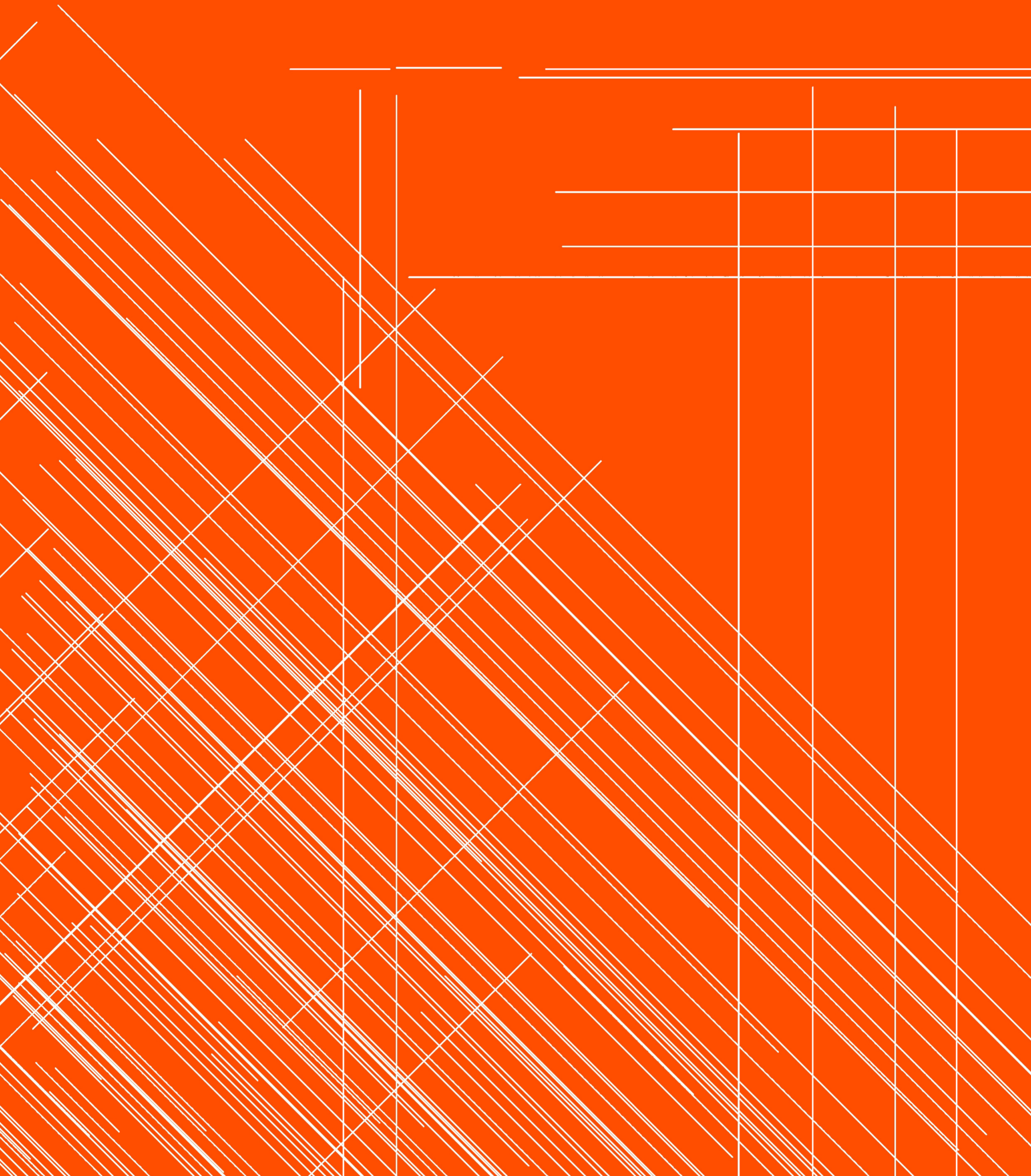
joshua chelashaw
student id: 24481208



Assessing the profitability of a Systematically Investing in High Financial Health Strategy

Joshua Chelashaw

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Contents

1 Introduction

Many firms offer similar products based on a mixture of traditional investment factors such as value, momentum, and profitability. The recent increase in interest rates has placed leveraged companies in difficult positions, making it challenging for them to generate sufficient cash flows to service their current and future debt. Therefore, the idea of investing in companies with a strong ability to service their debt appears promising.

