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Finance 496 “Quant Finance”

May 4, 2024

Machine Learning and Momentum

I. Background

A number of papers were reviewed to formulate a historically grounded definition of momentum. Research on momentum is long founded, but despite the wide body of research, definitions and calculations of momentum, have focused on causality or factor loadings in many cases. The result is that the initial premise isn’t governed by a strict definition because it is frequently adapted paper by paper, seeking to find causality under the new momentum calculation.

One thing remains true across the research reviewed. Momentum portfolios involve going long in the top decile of price performance for some formulation period. Additionally, to isolate the factor’s effects on returns as opposed to market movement during the same period, the portfolio goes short the bottom decile of performers in the same metrics. What remains is that factors impact on return extraneous to broader market drifts in the holding period.

The causality of the positive profits from the momentum portfolios has been of keen interest to researchers. The finding of this causality is referred to as factor loadings and seeks to decompose the return into factor loadings. If the factor loadings have a high degree of explainability on the returns of the factor, then the research has been successful in attributing causality to the success of a factor.

In Momentum, Risk, and Underreaction, researchers Rachwalski and Wen attempted to decompose the loadings of their momentum factor into 2 categories: Risk and Underreaction (Rachwalski and Wen, 2012). Ultimately, the research endeavored to determine whether momentum profits can be attributed to risk and underreaction factor loadings. This research built off the work of Jegadeesh and Lehmann who hypothesized in a 1990 paper that short term reversals have a direct impact on the returns of the momentum factor (Jegadeesh and Lehman, 1990). As a result, Rachwalski and Wen omit from the formation period of their factor selection, the most recent month. i.e., If the formation period is two months, only the price performance in months one and two were used to determine what stocks are held upon rebalancing at the end of period 3.

This approach resulted in a 12-month formation period being the most successful, having tested 3-, 6-, and 12-month periods. The 12-month period outperformed the 3-month period by 0.578% per year, which offers a unique insight into what may drive momentum. The paper goes on to analyze the characteristics of the long portion of the portfolio (the top decile of returns from the formation period). It found that stocks in this area may be there because of decreases in risk, and the reaction of investors to this phenomenon is not instantaneous. The researchers propose that this *under-reaction tendency* lasts into the holding period, thus driving momentum returns.

The implications of the work from Momentum, Risk, and Underreaction by Rachwalski and Wen supports further research into risk. It also warrants investigation of longer holding periods on the formation period. If the development of company-specific risk is reflected in the previous 12 months of a stock's price performance and is observed to continue in the future three for a holding period, it may support that investors are slow to react to changes in risk, and this underreaction creates an opportunity for momentum investors for very long periods.

The study of risk with respect to momentum returns was further researched in Momentum by Jagadeesh and Titman in 2002. The paper aimed at answering if Momentum returns were attributable to innate factor loadings that increase non-systematic risk in momentum portfolios.

The paper created momentum portfolios of the same formation period and decile structure with one key change; instead of omitting the last month from the formation period, only the last week was omitted. This was a control introduced because previous research identified that momentum portfolios tended to include stocks with a larger bid ask spread.

The same 3-, 6- and 12-month holding periods were used, and cross-sectional regression analysis was performed to identify if any of the factors driving momentum also drive company-specific risk. This is an important topic of study, because momentum profits are less viable in a non-academic environment if they increase diversifiable risk. The findings of Jagadeesh and Titman reinforce the hypothesis presented in Momentum, Risk, and Underreaction. Ultimately, the long profits were attributed to slow market reactions to good news in or before the formation period. The thinking is that this news was not immediately priced and caused a drift in the returns during the formation period, biasing these stocks towards the top decile in the formation period. Then, in the subsequent holding period, the risk premiums of these company-specific risks changed, continuing to drive the returns seen in the formation period.

The shorted stocks, those in the bottom decile of formation period returns, also had interesting biases identified. Selection in the short decile tended to small cap and more illiquid stocks; this finding will interact with the third paper studied, which considers net returns by including transaction costs in the study of momentum.

