market $\beta$ when markets are doing poorly in general, but once the markets rebound the short leg will rebound very strongly as well. This rebound of the short leg destroys the WML momentum portfolio returns, and thus I try to devise model which anticipates the rebound and takes a long position in the short leg in order to benefit from rebound. (Daniel & Moskowitz, 2016.)

Then the portfolio return is given by:

$$
r_{p,t}(\delta) = \left(1 - I_t^p(\delta)\right)\left(r_{W,t} - r_{L,t}\right) + I_t^p(\delta)\left(\frac{1}{2}\left(r_{W,t} + r_{L,t}\right) - r_{f,t}\right) \tag{6}
$$

Here,

$$r_{W,t} = \text{10th, winner momentum decile}$$
$$r_{L,t} = \text{1st, loser momentum decile}$$
$$r_{f,t} = \text{risk free rate}$$

Thus, in the absence of a panic, I construct a zero-investment long-short momentum portfolio (WML). In a panic state, I assign equal weights to both the short and the long legs, from which I deduct the risk-free rate to calculate the excess return. The nominal return of the long-short zero-investment portfolio effectively includes the risk-free rate as it cancels out, given by $(r_t^W + r_{f,t}) - (r_t^L + r_{f,t}) = r_t^W - r_t^L$.

The parameter $\delta$ governs the indicator variable $I_t^p$, setting the threshold for when the market is performing "too poorly" relative to its long-term mean. The task is to find the optimal $\delta$ that determines the weighting of the standard deviation subtracted from the market return to establish a trigger level. Since $\delta$ is not analytically solvable, I aim to optimize it dynamically concerning.

The delta is not analytically solvable since I want to optimize dynamically it wrt.

$$SR = \frac{r_{p,t}(\delta)}{\sigma_p(\delta)} \tag{7}$$

## 3.6 Methods for Equally and value weighted models with crash measure

To determine the time-invariant $\delta$ referenced in 5, I will generate in-sample returns from the period January 1971 through August 2003, yielding a total of 392 data points per series. To capture the data structure accurately, I will create 2500 series, each consisting of 98 blocks of 4 returns (i.e., $98 \cdot 4 = 392$), using a bootstrap method (with replacement) on the matrices of monthly real returns:

$$\mathbf{r_v} = [\mathbf{r_{m,t}}, \mathbf{r_{f,t}}, \mathbf{r_{W,t}}, \mathbf{r_{L,t}}] \in \mathbb{R}^{4\times 4}$$

This approach helps maintain the inherent structure of the data, recognizing that stock (market) returns are not independent and identically distributed (i.i.d). The data-generating process of stock market returns is not time-invariant nor stochastically stable, so block bootsrapping is one way to simulate returns without considering more complex models which need parameter estimation as well.

It is well-documented that market returns exhibit autocorrelation—a fundamental aspect of the momentum anomaly—and heteroskedasticity (Wiest, 2023). Bootstrapping individual returns without considering these characteristics would overlook essential features like autocorrelation and heteroskedasticity, which are naturally present in the data. The method of block bootstrapping for non-i.i.d time series data is thoroughly described by Politis, Romano, and Wolf (2012).

Although estimating variance with GARCH models such as GJR-GARCH and GARCH(1,1) could be considered, using these models to scale volatility and generate return series might not be ideal. Thehe available sample may not be large enough for robust estimates. Moreover, GARCH models are typically applied to daily or weekly data, less so to monthly data, as noted by Cont (2000).

Upon simulating these datasets, I will explore various $\delta$ values within the range $(0, 2]$ as defined in 5, across the 2500 datasets, to optimize the Sharpe ratio of the strategy (6, 7). This simulation will involve testing different market conditions and $\delta$ values to calibrate the optimal $\hat{\delta}$. Subsequently, this calibrated $\hat{\delta}$ will be tested in an out-of-sample scenario using real returns from December 1993 to December 2023, with the first 120 months employed to establish the long-run scenario and exclude reversal effects. The first return calculation, $r_t^p(\hat{\delta})$, will thus commence in January 2004, 2004-01.

# 4 Results

## 4.1 Results for methods in 3.1-3.4

Firstly, I will present the regressions for the momentum portfolios as specified in the sections 3.1-**??**. Each summary statistic and regression table will report the following calculated values: excess return $\overline{r - r_f}$, where $r$ represents the return of the portfolio and $r_f$ the risk-free return; the standard deviation of excess returns denoted as $\sigma$; CAPM $\alpha$ and its corresponding $t$-statistic; CAPM $\beta$; and skewness $sk(m)$. All values, except for CAPM $\beta$ and skewness $sk(m)$, are presented in annualized form. The average monthly excess returns $\overline{r - r_f}$ and CAPM $\alpha$ are scaled by 12, while the standard deviation of monthly excess returns is scaled by $\sqrt{12}$, resulting in the annualized standard deviation $\sigma$. The WML (Winner Minus Loser) is calculated as the return of the 10th decile minus the return of the 1st decile.

CAPM $\alpha$, $t(\alpha)$ and $\beta$ are obtained via regressing the excess returns of the portfolio $p$, $r_{p,t} - r_f, t$, on excess market returns $r_{m,t} - r_{f,t}$:

$$r_{p,t} - r_{f,t} = \alpha_p + \beta_p(r_{m,t} - r_{f,t}) + \varepsilon_{p,t}$$

To obtain robust standard errors I use Newey-West estimator with a lag of 4. These timeseries will display autocorrelation and heteroscedasticity by construction, thus making regular OLS inaccurate. The Sharpe ratio $SR$ is defined as:

$$SR = \frac{\overline{r_p - r_f}}{\sigma_p}, \text{ where } \sigma_p^2 = (12)\frac{1}{T}\sum_{t=1}^{T}(r_{p,t} - \overline{r_p})^2$$

Returns $r_{p,t}$ are monthly returns so they need to be scaled by 12 when calculating the variance.

