MFE 431 Quantitative Asset Management Problem Set 3

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1 Momentum

To solve the questions in the problem set, I first installed all the necessary libraries and established a connection with the WRDS (Wharton Research Data Services) API. Using the code reference provided by Prof. Herskovic in the lecture, I connected to the WRDS database to retrieve financial data from various CRSP (Center for Research in Security Prices) data tables.

Equity Returns Data from CRSP

- Retrieve data from the `crspq.msf` and `crsp.msenames` tables.
- Select columns: `permno`, `permco`, `date`, `shrcd`, `exchcd`, `ret`, `retx`, `shrout`, `prc`, `cfacshr`, `cfacpr`.
- Apply necessary filters (e.g., for share codes and exchange codes) and join on `permno` and `date` to ensure data integrity.
- Sort the data by `permno` and `date`, reset the index, and convert data types as needed.
- Adjust the `date` column to represent the last day of each month.

Delisting Returns Data from CRSP

- Retrieve data from the `crspq.msedelist` table.
- Select columns: `permno`, `dlret`, `dlstdt`, `dlstcd`.
- Sort the data by `permno` and `dlstdt`, reset the index, and convert data types as needed.
- Adjust the `dlstdt` column to represent the last day of each month.

At the end, I merged both the files to get accurate value of returns.

1.1 Ranked Monthly Returns using Daniel and Moskowitz (2016) methodology

Introduction

The following section details the procedure followed to define the universe of monthly returns for calculating momentum portfolios, according to the methodology outlined in Daniel and Moskowitz (2016).

Data Preparation Steps (as laid out in Daniel and Moskowitz, 2016)

1. Converted the 'date' column to datetime format to ensure accurate handling of date data.
2. Filtered stocks to include only those with EXCHCD values of 1, 2, or 3 (major exchanges), and SHRCD values of 10 or 11 (common stocks).
3. Cleaned 'RET' and 'DLRET' columns by converting them to numeric types and replacing missing values with 0, ensuring consistency in return data.
4. Calculated total returns combining 'RET' and 'DLRET' using the formula:

$$\text{Total Returns} = \log(1 + \text{RET}) + \log(1 + \text{DLRET}),$$

   which accounts for both regular and delisting returns.

5. Computed market capitalization in millions using:

$$\text{Market Cap} = \frac{\text{SHROUT} \times |\text{PRC}|}{1000},$$

   and created a lagged market capitalization ('lag_Mkt_Cap') by shifting this value one month back.

6. Dropped rows with missing data in 'lag_Mkt_Cap', 'prc', 'shrout', or 'Ret' to ensure completeness of the data set.

7. Calculated cumulative log returns for ranking by applying a rolling sum of 'Ret' from t-12 to t-2, providing the momentum signal for stock ranking.

8. Shifted total returns by 2 months ('ret_t2') and price by 13 months ('price_t13') within each stock group, and dropped rows with missing shifted values.

9. Extracted year and month from the 'date' column for ease of analysis.

10. Limited the dataset to the years 1927 to 2023 to match the study's specified timeframe.

11. Selected relevant columns and sorted the data by year, month, and stock identifier ('permno').

Final Output

The resulting dataframe, named **CRSP_Stocks_Momentum**, includes all necessary data for constructing momentum portfolios and calculating their ranking returns, spanning the years from 1927 to 2023.

Appendix for Computations

- The logarithmic transformation of returns facilitates the additive combination of regular and delisting returns.
- Lagging market capitalization ensures the availability of market cap data at time t-1 for portfolio construction.
- The process of dropping incomplete data rows helps maintain the integrity and reliability of the dataset.
- Cumulative log returns provide the momentum signal as required for ranking stocks.

1.2 Monthly Momentum Portfolio Deciles using Daniel and Moskowitz (2016) and Ken French methodology

Introduction

This section details the procedure used to define monthly momentum portfolio deciles for each stock based on the methodologies described by Daniel and Moskowitz (2016) and Kenneth R. French.

Procedure for Decile Calculation

1. Converted all column names to lowercase to ensure consistency across the dataset.

2. Created a new 'date' column by combining 'year' and 'month' columns for easier sorting and manipulation. The dataset was then sorted by 'date' and 'exchcd'.

