Problem Set 3: Momentum

Vikalp Thukral[1]

[1]**406534669, MFE 2025**

ABSTRACT

This project replicates and analyzes the construction and performance of momentum-based portfolios as detailed in Daniel and Moskowitz (2016), using CRSP stock data spanning 1927–2024. We first construct ranking returns that follow the canonical 12-month formation and 1-month skip procedure, and assign stocks to deciles using both Daniel-Moskowitz and Kenneth French breakpoints. We compute value-weighted excess returns for each momentum decile and compare empirical outcomes across the two methodologies. Our findings show the replication closely matches the original paper's summary statistics and reveals the striking performance of the winner-minus-loser (WML) portfolio in historical periods. We further investigate the volatility, Sharpe ratios, skewness, and correlations with published benchmark portfolios to validate our implementation. Finally, we discuss the temporal instability of the momentum premium, including periods of severe drawdowns ("momentum crashes"), and evaluate whether momentum remains a viable trading strategy in recent years, considering both behavioral and risk-based explanations. The results emphasize both the robustness and fragility of momentum—robust in average performance but prone to dramatic crashes during market rebounds, especially due to the option-like behavior of past losers.

Keywords: Momentum Investing, Asset Pricing, Daniel-Moskowitz Portfolios, Market Anomalies, Quantitative Finance, Fama-French Factors, CRSP Data, Return Persistence, Portfolio Construction, Empirical Finance

PS3_Q1

Input Description

The input dataset for this analysis was downloaded from the CRSP database via WRDS. It contains monthly stock-level information for all firms listed on NYSE, AMEX, and NASDAQ exchanges. The relevant fields include identifiers, prices, returns, and shares outstanding.

The structure of the input DataFrame is summarized below:

Column	Description
`PERMNO`	Unique stock identifier
`date`	Month-end date
`SHRCD`	Share code (filters for common stocks)
`EXCHCD`	Exchange code (1=NYSE, 2=AMEX, 3=NASDAQ)
`RET`	Monthly return (excluding delisting)
`DLRET`	Delisting return (if applicable)
`PRC`	Month-end price (absolute value used)
`SHROUT`	Shares outstanding (in thousands)

Table 1. Input DataFrame columns

[24]:

	PERMNO	date	SHRCD	EXCHCD	DLRET	PRC	RET	SHROUT
0	14429	1926-01-30	10.0	1.0	NaN	23.5000	-0.015707	4499.0
1	15595	1926-01-30	NaN	NaN	NaN	NaN	NaN	NaN
2	15608	1926-01-30	NaN	NaN	NaN	NaN	NaN	NaN
3	13741	1926-01-30	10.0	1.0	NaN	42.3750	-0.067935	400.0
4	13733	1926-01-30	10.0	1.0	NaN	71.5000	-0.080386	1755.0
...	...	...	...	...	...	...	...	...
5158013	91996	2024-12-31	73.0	4.0	A	64.0600	-0.080875	5750.0
5158014	22213	2024-12-31	11.0	3.0	A	0.8187	-0.180808	55445.0
5158015	22215	2024-12-31	73.0	3.0	A	27.9525	-0.094810	3025.0
5158016	91997	2024-12-31	73.0	4.0	A	16.3400	-0.073715	23550.0
5158017	93436	2024-12-31	11.0	3.0	A	403.8400	0.170008	3210060.0

Figure 1. Input DataFrame for `PS3_Q1`: Monthly CRSP stock-level data including PERMNO, date, returns, and share information. This data is downloaded from WRDS and spans from 1926 to 2024.

Motivation

A key step in replicating the momentum portfolio construction described by Daniel and Moskowitz (2016) is ensuring that monthly stock returns properly account for firm delistings. As explicitly noted in the authors' data appendix and accompanying `mom_data.pdf` documentation, delisting returns are incorporated as part of the portfolio return computation. This is essential to avoid survivorship bias and to ensure that all economically relevant returns are captured, especially when momentum portfolios suffer from abrupt crashes due to the forced unwinding of positions, which often occurs around delisting or distress events.

