Machine Learning for Finance

Problem Set 2

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0 Introduction

A two question problem set on the analysis of Market Trends using volatility indicators and regression modelling. All authors contributed equally.

1 Question 1

For this question we selected stocks from Apple (AAPL) and Facebook (FB). Our trading strategy with respect to those is based on a premise we would like to try: "Is the Bull-Bear ratio a good-enough indicator to buy?"

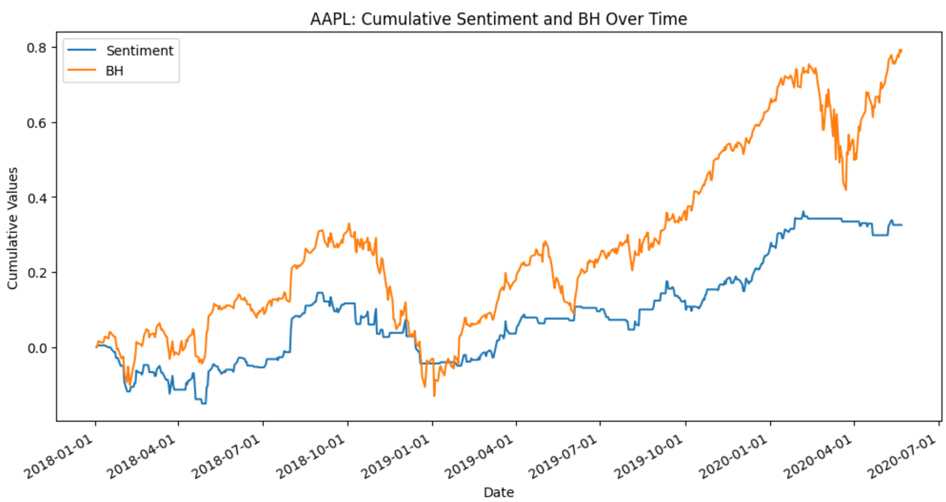
In order to implement it, our program would signal to buy every time that the BBr goes over a certain threshold and would signal to not buy or to sell (depending on whether we are going long-only or long-short) when below that threshold. We decided to test it against the most simple but yet effective strategy of all "buy and hold". For this benchmark, we always signal to buy and that's it, we just aggregate the returns for the whole period.

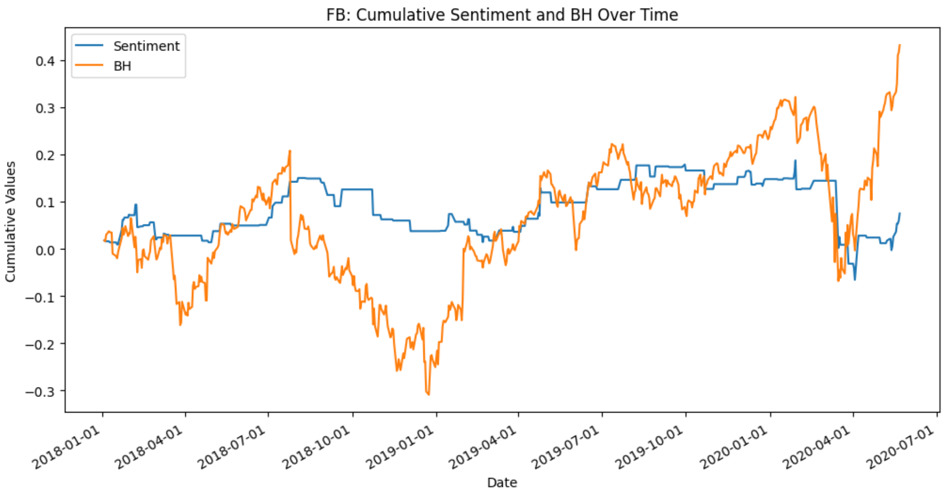
We also tried a more complex strategy where we added "RVT" to the mix but the results were not great either (at least at the beginning) so we decided to continue with the initial plan.

1.1 Testing long options and window sizes

Having selected AAPL and FB, we decided to set up a common initial threshold to do some testing of the following options: long-only strategy, long-short strategy, 1 year rolling window periods and 6 months rolling window periods. In total, those 4 options lead to 4 possible combinations (LO + 1yr, LS + 1yr, LO + 6mo & LS + 6 mo). To try things out we set up the common threshold at 50 because it was nearly on the mean but it still was sort of selective (the average BBr for both stocks is slightly below 50). We decided to set that up because our benchmark was the "buy-and-hold" strategy so a good starting point for our alternative strategy should be to get away from buying all the time.

First we tested Long-Only with window size of 1 year and the results were not great:





Our strategy was performing very poorly on both the AAPL and FB stocks for the cumulative returns and the rolling window returns were also very poor, with average performances of returns half of those of the benchmark. Our strategy was even worse when looking at the performance with the costs also taken into account (we have to note here that the graphs shown above are just the cumulative returns but without taking into account the trading costs). We set costs to a stable value of 0.01, which seems to be a standard cost for this matter, and we received the following results:

Table 1: AAPL Results

	Sentiment	BH
Cumulative Return	-1.844259	0.771744
Annual Return	NaN	0.271535
Annualized Sharpe Ratio	NaN	199.379302
Win %	0.517647	0.541667
Annualized Volatility	0.165831	0.343199
Maximum Drawdown	-0.512420	-0.923330
Max Length Drawdown	0.000000	0.000000
n.trades	217.000000	2.000000

Table 2: FB Results

	Sentiment	BH
Cumulative Return	-1.562892	0.393796
Annual Return	NaN	0.149645
Annualized Sharpe Ratio	NaN	99.713469
Win %	0.544715	0.525084
Annualized Volatility	0.162978	0.378188
Maximum Drawdown	-0.178267	-0.740794
Max Length Drawdown	0.000000	0.000000
n.trades	162.000000	2.000000

The NaN values come from the fact that the cumulative returns with costs subtracted end up being negative returns, so when computing the annual returns the function crashes and instead throws a NaN value (we are using "np.power()" and "the power calculation requires the base to be greater than 1"). In short, whenever we get a NaN value for both the Annual Return and the Annualized Sharpe Ratio, it means that the cumulative return of the strategy was below 0 (and, subsequently, also below our benchmark).

