Sefirot

Financial Research

Adaptive Asset Allocation (1)

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1 Introduction

Within the financial world one can be sure of few things, but the study of returns, variances, and correlations can help in the construction of portfolios that achieve positive expected performance.

Research has produced strategies that can adapt to conditions observed in the market, introducing dynamic investment strategies, moving beyond static strategies. Among these, *Adaptive Asset Allocation* adjusts the composition of an investor's portfolio over time to match changes in the return expectations of different asset classes, while respecting the overall risk of the portfolio.

Going deeper, *Adaptive Asset Allocation* allows the investor to set a time interval (weekly, monthly, etc.) and calculate efficient asset allocations in order to adapt the portfolio to market changes, weighting the assets through the analysis of historical data to integrate the different inherent characteristics of the major asset classes.

One of the main differences between static strategies and dynamic strategies lies in the fact that historical data analysis is mostly used in static investment strategies because they consider long-term historical returns as inputs to their models that are valid for long-term forecasts.

Click *here* to find the database and matlab code.

2 Framework

My work was developed through the creation of a dataset, called *Strat*, which contains more than 25,000 daily observations over the time period from 2009 to 2019.

The reason behind the choice of this time frame stems from the desire to reduce the depth of daily observations in order to exclude from the analysis the effects that have influenced downward market trends. I refer specifically to the subprime mortgage crisis that characterized the year 2008.

In this way, it is possible to test strategies in market conditions that are not excessively volatile, allowing a better understanding of the validity of the applied strategies and avoiding incorrect judgments.

Within the dataset, the saved information starts on 09/30/2009, but when processing the graphs MATLAB approximates the monthly returns and shows the trend on the screen starting in 2010. This approximation is due to the fact that the graphs are constructed on the basis of monthly returns and, for 2009, the observations are not sufficient.

The dataset mentioned above was constructed from daily observations of 10 ETFs, comprising stocks and bonds, from different geographic areas.

Specifically, the database consists of ETFs focused on the following categories:

Figure 1: * ETF EQUITY/BONDS EM - ETF EQUITY/BONDS EMERGING MARKETS; ** ETF EQUITY CM - ETF EQUITY COMMODITIES

3 Strategies

3.1 Equally Weighted

The first strategy developed is *Equally Weighted*. This strategy involves assigning a weight to each asset class equal to $1/N$ (where N is the number of asset classes), which remains constant throughout the entire time frame of the strategy.

The *Equally Weighted* is not a dynamic strategy but a static one, and it will be used as a benchmark to evaluate the goodness-of-fit of all other strategies.

From the graph it can be seen that, against an initial investment of $100, the portfolio ends with a final value of $116.39.

The conclusion section will analyze the *Equally Weighted* strategy, which serves as a benchmark against the other strategies, using additional performance indicators.
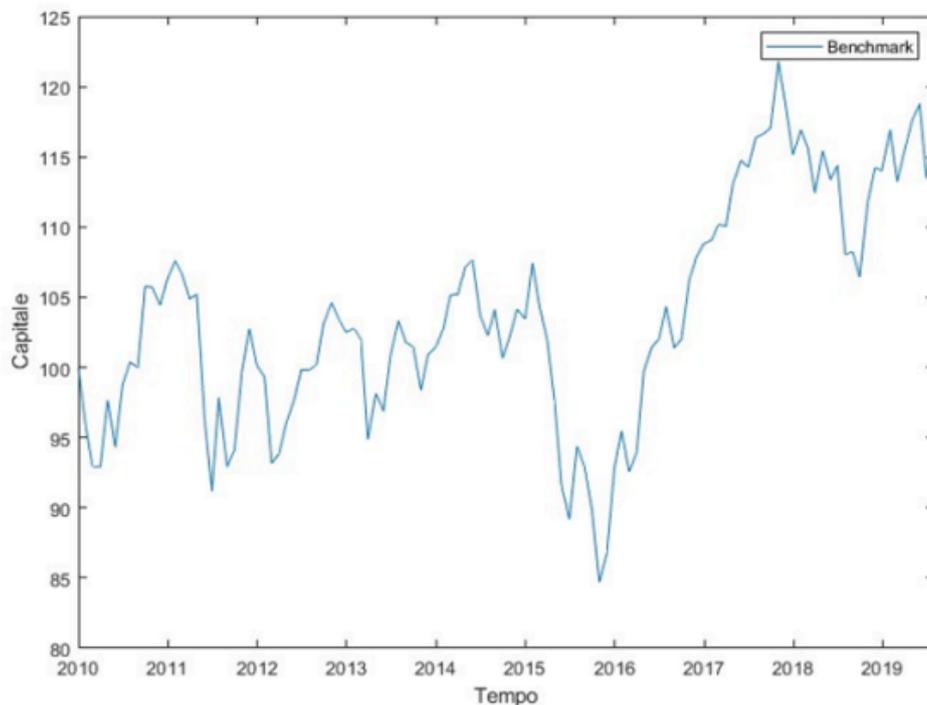
Figure 2: Equally Weighted