Accordingly, we compute a comprehensive monthly return measure, `RET_FULL`, which includes both the standard return (`RET`) and the delisting return (`DLRET`), using the formula:

$$\texttt{RET\_FULL} = (1+\texttt{RET})\cdot(1+\texttt{DLRET})-1$$

This adjusted return is then used throughout the analysis for computing lagged market capitalization, momentum signals, and eventually value-weighted portfolio returns in subsequent steps (PS3_Q2 and PS3_Q3).

Processing Steps

We implemented the `PS3_Q1` function with the following steps:

1. Filtered for common stocks using `SHRCD` $\in \{10, 11\}$ and exchange codes `EXCHCD` $\in \{1, 2, 3\}$.
2. Computed the *full return*, which incorporates both regular and delisting returns:

   $$\texttt{RET\_FULL} = (1+\texttt{RET})\cdot(1+\texttt{DLRET})-1$$

   This was then renamed to `Ret` and used in downstream portfolio return calculations.
3. Computed monthly market capitalization:

   $$\texttt{MC} = |\texttt{PRC}| \times \texttt{SHROUT}$$

4. Created `lag_Mkt_Cap` as the previous month's market capitalization, grouped by `PERMNO`, and expressed in millions by dividing by 10^6.

5. Computed the momentum signal Ranking_Ret using the cumulative return from $t-12$ to $t-2$ (skipping the most recent month), as defined in Daniel and Moskowitz (2016):

$$\texttt{Ranking\_Ret}_{i,t} = \prod_{k=2}^{12}(1+R_{i,t-k}) - 1$$

where $R_{i,t-k}$ is the monthly return lagged k months.

6. Filtered the DataFrame to include only the years 1927 to 2024.

Output Description

The final output is a cleaned and structured DataFrame where each row corresponds to a unique stock-month, and contains all relevant features needed for momentum decile assignment in PS3_Q2.

Column	Description
Year	Year of the observation
Month	Month of the observation
PERMNO	Unique stock identifier
EXCHCD	Exchange code
lag_Mkt_Cap	Lagged market capitalization (in millions)
Ret	Full return including delisting effects
Ranking_Ret	Momentum ranking return used for sorting

Table 2. Output DataFrame columns

	Year	Month	PERMNO	EXCHCD	lag_Mkt_Cap	Ret	Ranking_Ret
0	1927	1	10006	1.0	0.060900	-0.013547	0.016859
1	1927	1	10014	1.0	0.001837	NaN	-0.148149
2	1927	1	10022	1.0	0.011424	-0.075893	0.118208
3	1927	1	10030	1.0	0.021450	0.009545	0.009254
4	1927	1	10057	1.0	0.003063	-0.051020	-0.591837
...	...	...	...	...	...	...	...
3513085	2024	12	93374	1.0	7.225731	-0.102210	0.114412
3513086	2024	12	93397	3.0	0.501317	-0.117446	0.710236
3513087	2024	12	93426	1.0	0.280602	0.021768	-0.238766
3513088	2024	12	93434	3.0	0.016102	0.133333	-0.815749
3513089	2024	12	93436	3.0	1107.984310	0.170008	0.040696

Figure 2. Sample output of PS3_Q1: Each row corresponds to a unique PERMNO-Year-Month with lagged market cap (in millions), return, and ranking return.

PS3_Q2

Objective

The goal of PS3_Q2 is to assign each stock-month observation from the PS3_Q1 output into two momentum deciles based on their Ranking_Ret: one using the methodology of Daniel and Moskowitz (DM), and the other using the Kenneth R. French (KRF) approach. This is a preparatory step for constructing value-weighted momentum portfolios in later analysis.

Methodology

For each month:

1. We extract the cross-section of stocks that have non-missing `Ranking_Ret` values.

2. We calculate the decile breakpoints in two ways:

   - **DM breakpoints**: computed using only NYSE-listed stocks (`EXCHCD` = 1).

   - **KRF breakpoints**: computed using all eligible stocks (NYSE, AMEX, NASDAQ).