Table 3: AAPL Rolling Performance

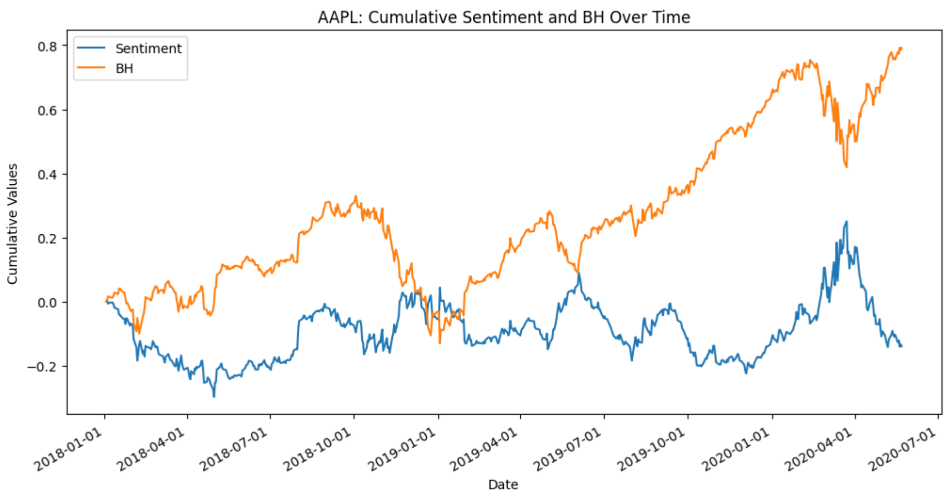
	BH	Me
AvgPerf	0.001050	0.000603
NumWindows	347	

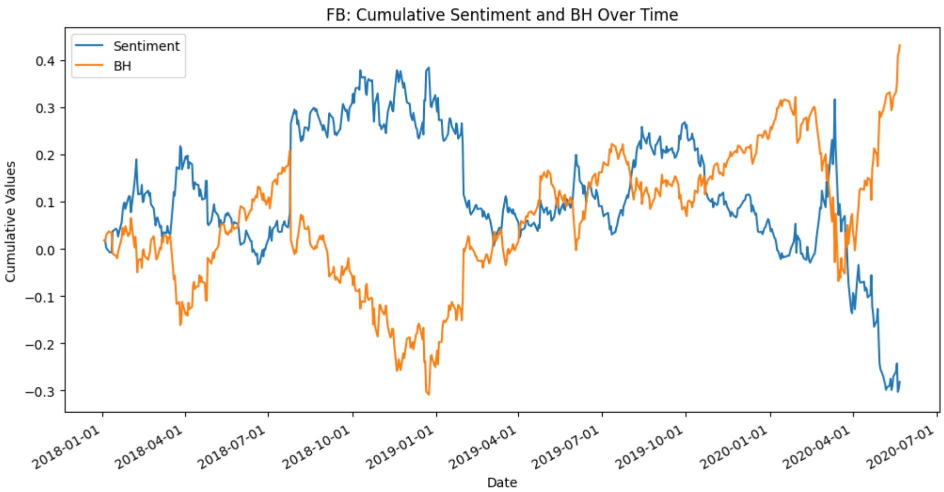
Table 4: FB Rolling Performance

	BH	Me
AvgPerf	0.000583	0.000147
NumWindows	347	

Here we can observe how the rolling window performances are also very bad and especially taking into account that the average performances are both below the benchmark by a considerable margin.

Continuing our analysis, Long-Short with 1 year windows did not improve the model greatly either:





In fact, the results looked even worse and the tables below confirm that the Long-Short strategy was performing even worse than the Long-Only strategy.

Table 5: AAPL Results

	Sentiment	BH
Cumulative Return	-2.310262	0.771744
Annual Return	NaN	0.271535
Annualized Sharpe Ratio	NaN	199.379302
Win %	0.473333	0.541667
Annualized Volatility	0.343819	0.343199
Maximum Drawdown	-0.548507	-0.923330
Max Length Drawdown	0.000000	0.000000
n.trades	217.000000	2.000000

Table 6: FB Results

	Sentiment	BH
Cumulative Return	-1.919580	0.393796
Annual Return	NaN	0.149645
Annualized Sharpe Ratio	NaN	99.713469
Win %	0.493311	0.525084
Annualized Volatility	0.378264	0.378188
Maximum Drawdown	-0.417003	-0.740794
Max Length Drawdown	0.000000	0.000000
n.trades	162.000000	2.000000

Table 7: AAPL Rolling Performance

	BH	Me
AvgPerf	0.001050	0.000157
NumWindows	347	

Table 8: FB Rolling Performance

	BH	Me
AvgPerf	0.000583	-0.000290
NumWindows	347	

Finally, lowering the rolling window length to 6 month periods improved the results very slightly regarding average performance although it still didn't beat the benchmark. For Long-Only with 6 months windows:

Table 9: AAPL Rolling Performance

	BH	Me
AvgPerf	0.001268	0.000761
NumWindows	474	

Table 10: FB Rolling Performance

	BH	Me
AvgPerf	0.000419	0.000116
NumWindows	474	

And for Long-Short with 6 months windows:

Table 11: AAPL Rolling Performance

	BH	Me
AvgPerf	0.001268	0.000254
NumWindows	474	

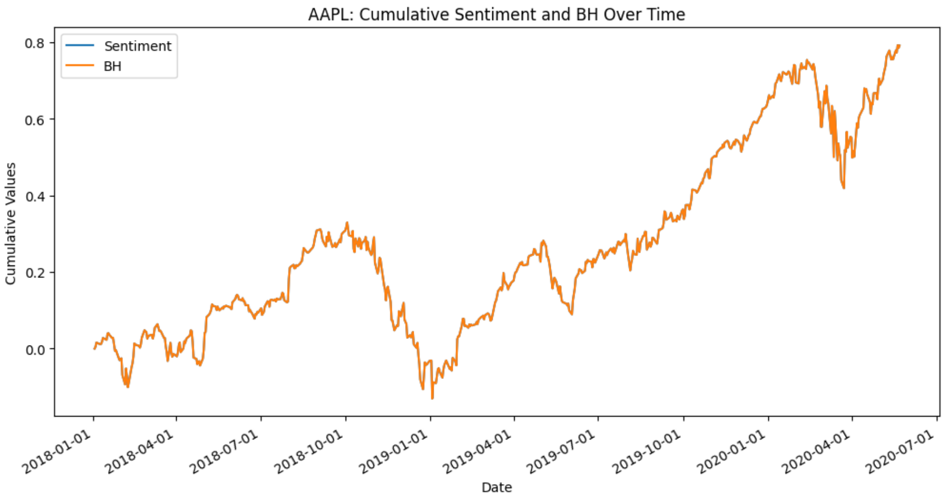
Table 12: FB Rolling Performance

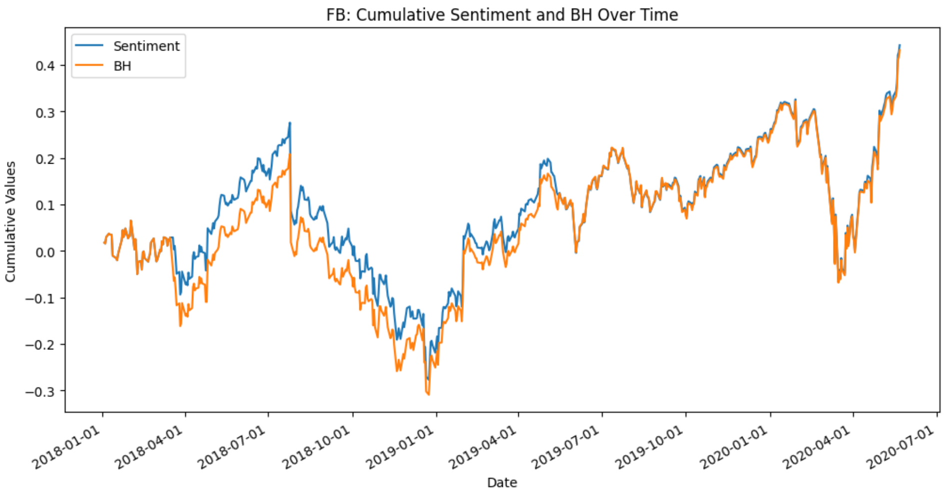
	BH	Me
AvgPerf	0.000419	-0.000186
NumWindows	474	

We can observe how in both the average performances are not as far away from the benchmark nominally but in percentage the difference is still considerably high. The average performance for Long-Short when considering a 6 month window is still negative even so those results were not great.

