Advanced Programming 2025

Momentum Strategy on the MSCI World Index

Final Project Report

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Abstract

Academic research has shown that stocks that performed well in the past tend to continue to outperform in the future, unlike those who performed poorly. This phenomenon contradicts the Efficient Market Hypothesis and is commonly known as the Momentum Effect. This project aims to evaluate if the Momentum Effect is still present over the past six years (2019-2025) in the global equity market, with the constituents of the MSCI World Index. Momentum is measured by selecting the best performing stocks based on their returns over a fixed look-back horizon, excluding the most recent month. Portfolios are built using different formation periods (1, 3, 6, 12 months) while maintaining a constant holding period of one month. Every month, portfolios are re-calibrated with the new best performing asset and theirs performance compared to the benchmark. All data processing and back-testing are executed in Python with the help of various libraries to help the computation and visualization (pandas, NumPy, matplotlib,...). Results display that equal-weighted momentum portfolios tend to perform better than the benchmark, demonstrating the presence of the momentum effect (or premium). In general, this project contributes to a better understanding of an investment strategy based on momentum, validating its presence in a diversified equity markets such as the MSCI World Index.

Keywords: data science, Python, finance, portfolio strategy, MSCI World Index

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1 Introduction

1.1 Motivation

"Momentum is the observation that financial assets trending strongly in a certain direction will continue to move in that direction. The concept of momentum is based on similar theories in physics, where an object in motion tends to stay in motion unless disrupted by an external force." (Corporate Finance Institute, n.d.).

The first research on the Momentum effect was conducted by Jegadeesh and Titman (1993), who discovered that stocks with strong past performance tend to perform better compared to stocks with poor past performance. Moreover, their study highlighted that such stocks outperformed the overall market over medium- and long term horizons. This contradicts the Efficient Market Hypothesis (EBSCO Research Starters, 2024) that states that it is impossible to perform better than the market. Thus, reveiling that the human factor, i.e. investors over/under reacting to certain news, allows financial trends to persist beyond what the historical financial theory would justify.

While the Momentum definition seems simple, financial experts classify the Momentum effect as a market anomaly. This project aims to analyze, using the Morgan Stanley Capital International (MSCI) World Index, the effectiveness of the momentum effect over the past six years (2019-2025) in the global equity market.

In a world where financial market are more interconnected than ever and events, such as the COVID-19 pandemic, the growing uncertainty and the geopolitical tension, understanding the presence of the Momentum effect in today's environment is crucial. If the Momentum effect still shows up under these conditions, it would suggests that structural inefficiencies are still embedded in nowadays's financial market.

1.2 Problem Statement

Most studies on momentum are based either on U.S. markets or typically use long-time data samples. Less is known with smaller time window and with a globally diversified universe of stocks. This project tests whether the momentum effect is still present in the MSCI World Index universe under these conditions and if portfolios size (top 10, 20, 30, 40, 50) and look-back periods affect the risk-return output. Previous work like Asness et al. (2013) already shows the momentum effect across different countries and asset classes. This analysis differs by narrowing the input to the recent period and a realistic global benchmark.

1.3 Objectives and Goals

The main goal of this project is to assess whether the momentum effect is observable in the global equity market between 2019 and 2025. To fulfill this, we focus on:

- Compute momentum value based on past returns for all stocks in the Index with different periods (1, 3, 6, 12 months);
- Construct equally weighted momentum portfolios selecting the top performing stocks (top 10 stocks, 20, 30, 40, 50);
- each month, compute the 1 month performance of the portfolios
- Compare the performances to the benchmark (iShares MSCI World ETF, market-capitalization-weighted);
- Analyze the performances and related metrics across portfolio sizes and look-back period;
- Assess if this strategy still outperforms a passive benchmark in recent years.

These objectives aim to determine whether a momentum strategy is still a valid argument in modern days under recent market conditions and how results change when choosing different sizes and horizons.

1.4 Report Organization

The project's report is structured as follows. Section 2 reviews the main academic and empirical literature related to the momentum effect, their approaches and methodologies. Section 3 presents the data that were used, describes the momentum computation procedure and the portfolio construction process. Section 4 reports and interprets the empirical findings, including performance comparisons with the benchmark. Section 5 discusses the results, highlighting their implications and limitations. Finally, Section 6 will summarizes the key finding and suggesting directions for future research on this topic.