The most notable observation from Table 1 is that the long leg of the WML portfolio performs better on its own than when paired with the short leg in the WML strategy. This is attributed to the fact that the short leg (decile 1), which ideally should perform poorly to ensure the success of a zero-investment long-short strategy, actually yields positive returns. This diminishes the expected excess returns of the WML portfolio over a purely long strategy. Although one might anticipate that the diversification benefits of combining both long and short legs would compensate for this slight return deficit, this is not observed. Instead, the volatility of the WML is higher than that of the long-only portfolio.

More crucial, however, is the observation regarding skewness. Negative skewness indicates a distribution with a longer or fatter left tail compared to its right tail, centered around the mean. A left (negative) skewed distribution implies that the median is higher than the mean, suggesting a higher likelihood of lower values at the left end of the distribution. This skewness value underscores the crashiness I previously discussed.

The WML portfolio exhibits a significantly negative skewness, indicating that when the long-short momentum portfolio experiences low returns, these returns are exceptionally low. This phenomenon is primarily driven by the short leg of the

**Table 1:** Summary Statistics and Regression Results of Equally Weighted Portfolios

This table contains the summary statistics of the section 3.1 specified portfolios from 1971-01 to 2023-12.

| Portfolio | $\overline{r - r_f}$ | $\sigma$ | $\alpha$ | $t(\alpha)$ | $\beta$ | $SR$ | $sk(m)$ |
|---|---|---|---|---|---|---|---|
| 1 | 0.24 | 36.57 | -0.94 | -3.32 | 1.58 | 0.01 | 1.38 |
| 2 | 3.94 | 25.98 | -0.44 | -2.46 | 1.26 | 0.15 | 0.66 |
| 3 | 6.50 | 22.13 | -0.16 | -1.10 | 1.15 | 0.29 | 0.13 |
| 4 | 8.00 | 19.74 | 0.02 | 0.19 | 1.06 | 0.41 | -0.08 |
| 5 | 8.82 | 18.00 | 0.14 | 1.18 | 0.98 | 0.49 | -0.40 |
| 6 | 10.05 | 17.27 | 0.26 | 2.33 | 0.95 | 0.58 | -0.56 |
| 7 | 12.01 | 17.36 | 0.42 | 3.70 | 0.96 | 0.69 | -0.61 |
| 8 | 12.22 | 17.68 | 0.43 | 3.61 | 0.97 | 0.69 | -0.61 |
| 9 | 13.66 | 19.68 | 0.50 | 3.65 | 1.05 | 0.69 | -0.63 |
| 10 | 15.44 | 25.21 | 0.52 | 2.69 | 1.26 | 0.61 | -0.19 |
| WML | 15.20 | 26.55 | 1.46 | 5.57 | -0.32 | 0.57 | -2.47 |
| Market | 7.31 | 15.89 | 0 | | 1 | 0.46 | -0.50 |

portfolio, as indicated by these values. The addition of the short leg to the long leg provides minimal diversification benefit since $\sigma_{WML}$ is only slightly higher than $\sigma_{10}$. Meanwhile, the skewness of the long leg shifts dramatically from 0.22 to -2.07 upon the inclusion of the short leg. The positive skewness and fat right tail of the short leg occasionally yield very high returns, which, when subtracted in the calculation $r_{WML} = r_{10} - r_1$, result in very low returns for the WML portfolio, as highlighted by the negative skewness.

**Table 2:** Summary Statistics and Regression Results of Value Weighted Portfolios

This table contains the summary statistics of the section 3.2 specified portfolios from 1971-01 to 2023-12.

| Portfolio | $\overline{r - r_f}$ | $\sigma$ | $\alpha$ | $t(\alpha)$ | $\beta$ | $SR$ | $sk(m)$ |
|---|---|---|---|---|---|---|---|
| Decile 1 | -4.95 | 39.94 | -1.51 | -4.88 | 1.81 | -0.12 | 1.29 |
| 2 | 2.81 | 28.70 | -0.58 | -2.47 | 1.34 | 0.10 | 0.42 |
| 3 | 6.49 | 24.99 | -0.20 | -1.13 | 1.21 | 0.26 | 0.27 |
| 4 | 4.86 | 21.48 | -0.26 | -1.92 | 1.10 | 0.23 | -0.22 |
| 5 | 6.94 | 18.50 | -0.01 | -0.08 | 0.97 | 0.38 | -0.30 |
| 6 | 4.87 | 17.22 | -0.16 | -1.59 | 0.93 | 0.28 | -0.69 |
| 7 | 9.47 | 17.64 | 0.23 | 2.19 | 0.91 | 0.54 | -0.03 |
| 8 | 8.65 | 18.42 | 0.13 | 1.07 | 0.97 | 0.47 | -0.09 |
| 9 | 9.90 | 19.95 | 0.20 | 1.58 | 1.02 | 0.50 | -0.16 |
| 10 | 16.16 | 26.95 | 0.55 | 2.83 | 1.30 | 0.60 | 0.22 |
| WML | 21.11 | 35.37 | 2.07 | 5.63 | -0.51 | 0.60 | -2.07 |
| Market | 7.31 | 15.89 | 0 | | 1 | 0.46 | -0.50 |

All returns decrease quite a bit but the short leg gets quite positive excess returns which is decreases the returns of the WML. The exclusion of finance and banking industry increases the volatility of the WML which happens to the fact that banks and other financial institutions have generally low betas. Also, when other returns are low, the banks keep earning through rather stable interest rates making their returns counter cyclical which is shown here as increased volatility.