1.2 Testing the limits

We decided that the best way to test if our strategy ever had at all the potential to beat the benchmark was to test its limits. To do that, we maintained Long-Only strategies fixed (which were the ones that performed less badly on the previous analysis) and set the threshold to both 1 and 99. We started setting it to 1, so the strategy would buy almost always. Non-surprisingly, the results resembled those of the benchmark:



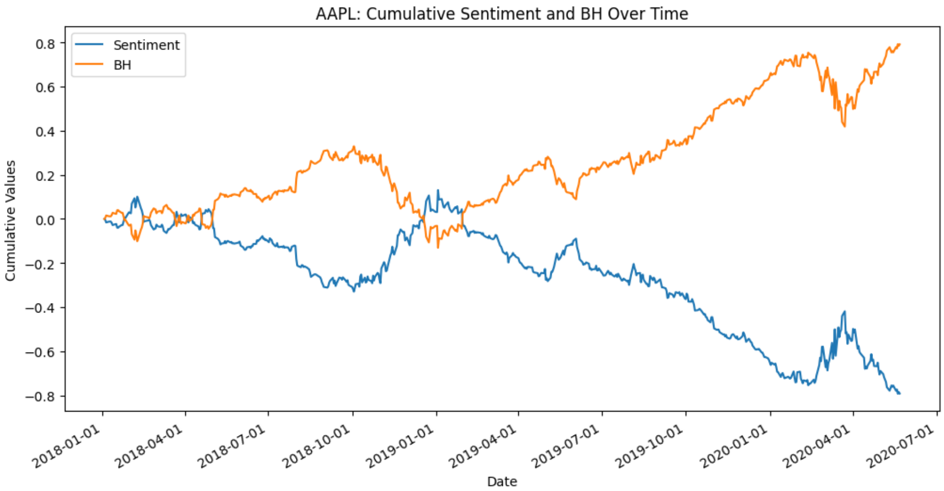


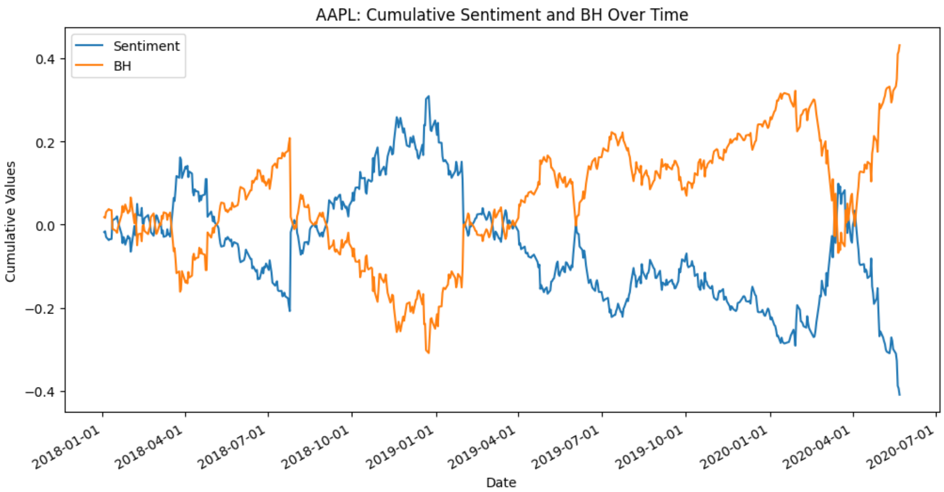
In this case for AAPl our strategy does in fact essentially follow "buy-and-hold" strategy and we don't even see the blue line for Sentiment in its graph. In contrast, regarding FB our strategy does correctly identify some extreme BEAR indicatives (BBr = 0 or BBr = 1) that the stock is going to fall at some point in march but those few correct catches are not enough to counter-weight the cost of the trades.

We will not show the results for this specific case because they are just the same as results shown above for the benchmark with the exception of the results for FB, which are close to but still worse than the benchmark.

Average performance from the rolling analysis with windows of 1 year in this case also turn out to be exactly the same as the benchmark for AAPL and slightly worse than the benchmark for FB.

On the other extreme, we also tried setting the threshold = 99 so that the model would almost never buy and the result was that the performance was just the opposite of the benchmark, as expected, so the results were also bad. In this specific case, though, we needed to set the strategy to Long-Short because otherwise the Long-Only model would never buy, leave all signals at 0 and the formula for the Win % would become a division by zero. We can observe the graphs for both:





The results are more or less the opposite to the benchmark as well in terms of returns:

Table 13: AAPL Results

	Sentiment	BH
Cumulative Return	-0.811744	0.771744
Annual Return	-0.504099	0.271535
Annualized Sharpe Ratio	-370.143386	199.379302
Win %	0.458333	0.541667
Annualized Volatility	0.343199	0.343199
Maximum Drawdown	-0.460220	-0.923330
Max Length Drawdown	0.000000	0.000000
n.trades	2.000000	2.000000

Table 14: FB Results

	Sentiment	BH
Cumulative Return	-0.451476	0.393796
Annual Return	-0.222926	0.149645
Annualized Sharpe Ratio	-148.537038	99.713469
Win %	0.474916	0.525084
Annualized Volatility	0.378205	0.378188
Maximum Drawdown	-0.517269	-0.740794
Max Length Drawdown	0.000000	0.000000
n.trades	6.000000	2.000000

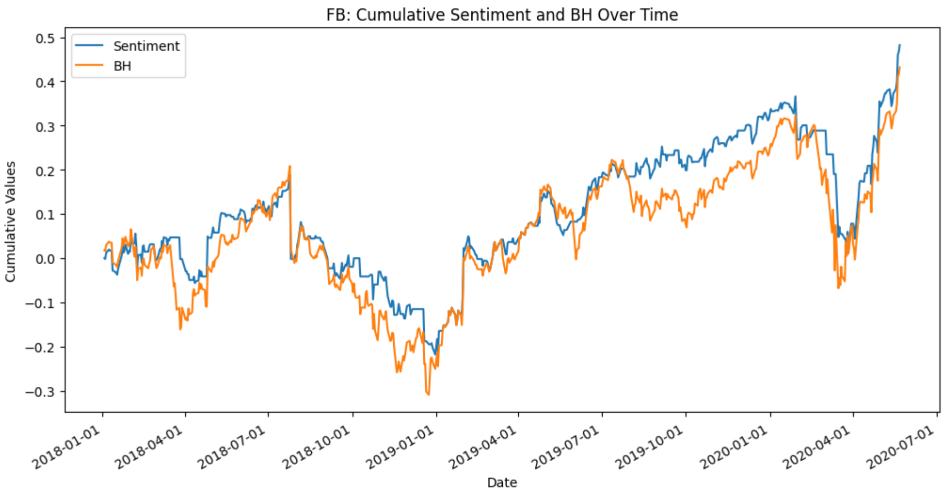
Additionally, it is not difficult to imagine that if we really were to compute returns for a strategy using Long-Only on a threshold = 99 we would just end up with a 0% return on everything because the strategy would never signal to buy so we would never buy anything.