3.2 Momentum

The second investment strategy is *Momentum*. This strategy selects assets following a bullish or bearish trend based on a timeframe that can be 3, 6, or 12 months.

The underlying assumption is that an asset exhibiting a bullish trend will continue to maintain it in the short to medium term, while assets that underperform will continue to do so.

In this case, the strategy was implemented by constructing a portfolio in which a long position was taken on the five assets with the highest returns, while a short position was taken on the five assets with the lowest returns. The selected timeframe for the analysis is six months.
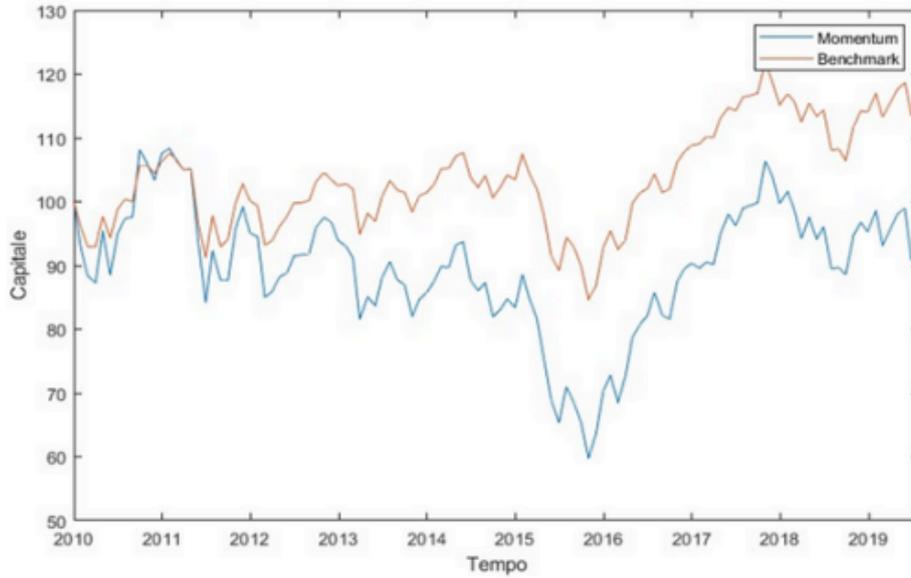
Figure 3: Momentum

Strategy	Return	Std. Dev.	Sharpe Ratio	Max Drawdown	Final Capital
Benchmark	0.0212	0.098	0.0127	0.23	116.39
Momentum	-0.0083	0.16	-0.077	3.55	9.898

Table 1: Performance comparison between Benchmark and Momentum strategies

The *Momentum* strategy achieves a lower final result than the *Equally Weighted* strategy, and the value of the invested portfolio also ends below the initial capital.

During bearish market phases, the *Momentum* strategy experiences a larger decline than the *Equally Weighted* strategy which, being more diversified, reduces overall risk. Consistently with this observation, the *Momentum* strategy shows a higher standard deviation. Conversely, the capital invested through the *Momentum* strategy fails to take sufficient advantage of bullish market phases to recover at least the initial capital.

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3.3 Minimum Variance

The third strategy is *Minimum Variance*, which is based on classical portfolio optimization theory derived from Modern Portfolio Theory.