**Table 3:** Summary Statistics and Regression Results of Equally Weighted Portfolios, excluding Finance and Banking sectors

This table contains the summary statistics of the section 3.1 and 3.3 specified portfolios from 1971-01 to 2023-12.

| Portfolio | $\overline{r-r_f}$ | $\sigma$ | $\alpha$ | $t(\alpha)$ | $\beta$ | $SR$ | $sk(m)$ |
|---|---|---|---|---|---|---|---|
| Decile 1 | 3.16 | 38.82 | -0.72 | -2.19 | 1.61 | 0.08 | 1.31 |
| 2 | 4.54 | 28.91 | -0.44 | -1.98 | 1.35 | 0.16 | 0.66 |
| 3 | 5.13 | 24.29 | -0.31 | -1.81 | 1.21 | 0.21 | 0.18 |
| 4 | 7.22 | 21.84 | -0.08 | -0.57 | 1.12 | 0.33 | 0.13 |
| 5 | 8.07 | 19.93 | 0.03 | 0.21 | 1.06 | 0.40 | -0.34 |
| 6 | 8.61 | 18.77 | 0.10 | 0.85 | 1.01 | 0.46 | -0.35 |
| 7 | 11.34 | 19.56 | 0.31 | 2.50 | 1.04 | 0.58 | -0.24 |
| 8 | 11.08 | 18.90 | 0.31 | 2.36 | 1.01 | 0.59 | -0.52 |
| 9 | 14.17 | 21.85 | 0.49 | 3.24 | 1.13 | 0.65 | -0.18 |
| 10 | 15.46 | 26.50 | 0.51 | 2.42 | 1.29 | 0.58 | -0.07 |
| WML | 12.30 | 29.32 | 1.22 | 3.93 | -0.32 | 0.42 | -2.16 |
| Market | 7.31 | 15.89 | 0 | | 1 | 0.46 | -0.50 |

The exclusion of the finance and banking industry tends to increase the volatility of the WML portfolio, due primarily to the fact that banks and other financial institutions generally exhibit low betas. Moreover, when returns are generally low, banks maintain earnings through relatively stable interest rates, making their returns countercyclical, as reflected by the increased volatility observed in this analysis.

In Table 4, the WML performs worse compared to the previous value-weighted momentum portfolio shown in Table 2. This underperformance is particularly noticeable in the short leg, where less negative returns negatively impact the overall returns of the WML portfolio. A significant portion of these negative returns appears to be driven by the banking and finance industry, particularly during events such as the Great Financial Crisis, during which the finance sector in the US nearly collapsed.

The tables 3 and 4 raise the question of whether the returns are driven by leverage, as previously suggested by Goyal and Jegadeesh (2018). To explore this hypothesis further, using the methods described in Tables 1 through 4, I will conduct regression analyses of each of these portfolio construction methods against the Fama-French 3-factor model, where the value factor may provide insights into leverage dependency.

When scaling the return signals with volatility, the standard deviations across all portfolios begin to stabilize, eliminating the previously observed "volatility smile" across the decile portfolio returns. This adjustment significantly enhances the Sharpe ratios compared to other equally weighted portfolios without volatility-scaled return

**Table 4:** Summary Statistics and Regression Results of Value Weighted Portfolios, excluding Finance and Banking sectors

This table contains the summary statistics of the section 3.2 and 3.3 specified portfolios from 1971-01 to 2023-12.

| Portfolio | $\overline{r - r_f}$ | $\sigma$ | $\alpha$ | $t(\alpha)$ | $\beta$ | $SR$ | $sk(m)$ |
|---|---|---|---|---|---|---|---|
| Decile 1 | -1.56 | 42.35 | -1.25 | -3.78 | 1.83 | -0.04 | 0.86 |
| 2 | 0.26 | 30.43 | -0.82 | -3.65 | 1.38 | 0.01 | 0.43 |
| 3 | 4.40 | 24.72 | -0.37 | -1.95 | 1.20 | 0.18 | 0.36 |
| 4 | 4.93 | 22.38 | -0.26 | -1.71 | 1.10 | 0.22 | -0.37 |
| 5 | 6.57 | 19.44 | -0.06 | -0.39 | 0.99 | 0.34 | -0.24 |
| 6 | 5.23 | 18.92 | -0.18 | -1.71 | 1.01 | 0.28 | -0.22 |
| 7 | 10.15 | 18.24 | 0.25 | 2.45 | 0.97 | 0.56 | -0.14 |
| 8 | 7.70 | 18.05 | 0.06 | 0.52 | 0.96 | 0.43 | -0.31 |
| 9 | 10.23 | 21.05 | 0.21 | 1.52 | 1.05 | 0.49 | -0.52 |
| 10 | 14.04 | 26.36 | 0.40 | 2.02 | 1.26 | 0.53 | -0.28 |
| WML | 15.60 | 38.43 | 1.65 | 4.18 | -0.58 | 0.41 | -1.36 |
| Market | 7.31 | 15.89 | 0 | | 1 | 0.46 | -0.50 |

**Table 5:** Summary Statistics and Regression Results of Equally Weighted Portfolios, Volatility scaled

This table contains the summary statistics of the section 3.1 and 3.4 specified portfolios from 1971-01 to 2023-12.

| Portfolio | $\overline{r - r_f}$ | $\sigma$ | $\alpha$ | $t(\alpha)$ | $\beta$ | $SR$ | $sk(m)$ |
|---|---|---|---|---|---|---|---|
| Decile 1 | -0.38 | 25.87 | -0.77 | -3.80 | 1.21 | -0.01 | 0.34 |
| 2 | 1.00 | 26.14 | -0.67 | -3.46 | 1.23 | 0.04 | 0.49 |
| 3 | 5.77 | 26.14 | -0.28 | -1.49 | 1.25 | 0.22 | 0.61 |
| 4 | 7.17 | 24.13 | -0.14 | -0.82 | 1.21 | 0.30 | 0.33 |
| 5 | 8.03 | 21.86 | -0.04 | -0.28 | 1.16 | 0.37 | -0.10 |
| 6 | 10.30 | 20.87 | 0.18 | 1.34 | 1.11 | 0.49 | -0.16 |
| 7 | 11.49 | 20.10 | 0.30 | 2.31 | 1.08 | 0.57 | -0.34 |
| 8 | 12.76 | 19.10 | 0.43 | 3.40 | 1.04 | 0.67 | -0.36 |
| 9 | 14.58 | 18.98 | 0.60 | 4.51 | 1.01 | 0.77 | -0.54 |
| 10 | 16.92 | 20.80 | 0.76 | 4.94 | 1.07 | 0.81 | -0.41 |
| WML | 17.30 | 20.02 | 1.52 | 6.87 | -0.14 | 0.86 | -0.76 |
| Market | 7.31 | 15.89 | 0 | | 1 | 0.46 | -0.50 |

signals, as noted in Table 1 where the Sharpe ratio of the WML is 0.57.