2 Literature Review

Since 1990s, momentum based strategies have been studied in finance with the first introduction by Jegadeesh and Titman in 1993 with the paper *Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency*. Their study analyzes only U.S. stock from 1965 to 1989; they discovered that stocks which performed best in the previous months (normally 6-12 months) continued to outperform those stocks that had a worst prior performance. The strategy was simple: buy the winners and sell the losers. By doing this, the yield of returns was significantly positive over medium and long horizons, suggesting that deviations from the efficient market hypothesis was possible. Since then, momentum effect was later incorporated as a main factor in asset pricing and asset allocations. A multitude of studies and research continued to expand the knowledge on the topic, settling it as one of the most famous and robust anomalies in the finance world (Nicholson, 2025).

The evidence of momentum premiums is visible not only in the U.S. equities markets, but it spans across internationals markets, such as Europe, Asia and other emerging markets. As well, this phenomenon is present in other asset classes such as commodities, bonds or even in the currencies market (Bhardwaj et al., 2024). Moreover, this behavior has persisted after it became public knowledge, posing once again in question the efficient market hypothesis. This pose the momentum effect as a market fundamental rather than a simple statistical anomaly. Given the evidence, momentum is nowadays accepted and implemented in many trading strategies (Asness et al., 2013).

Methodologically, momentum strategies analysis follow a similar approach across the literature. Depending on the study, daily or monthly returns are computed. Assets are then ranked by a predefined look-back period (usually 6 to 12 months) and then divided into winner and losers group or by percentile. The basic strategy goes long on the winners and short on the losers group of asset, thus re-balancing these portfolios at regular intervals. This approach was originally documented by Jegadeesh and Titman (1993) in their study and remains a standard way to construct a momentum portfolio. Further research applied variations in the look-back period, holding period or the weight attribution but the core idea remain identical. Datasets used in these studies are typically return records and price history such as the NYSE/AMEX or the MSCI World Index, while other studies have employed larger and longer time horizons, decade or century-long dataset, to verify the momentum effect over time. Generally, dataset's choice strictly depends on the type of study and area of focus.

In addition to the classical cross-sectional momentum (computation of only the relative performance across assets), professionals have also explored the time-series momentum, which is called trend-following. This trend was documented by Moskowitz, Ooi, and Pedersen (2011) and it describes how an asset's own past 12-month excess return is a strong and positive predictor of future returns and persists for about a year, acting like a cross-sectional momentum effect. In a nutshell, if a stock has a positive trend, a time-series momentum strategy suggests continuing to hold that asset in the portfolio (and vice versa if the stock has been trending down). Time-series' approach differs to the conventional cross-sectional on what is compared. Instead of evaluating assets against each other, the time-series criteria evaluate each asset return against its historical performance. However, both approaches share the same main idea that prices trends can be exploited to gain a premium that would be lost with a simple passive strategy.

To sum up, academia shows that momentum portfolio strategies are both present and quantifiable. Moreover, these strategies deliver abnormal returns across all asset types, markets, and different time frame. This prior work provides a solid foundation for all new projects focusing on the momentum effect. It emphasizes previous methods and approaches that have been effective and offer a reference for what kind of results and performance is achievable with this strategy. By conducting new analysis on these well-established papers and findings, researcher can evaluate new momentum trading models, having a benchmark on what to expect for behavior and even potential pitfalls.

3 Methodology

3.1 Data Description

The dataset used in this project is based on the constituent MSCI World Index, which considers mid and large capitalization stocks across developed markets countries (MSCI Inc., 2025). It contains roughly 1400 stocks, depending on the considered time window. For this project, two different datasets have been used: the first one contains the basic data for each company listed in this Index, such as the name, the market capitalization and the economic sector, Table 1. The second dataset lists the end month total return index, including dividend, of each stock in converted in US Dollars and the benchmark (iShares MSCI World) that are used for return computation, as shown in Table 2. Stocks included in this project are the ones that were presents in the MSCI World Index at 31.12.2018 in order to avoid a look-ahead bias in the back-test. Datasets have been obtained from the Reuters (2025) platform, which guarantee the completeness and quality of data. That is because all returns values have been treated consistently in respect to their price series. For an efficient manipulation of the datasets, the CSV files has been processed in Python using the `pandas` library.