This strategy takes into account both returns and risk, where risk is measured by the standard deviation of individual assets. In this framework, the efficient frontier is recalculated for each period, allowing the selection of the portfolio located at the far left of the frontier, namely the portfolio with the minimum variance.
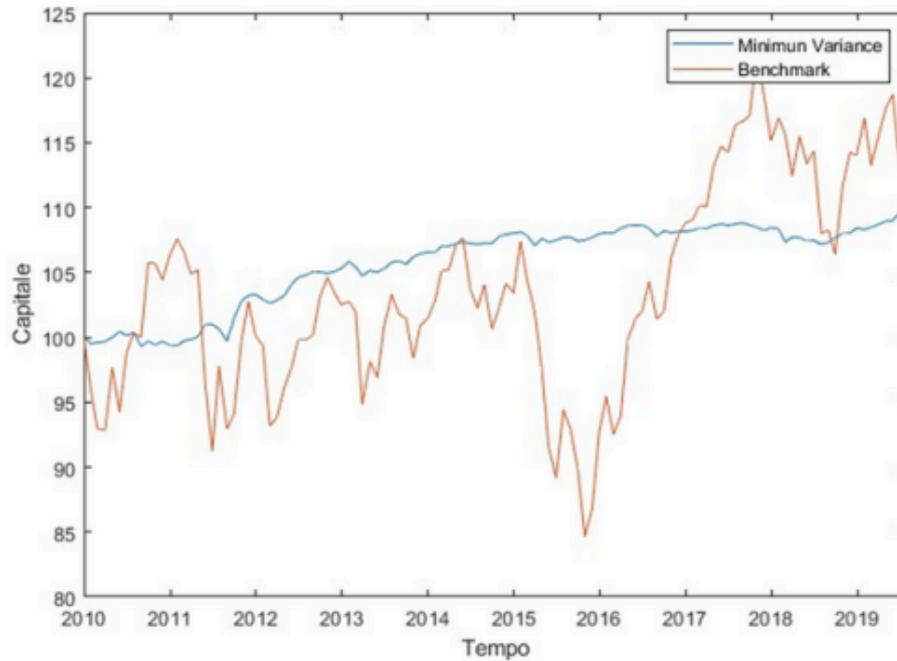

Figure 4: Minimum Variance

Strategy	Return	Std. Dev.	Sharpe Ratio	Max Drawdown	Final Capital
Benchmark	0.0212	0.098	0.0127	0.23	116.39
Minimum Variance	0.09	0.012	-0.9403	4.38	108.75

Table 2: Performance comparison between Benchmark and Minimum Variance strategies

The *Minimum Variance* strategy, due to its conservative nature aimed at minimizing portfolio variance, exhibits a very low standard deviation, as reflected in the relatively modest capital obtained at the end of the investment horizon.

The final capital obtained with the strategy is $108.75, which is lower than the value achieved with the *Equally Weighted* strategy given the same initial investment. This result is consistent with the expected behavior of the *Minimum Variance* strategy.

3.4   Volatility Parity

The third strategy is *Minimum Variance*, which is based on classical portfolio optimization theory derived from Modern Portfolio Theory.

The fourth strategy is called *Volatility Parity*, which involves constructing an inverse volatility-weighted portfolio. This strategy aims to create a diversified portfolio that is not overly concentrated by assigning each asset a weight inversely proportional to its volatility.

To implement this strategy, an asset with a high standard deviation is assigned a low weight in the portfolio, subject to the asset constraints, while assets with a low standard deviation are assigned a higher weight.

One of the main advantages of this strategy lies in the simplicity of calculating the weights, as the weight of each asset is computed as a weighted average of the inverse of the asset's standard deviation.

The main limitation of this approach, however, is that it does not take into account the correlations between assets, and thus may not fully reflect the actual risk contributed by the individual securities to the portfolio.

Figure 5: Volatility Parity

Strategy	Return	Std. Dev.	Sharpe Ratio	Max Drawdown	Final Capital
Benchmark	0.0212	0.098	0.0127	0.23	116.39
Volatility Parity	0.0158	0.037	-0.1202	9.96	114.38

Table 3: Performance comparison between Benchmark and Volatility Parity strategies

The *Volatility Parity* strategy performs particularly well during market downturns, while maintaining a final return that is broadly in line with the benchmark.