In Table 6, although the returns are calculated using the same volatility-scaled return signals and value-weighting each stock within their respective decile, both Jensen's $\alpha$ and the Sharpe ratio are smaller. Despite this, the skewness is less negative than in Table 5. As previously mentioned, a more positive skewness, all else being equal, is preferable from a utility perspective. Investors must make a trade-off between

**Table 6:** Summary Statistics and Regression Results of Value Weighted Portfolios, Volatility scaled

This table contains the summary statistics of the section 3.2 and 3.4 specified portfolios from 1971-01 to 2023-12.

| Portfolio | $\overline{r - r_f}$ | $\sigma$ | $\alpha$ | $t(\alpha)$ | $\beta$ | $SR$ | $sk(m)$ |
|---|---|---|---|---|---|---|---|
| Decile 1 | -2.66 | 25.58 | -0.97 | -5.50 | 1.22 | -0.10 | -0.14 |
| 2 | 3.98 | 23.38 | -0.34 | -1.79 | 1.10 | 0.17 | 0.04 |
| 3 | 5.65 | 22.28 | -0.17 | -1.03 | 1.05 | 0.25 | -0.30 |
| 4 | 4.47 | 21.51 | -0.31 | -2.33 | 1.12 | 0.21 | -0.19 |
| 5 | 3.56 | 20.34 | -0.36 | -2.98 | 1.08 | 0.17 | -0.40 |
| 6 | 4.44 | 18.93 | -0.24 | -2.29 | 1.01 | 0.23 | -0.37 |
| 7 | 9.51 | 17.86 | 0.21 | 1.90 | 0.95 | 0.53 | -0.05 |
| 8 | 8.86 | 18.17 | 0.15 | 1.39 | 0.97 | 0.49 | -0.22 |
| 9 | 10.01 | 17.75 | 0.25 | 2.36 | 0.95 | 0.56 | -0.44 |
| 10 | 12.21 | 21.01 | 0.38 | 2.59 | 1.04 | 0.58 | 0.10 |
| WML | 14.86 | 24.81 | 1.35 | 5.08 | -0.18 | 0.60 | -0.15 |
| Market | 7.31 | 15.89 | 0 | | 1 | 0.46 | -0.50 |

pure Sharpe Ratio ($SR$) and skewness ($sk(m)$), which is not trivial. Investors are often willing to sacrifice a higher $SR$ to achieve a less negative $sk(m)$. Among these six different approaches, it appears that the decision on the trade-off will be made between the methodologies discussed in **??** and the evidence shown in the tables 5 and 6.

## 4.2 Equally weighted models with crash measure

Following the methodology described in section 3.6, I initially determine $\hat{\delta}$ through the simulation of past returns for in-sample calibration. Utilizing 2500 block bootstrapped time series, I generate multiple $\delta$ to select the optimal $\delta$ per each single series, and then choose $\hat{\delta}$ as the mean of these optimized samples.

Subsequent analyses utilize the panic-adjusted returns $r_p^p(\hat{\delta})$ for the period from February 1981 through August 2003, after establishing the rolling values. This data is used to compute Newey-West adjusted estimates for Jensen's alpha and CAPM beta, Sharpe ratio ($SR$), and skewness ($sk(m)$).

As indicated in Figure 3, the $\hat{\delta}$ estimates (now set at 0.81) exhibit a positively skewed distribution. This skewness naturally arises from the data-generating process (DGP) of $r_p^p(\delta)$, where the $\delta$ level specifies the required deviation of the short-run market trend from the long-run market trend to trigger a strategic shift from a long-short to a dual-long position in both the first and tenth deciles. Given that momentum crashes are typically driven by sudden and significant increases in short leg returns, $\delta$ plays a crucial role in anticipating and mitigating negative impacts on WML returns. The larger the $\delta$, the more it compensates for scenarios where the short leg yields unexpectedly high returns, thereby optimizing the overall Sharpe ratio of the WML portfolio.

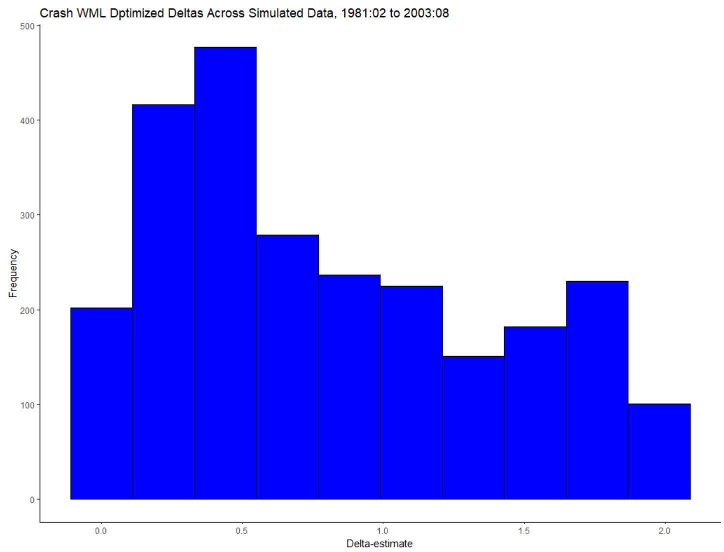


**Figure 3:** Distribution of $\hat{\delta}$ estimates, indicating the adjustment level required to optimize the WML portfolio during varying market conditions.