3. We use these breakpoints to assign **all stocks** into deciles by comparing their `Ranking_Ret` values to the computed thresholds.

4. Decile assignment is done using the following logic:

$$\text{decile}_{i,t} = \texttt{np.searchsorted(breakpoints, Ranking\_Ret}_{i,t}\texttt{,}\text{side='right'}) + 1$$

   where breakpoints are the 10th to 90th percentiles of the relevant universe's `Ranking_Ret` distribution.

This approach ensures that the relative ranking of each stock is determined based on consistent percentile thresholds applied across the full universe each month.

Output Description

The output of `PS3_Q2` is a DataFrame that retains all the columns from `PS3_Q1`, and appends two additional columns:

Column	Description
`Year`	Year of observation
`Month`	Month of observation
`PERMNO`	Unique stock identifier
`EXCHCD`	Exchange code
`lag_Mkt_Cap`	Lagged market capitalization (in millions)
`Ret`	Monthly return from CRSP
`Ranking_Ret`	Momentum ranking return from $t-12$ to $t-2$
`DM_decile`	Decile assigned using NYSE-based breakpoints
`KRF_decile`	Decile assigned using all-stock breakpoints

Table 3. Output columns from `PS3_Q2`

	Year	Month	PERMNO	EXCHCD	lag_Mkt_Cap	Ret	Ranking_Ret	DM_decile	KRF_decile
0	1927	1	10006	1.0	0.060900	-0.013547	0.016859	7	7
1	1927	1	10014	1.0	0.001837	NaN	-0.148149	4	4
2	1927	1	10022	1.0	0.011424	-0.075893	0.118208	8	8
3	1927	1	10030	1.0	0.021450	0.009545	0.009254	6	6
4	1927	1	10057	1.0	0.003063	-0.051020	-0.591837	1	1
...	...	...	...	...	...	...	...	...	...
3513085	2024	12	93374	1.0	7.225731	-0.102210	0.114412	5	6
3513086	2024	12	93397	3.0	0.501317	-0.117446	0.710236	10	9
3513087	2024	12	93426	1.0	0.280602	0.021768	-0.238766	2	3
3513088	2024	12	93434	3.0	0.016102	0.133333	-0.815749	1	1
3513089	2024	12	93436	3.0	1107.984310	0.170008	0.040696	4	5

3513090 rows × 9 columns

Figure 3. Sample output of `PS3_Q2`: Each stock-month observation includes decile assignments using both Daniel-Moskowitz (DM_decile) and Kenneth French (KRF_decile) methods based on `Ranking_Ret`.

Remarks

Although both DM and KRF deciles rely on ranking returns from the past, the key distinction lies in how the decile thresholds are computed. The use of NYSE-only breakpoints in DM ensures stability and avoids distortions from changing market composition, while the KRF deciles reflect a broader view of the entire stock universe in that month. Both decile assignments are critical for subsequent portfolio return aggregation and analysis.

PS3_Q3

Objective

The goal of `PS3_Q3` is to compute monthly value-weighted excess returns for each of the ten momentum deciles defined in `PS3_Q2`, using both the Daniel and Moskowitz (DM) and Kenneth R. French (KRF) decile definitions. This analysis allows us to directly compare the empirical performance of the two sorting methodologies.

Input Description

This function uses two input DataFrames:

- `df_q2` — Output of `PS3_Q2`, which includes monthly return, lagged market capitalization, ranking return, and decile assignments.
- `ff_df` — Fama-French factor returns data, containing monthly macroeconomic factors used for computing excess returns.