However, this strategy underperforms during bullish market phases because, as shown in the chart, it fails to fully take advantage of positive momentum.

3.5 Risk Parity

The fifth strategy considered is *Risk Parity*, which, like the previous strategy, does not incorporate expected asset returns in the weighting process, but instead focuses on optimizing the distribution of portfolio risk among its components.

Specifically, the marginal risk contributions (percentage contribution to total risk) of all portfolio components are equalized for a given level of portfolio volatility.

This strategy, unlike the *Volatility Parity* approach, explicitly considers asset risk in the form of variance.

The primary objective of this strategy is to improve portfolio performance during market downturns, potentially at the expense of absolute returns.
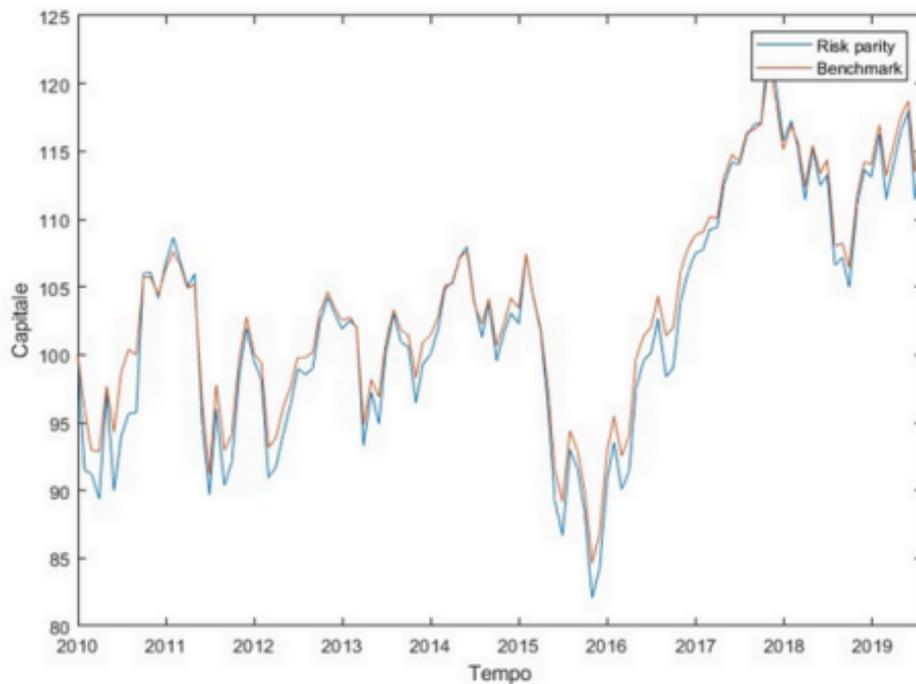

Figure 6: Risk Parity

Strategy	Return	Std. Dev.	Sharpe Ratio	Max Drawdown	Final Capital
Benchmark	0.0212	0.098	0.0127	0.23	116.39
Risk Parity	0.0231	0.1092	0.0296	27.34	116.15

Table 4: Performance comparison between Benchmark and Risk Parity strategies

The *Risk Parity* strategy performs almost identically to the Benchmark; in fact, the return, standard deviation, and final investment value are very similar.

However, the strategy does not effectively mitigate portfolio drawdowns during market downturns.

4 Combined Strategies

4.1 Momentum Minimum Variance

Momentum Minimum Variance is an investment strategy that seeks to balance the positive momentum (*Momentum*) of a security or group of securities with portfolio variance minimization.