Moreover, the positive $\beta$ values of the short leg portfolios suggest that these portfolios are highly correlated with market movements. When shorting the first decile, any abrupt upward market shifts result in corresponding increases in the decile 1 returns, which can adversely affect the performance of the long-short momentum portfolio.

**Table 7:** Out of Sample Summary Statistics and Regression Results of Equally Weighted Crash Portfolios

This table contains the summary statistics of the section 3.1 and 3.6 specified portfolios from 2004-01 to 2023-12.

| Portfolio | $\overline{r - r_f}$ | $\sigma$ | $\alpha$ | $t(\alpha)$ | $\beta$ | $SR$ | $sk(m)$ |
|---|---|---|---|---|---|---|---|
| Decile 1 | 3.45 | 38.43 | -1.15 | -2.40 | 1.86 | 0.09 | 1.12 |
| Decile 10 | 9.84 | 23.84 | -0.17 | -0.70 | 1.29 | 0.41 | -0.06 |
| Crash-WML | 16.67 | 24.79 | 1.53 | 3.83 | -0.19 | 0.67 | -0.98 |
| Real-WML | 6.39 | 25.99 | 0.98 | 2.17 | -0.58 | 0.25 | -2.16 |
| Market | 9.23 | 15.40 | 0 | | 1.00 | 0.60 | -0.52 |

In Table 7, the Crash-WML portfolio demonstrates the highest Sharpe ratio and a significant Jensen's $\alpha$, with Newey-West adjusted estimates employing a 4-lag model. The Crash-WML outperforms by a considerable margin in terms of returns, while maintaining volatility levels similar to those of the standard equally weighted momentum portfolio. This superiority is not only reflected in the Sharpe ratio but also in the reduced skewness, which is half that of the actual Real-WML. Such a reduction in skewness is advantageous for the WML portfolio returns, as it indicates that significant market crashes are less severe compared to those under a simpler model.

**Table 8:** Equally Weighted WML Portfolios during periods from 1971-01 to 1999-12 and from 2000-01 to 2023-12. Robust standard erros in parenthesis.

| | *Dependent variable:* | |
|---|---|---|
| | WML | |
| | Post 2000 | Pre 2000 |
| Excess Market return | $-0.701^{***}$ | $-0.035^{***}$ |
| | (0.0003) | (0.0001) |
| SMB | $-0.078^{***}$ | $-0.538^{***}$ |
| | (0.0002) | (0.00004) |
| HML | $-0.156^{***}$ | $-0.580^{***}$ |
| | (0.0001) | (0.0001) |
| Constant | $0.009^{***}$ | $0.022^{***}$ |
| | (0.00002) | (0.00001) |
| Observations | 288 | 348 |
| $R^2$ | 0.120 | 0.146 |
| Adjusted $R^2$ | 0.110 | 0.138 |
| Residual Std. Error | 0.091 (df = 284) | 0.050 (df = 344) |
| F Statistic | $12.851^{***}$ (df = 3; 284) | $19.570^{***}$ (df = 3; 344) |
| *Note:* | | $^{*}$p<0.05; $^{**}$p<0.01; $^{***}$p<0.001 |

The notably low, near-zero $\beta$ of this strategy adds to its appeal, suggesting minimal influence from broader market trends. I will further analyze these portfolios using the Fama and French 3-factor model to ascertain if other factors might explain the performance of the Crash-WML. The preliminary results with Crash-WML have effectively "revitalized" the concept of the simple long-short momentum strategy.

## 4.3 Robustness regressions with Fama-French 3 factor

As previously, I continue to use the Newey-West estimators with lag of 4. Now I regress portfolio returns on Fama-French 3 Factor model (Fama & French, 1992) which is specified as:

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_{MKT}(r_{m,t} - r_{f,t}) + \beta_{SMB} r_{SMB,t} + \beta_{HML,t} r_{HML,t}$$

where $r_{SMB,t}$ is the return of small stocks minus the return of large stocks and $r_{HML,t}$ is the return of high book-to-market stocks minus the the return of low book-to-market stocks.

From the regression analyses, it is evident that the abnormal returns, i.e., the constants, have significantly decreased in more recent periods. Notably, during the pre-2000 era, returns were highly correlated with the SMB and HML factors, whereas post-2000, this correlation diminished substantially.

As hypothesized, the momentum portfolios exhibit considerable sensitivity to the $HML$ factor, particularly when the finance and banking industry is included. It is crucial to note that with a negative $HML$ factor loading, the WML portfolio

**Table 9:** Regression Results for Equally Weighted portfolios on Fama French 3 factor-model, data from 1971-01 to 2023-12. Standard errors in parenthesis.

| | *Dependent variable:* | | |
|---|---|---|---|
| | WML | | |
| | EW | EW excl. Finance | EW, Vola scaled |
| Excess Market return | $-0.316^{***}$ | $-0.305^{***}$ | $-0.159^{***}$ |
| | (0.0001) | (0.0001) | (−0.00001) |
| SMB | $-0.339^{***}$ | $-0.350^{***}$ | $-0.217^{***}$ |
| | (0.0001) | (0.0002) | (0.0001) |
| HML | $-0.418^{***}$ | $-0.342^{***}$ | $-0.441^{***}$ |
| | (−0.0001) | (−0.0001) | (−0.0001) |
| Constant | $0.016^{***}$ | $0.014^{***}$ | $0.017^{***}$ |
| | (0.00001) | (0.00001) | (0.00001) |
| Observations | 636 | 636 | 636 |
| $R^2$ | 0.076 | 0.057 | 0.072 |
| Adjusted $R^2$ | 0.072 | 0.052 | 0.068 |
| Residual Std. Error (df = 632) | 0.074 | 0.082 | 0.056 |
| F Statistic (df = 3; 632) | $17.384^{***}$ | $12.722^{***}$ | $16.388^{***}$ |
| *Note:* | | | $^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$ |

returns increase as the HML factor performs poorly, which occurs when value stocks (high book-to-market) underperform compared to growth stocks (low book-to-market). According to García-Feijóo & Jorgensen (2010), value stocks are generally more leveraged, suggesting that momentum is somewhat independent of leverage or the value anomaly.