Table 1: Excerpt from the MSCI World Company Information Dataset (31.12.2018)

Symbol	**Company Name**	**Sector**	**Market Cap (B)**
AAPL	Apple Inc.	Information Technology	748.539
MSFT	Microsoft Corp.	Information Technology	779.673
JNJ	Johnson & Johnson	Health Care	346.626

Table 2: Monthly total return series

Date	**iShares**	**Apple**	**Microsoft**	**Amazon**
31.12.2018	247.54	38119.78	159643.10	76696.31
31.01.2019	258.51	40222.23	164138.30	87764.88
28.02.2019	264.13	42023.04	176839.50	83736.00

3.2 Approach

Momentum is measured by selecting the top-performing stocks based on their cumulative returns over a fixed look-back period (excluding the most recent month) and then assessing their subsequent performance relative to the MSCI World Index. Momentum is measured by selecting the top-performing stocks based on their cumulative returns (inclusive of dividends) over a fixed look-back period (excluding the most recent month) and then assessing their subsequent performance relative to the MSCI World Index and other metrics. Momentum for each stock i at time t is defined according to the MSCI Momentum Indexes framework (2021):

$$M_{i,t} = \frac{P_{i,t-1}}{P_{i,t-k}} - 1$$

where $P_{i,t}$ is the closing price of stock i at time t, and k is the look-back period in months. To simplify calculations, it can be assumed that the risk-free rate is constant and therefore it is not subtracted in the formula. That is because the risk-free rate tends to cancels out in these types of analysis with large samples (Asness et al., 2014). Each month, all stocks are ranked according to their momentum score. This is where the top N stocks (where $N = 10, 20, 30, 40, 50$) are selected and used to build an equal-weighted portfolio. Each portfolio is kept one month and its performance is compared to the benchmark, which is market-capitalization weighted and it includes all stocks of the universe considered. Additionally, key metrics such as the Sharpe Ratio, volatility or the mean monthly return are computed.

3.3 Implementation

All computations have been implemented in **Python 3.13**. Some of the libraries used are:

- `pandas` for data handling and time-series transformations;
- `numpy` for numerical computations;
- `matplotlib` and `seaborn` for visualization;
- `statsmodels` and `scipy` for statistical evaluation.

A modular structure is used for this project. Core functions are implemented inside the `src/momentum/` directory, which contains:

- `data_io.py`: load and clean the raw MSCI World data;
- `metrics.py`: build functions to calculate performance metrics such as annualized return, volatility, Sharpe ratio, Sortino ratio, and HAC p-values.

Inside the `scripts/` are all scripts that compute the main stages of the analysis:

- `build_portfolio.py`: builds equal-weighted momentum portfolios for all look-back horizons (1m, 3m, 6m, 12m);
- `pretty_table.py`: displays performance metrics in the form of tables (PNG format);
- `summarize_results.py`: compares portfolios across horizons, plots returns;
- `run_all.py`: for final user, it runs every step in sequence.

Lastly, all graphical output are saved in the `results` folder and the `requirements.txt` files, when runned, ensures that all libraries used are installed.

Example code snippet:

```python
def load_monthly_data() -> pd.DataFrame:
    """Reads Monthly_Data.csv (semicolon-delimited), parses date, returns wide DataFrame."""
    path = RAW / "Monthly_Data.csv"
    df = pd.read_csv(path, sep=";")
    date_col = df.columns[0]
    df[date_col] = pd.to_datetime(df[date_col], errors="coerce", dayfirst=True)
    return df.rename(columns={date_col: "date"})
```

Listing 1: Function to Load Monthly Price Data

4 Results

4.1 Experimental Setup

All computations have been run using Python 3.13, including libraries such as `pandas`, `numpy`, `matplotlib`, and `statsmodels`. Given the lightweight of the computational process, all backtests have been executed on a standard laptop. The dataset used include monthly closing prices of the MSCI World Index from 2019 to 2025, where the iShares serves as benchmark. Momentum is computed for every stock over look-back periods of 1, 3, 6, 12 months, excluding the most recent month in order to avoid some kind of short-term reversals.

Each month, the top N stocks ($N = 10, 20, 30, 40, 50$) have been selected based on momentum to build a new equal-weighted portfolio that is held for one month and then sold. Returns of these portfolios have been then compared to the benchmark using the annual return, annualized volatility, Sharpe Ratio and Sortino (this last two are risk-adjusted). Additionally, the Newey-West (HAC) p-values are calculated as the project tests whether the portfolios returns are statistically different from the benchmark. The main evaluation metrics are defined as follows:

$$\sigma_{ann} = \sigma_m \times \sqrt{12}$$

$$\text{Sharpe Ratio} = \frac{\bar{r}_p - r_f}{\sigma_p}$$

$$\text{Sortino Ratio} = \frac{\bar{r}_p - r_f}{\sigma_d}$$

where σ_m is the standard deviation of monthly returns, σ_d is the downside deviation (returns below zero), and r_f is the risk-free rate (set to zero as discussed precedently) (Kolbadi & Ahmadinia, 2011).

4.2 Performance Evaluation

To illustrate the results, the forming period of lagged period of 12 months is the one more significant in term of showing momentum, as shown in Table 3 and Figure 1. The sample period is from 31.12.2018 to 30.09.2025.