This report investigates the profitability of an investment strategy based on the investing in companies with high degrees of financial health, as measured by their: Interest Coverage Ratio, Cash Flow to Current Liabilities Ratio, and Cash Flow to Debt Ratio.

2 Statistical Analysis

We create the synthetic (average) factor by collating the data from the three financial ratios and calculating the mean.

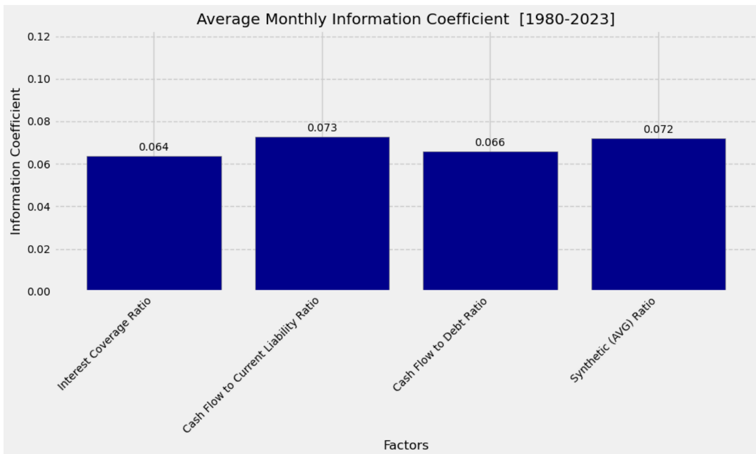

Figure 1: Monthly IC Over Sample

Figure 1 displays the strength of the factors' predictive powers over the entire sample, calculated as the average monthly information coefficient of each factor.

It shows that in an average month there is a positive information coefficient for all the factors, suggesting that high degrees of financial health measured by abilities of a company to service its debt is associated with better stock performance, albeit somewhat weakly.

Among the new factors, the cash flow to current liabilities ratio is the strongest signal, and the interest coverage ratio is the weakest

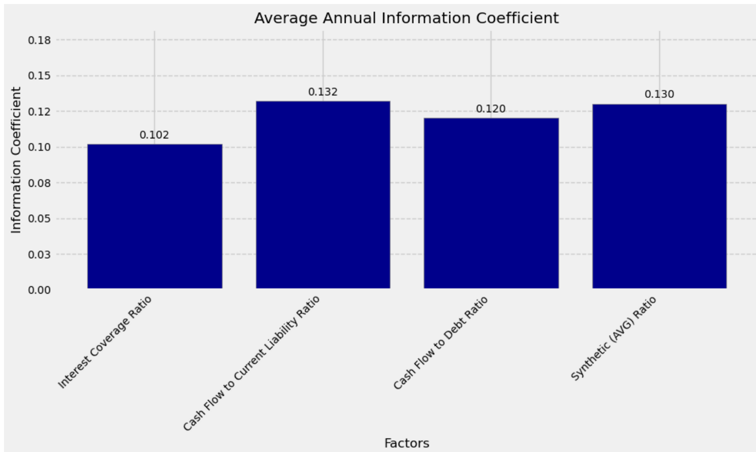

Figure 2: Annual IC Over Sample

For a clearer picture, we plot the average annual information coefficient and within Figure 2, see that the predictive power for each factor is stronger at longer horizons.

To visualise how the predictive power changes through time, we use trend-line graphs containing monthly information coefficients and 12 month moving averages.