Notably, combining the HML portfolio with the WML could yield significant diversification benefits, as they are negatively correlated, judging by the estimated $\beta_{HML}$. The $SMB$ (small minus big) factor loadings are comparable in magnitude to the $HML$ loadings. This concept of combining value and momentum has also been documented by Asness, Moskowitz, and Pedersen (2013).

**Table 10:** Regression Results for Value Weighted portfolios on Fama French 3 factor-model, data from 1971-01 to 2023-12. Standard errors in parenthesis.

| | *Dependent variable:* | | |
|---|---|---|---|
| | | WML | |
| | VW | VW excl. Finance | VW, Vola scaled |
| Excess Market return | −0.540*** | −0.585*** | −0.238*** |
| | (0.0001) | (0.0001) | (−0.00003) |
| SMB | −0.348*** | −0.390*** | −0.040*** |
| | (0.0001) | (0.0001) | (0.0001) |
| HML | −0.679*** | −0.565*** | −0.466*** |
| | (0.00001) | (−0.0002) | (−0.0002) |
| Constant | 0.023*** | 0.019*** | 0.015*** |
| | (0.00001) | (0.00002) | (0.00001) |
| Observations | 636 | 636 | 636 |
| $R^2$ | 0.099 | 0.088 | 0.052 |
| Adjusted $R^2$ | 0.094 | 0.084 | 0.047 |
| Residual Std. Error (df = 632) | 0.097 | 0.106 | 0.070 |
| F Statistic (df = 3; 632) | 23.077*** | 20.359*** | 11.525*** |
| *Note:* | | | *p<0.05; **p<0.01; ***p<0.001 |

In Table 10, the factor loadings for the value-weighted WML portfolios are significantly higher than those for equally weighted portfolios. The $SMB$ factor loadings are roughly the same, but the $HML$ factor loadings in Table 9 are significantly higher, driven by large companies with high book-to-market stocks in the long and short deciles.

In Table 11, the CWML portfolio continues to perform well, even under the scrutiny of a multi-factor model, in this case, the Fama French 3-factor model. The $\alpha$

**Table 11:** Out of Sample Summary Statistics and Regression Results of Equally Weighted Crash Portfolio (CWML) and "Real" Equally Weighted Momentum Portfolio (RWML). From 2004-01 to 2023-12. $\hat{\delta} = 0.81$

| | *Dependent variable:* | |
|---|---|---|
| | CWML($\hat{\delta}$) | RWML |
| Excess Market return | $-0.115^{***}$ | $-0.428^{***}$ |
| | $(-0.00002)$ | $(0.0004)$ |
| SMB | $-0.287^{***}$ | $-0.584^{***}$ |
| | $(0.00003)$ | $(-0.00002)$ |
| HML | $-0.125^{***}$ | $-0.285^{***}$ |
| | $(0.0004)$ | $(0.0004)$ |
| Constant | $0.015^{***}$ | $0.009^{***}$ |
| | $(0.00002)$ | $(0.00002)$ |
| Observations | 240 | 240 |
| $R^2$ | 0.025 | 0.165 |
| Adjusted $R^2$ | 0.013 | 0.154 |
| Residual Std. Error (df = 236) | 0.071 | 0.069 |
| F Statistic (df = 3; 236) | 2.044 | $15.496^{***}$ |
| *Note:* | $^{*}$p<0.05; $^{**}$p<0.01; $^{***}$p<0.001 | |

remains significant, yet the portfolio loadings for the CWML are significantly smaller. By maintaining lower factor loadings, the portfolio minimizes exposure to systematic risk channels that cannot be diversified away. With a 0-beta portfolio that maintains a non-zero $\alpha$, it is possible to scale returns to any arbitrary level using leverage.

These results underscore that the Crash WML portfolio I constructed is robust and that the simulation approach taken provides valuable insights into parameter selection, despite being time-invariant in this simplified scenario.

# 5 Summary

In my exploration of momentum portfolio strategies, I demonstrated that it is possible to enhance both the Sharpe ratio and abnormal returns, for example through the Crash-WML (CWML) approach. This strategy significantly mitigates momentum crashes, showcasing resilience in periods of market downturns. Also, I discovered that how one calculates portfolios—whether equal weighted or value weighted, or volatility scaled—results in different sensitivities to financial factors, influencing Sharpe ratios, alphas, and skewness distinctly. I tried to do a good job documenting the process of how I constructed my portfolios which is not always present in the literature.

The CWML, I crafted to withstand testing across various conditions without falling to the pitfalls of data snooping, proves the robustness of simpler, more transparent methods in financial modeling. Yet the true data-generating process of CWML proved to be fairly complicated, therefore, I have not included it. It is essential to understand what kind of expected returns, expected volatility, expected kurtosis and skewness the strategy displays in order to make it tradeable in reality, all the previous ones should also be understood conditionally.

In general, when creating trading strategies based on anomalies there are a few to things to consider. In the realm of portfolio construction, simplicity often trumps complexity, especially given the volatile nature of stock returns. Anomalies that can be traded and demonstrated with clarity tend to offer more consistent results. Yet, this simplicity brings forth the perennial question in asset pricing: Are such anomalies true risk factors or merely artifacts of market inefficiencies?