The combination of these two approaches aims to achieve a balance between pursuing positive performance and reducing risk through variance minimization. In practice, this involves selecting stocks or assets that have demonstrated strong past performance while also being relatively uncorrelated with each other to reduce the overall volatility of the portfolio.
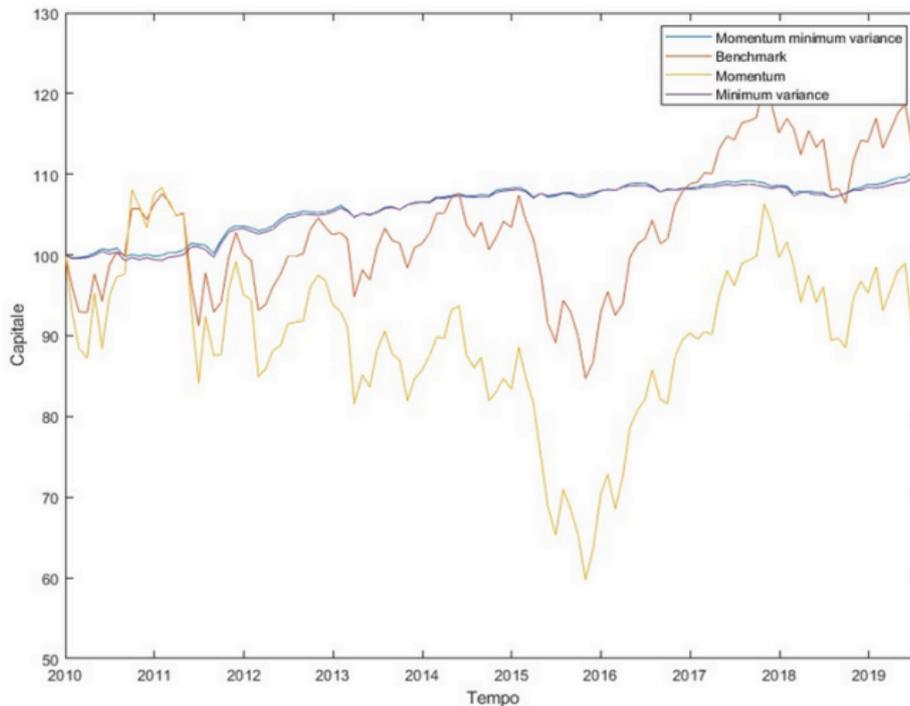

Figure 7: Momentum Minimum Variance

Strategy	Return	Std. Dev.	Sharpe Ratio	Max Drawdown	Final Capital
Benchmark	0.0212	0.098	0.0127	0.23	116.39
Momentum	-0.0083	0.16	-0.077	3.55	9.898
Minimum Variance	0.09	0.012	-0.9403	4.38	108.75
Momentum Minimum Variance	0.0096	0.013	-0.8039	0.0476	109.14

Table 5: Performance comparison among Benchmark, Momentum, Minimum Variance, and Momentum Minimum Variance strategies

The *Momentum Minimum Variance* strategy achieves, albeit modestly, an improvement over the *Minimum Variance* strategy through the incorporation of *Momentum*.

Thus, while this strategy remains particularly conservative, the addition of *Momentum* enhances its performance. This, however, comes at the cost of a higher standard deviation and increased maximum drawdown, while still remaining below the Benchmark.

Overall, the *Momentum Minimum Variance* strategy proves to be slightly more profitable and aggressive, while retaining its inherently conservative characteristics.

4.2   Momentum Volatility Parity

Momentum Volatility Parity is a portfolio management strategy that seeks to balance the positive momentum of a security or group of securities with portfolio volatility management, aiming to achieve a balance between pursuing positive performance and controlling risk.

In practice, the *Momentum Volatility Parity* strategy involves using different financial instruments, such as diversifying across various stocks or assets that exhibit strong momentum, while simultaneously balancing the overall portfolio volatility through careful asset allocation management.
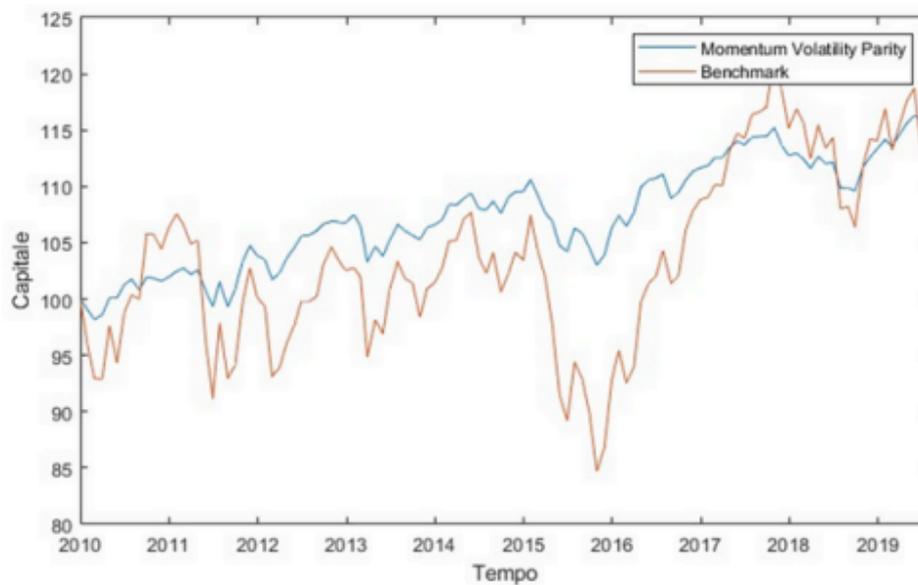