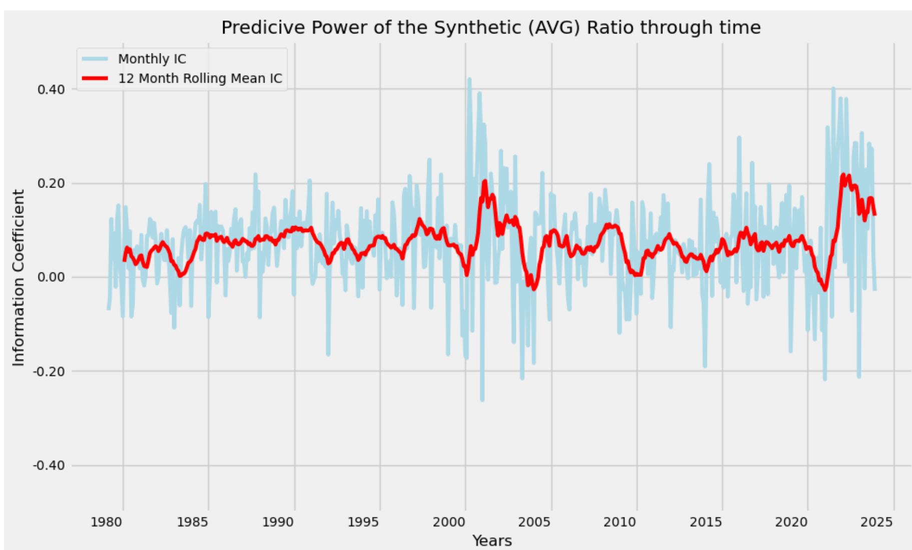

Figure 3: Synthetic IC trend

Figure 3 contains very high monthly volatility, we use the rolling 12 mean to reduce noise and monitor the major trends in the predictive power. Significant strength peaks are shown in the early 2000's. After a sharp 2020 downturn, similar peaks are observed around 2021-22. Significant downturns are observed around the periods of the bear market of 2002-04, the Global Financial Crisis (GFC) in 2007-09 and COVID-19 in 2020-21. From fundamental knowledge, we attribute the predictive power of downturns to be in-line with significant market-wide downturns where companies with high financial health also suffer significantly.
As displayed within the 'monthly IC Analysis info:' section, each t-statistic is quite high (14.7 to 17.3) and all p-values are close to zero, suggesting that each of the relationship between these factors and returns is statistically significant and not due to random chance.

For each factor, we note the percent of positive periods, as printed out within the notebook onto Table 1.

Ratio	**Monthly** (%)	**Annually** (%)
Interest Coverage Ratio	77.1	79.5
Cash Flow to Current Liabilities Ratio	79.0	88.6
Cash Flow to Debt Ratio	81.6	90.9
Synthetic Ratio	79.9	88.6

Table 1: Percent of Positive Periods for New Factors' IC

The signals are positively correlated with future returns around 80% of the time. The cash flow to debt factor consistently has the most months and years with positive correlations. Overall this further displays the reliability of these factors' predictive power.

3 Back-testing

The back-testing is based on the following:

- An over-investment in the top 300 stocks and under-investment in the bottom 300.
- An active percentage of 30%
- Sample between 2007 and 2023.
- Monthly re-balancing
- Assumes an 0.2% round-trip of transaction costs.

To ensure we don't complete a 'deadly back-testing sin' and overestimate the performance of our strategy, we limit our investable universe to the largest 1500 stocks. By doing this we also increase the validity of the back-testing. We rank the stocks by market capitalisation and keep only the top 1500. We do this, knowing that in reality we cannot short sell every stock and that this ability is normally limited only to medium and large cap stocks.

We complete the back-testing of our portfolio and record the performance diagnostics in Table 2, highlighting our active return of 3.2%, standard deviation of 3.7% and information ratio of 0.86.

	Long-Short Portfolio	**Benchmark**	**Active Performance**
Mean Return	10.13%	6.92%	3.21%
St. Dev.	14.84%	15.94%	3.73%
RR Ratio	0.68	0.43	0.86
% Positive	66.18%	64.22%	58.82%
Worst Month	-15.08%	-18.87%	-2.48%
Best Month	12.79%	12.77%	3.93%
Max DrawDown	-51.36%	-59.86%	-7.4%

Table 2: Back-testing Performance Diagnostics

In Figure 4, we plot the returns by calculating the value of the portfolio and the benchmark at the end of every month assuming an initial investment of 1 dollar.