# 6 References

**I used ChatGPT to edit the text.**


Asness, C. S., Moskowitz, T. J., & Pedersen, L. H. (2013). *Value and Momentum Everywhere*. The Journal of Finance, 68(3), 929-985. https://doi.org/10.1111/jofi.12021

Cont, R. (2001). *Empirical properties of asset returns: stylized facts and statistical issues*. Quantitative Finance, 1(2), 223-236. https://doi.org/10.1080/713665670

Daniel, K., & Moskowitz, T. J. (2016). *Momentum crashes*. Journal of Financial Economics, 122, 221-247. https://doi.org/10.1016/j.jfineco.2015.12.002

Fama, E. F., & French, K. R. (1992). *The Cross-Section of Expected Stock Returns*. Journal of Finance, 47(2), 427-465. https://doi.org/10.1111/j.1540-6261.1992.tb04398.x

Fama, E. F., & French, K. R. (2008). *Dissecting Anomalies*. Journal of Finance, 63(4), 1653-1678. https://doi.org/10.1111/j.1540-6261.2008.01371.x

Fan, M., Kearney, F., Li, Y., & Liu, J. (2022). *Momentum and the Cross-section of Stock Volatility*. Journal of Economic Dynamics and Control, 144, 104524. https://doi.org/10.1016/j.jedc.2022.104524

French, K. (2024). Data library. Tuck School of Business at Dartmouth.
https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data$_library.html$

García-Feijóo, L., & Jorgensen, R. D. (2010). *Can Operating Leverage Be the Cause of the Value Premium?*. Financial Management, 39(3), 1127-1154. https://doi.org/10.1111/j.1755-053X.2010.01106.x

Goyal, A., & Jegadeesh, N. (2018). *Cross-Sectional and Time-Series Tests of Return Predictability: What Is the Difference?*. The Review of Financial Studies, 31(5), 1784-1824. https://doi.org/10.1093/rfs/hhx131

Jegadeesh, N., & Titman, S. (1993). *Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency*. The Journal of Finance, 48(1), 65-91. https://doi.org/10.2307/2328882, https://www.jstor.org/stable/2328882

Moskowitz, T. J., Ooi, Y. H., & Pedersen, L. H. (2012). *Time series momentum*. Journal of Financial Economics, 104(2), 228-250. https://doi.org/10.1016/j.jfineco.2011.11.003

Politis, D. N., Romano, J. P., & Wolf, M. (2012). *Subsampling* (Springer Series in Statistics). Springer New York, NY. https://doi.org/10.1007/978-1-4612-1554-7
. https://doi.org/10.1007/s11408-022-00417-8

Wiest, T. (2023). *Momentum: what do we know 30 years after Jegadeesh and Titman's seminal paper?*. Financial Markets and Portfolio Management, 37, 95–114. https://doi.org/10.1007/s11408-022-00417-8

# A Appendix: Dollar investments

The following figures show how 1$ investment would have developed over time given different strategies. See how the momentum WML has periodicity and crashiness in its path.