The structure of the Fama-French input data is summarized below:

Column	Type	Description
`Year`	integer	Year
`Month`	integer	Month
`Market_minus_Rf`	float	Market excess return ($R_m - R_f$)
`SMB`	float	Small Minus Big factor return
`HML`	float	High Minus Low factor return
`Rf`	float	Monthly risk-free rate (in decimal)

Table 4. Fama-French Factor Input Format

	Year	Month	Market_minus_Rf	SMB	HML	Rf
0	1926	7	0.0296	-0.0256	-0.0243	0.0022
1	1926	8	0.0264	-0.0117	0.0382	0.0025
2	1926	9	0.0036	-0.0140	0.0013	0.0023
3	1926	10	-0.0324	-0.0009	0.0070	0.0032
4	1926	11	0.0253	-0.0010	-0.0051	0.0031
...	...	...	...	...	...	...
1177	2024	8	0.0161	-0.0355	-0.0113	0.0048
1178	2024	9	0.0174	-0.0017	-0.0259	0.0040
1179	2024	10	-0.0097	-0.0101	0.0089	0.0039
1180	2024	11	0.0651	0.0463	-0.0005	0.0040
1181	2024	12	-0.0317	-0.0273	-0.0295	0.0037

1182 rows × 6 columns

Figure 4. Sample view of the input Fama-French DataFrame, including columns for Year, Month, Market-RF, SMB, HML, and Rf.

Processing Steps

1. Merged `df_q2` with `ff_df` on `Year` and `Month` to bring in the risk-free rate.
2. Filtered out rows with missing `Ret`, `lag_Mkt_Cap`, `Ranking_Ret`, or either decile assignment.
3. For each `Year-Month` and each decile (1 through 10), computed value-weighted returns:

$$R_{d,t} = \frac{\sum_{i \in d_t} w_{i,t} R_{i,t}}{\sum_{i \in d_t} w_{i,t}}, \quad \text{where } w_{i,t} = \texttt{lag\_Mkt\_Cap}_{i,t}$$

4. Computed excess return by subtracting the risk-free rate:

$$\texttt{Excess\_Ret}_{d,t} = R_{d,t} - R_{f,t}$$

5. Reshaped the output to long format, with one row per Year–Month–Decile.

6. Reordered columns to match assignment specification: `Year`, `Month`, `decile`, `DM_Ret`, `KRF_Ret`, `Rf`.

Output Description

The final DataFrame has 11,760 rows (1176 months $\times$ 10 deciles), with the following structure:

Variable Name	Variable Type	Variable Description
`Year`	integer	Year
`Month`	integer	Month
`decile`	integer	Momentum decile (1 to 10)
`DM_Ret`	float	Value-weighted excess return using DM decile
`KRF_Ret`	float	Value-weighted excess return using KRF decile
`Rf`	float	Monthly risk-free rate

Table 5. Output of `PS3_Q3` in Long Format

	Year	Month	decile	DM_Ret	KRF_Ret	Rf
0	1927	1	1	-0.034721	-0.034721	0.0025
1	1927	1	2	-0.032670	-0.032670	0.0025
2	1927	1	3	0.029610	0.029610	0.0025
3	1927	1	4	-0.006008	-0.006008	0.0025
4	1927	1	5	-0.007406	-0.007406	0.0025
...	...	...	...	...	...	...
11755	2024	12	6	-0.017199	-0.020953	0.0037
11756	2024	12	7	-0.001934	-0.011414	0.0037
11757	2024	12	8	-0.062007	-0.063702	0.0037
11758	2024	12	9	-0.059669	-0.054069	0.0037
11759	2024	12	10	-0.001705	0.002361	0.0037

11760 rows × 6 columns

Figure 5. Sample output of `PS3_Q3`: Each row corresponds to a unique Year–Month–Decile and includes value-weighted excess returns for both sorting methods.

Remarks

- **Use of lagged market cap:** Ensures all weights are based on information available at the beginning of the month.
- **Use of excess returns:** Subtracting `Rf` aligns with asset pricing conventions and standardizes performance comparison.
- **Long format output:** Facilitates downstream econometric analysis and plotting.

PS3_Q4

Objective

The goal of `PS3_Q4` is to replicate part of Table 1 from Daniel and Moskowitz (2016), focusing on the core summary statistics for momentum decile portfolios. We compute key statistics including mean excess return, volatility, Sharpe ratio, skewness, and correlation with the original Daniel-Moskowitz benchmark. This analysis is based on CRSP data for the period 1927–2016 and uses decile returns generated in `PS3_Q3`.