Table 3: Performance Metrics — 12-Month Momentum

Portfolio	Ann. Return %	Ann. Vol. %	Sharpe	Sortino	p-HAC (vs BM)
Top 10	47.9	29.9	1.5983	3.3287	0.0012***
Top 20	24.4	24.3	1.0038	1.8571	0.0753*
Top 30	26.1	22.4	1.1606	2.4054	0.0248**
Top 40	23.8	20.4	1.1679	2.1192	0.0427**
Top 50	21.6	19.1	1.1342	1.9102	0.0571*
Benchmark	13.9	12.3	1.1286	1.8286	—

The 12 month horizon shows the strongest momentum effect. All portfolios of this period outperform the iShares benchmark in the annualized return. The top 10 portfolio is the one carrying the bigger results, with an annualized return nearly four times the benchmark return (0.4761 vs 0.1262). Sharpe Ratio is also significally higher for the top 10 portfolio. The HAC p-values state that returns of portfolios are statistically different from the benchmark. In this case at the 1% significancy for the top 10 portfolio and almost always below 10% for the others.

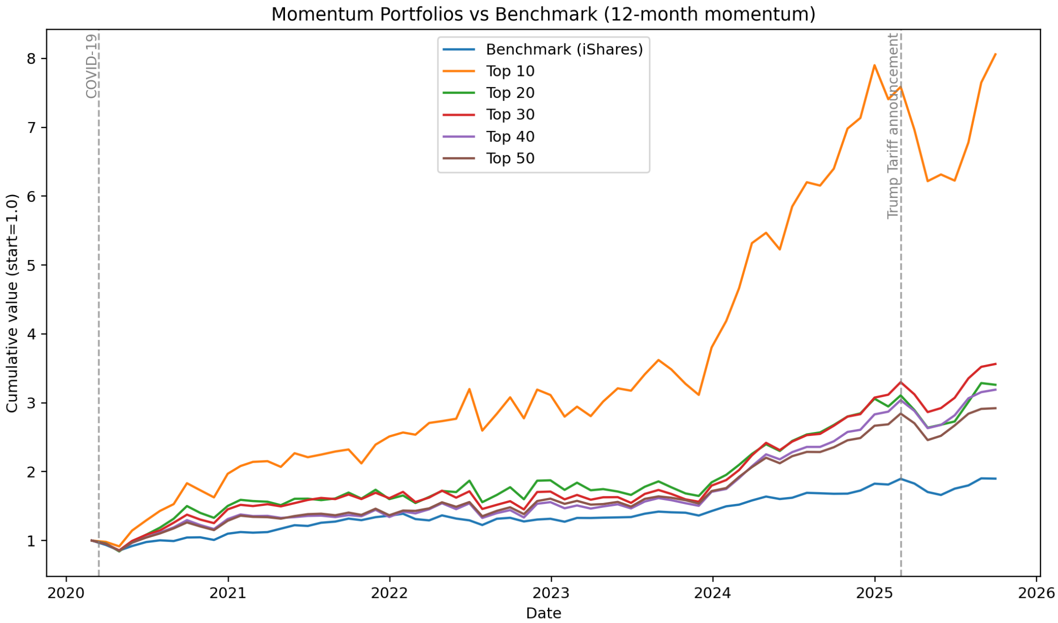

Figure 1: Cumulative performance of equal-weighted momentum portfolios versus the benchmark (2019–2025, 12-month lookback).

Figure 1 shows how momentum portfolios consistently beat the benchmark overall. The highest growth is carried by the top 10 portfolio but it is paired with a greater volatility (0.2998). This volatility is amplified during shocks like the COVID-19 or the announcement of new tariffs made by Donald Trump. Larger portfolios delivers a smoother performance, highlighting how a well diversified strategy can reduce volatility while holding the momentum premium.

4.3 Visualizations

Figures 2 and 3 summarize the results across horizon and portfolios sizes. These plots show the evolution of the Sharpe Ratio and the volatility across horizons and portfolio's size. It is worth to notice how the volatility decreases as the the portfolio's size increases. This is totally expected and it is consistent with the diversification principle by Markowitz (1952) , which states that holding a diversified asset portfolio helps to reduce the volatility of this one. Moreover, Sharpe ratios tends to improve when taking longer look-back horizons, especially when we consider smaller portfolios like the Top 10-30. This suggests that over longer periods, momentum effect is stronger. This strengthens the belief that returns are more affected by noise in the short-term while medium/long-term captures more persistent trends.