1.3 Testing the in-betweens

At this point we already had little faith left for the strategy, and rightfully so, but we still tried a couple more in-between values for the threshold but the results didn't improve. When we set the threshold to values closer to 100, we got either 0% (with LO) or inverse of the benchmark (with LS), and when we set the threshold to values closer to 0 we got very similar values to the benchmark (with both LO and LS). It really seems like the cap of this approach are the benchmark returns of the "buy-and-hold" strategy.

We also tried to tweak the strategy using "RVT", as mentioned above but it only made the model either too picky or not picky enough, which were both not great enough.

As a final silver-lining, though, we did get some very interesting results with this final model using both BBr and RVT > 0.001 when we set the threshold for BBr at 30 (we tried more options for those parameters but this is the combination that got us the best results from the ones we tried; At this point we prefer not to swamp the report with more graphs and tables of the same bad results). We got the following graph for FB:



We can see how it looks like the model could be outperforming the benchmark for FB and, effectively, if we set the trading costs equal to 0, it does:

Table 15: FB Results

	Sentiment	BH
Cumulative Return	0.481867	0.413796
Annual Return	0.179614	0.156545
Annualized Sharpe Ratio	148.480521	104.311148
Win %	0.527845	0.525084
Annualized Volatility	0.304839	0.378188
Maximum Drawdown	-0.699894	-0.740794
Max Length Drawdown	0.000000	0.000000
n.trades	201.000000	2.000000

These results are a nice final touch but we do have to note that even with costs as low as 0.001 (just a tenth of what we have been using throughout the rest of our analysis) the strategy becomes non-profitable again.

1.4 Conclusions

Our approach is not profitable mainly due to having positive trading costs. In order for our strategy to work with those trading costs, we would need to tune it so that instead of performing a lot of trades it could detect key times when sentiment changes and adapt accordingly to avoid the losses of the "buy-and-hold" strategy while also following it close when the stock is going up.

2 Question 2

In our analysis of the US Stock market, we have chosen the following stocks for the period 01-01-2015 through 12-31-2016:

- 'AAPL' - Apple Inc. is a leading technology company known for its innovative consumer electronics, software, and online services. Its flagship products include the iPhone, iPad, Mac computers, Apple Watch, and Apple TV. Apple also offers services like the App Store, Apple Music, iCloud, and Apple Pay.
- 'ABBV' - AbbVie Inc. is a global biopharmaceutical company that focuses on developing and marketing advanced therapies. Its product portfolio includes treatments for conditions such as immunology, oncology, virology, and neuroscience. One of its most notable products is Humira, used to treat autoimmune diseases.
- 'AMZN' - Amazon.com Inc. is a multinational technology company primarily known for its online retail marketplace. In addition to e-commerce, Amazon has significant operations in cloud computing (Amazon Web Services), digital streaming (Amazon Prime Video), and artificial intelligence (Alexa).
- 'DB' - Deutsche Bank AG is a leading global investment bank and financial services company headquartered in Germany. It provides a wide range of banking and financial services, including investment banking, corporate finance, asset management, and retail banking.
- 'DIS' - The Walt Disney Company is a diversified international family entertainment and media enterprise. It operates through segments such as media networks, parks and resorts, studio entertainment, and direct-to-consumer streaming services (Disney+).
- 'FB' - Meta Platforms Inc. (formerly Facebook Inc.) is a technology company known for its social media platforms, including Facebook, Instagram, WhatsApp, and Messenger. The company also invests heavily in virtual reality (Oculus) and other technologies.
- 'GOOG' - Alphabet Inc. is the parent company of Google, the world's leading search engine. It operates through various segments, including online advertising, cloud computing (Google Cloud), consumer electronics (Pixel, Nest), and autonomous vehicles (Waymo).
- 'HAL' - Halliburton Company is one of the world's largest providers of products and services to the energy industry. It offers services and solutions for oil and gas exploration, development, and production, including well construction, well completion, and production enhancement.
- 'HSBC' - HSBC Holdings plc is a multinational banking and financial services company. It provides a wide range of financial products and services, including retail banking, commercial banking, investment banking, and wealth management, with a strong focus on Asia.

Now's lets understand what is the general behaviour of the returns on the stocks analyzed.

In our initial analysis, it appears that most companies have had similar average performance, except for Amazon (AMZN), which has significantly outperformed the market.