Figure 8: Momentum Volatility Parity

Strategy	Return	Std. Dev.	Sharpe Ratio	Max Drawdown	Final Capital
Benchmark	0.212	0.098	0.0127	0.23	116.39
Momentum Volatility Parity	0.0158	0.037	0.1202	0.0996	114.37

Table 6: Performance comparison between Benchmark and Momentum Volatility Parity strategies

For the second strategy, namely *Momentum Volatility Parity*, the graph shows the comparison with the Benchmark. This is because, in the application of the combined strategy, the *Momentum* component had no effect, so the graph and other comparative values are essentially identical to those of the Benchmark.

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4.3 Momentum Risk Parity

The *Momentum Risk Parity* strategy is a combination of two investment concepts: *Momentum* and *Risk Parity*. This strategy seeks to balance the positive momentum of a security or group of securities with risk management, so that the portfolio maintains an equal distribution of risk among the selected assets.

The *Momentum Risk Parity* strategy aims to combine these two concepts. Investors attempt to identify securities or assets that demonstrate strong momentum while simultaneously applying active risk management to balance risk across different positions in the portfolio. The objective is to construct a portfolio that benefits from positive momentum while maintaining balanced risk exposure.
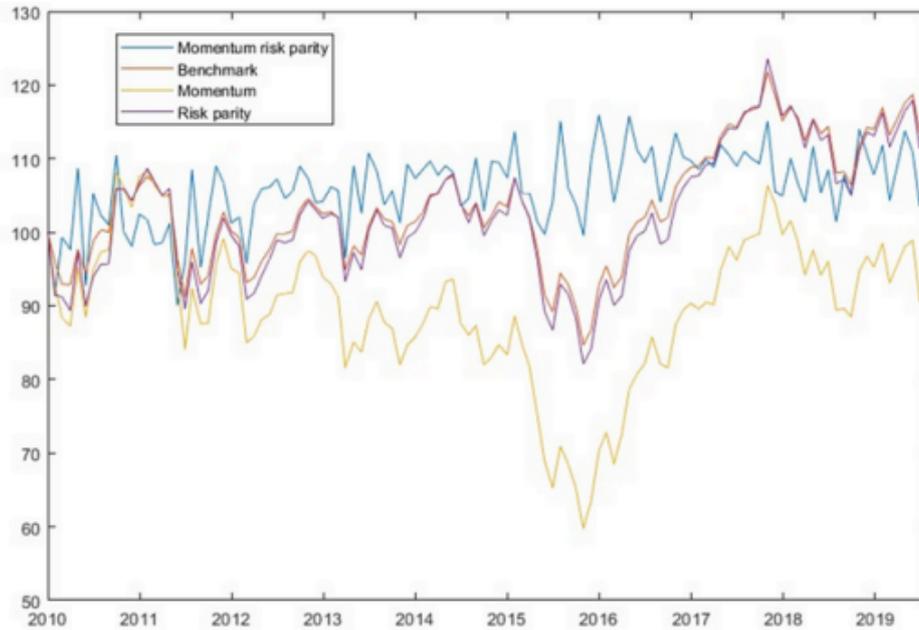

Figure 9: Momentum Risk Parity

Strategy	Return	Std. Dev.	Sharpe Ratio	Max Drawdown	Final Capital
Benchmark	0.0212	0.098	0.0127	0.23	116.39
Momentum	-0.0083	0.16	-0.077	3.55	9.898
Risk Parity	0.0231	0.109	0.0296	27.34	116.15
Momentum Risk Parity	0.0201	0.109	0.029	0.2734	110.98

Table 7: Performance comparison among Benchmark, Momentum, Risk Parity, and Momentum Risk Parity strategies

In this case, the *Momentum Risk Parity* strategy fails to improve the performance of the underlying *Risk Parity* strategy, resulting in a slightly worsened Sharpe Ratio.