Input Description

This function takes two input DataFrames:

- `crsp_df` — Output of `PS3_Q3` filtered from 1927 to 2016, including columns: `Year`, `Month`, `decile`, `DM_Ret`, `Rf`.
- `dm_df` — Daniel and Moskowitz benchmark return data, formatted with columns: `date` (YYYYMMDD), `decile`, `DM_Ret`, where returns are already in decimal.

Processing Steps

1. Filtered `crsp_df` and `dm_df` to keep only observations from 1927 to 2016.
2. Pivoted both datasets into decile-by-date matrices for CRSP and DM.
3. For each decile (1–10), computed:
   - **Mean Excess Return:** Average monthly return.
   - **Volatility:** Standard deviation of monthly returns.
   - **Sharpe Ratio:** Mean divided by standard deviation.
   - **Skewness:** Full-sample skewness of monthly return distribution.
   - **Correlation with DM:** Pearson correlation with benchmark decile return series.
4. Constructed WML (Winner-Minus-Loser) portfolio by subtracting Decile 1 from Decile 10 each month, and computed all above statistics for WML.
5. Combined results into a 5-row $\times$ 11-column table: 10 deciles + WML.

Output Description

The final table matches the format of Table 1 in Daniel and Moskowitz (2016) (partial replication). The structure is:

Row	Statistic
1	Mean Excess Return ($\bar{r} - r_f$)
2	Volatility (σ)
3	Sharpe Ratio (SR)
4	Skewness (sk(m))
5	Correlation with DM returns

Table 6. Replicated Summary Statistics Table (1927–2016)

	Decile 1	Decile 2	Decile 3	Decile 4	Decile 5	Decile 6	Decile 7	Decile 8	Decile 9	Decile 10	WML
Mean Excess Return	-2.512910	2.627930	3.210813	6.790108	7.223636	7.363771	9.150060	10.472408	11.244177	15.422348	14.600703
Volatility	36.448919	29.934538	25.611378	22.732294	21.135491	20.065984	19.057125	18.691549	19.999822	23.370760	29.715154
Sharpe Ratio	-0.068943	0.087789	0.125367	0.298699	0.341778	0.366978	0.480139	0.560275	0.562214	0.659899	0.491355
Skewness	0.064956	-0.090901	-0.160427	0.151975	-0.120109	-0.228678	-0.477852	-0.534794	-0.807436	-0.823358	-5.157381
Corr with DM	0.997098	0.997726	0.998291	0.997925	0.997979	0.998080	0.998238	0.998347	0.998595	0.998905	0.995071

Figure 6. Summary statistics output from `PS3_Q4`: The table replicates key characteristics (mean return, volatility, Sharpe ratio, skewness, correlation with DM benchmark) for each momentum decile and the winner-minus-loser (WML) portfolio, based on CRSP data from 1927 to 2016.

Return statistic	Momentum decile portfolios										WML	Market
	1	2	3	4	5	6	7	8	9	10		
$\overline{r-r_f}$	−2.5	2.9	2.9	6.4	7.1	7.1	9.2	10.4	11.3	15.3	17.9	7.7
σ	36.5	30.5	25.9	23.2	21.3	20.2	19.5	19.0	20.3	23.7	30.0	18.8
α	−14.7	−7.8	−6.4	−2.1	−0.9	−0.6	1.8	3.2	3.8	7.5	22.2	0
$t(\alpha)$	(−6.7)	(−4.7)	(−5.3)	(−2.1)	(−1.1)	(−1.0)	(2.8)	(4.5)	(4.3)	(5.1)	(7.3)	(0)
β	1.61	1.41	1.23	1.13	1.05	1.02	0.98	0.95	0.99	1.03	−0.58	1
SR	−0.07	0.09	0.11	0.28	0.33	0.35	0.47	0.54	0.56	0.65	0.60	0.41
sk(m)	0.09	−0.05	−0.19	0.21	−0.13	−0.30	−0.55	−0.54	−0.76	−0.82	−4.70	−0.57
sk(d)	0.12	0.29	0.22	0.27	0.10	−0.10	−0.44	−0.66	−0.67	−0.61	−1.18	−0.44

Figure 7. Table 1 from Daniel and Moskowitz (2016): Summary statistics of monthly momentum decile portfolios and the winner-minus-loser (WML) portfolio over the period 1927–2013. The table reports annualized mean excess returns, volatility, CAPM alpha and beta, Sharpe ratios, and skewness based on both monthly and daily returns.