Additional figures and results are in Section A (*A Additional Figures*). They present the set of results across the other look-back periods and portfolio sizes, exposing a more complete view of how a momentum strategy change across horizons.

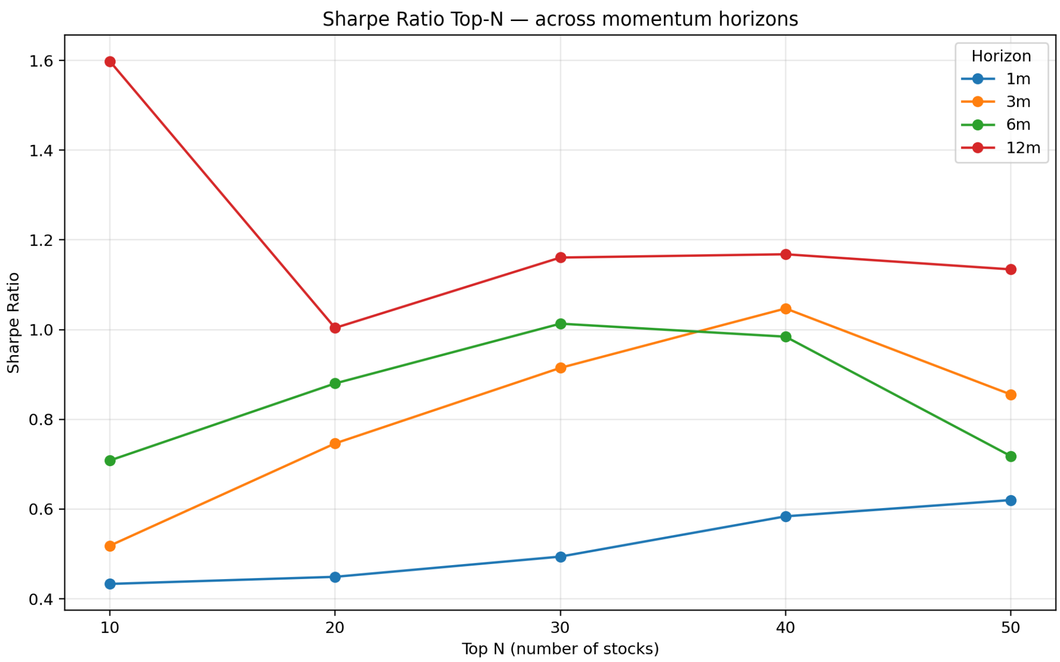

Figure 2: Sharpe ratio across momentum horizons and portfolio sizes. The 12-month horizon yields the highest Sharpe ratios, especially for smaller portfolios (Top 10–30), highlighting a strong momentum premium. This Sharpe ratio for the Top 10 is probably an outlier and should be necessary further inspection, as we see it immediately corrects its value for the other portfolio's size. This trend stabilizes for the Top 30 and gently descending after that. Moreover, 30 stocks is generally recognized as a good diversified portfolio (James et al., 2022).