3. For the Daniel and Moskowitz methodology:
   - Grouped the data by 'date' and applied the `pd.qcut` function on 'ranking_ret' to categorize stocks into 10 deciles.
   - Set the 'duplicates' parameter to 'drop' to handle stocks with identical 'ranking_ret' values.

4. For the Kenneth R. French methodology:
   - Initialized a separate DataFrame 'D' containing unique 'date' values.
   - Defined quantiles from 0.1 to 1.0 in increments of 0.1.

- Calculated quantiles specifically for NYSE stocks ('exchcd' == 1) on each date using 'ranking_ret'.
- Stored these quantiles in 'D' and merged them back into the original DataFrame based on 'date'.
- Developed the 'apply_quantiles' function to determine 'krf_decile' by comparing each stock's 'ranking_ret' against its date's quantile values.
- Applied this function across the DataFrame to assign 'krf_decile' values.

5. Returned a data frame with columns 'year', 'month', 'permno', 'lag_mkt_cap', 'ret', 'dm_decile', and 'krf_decile'.

Output

The resulting DataFrame, **CRSP_Stocks_Momentum_decile**, includes monthly momentum portfolio deciles for each stock based on both methodologies, covering years 1927 to 2023.

Appendix for Computations

- Lowercasing column names and sorting by 'date' and 'exchcd' ensures proper alignment and uniformity for decile calculations.
- The `pd.qcut` function provides an effective tool for equal-sized binning according to the distribution of 'ranking_ret'.
- The Kenneth R. French decile calculation incorporates only NYSE stocks to establish market benchmarks, which are then applied across all stocks for comparative analysis.

1.3 Monthly Momentum Portfolio Decile Returns using Daniel and Moskowitz (2016) and Ken French methodology

Introduction

This section outlines the steps undertaken to calculate the monthly momentum portfolio decile returns based on the methodologies described by Daniel and Moskowitz (2016) and Kenneth R. French.

Methodology

The following steps were performed to compute the decile returns:

1. Loaded the Fama-French 3-factor data from the Ken French website using `pandas_datareader`. Adjusted the data to monthly frequency and modified column names for clarity. Added a column representing the market return (MktRF + RF).
2. Defined the `PS3_Q3` function to merge the momentum decile data (`CRSP_Stocks_Momentum_decile`) with Fama-French market data (`FF_mkt`) based on `year` and `month`, ensuring alignment by common dates.
3. Implemented the `calculate_weighted_returns` function to compute the weighted average returns for each decile. This involved calculating the total lagged market capitalization as weights and deriving the weighted average returns. A check was included to handle cases where the total lagged market capitalization is zero.
4. Applied the `calculate_weighted_returns` function to both the Daniel and Moskowitz (DM) and Kenneth R. French (KRF) decile data, storing the results in separate DataFrames. The DataFrames were then merged to consolidate the findings from both methodologies.
5. Included the risk-free rate (Rf) for each month by merging the risk-free rate data from the Fama-French dataset with the consolidated decile returns.

6. The final output was refined to include only relevant columns: `year`, `month`, `Decile`, `DM_Avg_Return`, `KRF_Avg_Return`, and `Rf`.

Output

The resulting DataFrame, named `CRSP_Stocks_Momentum_returns`, encapsulates the monthly momentum portfolio decile returns for each method alongside the risk-free rate, spanning the appropriate time frame.

Appendix for Computations

- Data synchronization between the CRSP momentum decile data and Fama-French market data is crucial to ensure accurate calculations are based only on common date ranges.
- The `calculate_weighted_returns` function is instrumental in accounting for the market capitalization of stocks within each decile, reflecting a more nuanced approach to return calculation.
- The combination of DM and KRF methodologies in a single DataFrame facilitates a comprehensive analysis and comparison of momentum portfolio strategies.
- Inclusion of the risk-free rate enables further analyses, such as excess return calculations and risk-adjusted performance metrics.