The lead-lag phenomenon was another trend identified by Jagadeesh and Titman. In layman's terms, lead-lag refers to investors' slow reaction to good news. Though the term was not mentioned explicitly in the formerly reviewed papers, it was alluded to in the findings. This idea was supported by a thoughtful analysis of the beta of the long and short deciles. When a positive drift is present in the market, high beta stocks may move with the market, but quantitatively, not by as much as their beta would indicate. This supported further analysis in this area as to whether a lead-lag effect was present within the momentum factor, and perhaps underlying a portion of the factor's returns.

Qualitatively, this effect was believed to be due to institutional investors' bias toward buying stock in baskets. Though less intuitive, Comovement by Barberis, Schleifer, and Wurgler in 2005 found that sentiment and news trends in stocks can drive investors to buy or sell baskets of the impacted stocks (Barberis, Nicholas, et al, 2005). Broad market shifts in sentiment can cause correlated price movements, and collectively, this behavior could be a contributor to the observed lead-lag effect as some stocks are less insulated to sentiment changes and react quicker than others.

When studied by Jagadeesh and Titman, they found a market wide lead lag effect was not present market-wide in a statistically significant manner. This finding was used to assert that the presence of lead lag effects in momentum stocks could be driving returns of the momentum factor.

The implications of Momentum on my research underlie my interest in the predictability of a stock being present in the top decile of returns based on its trailing price performance. If, in fact, lead lag effects were a driver of momentum profits, would it be a strong enough causal relationship to predict top decile returns? The importance of omitting a period between the formation and holding periods was also of key interest. Though present in both papers, the practice lacked strong intuition, so I sought to test the results of this thesis without a gap in these periods.

The third paper reviewed was Low-Cost Momentum Strategies (Li and Brooks, 2009). Unlike the former two papers, Li's research included only UK-based stocks in the tradable stocks and focused on net returns instead of gross returns, seeking to address the high transaction costs associated with the momentum factor. Historically, momentum is based on the top and bottom deciles of a forecasting period. At any given time, the portfolio is concentrated in roughly 20% of the total tradable universe for the strategy. Accordingly, from period to period, the turnover of the holdings is very high, and in more practical applications, produce very high transaction costs. This is a further concern when addressing the rebate fees associated with borrowing stocks for short selling. All the papers reviewed have been hedged strategies of equal weight long and short positions to isolate the momentum factors.

While this practice is very useful for identifying factor loadings, which could be diluted by broad market trends if one side outweighed the other, it is inefficient with respect to transaction costs. Stock loan rebate fees incurred while short selling add a significant transaction cost premium to short selling. Intuitively, this can be thought of as the fee required for a stockholder in a long position to be willing to lend their shares to short sellers. Drivers of high prices include the limited supply of these shares and lower volume, both of which can lead to increased difficulty in borrowing shares and, thus, higher rebate costs. It also happens that multiple studies of momentum have found that the short decile tends to favor smaller cap stocks with lower volume, creating a gap between the desirable gross returns and net returns after this is reflected in transaction costs of the portfolio.

> Low-Cost Momentum Strategies used a JK momentum portfolio, where J is the number of months of past performance, and K is the number of months the stock was held for before rebalancing. No gap period was used, and 20 years of stock data was compiled from Dec. 31, 1985-Dec. 31, 2005. Additionally, screens to the data were used to eliminate stocks in the bottom 5% of their investable universes market cap, as well as stocks with a price of less than 5 pounds per share over concerns of illiquidity and small cap effects impacting momentum. The researchers expressed a desire to create an imperfectly hedged portfolio, going long a larger proportion of the portfolio with the most liquid stocks, but for continuity with previous research, opted for an equal weight on long and short components.
>
> The research found that the transaction costs of a 3-month holding period were nearly 4 times more than that of a 12-month holding period, finding little continuity in the long and short decile stock picks from period to period. Gross returns for the momentum strategy averaged 23.14% in their time period. Transaction costs were found to be very significant, especially in K = 3; this portfolio had a negative return after adjusting to net returns.
>
> Another finding was that longer holding periods and shorter formation periods yielded much lower portfolio turnover, and thus more attractive net returns. This interestingly interacts with the findings in Momentum by Jagadeesh and Titman, which showed the lead-lag effect could plausibly cover periods up to 15 months (12-month formation and 3-month holding periods).
>
> Additionally, an interesting effect was found when contrasting buying small-cap vs large-cap stocks. Buying large-cap stocks was much cheaper, and market cap was inversely correlated with transaction costs. This is plausibly attributable to lower volume and, thus, wider bid-ask spreads, which were accounted for in the conversion to net returns.
>
> The optimal JK momentum strategy was found to be the 12:3 portfolio, trading only the most liquid stocks in each category. This additional characteristic lowered transaction costs from 19.27% to 10.10%, generating an average annual net return of 18.24% in the liquidity-adjusted portfolio.