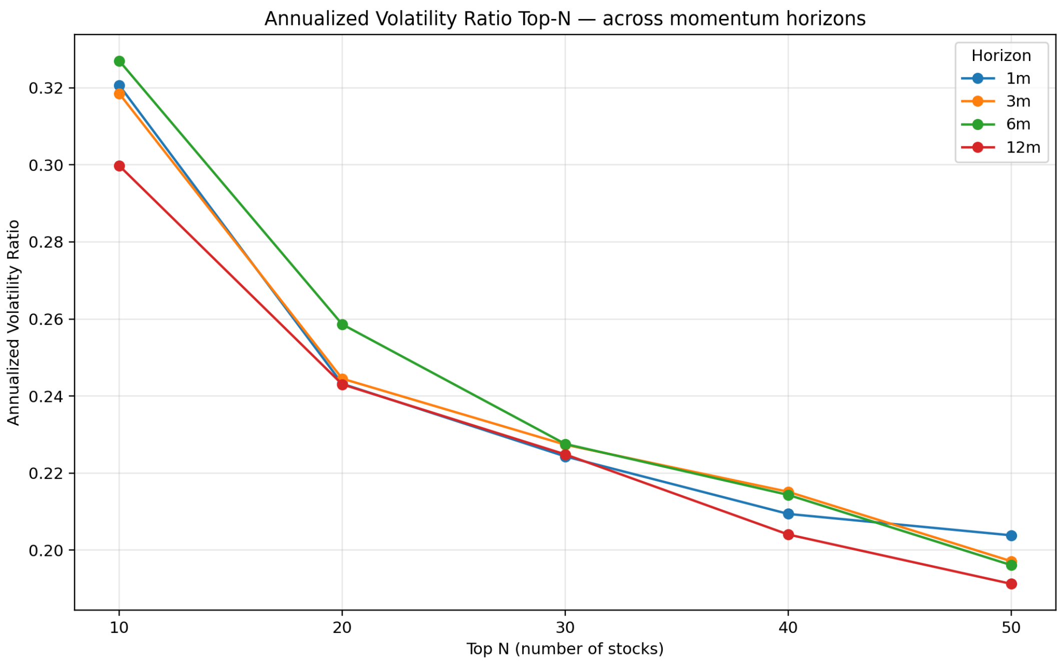

Figure 3: Annualized volatility ratio across momentum horizons and portfolio sizes. As expected, volatility decreases with bigger portfolios.

5 Discussion

The results of this project show that the momentum effect is still present in modern global equity markets. This phenomenon is particularly observable for the longest look-back periods like the 6 and 12 months horizons. These portfolios capture the most momentum effect as they are the ones who better outperformed the benchmark, both in terms of returns and risk-adjusted metrics. The 12 month Top 10 portfolio carries the strongest performance with an annualized return of 0.4791 and a Sharpe ratio of 1.5983. This project confirm the persistence of momentum profits as documented by Jegadeesh and Titman (1993). It is crucial to notice how the HAC p-values change across the time frames considered. Moreover, if more historical periods are added, the portfolios are going to be statistically different from the benchmark. This means that for shorter look-back period the active portfolio strategy might deliver the same results as the passive strategy, meaning that the momentum effect is stronger for long horizons.

The 1-month horizon delivered the poorest performance. This may be explained with the presence of what is called *short-term reversals* (Covel, 2013). This phenomenon is often observed after a considerable price shock or price correction. As a matter of fact, assets that performed extremely well or extremely poorly, the next period are very likely to behave the opposite. These weaker results for short horizons imply that momentum requires more time to be effective, and that it is not really effective for a short-term strategy.

Speaking about risk-adjusted metrics, the results show a common pattern. Portfolios with larger samples, such as the Top 40-50, exhibit a lower volatility compared to the smaller ones. This is due to the diversification effects. The counterpart of this diversification is that returns are more diluted, suggesting that an investor should do a trade-off between the concentration and the stability of returns of the portfolio.

The main limitations of this project are related to data coverage and the model simplicity. The period considered (2019-2025) contains extreme events like the COVID-19 crisis and the announcement of new tariffs imposed by Donald Trump. These shocks may have a relevant impact in short-term dynamics and results may be distorted by these. Inputs like transaction costs or the risk-free rate were not included and this might emphasize the real-world profitability. Moreover, the project considers a long-only strategy with equal-weighted portfolios, where more complexes analysis consider going short on the bad performing stocks.

6 Conclusion and Future Work

6.1 Summary

Overall, the project's results align with expectations provided by the literature, highlighting the presence of 1 month Momentum for formation period of 6 and 12 months on the recent history of the equity market. Portfolios based on Momentum outperformed the benchmark, with the best results for concentrated portfolios. The analysis also shows the characteristic trade-off between size and volatility, validating that a diversified portfolio reduce risk but with lower returns.

6.2 Future Directions

Several implementations might improve this analysis. Future work and research could integrate in the analysis more factors like daily data, cross-sectional/time-series variables or the integration of a multi-factor model like the Fama-French-Carhart model (TIOmarkets, 2024) that includes risk, price and the company size. Additionally, including macroeconomic factors or investors sentiment can improve the momentum signal quality.

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A Additional Figures

Table 4: Performance Metrics — 1-month Momentum

Portfolio	Ann.Return %	Ann.Vol %	Sharpe	Sortino	p-HAC (vs BM)
Top 10	13.8	32.07	0.4331	0.7236	0.6271
Top 20	10.9	24.3	0.4489	0.7153	0.9837
Top 30	11.08	22.4	0.4940	0.7278	0.9816
Top 40	12.2	20.9	0.5838	0.9465	0.9220
Top 50	12.6	20.3	0.6200	1.0131	0.8802
Benchmark	13.9	12.3	1.1286	1.8286	—