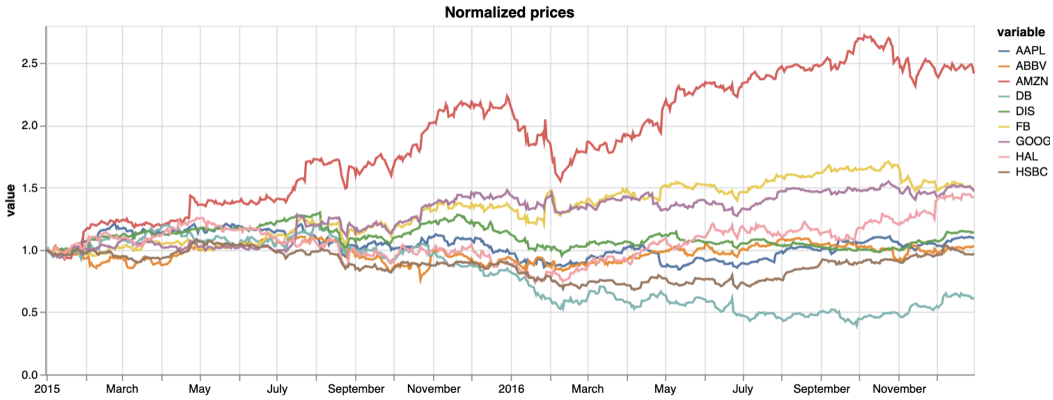
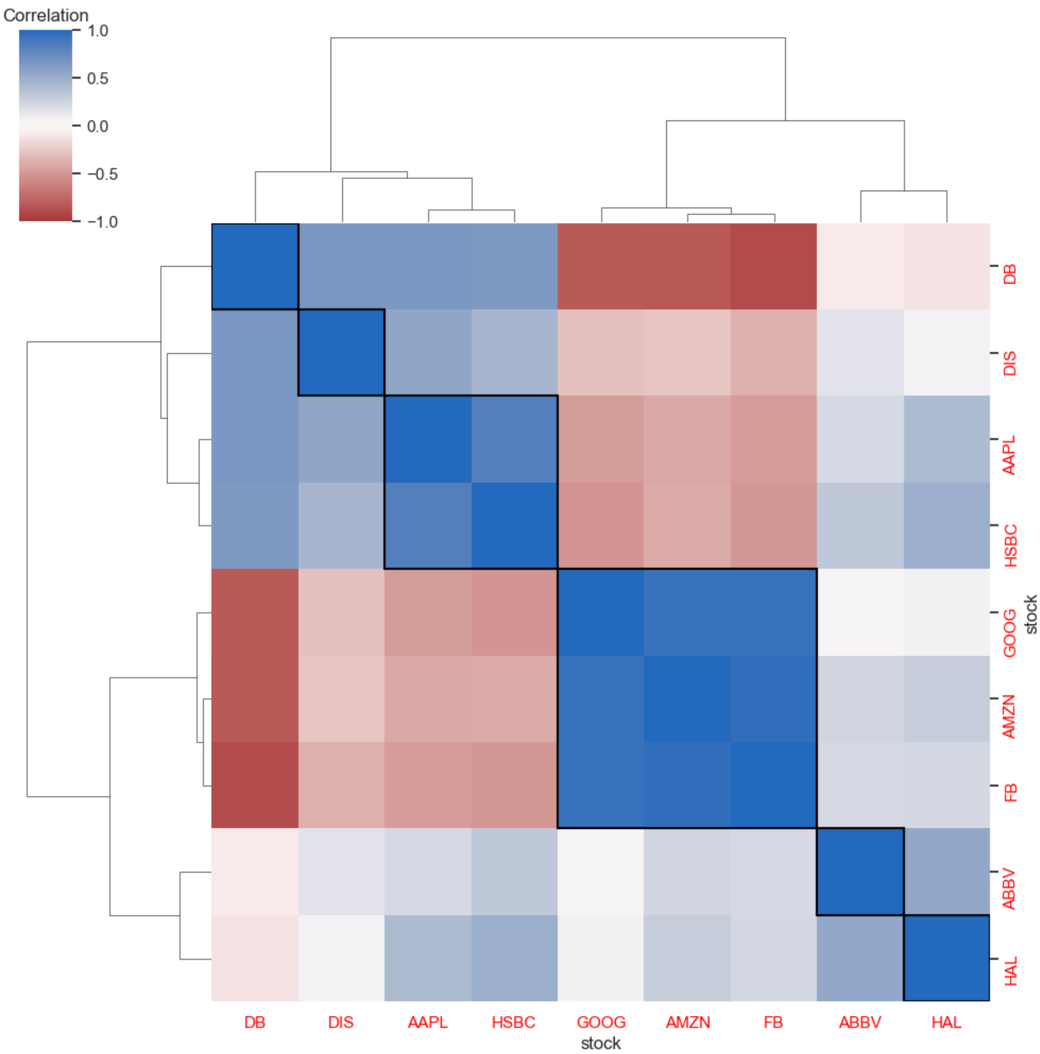


Figure 1: Overall trend of the normalized prices of the stock analyzed in our time frame

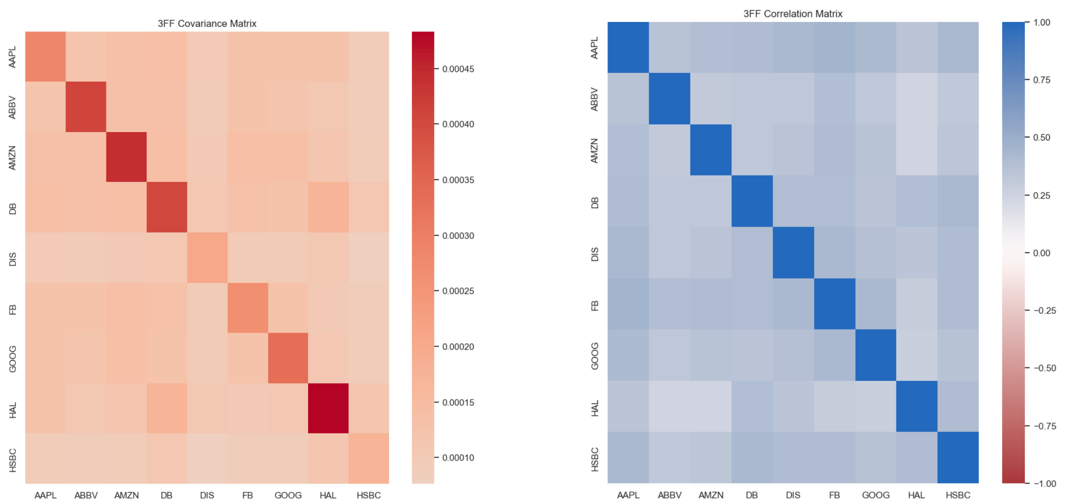
Notably, there was a pronounced downward trend at the start of 2016, likely influenced by political factors and oil market volatility. Both Facebook (FB) and Google (GOOG) concluded the analysis period with a normalized value of 1.5. In December, Halliburton (HAL) exhibited a notable increase. Additionally, Deutsche Bank showed a downward trend, attributed to its deteriorating financial performance. Now, we will understand whether there is a correlation between the variance of each stock.



Upon analyzing the graph, we observe two distinct clusters. The first group consists of three major technology companies—Google (GOOG), Amazon (AMZN), and Facebook (FB). This strong correlation likely stems from the shared market dynamics that significantly influence these tech giants. Surprisingly, Apple (AAPL) is not part of this cluster but instead shows a high correlation with HSBC, which might be an incidental or spurious correlation. Additionally, it is noteworthy that Deutsche Bank (DB) displays a negative correlation with GOOG, AMZN, and FB. This observation aligns with expectations, as the tech companies have shown strong returns, whereas DB has experienced a declining trend. However there does not seem to be a causality within them.

2.1 3 Fama French Factors Model

The 3 Fama Factors model is created by designed in 1992 by Eugene Fama and Kenneth French to describe stock returns. They consist of the Market Risk Premium, the Size Factor, and the Value Factor. The Market Risk Premium is the difference between the return of the market and the risk-free rate. The Size Factor is the difference between the return of small-cap stocks and large-cap stocks. The Value Factor is the difference between the return of value stocks and growth stocks. They are used to explain the returns of a stock portfolio. We use the precalculated 3FF from the online source to compute our model.