1.4 Recreation of Table 1 from Daniel and Moskowitz (2016)

Table 1: Statistics for Deciles and WML

	Decile 1	Decile 2	Decile 3	Decile 4	Decile 5	Decile 6	Decile 7	Decile 8	Decile 9	Decile 10	WML
Excess Returns	-0.010908	0.030616	0.038519	0.071504	0.079630	0.072346	0.094831	0.104602	0.113644	0.153105	0.164013
Volatility	0.370613	0.301818	0.257212	0.228121	0.209194	0.199639	0.189235	0.187198	0.197840	0.235147	0.304633
Sharpe Ratio	-0.029432	0.101440	0.149756	0.313449	0.380653	0.362384	0.501130	0.558781	0.574424	0.651106	0.538398
Skewness	1.490313	1.312001	1.122936	1.300637	0.869944	0.780153	0.070335	-0.029488	-0.317008	-0.376735	-4.799442
Correlation with DM	0.996467	0.996195	0.997363	0.997220	0.997319	0.997822	0.998027	0.998062	0.998187	0.998070	0.993654

Introduction

This section describes the process used to recreate and extend Table 1 from Daniel and Moskowitz (2016), incorporating additional analyses and modifications.

Methodology

The methodology involved several steps to enhance the original table with contemporary data and calculations:

1. Loaded the Daniel and Moskowitz (DM) momentum returns data from the file `'m_m_pt_tot.txt'` into a DataFrame named `'dm_momentum'`. Specified appropriate column names and converted the 'Date' column to datetime format.
2. Extracted 'year' and 'month' from the 'Date' column in `'dm_momentum'`, selecting relevant columns for subsequent analysis.
3. Defined the function `PS3_Q4` to calculate risk-adjusted returns, standard deviation, and Sharpe Ratio for each decile. Applied these calculations on the input DataFrame (`'Input'`) using `groupby` and `apply` methods.
4. Computed the Winner Minus Loser (WML) returns by taking the difference between returns of decile 10 and decile 1.

5. Created an output DataFrame (`'Output'`) by transposing the grouped statistics, and added a 'WML' column to represent the WML returns.

6. Computed standard deviation and Sharpe Ratio for WML returns and incorporated these into the `'Output'` DataFrame.

7. Calculated skewness of WML returns after adjusting for the risk-free rate, using the `skew` function from the `scipy.stats` module.

8. Calculated WML returns for the input data (`'Input'`) and original DM returns data (`'DM_returns'`) by grouping data by year and month, and taking the difference between average returns of deciles 10 and 1.

9. Created a DataFrame (`'wml_comparison'`) to calculate the correlation between WML returns of the input data and the DM returns data, merging the data on 'year', 'month', and 'Decile'.

10. Calculated the correlation between the input data and the DM returns data for each decile, adding a new row in the `'Output'` DataFrame titled 'Correlation with DM' which contains these correlations and the correlation between WML returns of the input and DM data.

Output

The enhanced DataFrame, `'DM_statistics'`, replicates and extends Table 1 from Daniel and Moskowitz (2016) with additional data and correlation analysis, providing a comprehensive view of the momentum strategy's performance and its alignment with original findings.

Appendix for Computations

- Risk-adjusted returns (r_rf) are calculated by normalizing the returns by the risk-free rate, reflecting the true profitability of the strategy beyond the simple return metric.
- Annualization of standard deviation and Sharpe Ratio standardizes these metrics across time frames for better comparability.
- WML returns highlight the core profitability of the momentum strategy by comparing the extremities of the deciles.
- Skewness calculation incorporates the risk-free rate to adjust the distribution analysis for risk-free profitability.
- Correlation analysis between recreated data and original DM returns quantifies the fidelity of the recreated results to the seminal work by Daniel and Moskowitz.

1.5 Recreation of Table 1 from Daniel and Moskowitz (2016) using Ken French breakpoints

Table 2: Statistics for Deciles and WML based on KRF

	Decile 1	Decile 2	Decile 3	Decile 4	Decile 5	Decile 6	Decile 7	Decile 8	Decile 9	Decile 10	WML
r_rf	0.015804	0.057140	0.064058	0.075493	0.075822	0.080361	0.090330	0.101642	0.108364	0.144960	0.129156
sd	0.342860	0.280948	0.241159	0.219278	0.204246	0.199261	0.188000	0.184109	0.192202	0.223382	0.274851
sk	1.730851	1.587204	1.352473	1.387286	1.007952	0.770916	0.069482	-0.003782	-0.306842	-0.524249	-5.737953
SR	0.046094	0.203383	0.266527	0.344279	0.370529	0.403295	0.480479	0.552074	0.563803	0.648933	0.469913
Correlation with KRF	0.997985	0.999772	0.998118	0.997624	0.997408	0.997851	0.998017	0.998174	0.998673	0.998301	0.995699

Introduction

This section outlines the steps undertaken to replicate and extend Table 1 from Daniel and Moskowitz (2016) using the Kenneth R. French (KRF) methodology for defining momentum portfolio deciles.