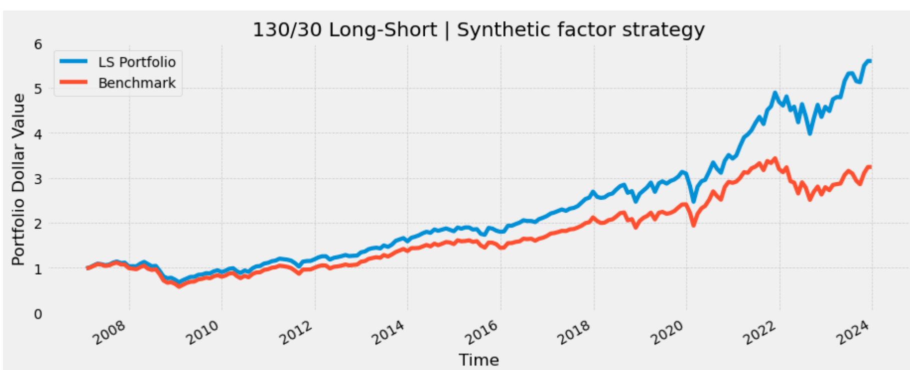

Figure 4: Annual IC Over Sample

Within this figure, we see that cumulative returns have a slight dip below $1 in late 2009, and take a general trend upwards until the most significant dip in 2020, attributable to COVID-19. The 2021-22 period has the steepest rise in return and grows the disparity between the portfolio and the benchmark.

Between 2022-23 we notice some greater month-month volatility of the portfolio in correlation with the benchmark. Some strong performance in late 2023 results in a final cumulative portfolio value of $5.60.

4 Optimisation

When performing back-tests for the strategy optimisation, we use the same time period and transaction costs as within the back-testing section. For the number of shares to over or underweight, we use two variations of less (than 300) shares (50 and 100) and one with more (500).

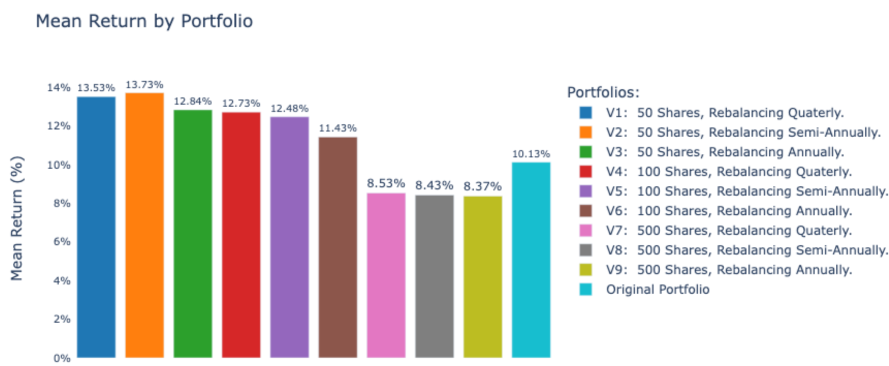

Figure 5: Mean Return of Portfolio Variations

Checking the average performance in Figure 5, calculated by the average return, we see the best portfolio is named 'V2' and has 50 shares over-under weighted re-balances every 6 months, providing a mean performance of 13.73%. This is significantly greater than the original synthetic portfolio of 10.13%. Moreover, the optimisation' trend shows us that performance rises with less shares selected for over-under weighting.

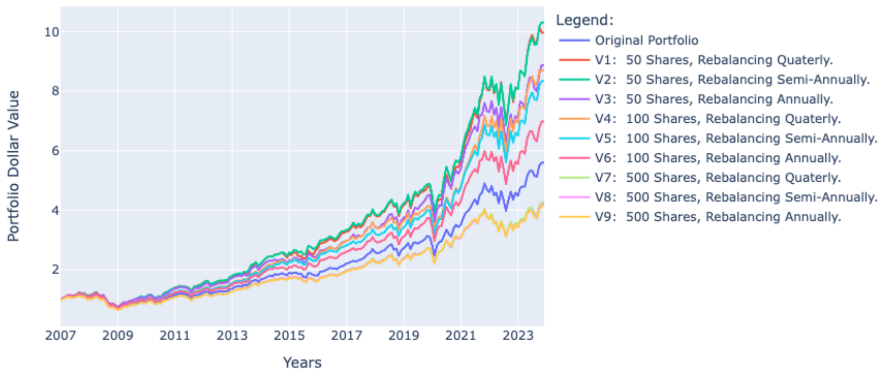

Figure 6: Cumulative Return of Portfolio Variations

As displayed in Figure 6, the final cumulative value of the most optimal portfolio ('V2') is $10.31, close double the $5.6 value of the original portfolio. The performance follows a similar trend in comparison to what was discussed above in terms of rising and falling periods.