By integrating *Momentum* into the *Risk Parity* strategy, the portfolio is able, unlike with the standalone *Risk Parity* strategy, to maintain the value of the invested capital during market downturns, albeit at the expense of absolute performance.

5 Conclusion

Of all the strategies applied, *Momentum* is the least profitable, as it exhibits the only negative return as well as the highest risk. Moreover, it also experiences the largest drawdown of 35%.

The *Volatility Parity* strategy achieves a non-negligible final capital despite a relatively low risk of 3.7%, while maintaining its primary characteristic of low volatility, evidenced by a standard deviation of 1.2% among all strategies.

In this case, through the application of *Momentum*, the *Minimum Variance* strategy manages to slightly improve its return while maintaining a low standard deviation.

Regarding the most profitable strategy, several aspects must be noted: the application of the *Equally Weighted* strategy yielded a slightly higher final capital in all cases except that the *Risk Parity* strategy achieved a slightly lower final capital. More specifically, *Risk Parity* has a higher Sharpe Ratio than *Equally Weighted*, indicating that it better compensates for the risk taken.

The negative performance of the *Momentum* strategy significantly affected outcomes when combined with *Risk Parity*, resulting in worse performance.
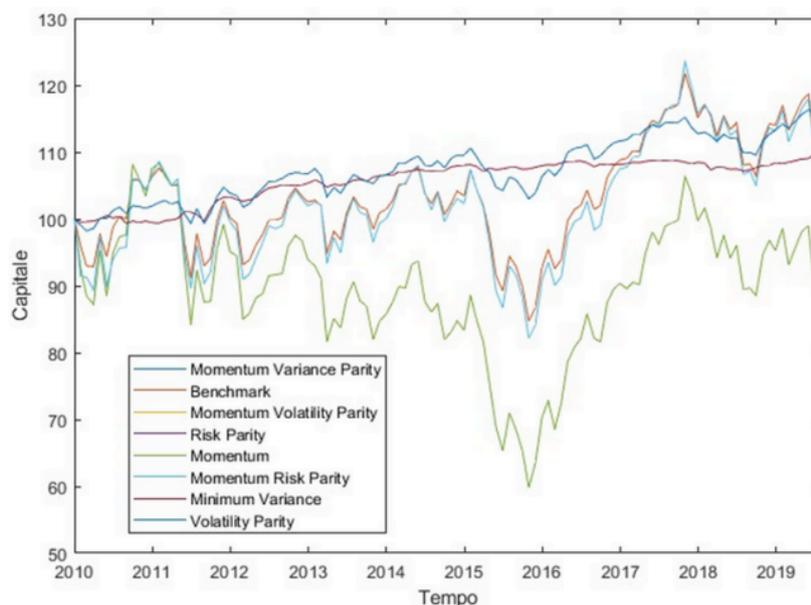
Overall, no strategy outperformed the Benchmark.

Figure 10: Conclusion

Strategy	Return	Std. Dev.	Sharpe Ratio	Max Drawdown	Final Capital
Benchmark	0.212	0.098	0.0127	0.23	116.39
Momentum	-0.0083	0.16	-0.077	3.55	9.898
Minimum Variance	0.09	0.012	-0.9403	4.38	108.75
Volatility Parity	0.0158	0.037	-0.1202	9.96	114.38
Risk Parity	0.0231	0.109	0.0296	27.34	116.15
Momentum Minimum Variance	0.0096	0.013	-0.8039	0.0476	109.14
Momentum Volatility Parity	0.0158	0.037	0.1202	0.0996	114.37
Momentum Risk Parity	0.0201	0.109	0.029	0.2734	110.98

Table 8: Performance comparison across all investment strategies