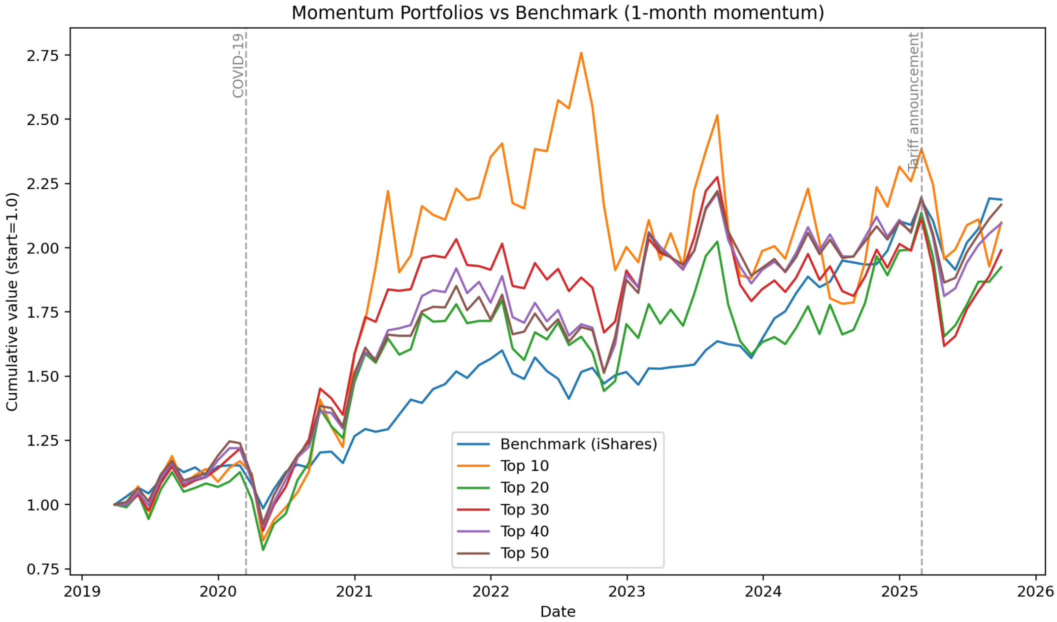

Figure 4: Cumulative performance vs benchmark (2019–2025), 1-month momentum.

Table 5: Performance Metrics — 3-month Momentum

Portfolio	Ann.Return %	Ann.Vol %	Sharpe	Sortino	p-HAC (vs BM)
Top 10	16.5	31.8	0.5183	1.2075	0.4431
Top 20	18.2	24.4	0.7463	1.4033	0.3021
Top 30	20.8	22.7	0.9147	1.6614	0.1949
Top 40	22.5	21.5	1.0471	1.7706	0.0953*
Top 50	16.8	19.7	0.8553	1.3569	0.3534
Benchmark	13.9	12.3	1.1286	1.8286	—

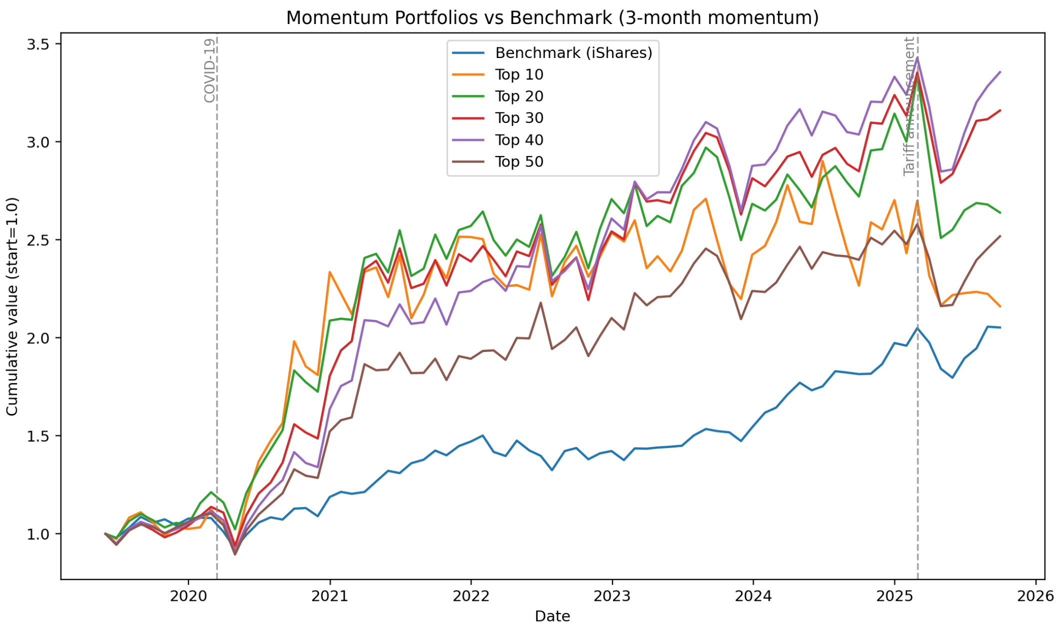

Figure 5: Cumulative performance vs benchmark (2019–2025), 3-month momentum.