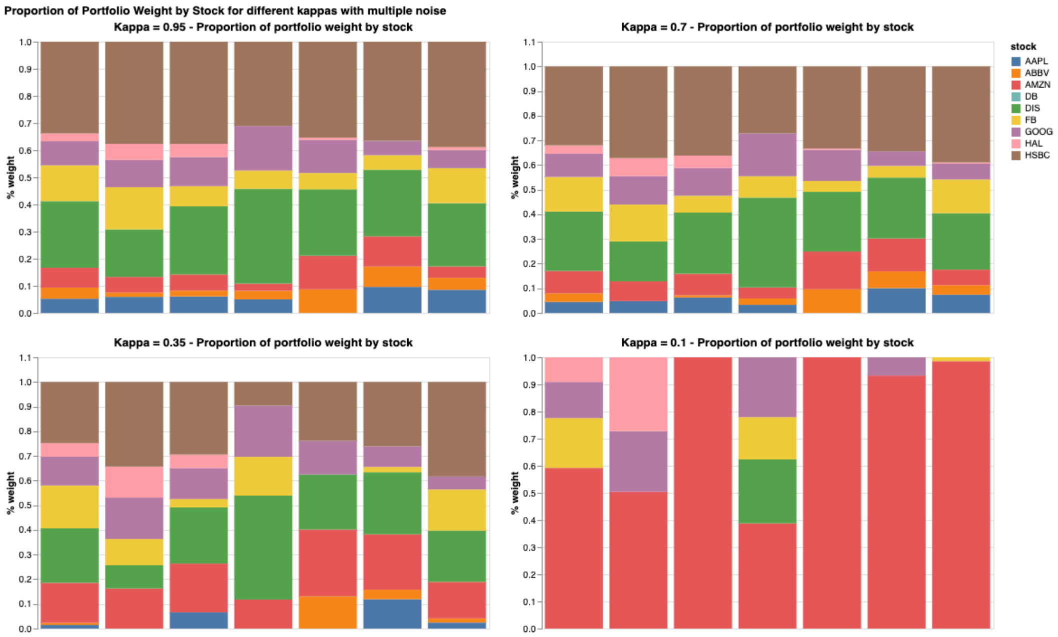
(a) 3FF Covariance Matrix (b) 3FF Correlation Matrix

Figure 2: Side-by-side comparison of the 3FF covariance and correlation matrices

We then looked at both the 3FF Covariance Variance matrix and the Correlation Matrix of the 3FF model. In the covariance variance matrix, the diagonal elements represent the variance of the stock prices. The off-diagonal elements represent the covariance between the stock prices. Meaning the higher the covariance, the more the stock prices move together and the lower the covariance, the more the stock prices move independently. The variance diagonal tells how volatile the stock prices are. Notably, Haliburton seems to have the highest variance. In North America during 2015-2016, the oil and gas industry went through a historic cycle, punctuated by an almost 80 percent decline in the U.S. land rig count. Additionally, a Iranian nuclear deal was made in the same time frame, which led to reduced sanctions on Iranian and OPEC controlled oil. In the correlation matrix, there is no super significant correlations between the 3FF model matrix. However, Apple seems to have relatively more correlation with all of the other stocks. This could be due to the increase in corporate partnerships and increased velocity of new product releases from APPL over the time frame.

Finally, we calculated the Maximum Robust Ellipsoid analysis on the 3FF model. The maximum robust ellipsoid (MRE) optimization is a method for finding the ellipsoid that contains the maximum number of points in a dataset. Using a varicance covariance matrix, the MRE can be used to find the ellipsoid that contains the maximum number of points in a dataset while optimizing for the minimum volume. The plane on which the data is contained is the eigenvector of the covariance matrix. We input a Kappa parameter, which controls the size of the ellipsoid, which will optimize for the robustness of the portfolio.

The two most significant results for the 3FF model are 0.95 and 0.35.



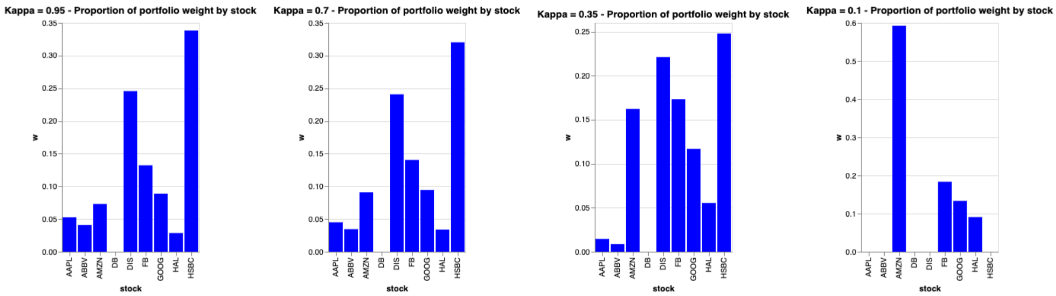
The 3FF model recommends that we invest in HSBC and DIS the most heavily. This makes sense because there was still ongoing recovery from the financial crisis, and safer more stable companies that provided inherit value and consistent returns to the stockholder are more attractive to the shareholders.

As we toggle Kappa, the portfolio will be optimized for robustness, looking more high risk stocks at low kappa that can diversify the portfolio strongly. This means lower 3FF covariance and potentially higher volatility.

At 0.35 the model selects AMZN more than other stocks which was previously unidentified. Because the lower Kappa demands higher risk, the model may be selecting more diversified activity from AMZN than in lower risk models. This may include the 3FF factors, size, value, and market risk. Additionally, AMZN showed low overall correlation with other stocks and high variance which indicates strong independent robustness for the stock. This is even further accentuated by the Kappa at 0.1 which indicates a portfolio composition of almost entirely Amazon stock.

In the above graph, we can observe the portfolio composition as a parallel indicator of each stock's risk. For example, with higher Kappa's there is less need for robust portfolio composition, and so the most of the concentration is focused on DIS, and HSBC. Two resilient and stable stocks. We can see the composition of these stocks go down as more risky tech companies are being added. Ultimately, the lowest Kappa as mentioned above takes the riskiest approach and has a portfolio composition of almost entirely AMZN.

These results went through a robustness check where the 3FF model was tested across multiple runs, with noise added from a random sample of a normal distribution. In the



appendix we can see that the graph clearly shows results consistent with the previous two graphs across all runs.