While this paper did not motivate my research efforts to adjust for liquidity, it did contextualize the discrepancy between paper returns (without transaction costs) and the impact that transaction costs can have on net returns. The interaction of the formerly described lead-lag effect and how it is used in different portfolio constructions is also reinforced by the findings of Low-Cost Momentum Strategies. The reviewed papers demonstrated the effects propensity to exist up to 15 months, due to the combined holding and formation period. However, the strength of this effect at different points remains unclear as continuous momentum portfolio performance graphs are not offered. Only end-of-period results are offered, and this leads to an uncertain strength of this effect in between the reporting periods in the papers. This is something that my research seeks to quantify by measuring the predictive power of different formation periods on my model's precision and accuracy.

II. Research Methodology

My methodology for answering if there was a predictive relationship between performance in the formation period and predicting whether a given stock would end up in the top decile of returns in the next period (or holding period) was contingent on the performance of a logistic regression model. The results of the logistic regression without modification are sufficient for assessing whether there is a predictive relationship by analyzing the model's confusion matrix, accuracy, and precision. This initial step was predicated on producing sufficiently accurate logistic regression results to rationalize expanding the findings to a fully hedged momentum portfolio.

Once sufficiently accurate model accuracy and precision was reached, the output of the model's betas can be used to convert the logistic regression's output into a probability that given a stock's betas in the formation period it will yield a binary 1 in the output in the model. When this framework is used, logistic regression can be converted from a discontinuous classification to a continuous function, that would be more suitable for the decile sorting required to form a momentum portfolio. For example, suppose the stock in an investable universe for a given period produces 100, 1 value, out of 500 total stocks. This would make it impossible to distinguish between 1 value suitable for the top decile and those that are not. However, if the data is transformed according to the below equation, it can be interpreted in probability form and decile sorting would eliminate this conflict.

$$Pr(Y = 1|X) = \frac{e^{\beta_0 + \beta_1 X}}{1 + e^{\beta_0 + \beta_1 X}}$$

Accordingly, the same system of transforming the variables can be used to find the probability that a given stock will yield a value of 0, or the probability it will not be in the top decile of returns. In this case, the highest probabilities would be used from each and then sorted into deciles and chosen for the portfolio according to the same framework described in the papers. There is an engrained assumption that the highest probability of a stock yielding a 0 could be equated to the lowest quartile of returns. In practice, this assumption does not hold up and could be remedied by creating a similar model simply predicting whether a stock will end up in the short decile in the holding period. However, due to trouble progressing the long momentum model, the short model was not able to be constructed.

$$Pr(Y = 0|X) = \frac{1}{1 + e^{\beta_0 + \beta_1 X}}$$

The 6-month formation period and holding period was the first model trained. The results of this model presented a novel finding that the model had an innate bias towards giving negative results due to the data proportions: 90%: 0 & 10%: 1. The model was able to achieve 88% precision in predicting 0 values in the test set simply by guessing all 0 values. The first iteration of the model produced all 0 values, equating to 0% precision in 1 predictions[See Appendix 1].

The class weight adjustment was used in the next iteration of the model to reflect that fact that the data was inherently biased towards 0 values. This improved the precision marginally by distributing the predictions more suitable across yes and no values. However, the precision of 1 guess was still insufficient to proceed into creating a momentum portfolio using the model betas [See Appendix 2].