5 Addressing the CIO's concerns

5.1 First Concern: Are these truly 'new' strategies?

Is this strategy simply a re-skinned version of some other well-known strategy such as value, momentum, low volatility or profitability? Are these truly "new" investment factors or just a different way of measuring older factors?

To assess this we begin with correlation analysis of the predictive powers.

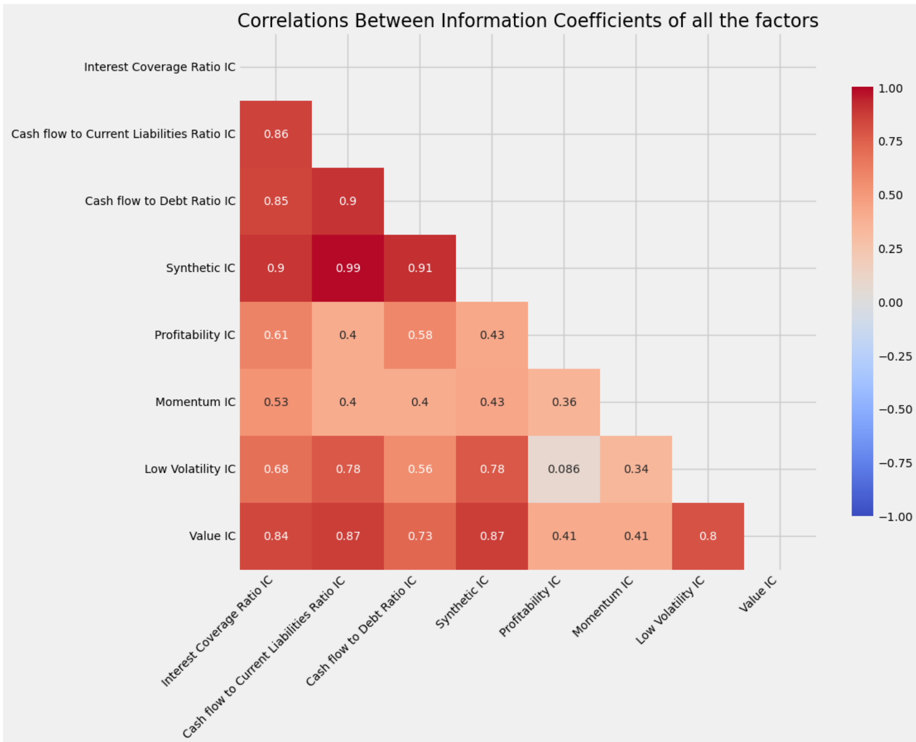

Figure 7: Monthly Correlation of Predictive Powers

Within Figure 7 we can see that between the new and old factors, value shares the highest correlation.
This is especially seen with both the synthetic and cash flow to current liabilities ratio, both having a correlation of 0.87 to the value signal. Low volatility also has a high correlation, 0.78 with the synthetic factor.
The remaining old-new factor correlations which are each less than 70% are deemed insignificant for demonstrating that the new factors are 're-skinned' versions of traditional factors.
From Figure 7, we can see that the value strategy may be re-skinned in our synthetic factor however to have confidence in this analysis, we shall conduct further comparisons.

To further determine whether these factors are truly new, we conduct Principal Component Analysis to reveal whether the new factors are capturing the same underlying dimensions as the old factors.

We plot the loadings of the first 3 principal components for better visualisation and as because, as shown in Table 3, with the first three principal components, we have explained approximately 92% of the total variance in the data.