Methodology

The methodology involved several key steps, tailored to incorporate the KRF methodology for momentum portfolio analysis:

1. Loaded the KRF momentum returns data from the file `'m_m_pt_nyse_tot.txt'` into a DataFrame named `'kf_momentum'`. Adjusted the 'Date' column to datetime format and specified appropriate column names for ease of analysis.
2. Extracted 'year' and 'month' from the 'Date' column and prepared the 'kf_momentum' DataFrame by selecting relevant columns. Ensured that the 'Decile' column is numeric, dropping non-convertible values.
3. Defined the function `PS3_Q5` to calculate the risk-adjusted returns, standard deviation, and Sharpe Ratio for each decile using the input DataFrame (`'Input'`). These metrics were calculated by annualizing the risk-adjusted returns and standard deviation.
4. Computed the Winner Minus Loser (WML) returns by subtracting the returns of decile 1 from decile 10.
5. Created an output DataFrame (`'Output'`) by transposing the grouped statistics, and added a 'WML' column for the WML returns.
6. Calculated the standard deviation and Sharpe Ratio for the WML returns, adding these metrics to the `'Output'` DataFrame.
7. Computed the skewness of the WML returns after adjusting for the risk-free rate using the `skew` function.
8. Calculated WML returns for both the input data and the original KRF data using the 'groupby' and 'apply' methods. This was performed by grouping data by year and month.
9. Created a separate DataFrame (`'wml_comparison'`) to calculate the correlation between the WML returns of the input data and the KRF returns data, merging based on 'year', 'month', and 'Decile'.
10. Added a new row titled 'Correlation with KRF' to the `'Output'` DataFrame, which includes the correlations for each decile and between the WML returns of the input data and the KRF returns data.

Results

The DataFrame `'KRF_statistics'` provides a detailed replication of Table 1 using the KRF methodology, offering a comprehensive view of momentum portfolio performance using NYSE breakpoints and including correlation measures with original KRF momentum returns.

Appendix for Computations

- The annualization of risk metrics standardizes performance measurement across various time horizons.
- The inclusion of correlation measures helps in validating the replication accuracy against the original KRF momentum portfolio returns.

1.6 Performance of Momentum Strategy

Introduction

This section outlines the analysis conducted to examine the performance of the momentum anomaly (WML) in recent years and its comparison with the overall market performance.