III. Findings

The portfolio produced using the 6 month formation and 3 month holding period according to the model had lower returns than a buy and hold 60/40 portfolio. However, it had a lower beta of 0. 0.782 and ~0.2 less volatility than the benchmark portfolio, with an annualized volatility of 0.085. It grew at a compound annual growth rate of 8.7% compared to 9.4% in the benchmark portfolio [See Appendices 3 & 4]. The momentum portfolio did not outperform the 60/40 buy and hold benchmark. Accordingly, alpha of -2% per year was generated. The lack of alpha was attributed to poor underlying model precision in identifying positive values in tandem with using a formation period of 6 months. Researchers in Low-Cost Momentum Strategies and Momentum found more significant profits within longer formation periods as the lead-lag effect has time to develop. Additionally, it is unclear if a period should have been omitted intermittently between the formation and holding period. Further Research is encouraged in these areas, along with using the described logistic regression transformations as a way to rank different formation periods. Please see the appendices for more thorough performance reporting across the momentum portfolio and benchmark. Additionally, instead of adjusting class weights, initially synthetic minority oversampling technique was used and optimized; however, due to the complex nature of synthetic data and a finite timeline for this research, it was abandoned in favor of a more interpretable model.

IV. Conclusion

The research showed that alpha could not be generated using an alternative factor formation that leverages machine learning. I remain optimistic about the prospect of a more robust momentum factor and believe that the logistic regression if tested with different periods, positive alpha may be generated. Though factor loadings make causal conclusions speculative, the research may present evidence that lead-lag factors only hold in longer formation periods. The most successful portfolios in Momentum and Low-Cost Momentum Strategies covered formation and holding periods summing to 15 months. Momentum, Risk, and Underreaction cited increases in diversifiable risk attributing to momentum profits. The research presented found contrarian evidence under a different methodology(cross-sectional regressions and factor loadings were not used). Appendix 5 shows that compared to the 60/40 benchmark, the momentum portfolio has less dramatic price swings, reinforced by lower volatility. The sharpe ratio of the portfolio was less than that of the benchmark because the returns of the momentum portfolio failed to exceed those of the benchmark. Comparatively, to other equity-only strategies, the momentum portfolio, which is partially hedged due to equal weight long and short positions, offers a global max drawdown of -20%[See Appendix 6]. In future research, more thorough efforts will be made to isolate variables, which will help better identify causality and produce more robust overall findings.