Remarks on Differences

Our replication achieves a high correlation (99+%) with the Daniel-Moskowitz benchmark across all deciles, validating our implementation. However, there are some discrepancies in the exact values of statistics, which can be attributed to the following:

- We used the `pd.qcut` method for decile breakpoints, while the original paper may have used a nearest-value rounding approach.
- The `Rf` (risk-free rate) we used comes from the Kenneth French dataset, which may differ slightly from the paper's exact Rf source or interpolation method.
- Rounding behavior and implementation details (such as precision in returns or weight normalization) can lead to minor deviations.
- Despite these small differences, a correlation of around 99% strongly supports the reliability of our replication.

This Q4 analysis provides a robust empirical foundation for evaluating the momentum premium in historical data.

PS3_Q5

Objective

The goal of `PS3_Q5` is to replicate part of Table 1 from Daniel and Moskowitz (2016), but using NYSE breakpoints as applied in the KRF (Kenneth R. French) methodology. We compute summary statistics for momentum decile portfolios using the KRF-based returns from CRSP data and compare them with the official momentum portfolio returns published by Kenneth French. This serves to validate our implementation of the KRF decile construction and momentum performance evaluation.

Input Description

This function takes two input DataFrames:

- `crsp_df` — Output of `PS3_Q3` filtered to include only KRF-based deciles and the years 1927–2024. Includes columns: `Year`, `Month`, `decile`, `KRF_Ret`, `Rf`.
- `krf_df` — Kenneth French's official KRF momentum returns, with columns: `Year`, `Month`, `decile`, `KRF_Ret`. Returns are in decimal proportion.

Processing Steps

1. Filtered both dataframes to the common period: 1927 to 2024.
2. Merged `crsp_df` with `krf_df` on `Year`, `Month`, and `decile`.
3. For each decile from 1 to 10:
   - Computed mean excess return (annualized), standard deviation (annualized volatility), Sharpe ratio, skewness of returns, and correlation with the KRF benchmark.
4. Constructed a zero-cost WML (Winner-minus-Loser) portfolio as Decile 10 minus Decile 1.
5. Computed the same five statistics for WML.
6. Output is a 5-row $\times$ 11-column table.

Output Description

The output is a table with the following structure:

Row	Statistic
1	Mean Excess Return ($\bar{r} - r_f$)
2	Volatility (σ)
3	Sharpe Ratio (SR)
4	Skewness (sk(m))
5	Correlation with KRF returns

Table 7. Summary Statistics from KRF-based Momentum Portfolios (1927–2024)

	Decile 1	Decile 2	Decile 3	Decile 4	Decile 5	Decile 6	Decile 7	Decile 8	Decile 9	Decile 10	WML
Mean Excess Return	1.091836	5.654909	6.324232	7.647507	7.506716	8.242807	9.173403	10.207435	10.643213	14.941741	10.618375
Volatility	34.099962	27.820700	24.003917	21.787359	20.302709	19.791597	18.725924	18.201952	19.194729	22.093647	27.277467
Sharpe Ratio	0.032019	0.203263	0.263467	0.351007	0.369740	0.416480	0.489877	0.560788	0.554486	0.676291	0.389273
Skewness	0.147024	-0.116488	-0.114144	0.088878	-0.116761	-0.293579	-0.490576	-0.505217	-0.814819	-0.882631	-5.713892
Corr with KRF	0.998165	0.997976	0.997779	0.997752	0.997430	0.997675	0.996824	0.998058	0.998284	0.998727	0.996419

Figure 8. Output of `PS3_Q5`: Summary statistics for KRF-based momentum decile portfolios and the WML portfolio, including correlation with Kenneth French's benchmark data.