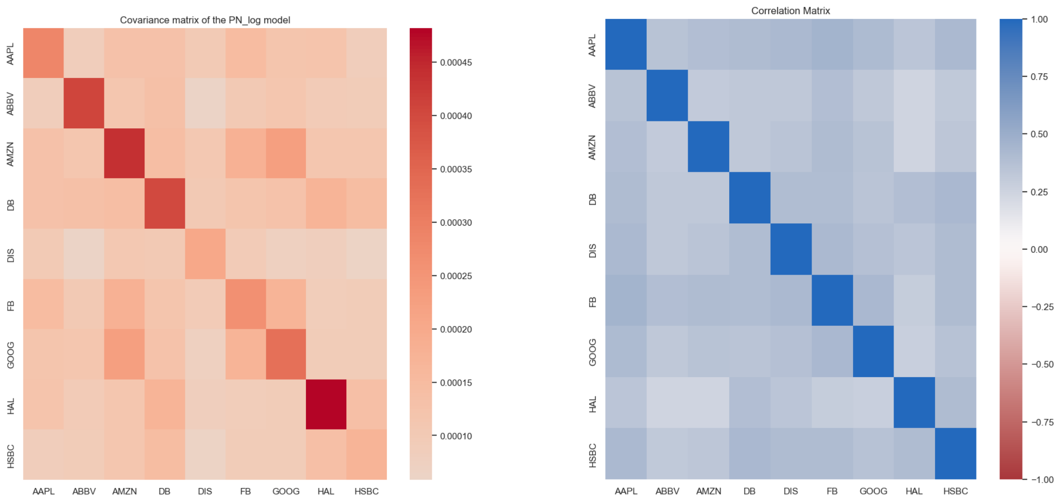
2.2 The Sentiment indicator PNlog factor model

Portfolio Optimization Using Sentiment Analysis in the Ellipsoid Model

The Robust Global Maximum Return Portfolio, optimized within an ellipsoid framework, is a method that aims to maximize expected returns while robustly managing risk through a modified covariance matrix. This method particularly adapts the standard quadratic risk assessment to a linear form using the Cholesky decomposition of the covariance matrix, thus representing the uncertainty in asset returns as an ellipsoid in the space of potential portfolio weights. In this csae, the portfolio optimization incorporates a sentiment indicator- the PNlog factor model- reflecting broader market sentiments that might influence asset prices. By leveraging the sentiment-based factor model, the covariance matrix used in the optimization (Σ_{PNlog}) not only captures traditional financial metrics but also integrates emotional and psychological market drivers. This integration allows for a nuanced portfolio construction that is aligned with both historical returns and current market dynamics, thus enhancing the predictive power and relevance of the model in real-world settings.

Relations between the PNlog sentiment of Portfolio

In trying to understand relation in the PNlog sigmas, we plot the figures like in fig **??**.



(a) PNlog Covariance Matrix

(b) PNlog Correlation Matrix

Figure 3: Side-by-side comparison of the PNlog covariance and correlation matrices

Analyzing the covariance matrix, we observe notable relationships among certain stocks, particularly within the tech sector. For instance, Facebook (FB) and Google (GOOG) display some covariance, which is logical considering their industry alignment. However, the covariance between Halliburton (HAL) and HSBC is also noticeable, though it's less intuitively clear why these companies from very different sectors (energy and banking, respectively) would exhibit this relationship, but this could be underlying factors, possibly related to broader economic conditions that impact both sectors, such as global economic growth rates or oil prices, which could influence both energy and financial markets.

From this matrix, we derive insights into how various companies have different levels of sentiment variability. Companies like Halliburton (HAL) and Amazon (AMZN) show higher covariance in their sentiment scores, potentially indicating more volatility in public sentiment or market reactions. In contrast, Facebook (FB) and HSBC display lower sentiment covariance, suggesting a more stable sentiment outlook. This might correlate with observed stock price behaviors; Amazon experiences more pronounced price fluctuations, which could drive more variable sentiment, while Facebook has shown more consistent growth, likely leading to steadier sentiment.

Furthermore, examining a correlation matrix would reinforce some of these findings. Apple (AAPL) appears somewhat correlated with the broader market. A cluster of low correlation among Deutsche Bank (DB), Disney (DIS), Facebook (FB), and Google (GOOG) suggests a nuanced relationship that, while perceptible, isn't particularly strong. However, the correlation between Facebook (FB) and Google (GOOG) again stands out, reinforcing the notion that their sentiment indicators are aligned, likely due to their shared sector characteristics. The correlation seen between Halliburton (HAL) and HSBC again sustains that there may be some relation between them.

Testing Portfolio Robustness Under Variability

The robustness of the optimized portfolio weights is assessed by introducing various 'noisy' scenarios and adjusting the risk-aversion parameter, κ. This process involves simulating multiple sets of asset returns by adding noise to the original mean returns (μ) using the original covariance matrix. This simulation generates realistic variations in market conditions. Recalculating the portfolio weights under these different conditions allows for the observation of how sensitive the optimal portfolio is to changes in market assumptions. This testing phase is crucial for validating the resilience of the portfolio strategy under various economic and market stress tests, and it provides insights into how adjustments in the risk-aversion parameter (κ) might influence the balance between risk and return in the portfolio.

In testing the portfolio weights across a range of κ values (0.95, 0.7, 0.35, 0.1), we aim to observe the influence of varying degrees of risk aversion on the portfolio composition. At the highest risk aversion level ($\kappa = 0.95$), the portfolio is expected to be more diversified and conservative, prioritizing stability and reduced volatility. As κ decreases to 0.7, the portfolio still maintains a cautious approach but allows for slightly greater exposure to higher-yielding assets, balancing moderate risk with potential for increased returns. At a lower risk aversion level ($\kappa = 0.35$), the portfolio becomes more aggressive, allocating more to assets that may offer higher returns at the cost of increased risk, showing a clear shift towards growth-oriented strategies. Finally, at the lowest risk aversion ($\kappa = 0.1$), the portfolio strategy is highly aggressive, significantly weighting the highest-performing stocks regardless of their volatility, aiming to maximize returns in exchange for a much higher risk exposure. This range of scenarios helps us understand how different risk tolerances can shape investment strategies, from extremely cautious to highly aggressive, providing a comprehensive view of potential outcomes.

Let's now plot what happens in each scenario. The variations within each stock are also plotted, but these are included in the appendix in fig 6.

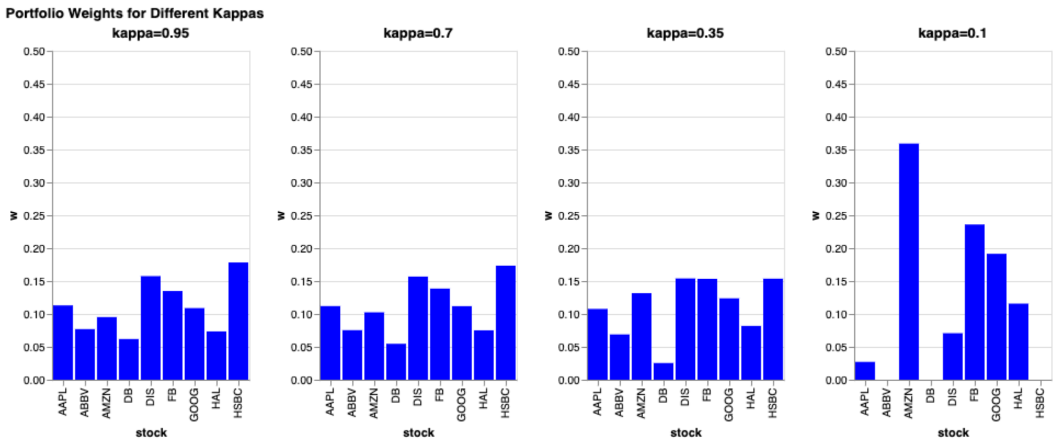


Figure 4: Portfolio weights for different kappa

In Fig. 4, the estimated portfolio weights are presented for various values of κ. A notable difference is observed for $\kappa = 0.1$ compared to other values. This portfolio configuration, which seeks to maximize returns potentially at the cost of higher risk, predominantly invests in AMZN (approximately 0.35) followed by FB (approximately 0.22) and GOOG (around 0.1). This approach is validated when considering the figure of normalized prices.