Works Cited

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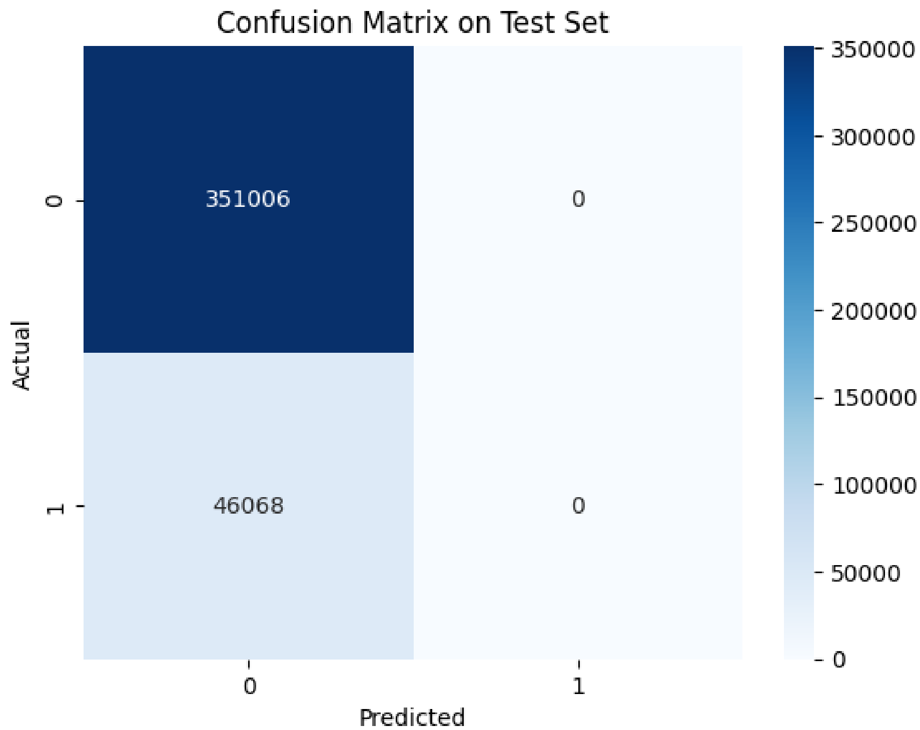
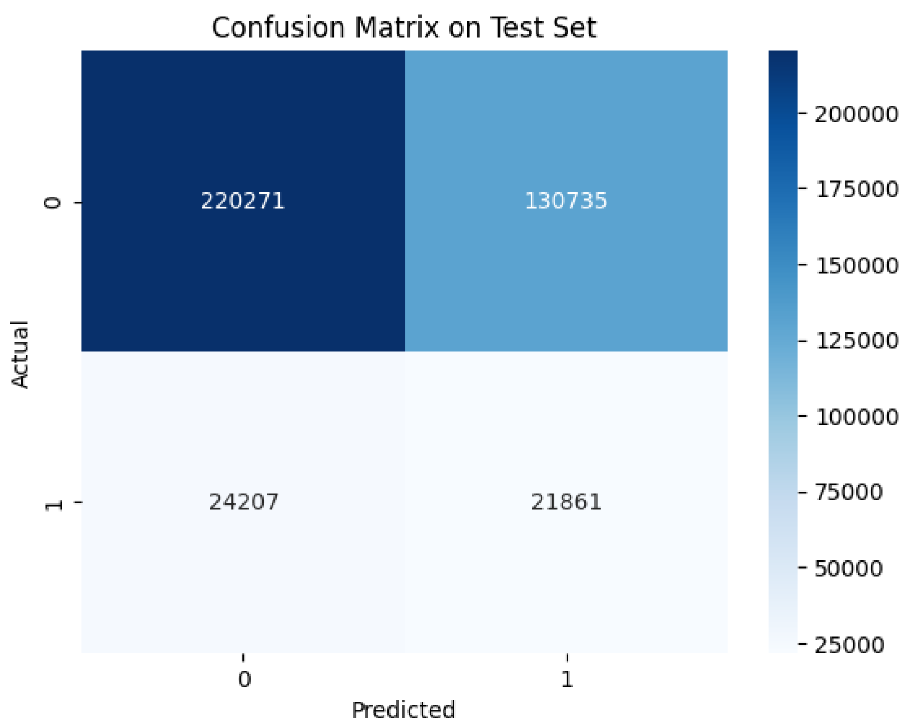
Appendices:

1.



2.