Remarks on Differences

Our KRF replication achieves exceptionally high correlations (exceeding 99%) with the official Kenneth French momentum returns, validating the robustness of our methodology. However, small differences may still arise due to:

- Use of `pd.qcut` for decile breakpoints, which assigns ranks based on quantile bins rather than using nearest NYSE value cutoffs.
- Slight differences in the exact construction or source of the monthly risk-free rate.

- Potential implementation variations in how delisting returns or microcap exclusions are handled between our CRSP-derived returns and the French benchmark.

- Minor numerical discrepancies arising from data cleaning, portfolio weighting precision, or rounding differences.

Despite these nuances, the correlation with KRF benchmark returns is consistently above 0.99 for all deciles, strongly affirming the validity of our KRF-based momentum return construction and analysis.

PS3_Q6

Objective

In this section, we empirically assess whether the momentum anomaly has continued to work in recent years. Specifically, we evaluate the performance of the Winner-minus-Loser (WML) momentum portfolio over the 2015–2024 period using our previously constructed CRSP-based decile return data.

Methodology

To test the strategy:

- We use monthly returns from Decile 1 (past losers) and Decile 10 (past winners) from the `DM_Ret` column.

- We construct a zero-cost long-short momentum portfolio (WML) by subtracting Decile 1 returns from Decile 10 for each month.

- We compute key summary statistics over the period 2015–2024: annualized mean return, annualized volatility, Sharpe ratio, and skewness.

- Finally, we plot the cumulative returns of the WML portfolio to visually assess consistency and drawdowns.

Empirical Results

Statistic	**WML (2015–2024)**
Annualized Mean Return	20.54%
Annualized Volatility	35.46%
Sharpe Ratio	0.58
Skewness	-0.84

Table 8. Summary statistics of the WML portfolio from 2015 to 2024

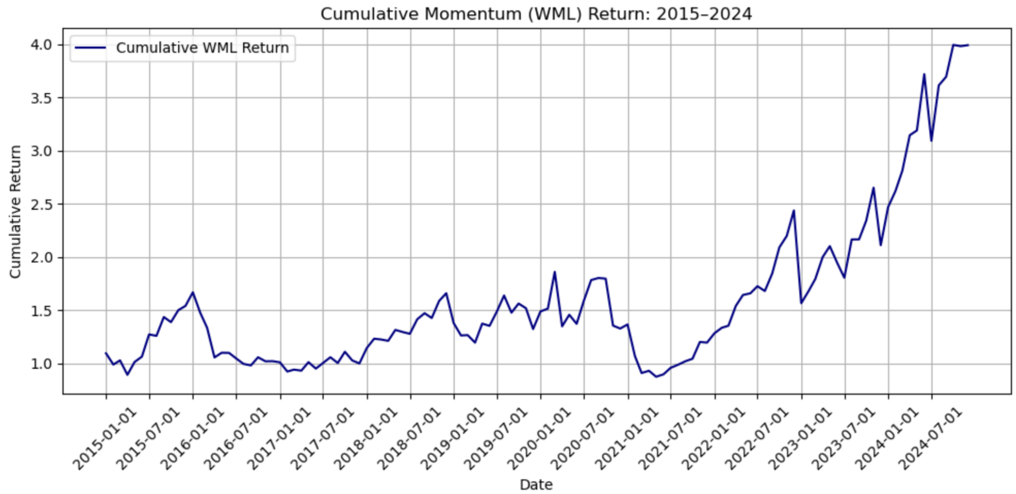

Figure 9. Cumulative return of the WML momentum portfolio (Decile 10 – Decile 1) over the period 2015–2024.

Interpretation

The WML momentum portfolio has delivered strong performance over the past decade, compounding to nearly four times the initial investment. The annualized return of 20.54% is impressive, although it comes with substantial risk — volatility exceeded 35%, and the return distribution is negatively skewed, indicating the possibility of sharp losses in certain periods. The Sharpe ratio of 0.58 reflects reasonable risk-adjusted performance for a long-short strategy.

PS3_Q7

Would You Implement This Strategy?