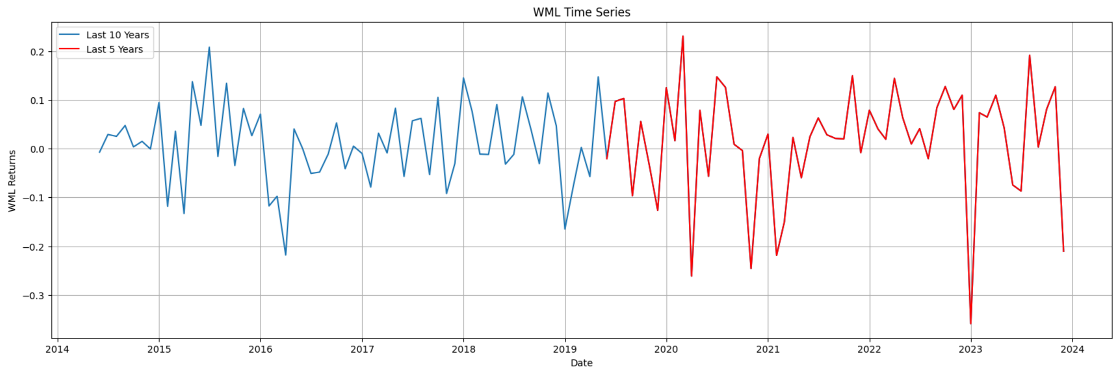

Figure 1: WML Returns over the Past 10 and 5 years

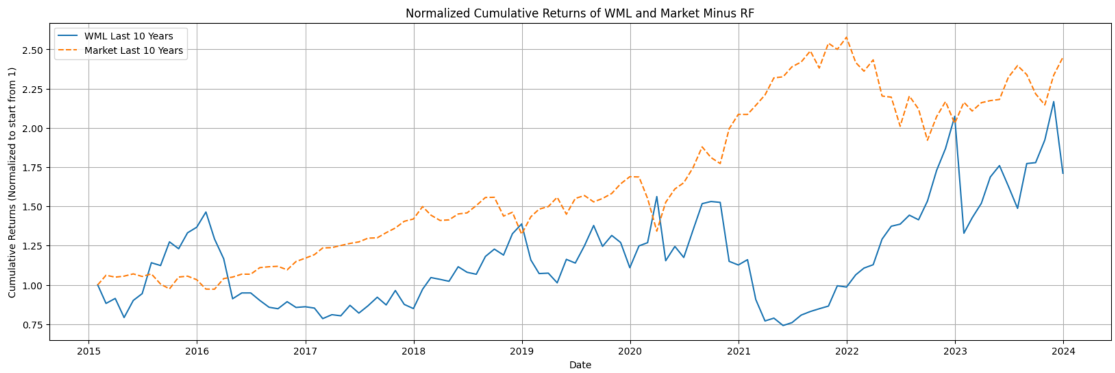

Figure 2: Market versus Momentum in the past 10 years

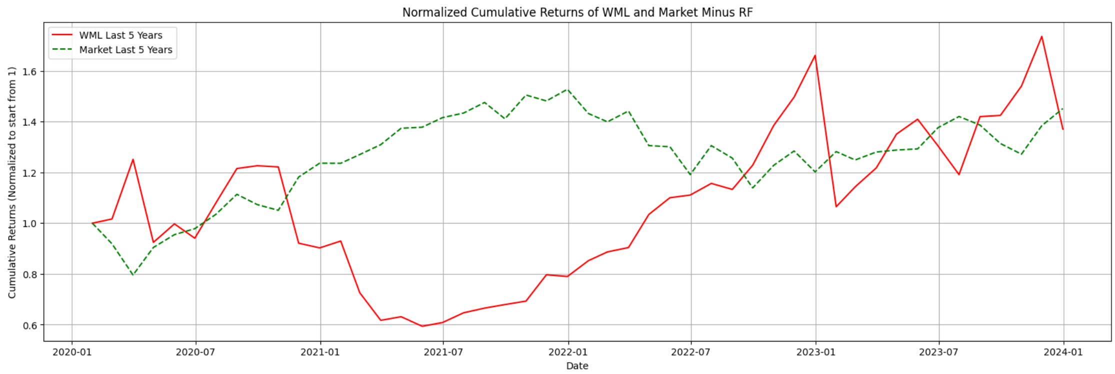

Figure 3: Market versus Momentum in the past 5 years

Table 3: Performance Metrics for WML and the Market Over the Last 10 and 5 Years

Period	WML Avg Return (%)	WML Volatility (%)	WML Sharpe Ratio	Market Avg Return (%)	Market Volatility (%)	Market Sharpe Ratio
Last 10 Years	12.67	33.91	0.3735	11.60	15.64	0.7415
Last 5 Years	12.89	40.28	0.3200	15.18	18.88	0.8041

Methodology

The methodology involved several key steps, structured to analyze the performance effectively:

Calculating WML Returns

1. Developed a function `compute_wml` that computes WML returns by determining the difference between the average returns of decile 10 and decile 1 for each year-month grouping.
2. Applied this function to the `CRSP_Stocks_Momentum_returns` DataFrame, resulting in a new DataFrame `wml_data` with year, month, and corresponding WML returns.
3. Formatted the 'date' column in `wml_data` for further analysis and plotting by combining year and month into a datetime format.