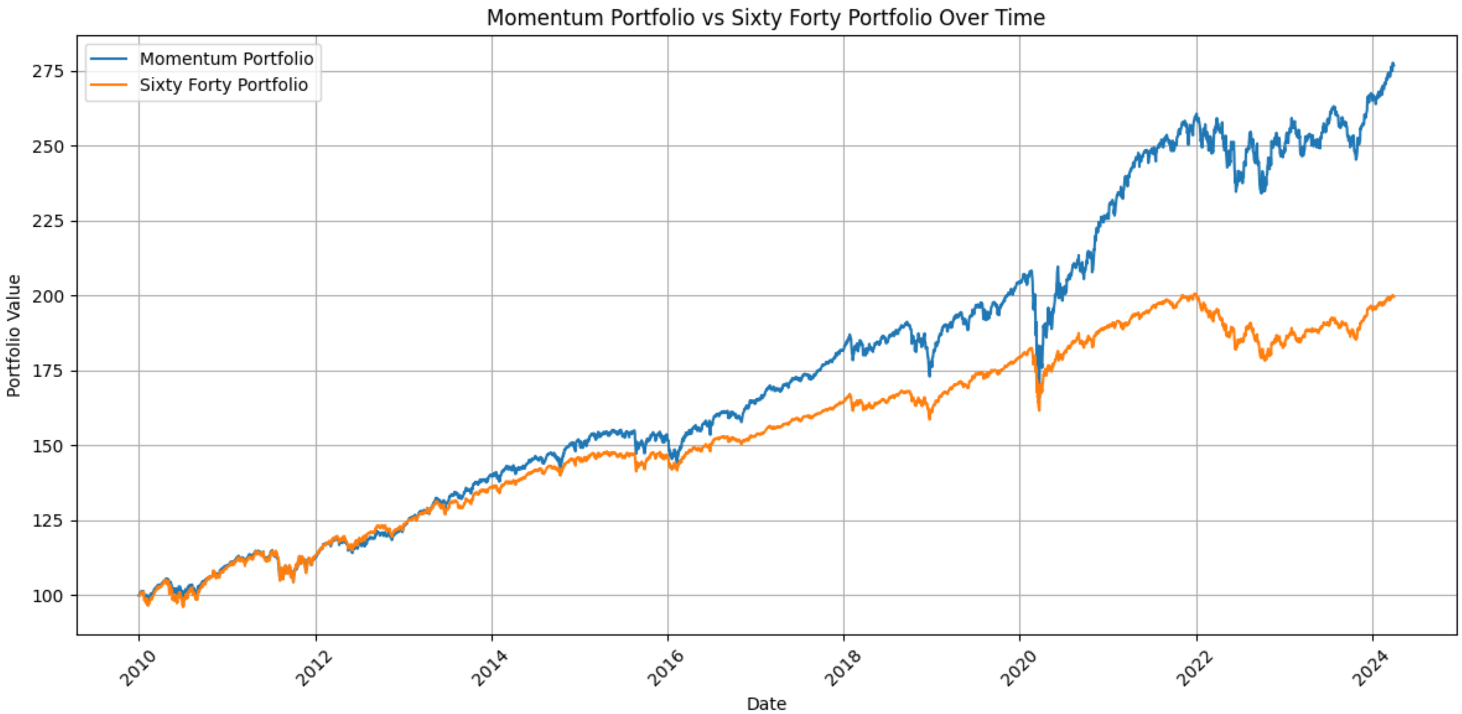
3.

Year	60/40 Annual Return	Momentum Annual Return
2010	12.3%	9.7%
2011	5.2%	2.4%
2012	11.2%	8.7%
2013	17.6%	15.1%
2014	10.7%	7.6%
2015	1.3%	1.0%
2016	8.4%	7.4%
2017	14.3%	10.8%
2018	-2.3%	-1.9%
2019	22.2%	14.8%
2020	15.6%	11.2%
2021	16.0%	14.2%
2022	-15.6%	-4.6%
2023	18.2%	7.9%
2024	24.2%	15.7%
CAGR	9.4%	8.7%