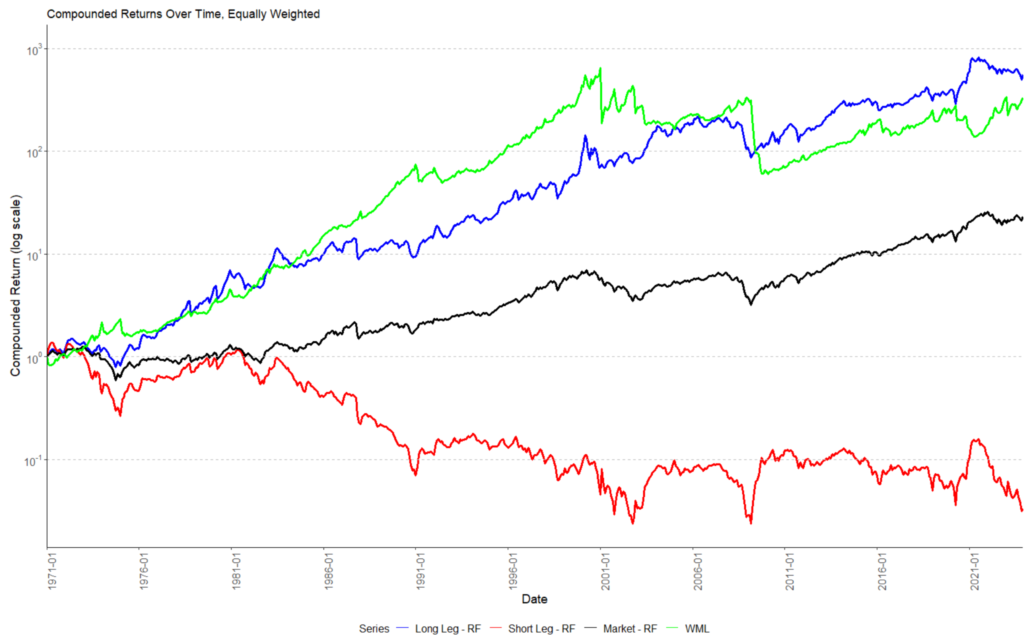


**Figure A1:** Equally weighted momentum portfolio returns from 1971-01 to 2023-12

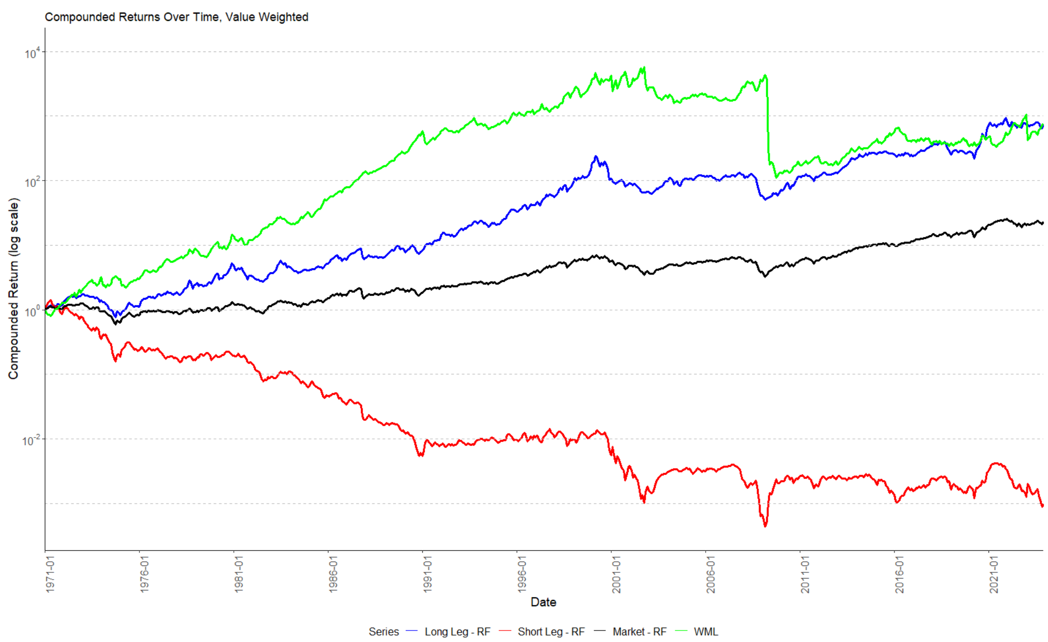


**Figure A2:** Value weighted momentum portfolio returns from 1971-01 to 2023-12

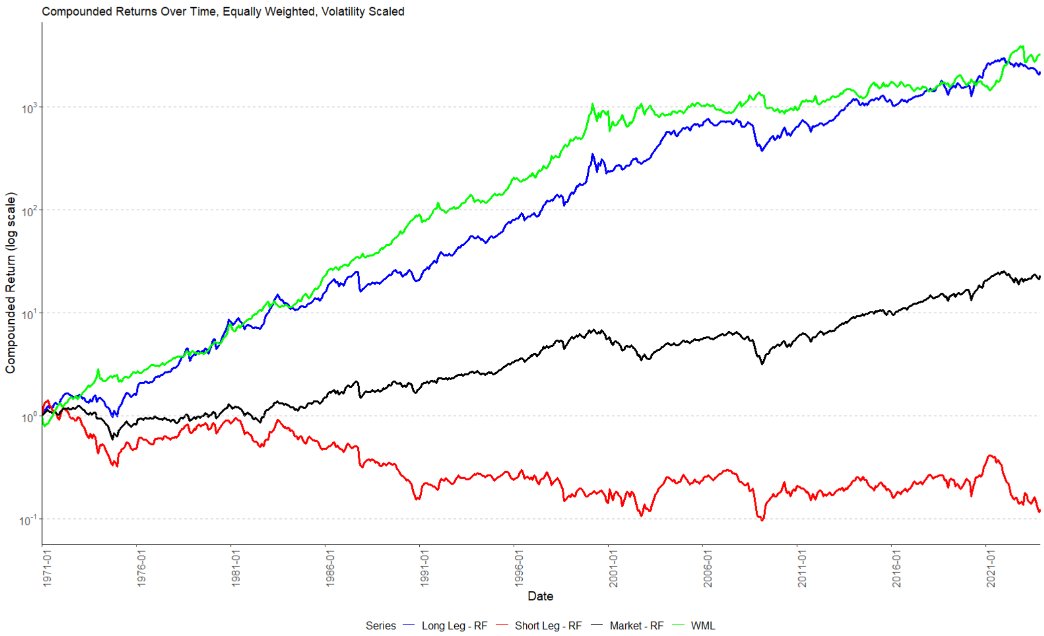


**Figure A3:** Equally weighted volatility scaled momentum portfolio returns from 1971-01 to 2023-12

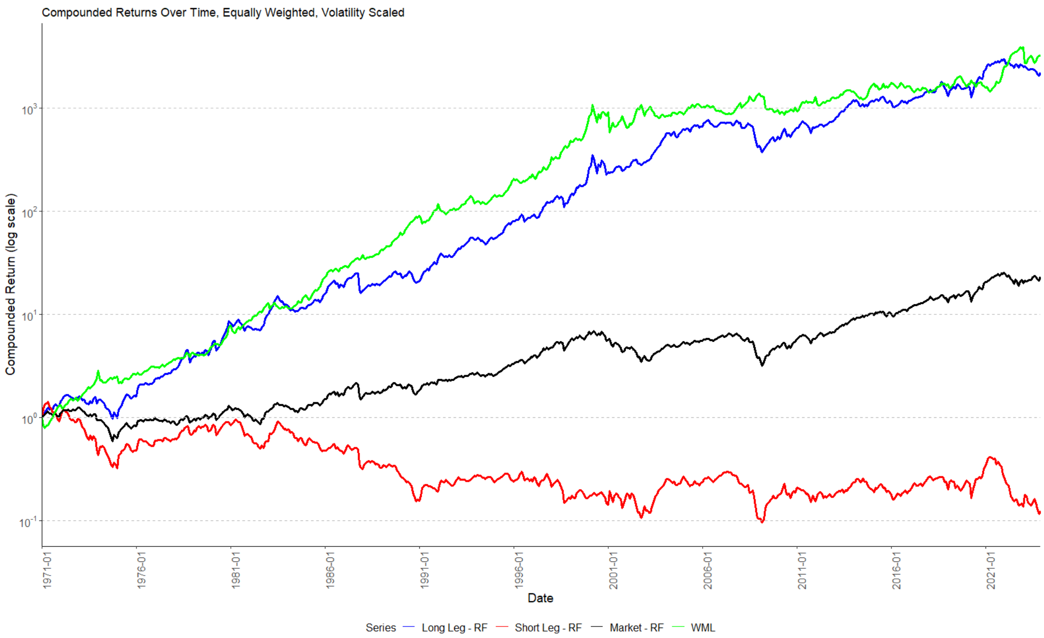


**Figure A4:** Value weighted volatility scaled momentum portfolio returns from 1971-01 to 2023-12