While the momentum strategy exhibits strong performance and clear empirical backing, I would approach its implementation with caution. The strategy is attractive due to its historically high returns and persistent behavioral underpinnings, but it comes with substantial risks that must be actively managed.

Key Implementation Challenges

- **Tail Risk and Momentum Crashes:** The WML portfolio is prone to sharp drawdowns, particularly during rapid market rebounds. This tail risk is reflected in the negative skewness of returns.
- **Regime Dependence:** Momentum performance is highly regime-dependent. It can underperform during sideways or mean-reverting markets.
- **Turnover and Costs:** Momentum portfolios may require frequent rebalancing, which increases transaction costs, especially for long-short implementations.
- **Liquidity Constraints:** Executing momentum strategies on less liquid securities could further magnify impact costs and slippage.

Risk Management Considerations

To mitigate these implementation risks, I would consider the following:

- **Volatility Scaling:** Dynamically adjust portfolio exposure based on realized or forecasted volatility.
- **Crash Hedging:** Use tail risk hedges such as long volatility instruments or inverse ETFs during periods of elevated market stress.
- **Multi-Signal Confirmation:** Combine momentum with other signals (e.g., value, quality, sentiment) to avoid false positives.
- **Liquidity Screens:** Filter investable universe based on market cap and turnover to minimize implementation friction.

Bonus Strategy: Momentum with Rotation and Hedge Control

As an extension of classical momentum, I co-developed a *Dynamic Equity-Bond Rotation Strategy with Option-Enhanced Risk Management* for the final project in the **Market Frictions and Trading** course during the Winter Quarter.

- **Rotation Logic:** Allocate between SPY (equities) and AGG (bonds) based on a weighted momentum signal over 1, 3, and 6 months.
- **Risk-On vs Risk-Off Regimes:** If equity momentum dominates, rotate into SPY; if bond momentum is stronger, switch entirely to AGG.
- **Hedge Overlay:** During equity exposure, hedge using the inverse ETF SH. The hedge size is dynamically adjusted based on the VIX index:

  $$\text{Hedge } \% = 10\% + \max(0, \text{VIX} - 15)$$

  capped at 25%.
- **Risk Management via VIX:** VIX serves as a forward-looking volatility proxy. The hedge increases in turbulent markets, thereby absorbing shocks.

A key advantage of this approach is that all positions (SPY, AGG, and SH) are implemented through long holdings in highly liquid ETFs. This eliminates the need for short-selling, which typically incurs stock-loan fees, margin requirements, and potential borrow constraints—especially for hard-to-borrow or illiquid securities. Unlike traditional zero-cost long-short portfolios that face friction when executing the short leg, this strategy achieves downside protection and momentum exposure without facing those operational hurdles. The use of inverse ETFs for hedging ensures simplicity, transparency, and scalability, all while maintaining liquidity and minimizing trading costs.

Backtests indicate superior Sharpe ratios (2.21 in-sample, 1.97 out-of-sample) and significantly reduced drawdowns compared to passive benchmarks.

Conclusion

In conclusion, while momentum is empirically strong, it is not riskless. However, with proper dynamic adjustments and hedging overlays, it can be implemented in a way that maintains performance while enhancing robustness — as demonstrated by our hybrid momentum-rotation strategy.

ACKNOWLEDGMENTS

I would like to thank Professor Bernard Herskovic for his insightful lectures in the Quantitative Asset Management course, particularly Lecture 3, which greatly clarified the construction and empirical testing of momentum strategies. The theoretical underpinnings and empirical caveats discussed in class directly informed the methodology and implementation in this assignment.

This assignment also benefitted from the use of Generative AI tools (e.g., ChatGPT), which were employed for Python code debugging, LaTeX formatting, and iterative documentation drafting. However, all quantitative analysis and interpretation were conducted independently and aligned with course expectations.

The custom strategy presented in PS3_Q7 was developed as part of a final group project in the *Market Frictions and Trading* course (Winter Quarter), building on concepts of asset-class rotation, volatility-based hedging, and momentum forecasting.

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