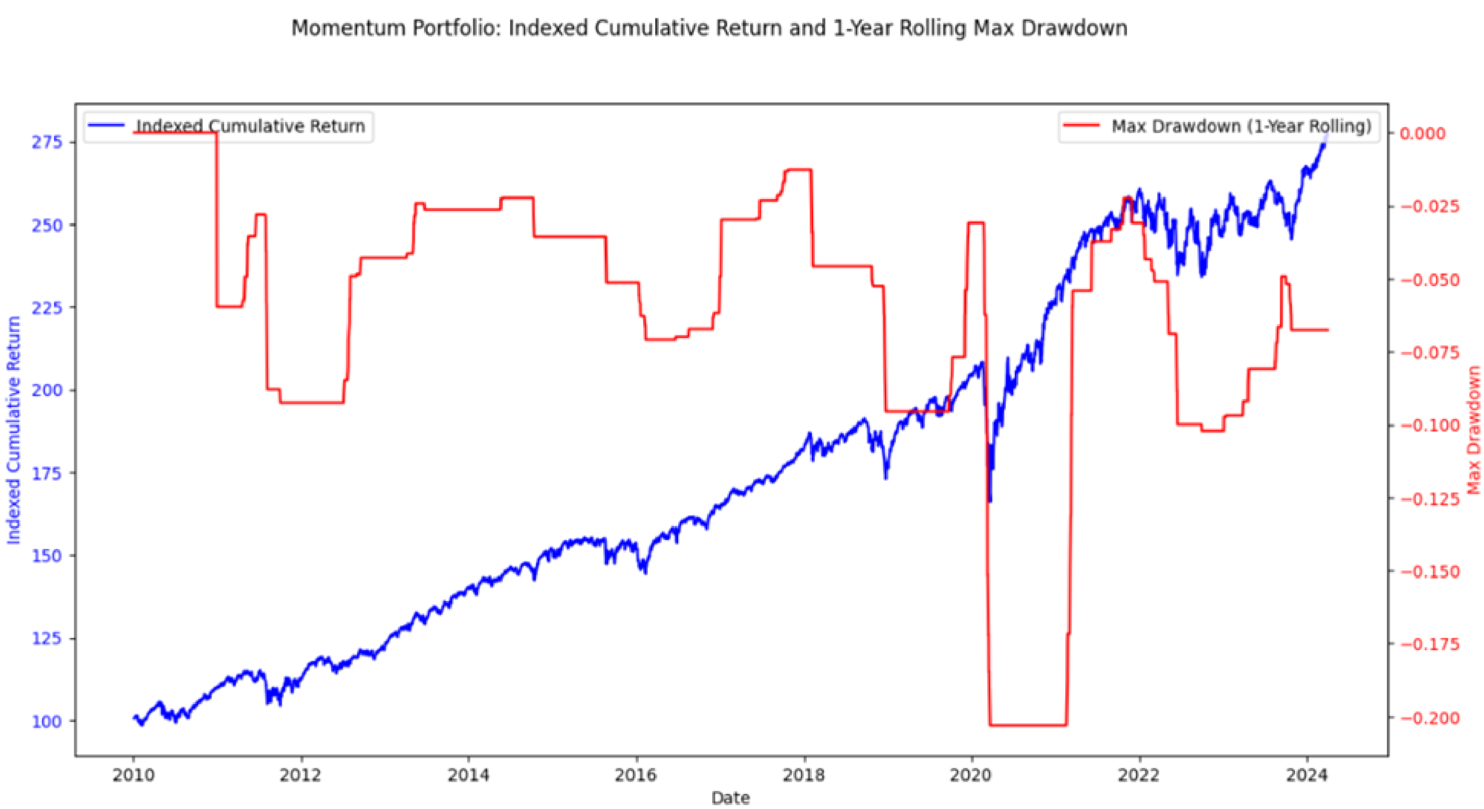
4.

	60/40	Momentum
Beta	1.00	0.0782
Volatility	0.010	0.085
Sharpe Ratio	12.3%	9.7%
Alpha	0.0%	-2.0%

5.


Momentum Portfolio vs Sixty Forty Portfolio Over Time
Momentum Portfolio
Sixty Forty Portfolio
Portfolio Value
Date
100
125
150
175
200
225
250
275
2010
2012
2014
2016
2018
2020
2022
2024

6.


Momentum Portfolio: Indexed Cumulative Return and 1-Year Rolling Max Drawdown
Indexed Cumulative Return
Max Drawdown (1-Year Rolling)
Indexed Cumulative Return
Max Drawdown
Date
100
125
150
175
200
225
250
275
0.000
−0.025
−0.050
−0.075
−0.100
−0.125
−0.150
−0.175
−0.200
2010
2012
2014
2016
2018
2020
2022
2024

7. SMOTE confusion matrix results & report

```
Classification Report:
              precision    recall  f1-score   support

         0.0       0.89      0.51      0.65      3084
         1.0       0.13      0.55      0.22       430

    accuracy                           0.51      3514
   macro avg       0.51      0.53      0.43      3514
weighted avg       0.80      0.51      0.59      3514

Confusion Matrix:
[[1563 1521]
 [ 194  236]]
Coefficients: [[-0.00035    -0.00412635]]
Intercept: [0.02301078]
```

8. Grid search optimized SMOTE, classifier model confusion matrix & report

```
Classification Report:
              precision    recall  f1-score   support

         0.0       0.88      0.68      0.77      3084
         1.0       0.12      0.32      0.18       430

    accuracy                           0.64      3514
   macro avg       0.50      0.50      0.47      3514
weighted avg       0.79      0.64      0.70      3514

Confusion Matrix:
[[2102  982]
 [ 292  138]]
```