Table 6: Performance Metrics — 6-month Momentum

Portfolio	Ann.Return %	Ann.Vol %	Sharpe	Sortino	p-HAC (vs BM)
Top 10	23.1	32.7	0.7082	1.7760	0.1316
Top 20	22.7	25.8	0.8800	1.4506	0.1098
Top 30	23.0	22.7	1.0132	1.4806	0.0424**
Top 40	21.1	21.4	0.9842	1.4498	0.0577*
Top 50	14.0	19.6	0.7180	1.0209	0.4305
Benchmark	13.9	12.3	1.1286	1.8286	—

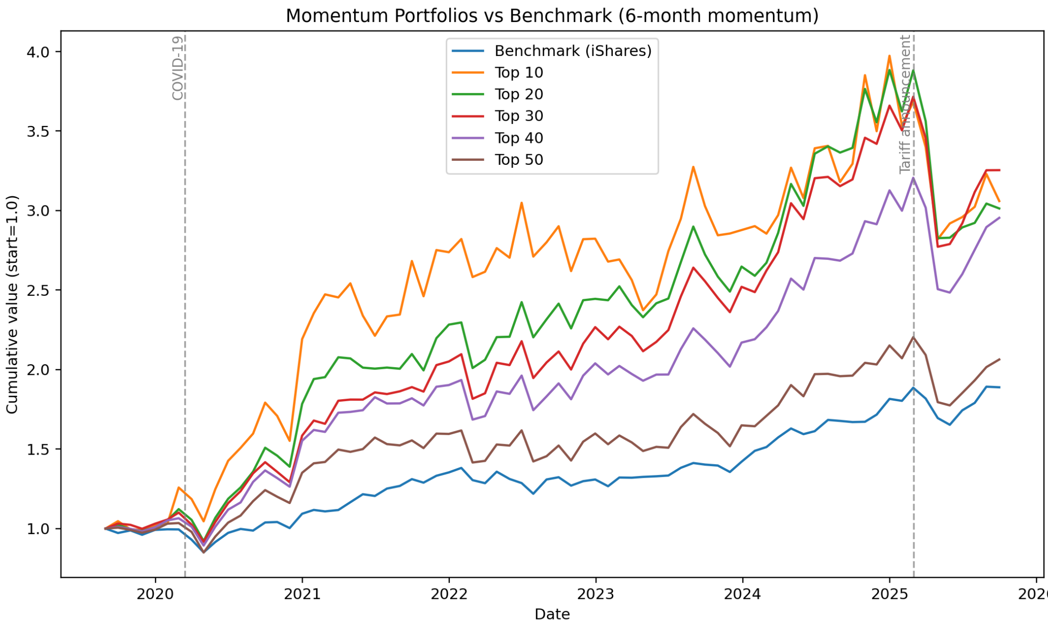

Figure 6: Cumulative performance vs benchmark (2019–2025), 6-month momentum.

B Code Repository

GitHub Repository: https://github.com/MatteoPiras-Unil/Matteo_Piras_Project

B.1 Repository structure

```
Matteo_Piras_Project/
|
|-- .venv/              # Virtual environment
|-- .vscode/            # VS Code settings
|
|-- config/             # Configuration files
|-- data/               # Datasets (raw and cleaned)
|-- results/            # Output: figures, tables, results
|-- scripts/            # Helper or setup scripts
|-- src/                # Core source code
|
|-- .env                # Environment variables
|-- .gitignore          # Git ignore file
|-- Proposal.md         # Project proposal
|-- README.md           # Documentation
|-- requirements.txt    # Python dependencies
|-- run_all.py          # Main pipeline runner
```

B.2 Installation and usage

On your terminal, clone the repository:

```
git clone https://github.com/MatteoPiras-Unil/Matteo_Piras_Project
cd /files/Matteo_Piras_Project
```

Create and activate virtual environment:

```
python -m venv .venv
source .venv/bin/activate    # On Windows: .venv\Scripts\activate
```

Install dependencies:

```
pip install -r requirements.txt
```

Run pipeline:

```
python run_all.py
```

This command will:

- Compute momentum scores
- Select top N stocks for each rebalance date
- Build equally weighted portfolios
- Calculate portfolio and benchmark returns
- Output all summary statistics and charts in the `results/` folder

B.3 How to reproduce results

To reproduce and visualize the results, simply run the file `run_all.py` after setting up the environment and installed the requirements. This script runs the full pipeline, computing all data transformations and creating portfolios. Once done, all outputs will be saved and available in the folder `results`.