Principal Component	Cumulative Variance Explained (%)
1	69.85
2	83.15
3	92.26
4	96.32
5	98.06
6	99.35
7	99.88
8	100.00

Table 3: Cumulative Variance of PCA Loadings

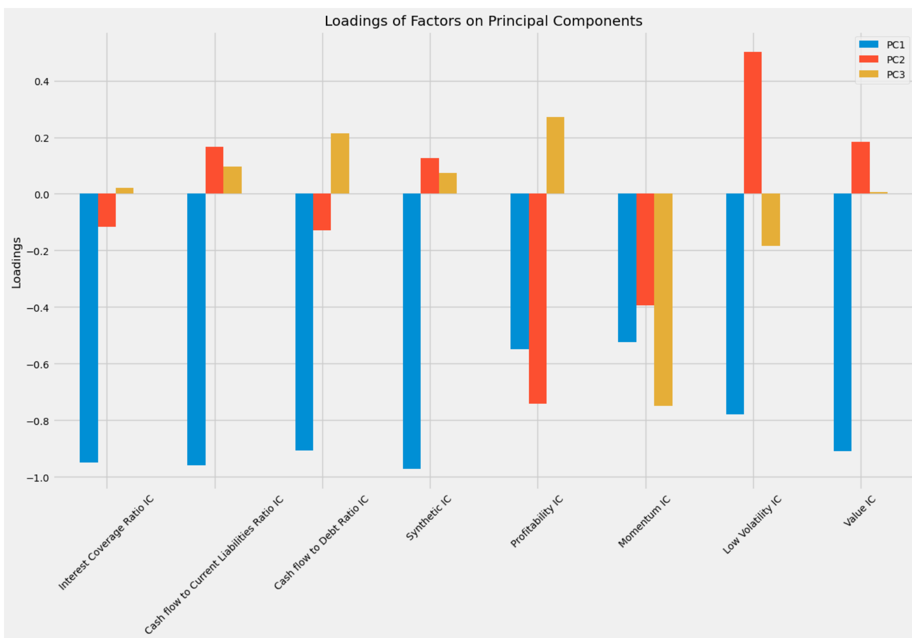

Figure 8: Principal Component Analysis Loadings

From 8 shows that the the new factors share a strong common underlying dimension with the older factors, as evidenced by the high loadings on PC1 and the large proportion (70%) of variance explained by PC1.
The presence of notable positive loadings on PC3 for the cash flow to debt ratio suggests that this factor might capture some unique aspects. However, it should be noted that the overall contribution to the explained variance (9.1%) is modest compared to PC1.
Our Principal Component Analysis demonstrates that of the old and new investment factors primarily **do** load on similar underlying dimensions. Therefore, we can determine that the new factors are not entirely independent

and mostly reflect shared underlying characteristics with traditional factors.

5.2 Second Concern: Is predictive power stronger when interest rates are higher?

The new ratios measure the ability of the company to generate enough cash flows to pay-off interest on existing debt and therefore, it stands to reason that the predictive power of these factors should be stronger when interest rates are higher. To assess this, we analyse the rolling mean trends of the new factors' information coefficients in comparison to the interest rates.

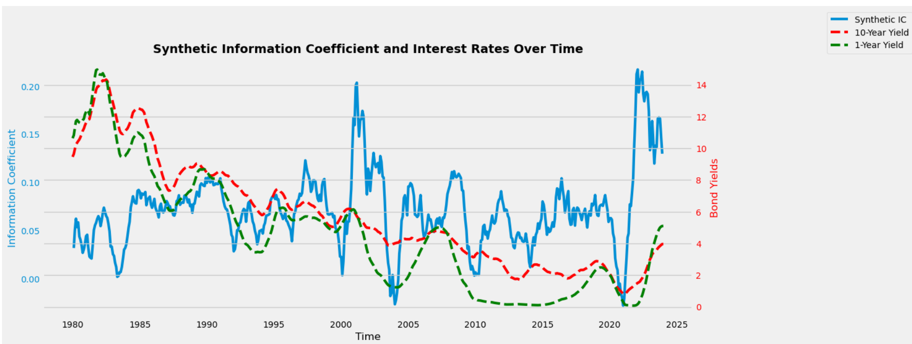

Figure 9: Synthetic Information Coefficient and Interest Rates, over time

Figure 9 shows that there are periods where bond yields and the Information Coefficient move in the same direction, especially with periods where there are rapid falls to interest rates. Despite this, there are far more significant periods where their movements diverge. This suggests that the predictive power is **not** stronger when interest rates are higher and that reasons other than interest rates are behind the strength of predictive power are at play.