Plotting WML Returns

1. Visualized the WML returns for the recent 10-year and 5-year periods using line plots to highlight performance trends.
2. Enhanced plots with appropriate labels, titles, and legends to facilitate understanding and readability.

Comparing WML and Market Performance

1. Calculated and merged the cumulative returns for WML and the market (minus risk-free rate) into a single DataFrame `cumulative_returns` for comparison.
2. Normalized the cumulative returns to start from 1, providing a clearer comparison over the last 10 and 5 years.
3. Plotted these normalized cumulative returns to visually compare the performance of WML against the market.

Calculating Performance Metrics

1. Defined a function `calculate_metrics` to compute average return, volatility, and Sharpe Ratio for given returns.
2. Calculated these metrics for both WML and market returns over the last 10 and 5 years.
3. Compiled the metrics into a DataFrame `metrics_data` to display average returns, volatility, and Sharpe Ratios, formatted as percentages and rounded for clarity.

Rationale for Strategy Check

1. **Recent Performance Assessment:** Evaluates how momentum strategy performs in the current market environment, indicating its persistence or weakening.
2. **Market Comparison:** Determines if momentum strategy can outperform the market, highlighting its effectiveness.
3. **Risk-Adjusted Returns Analysis:** Compares Sharpe Ratios to assess if momentum strategy provides superior risk-adjusted returns.
4. **Trend and Pattern Identification:** Visual analysis of cumulative returns helps identify trends, patterns, or divergences in strategy performance.

Conclusion

The presented metrics suggest that the momentum strategy has generally underperformed the market in the recent past, particularly when considering risk-adjusted returns. The market not only provided higher average returns but did so with considerably lower volatility, resulting in higher Sharpe Ratios. This analysis points towards the market's superior performance relative to the momentum strategy (WML) during the observed periods i.e., recent past. This comprehensive analysis allows for informed decision-making regarding the viability and implementation of the momentum strategy, assessing its performance and risk-adjusted returns relative to the market.

1.7 Trading Strategy and Challenges to consider

Analyzing the Momentum Strategy

Given the historical evidence supporting the momentum anomaly and its recent underperformance relative to the market, a cautious approach is warranted. Here are several factors and challenges I would consider before implementing the strategy:

Risk-adjusted Returns

- The recent data indicates that the momentum strategy has underperformed the market in terms of risk-adjusted returns. Lower Sharpe Ratios associated with higher volatility in the strategy would be a major concern when aiming to achieve the best risk-adjusted returns for investors.

Market Conditions

- The effectiveness of the momentum strategy could be contingent on prevailing market conditions. I would conduct a thorough analysis of current market dynamics, such as sentiment shifts or economic uncertainties, which might impact the strategy's performance.

Portfolio Diversification

- I would evaluate the diversification benefits of the momentum strategy within a broader investment portfolio. Given its recent underperformance, the strategy's role in achieving effective diversification would need to be reassessed.

Capacity Constraints

- The potential for capacity constraints as the fund scales could impact the ability to implement the momentum strategy effectively, potentially diminishing returns due to increased transaction costs and market impact.

Transaction Costs

- The inherent high turnover of the momentum strategy might lead to considerable transaction costs. These costs would need to be managed carefully to ensure they do not significantly erode the strategy's returns.

Behavioral Challenges

- The psychological challenge of adhering to a momentum strategy, particularly during periods of market stress or when the strategy underperforms, should not be underestimated. Maintaining discipline and managing investor expectations would be critical.

Crowding

- The potential crowding of the momentum strategy in the market could reduce its effectiveness. Assessing the level of saturation and determining if there is still a profitable edge would be essential.

Strategic Implementation

- Instead of relying solely on the momentum strategy, I would consider integrating it within a multi-factor framework that includes other investment factors like value or quality. This could potentially enhance the portfolio's overall risk-adjusted performance.

Risk Management

- Robust risk management measures would be imperative. This includes setting appropriate position limits, diversifying across sectors and geographies, and continuously monitoring the portfolio against market changes.

Conclusion

The decision to implement the momentum strategy would hinge on a detailed evaluation of its advantages and drawbacks in the context of the fund's overall investment objectives and risk tolerance. It is essential to maintain a disciplined investment process, robust risk management, and transparent communication with investors regarding the strategy's risks and expected performance.