6 Machine Learning

As the firm has been experimenting with decision trees, we round up the report with an analysis of the inclusion of the three signals in a decision tree model. In building the decision tree and assessing its predictive power, the following characteristics are used:

- Target Variable: the tree should try to predict if the next month return will be positive or negative.
- Sample: From the beginning of 2007 to the end of 2023.
- Max Depth: 3

- New factors: Interest Coverage Ratio, Cash Flow to Current Liabilities Ratio and Cash Flow to Debt Ratio
- Traditional factors: Value, Momentum, Profitability and Low Volatility

Decision tree with new factors included:

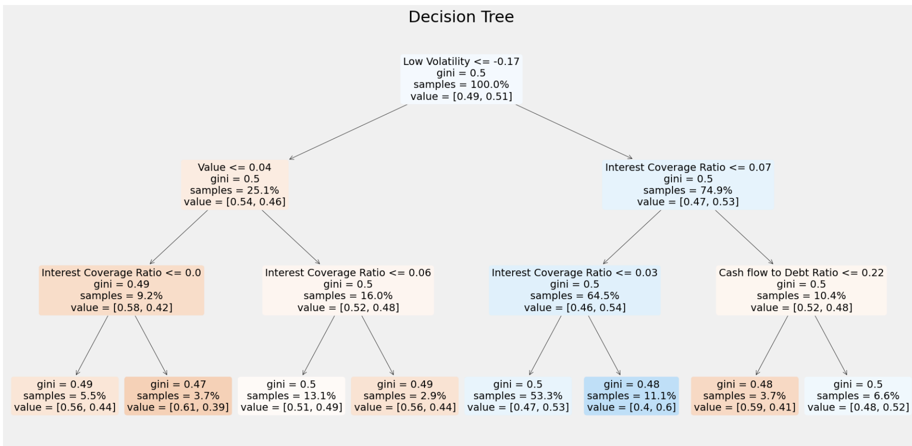

Figure 10: Decision Tree

Predictive Power of the Decision Tree:

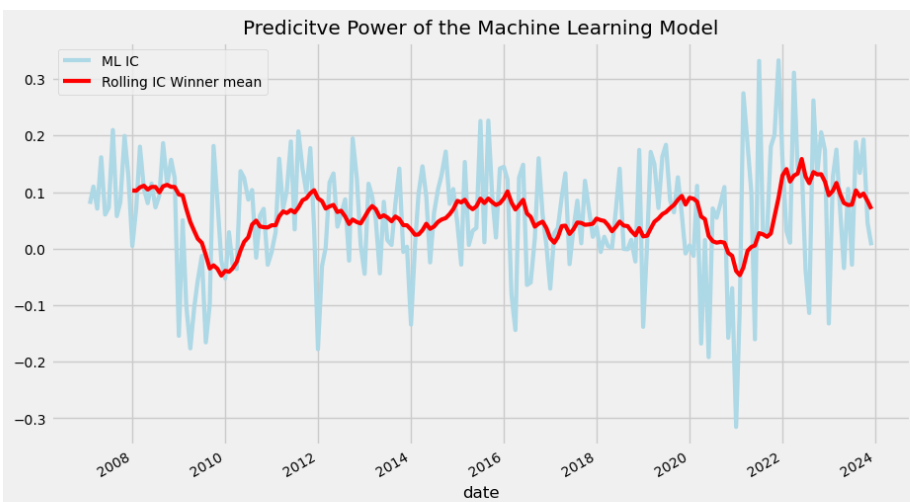

Figure 11: Decision Tree IC Analysis

Statistical IC Analysis:

- Average IC over the entire sample: 0.059.
- T-statistic: 8.172
- P-Value: close to zero
- Percent of positive periods is similar at 75.9%.

We assess whether the three new factors significantly affect how the decision tree predicts future performance, by analysing the feature importance of the decision tree.

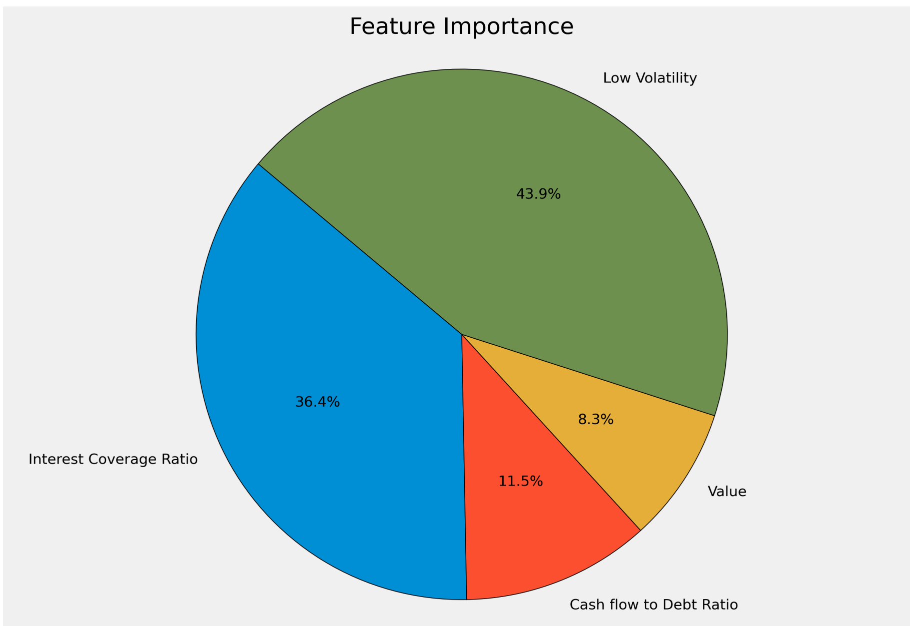

Figure 12: Feature Importance of the Decision Tree

Here we see that only the from the new factors, only Interest Coverage and Cash flow to Debt ratios are significantly affect the decisions tree predictions, representing 36.4% and 11.5% (respectively) of the important features.

We finish the machine learning section by assessing whether the three new factors increase the (out of sample) forecasting accuracy of the model.
To complete this, we create a baseline model and assess its out of sample accuracy:

Despite our baseline model being slightly lower we acknowledge that the difference is incredibly minute as both of these figures round to 0.54. Therefore we conclude that the inclusion of new factors does **not** increase the (out of sample) forecasting accuracy of the model.

Model	10-Folds Cross Validation Average Accuracy
Model with new factor inclusion	0.53892
Baseline Model	0.53951

Table 4: 10-Folds Cross Validation Average Accuracy

7 Conclusion

This report examined the profitability of an investment strategy focused on companies with high financial health, using the metrics: Interest Coverage Ratio, Cash Flow to Current Liabilities Ratio, and Cash Flow to Debt Ratio. Our analysis showed positive predictive power, with the Cash Flow to Current Liabilities Ratio being the strongest information signal.

Back-testing results indicated an active return of 3.2%, a standard deviation of 3.7%, and an information ratio of 0.86. The portfolio had a mean return of 10.13%. and a final cumulative value of 5.6. The synthetic portfolio outperformed the benchmark, especially during market downturns in post 2022.

Optimisation revealed that reducing the number of shares for over and under weighting improved performance, with the best portfolio (50 Shares, Rebalancing Semi-Annually) achieving a mean return of 13.73%. and a final cumulative value of 10.31.

Correlation and Principal Component Analysis suggested that the new factors capture some unique dimensions but are not entirely independent from traditional factors.

The relationship between predictive power and interest rates was found to be mostly uncorrelated, except during steep interest rate falls, where predictive power would also fall sharply.

Incorporating these factors into a decision tree model showed that they significantly influenced predictions, but did not improve the out-of-sample forecasting accuracy.

In summary, while the high financial health strategy shows some promise, its uniqueness relative to traditional factors is limited. Investing in companies with high financial health, as measured by our chosen ratios, can be a profitable strategy however, the lack of distinctiveness and the disparity between high interest rates and the strategies' predictive power hinders the suitability of the strategy.