For $\kappa = 0.3$, there is a noticeable shift in strategy. The portfolio now includes every stock, with AMZN's weight significantly reduced to about 0.14. Stocks such as DIS, FB, and HSBC are now approximately equal weights at around 0.15, indicating a strategy shift towards risk diversification.

Further analysis of $\kappa = 0.7$ and $\kappa = 0.95$ shows that the portfolio weights are quite similar between these values, with minor differences. At $\kappa = 0.7$, there is a slightly higher allocation to AMZN (0.15) compared to $\kappa = 0.95$ (just below 0.10). Conversely, DB receives a higher allocation at $\kappa = 0.95$. These portfolios demonstrate a pronounced focus on risk management and diversification, with the highest allocations in HSBC (around 0.17), DIS (0.16), and FB (0.15), and with the highest allocation to a underperforming stock (DB). The remaining stocks are balanced with allocations around 0.1, reflecting a strategic preference for reducing volatility over maximizing returns.

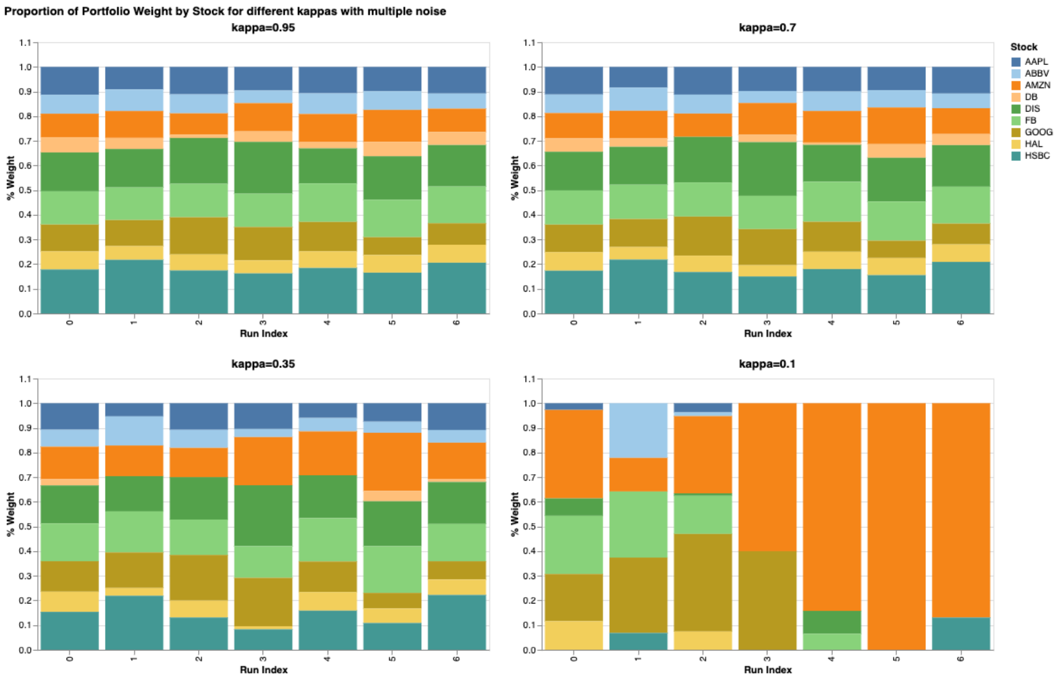


Figure 5: Analysis of sensitivity to each noise afor each kappa

The figure, Fig. 5, illustrates the sensitivity of portfolio weights to various noise-added scenarios, assessed across different levels of risk aversion parameterized by κ. In each simulation, noise was added to the mean asset returns (μ), while the covariance matrix (Σ) was kept consistent. The weights were recalculated to achieve the maximum return under robust conditions for each noisy version of μ.

At the highest level of risk aversion ($\kappa = 0.95$), the portfolio weights across different runs show a conservative and stable allocation strategy, with significant investment in HSBC, indicating a preference for stable assets. The allocations are relatively consistent, emphasizing risk minimization over return maximization. This approach leads to a diversified portfolio aiming to mitigate the impact of adverse market conditions by maintaining balanced exposure across a range of assets. The similarity in weights across multiple noisy scenarios suggests that the portfolio is well-cushioned against fluctuations in market conditions, which is characteristic of a risk-averse investment strategy.

At moderate levels of risk aversion ($\kappa = 0.7$ and 0.35), the portfolios exhibit some conservatism, but allow for more variability in asset allocation as κ decreases. Notably, the portfolio at $\kappa = 0.7$ demonstrates a composition that is relatively similar to that at $\kappa = 0.95$. This similarity suggests a less pronounced shift towards higher-yielding assets than might be expected, indicating that even a moderate reduction in risk aversion from the highest level does not significantly alter the conservative nature of the portfolio, thus making it also less sensitive to the different scenarios.

In contrast, at $\kappa = 0.35$, the portfolio exhibits more noticeable shifts toward aggressive investment strategies, significantly favoring stocks like AMZN, known for its higher volatility but also its potential for greater returns. Although these adjustments at $\kappa = 0.35$ are marked, the variation in asset weights across different runs is less pronounced than might be expected for such a substantially lower κ value. Despite this, distinctive variations in the weights of GOOG, AMZN, and HSBC are evident, reflecting notable differences in response to different noise scenarios. This variability could potentially suggest a heightened sensitivity to changes in estimated returns for these stocks, influenced by the noise characteristics in each simulation run.

At the lowest risk aversion level ($\kappa = 0.1$), the portfolio weights are distinctly more varied across different simulations, highlighting the aggressive nature of the strategy. This setting maximizes returns at the expense of higher risk, leading to significant fluctuations in the allocation to different stocks based on the noisy conditions. AMZN, FB and GOOG show the largest allocations, indicating that at low κ values, the portfolio is highly sensitive to (μ), making it more susceptible to market volatility. Furthermore, in one specific case, almost all of the stock (0.99) is put into AMZN. The greater divergence in portfolio weights from one simulation to the next under this scenario underscores the high-risk, high-reward nature of the strategy, heavily dependent on the performance of the highest-return stocks regardless of their inherent risks.

3 Conclusions

We can safely conclude that our ratios are not the most significant when trying to predict the returns of the S&P500. DP, DE and EP are not extremely useful when predicting the returns except if we have them on the same period of the price, of course, but then we are already on the period we try to predict so it renders the prediction moot.

The only ratio that seemed to get some better results (and only with the neural network model) was the DE. The rest of the combinations didn't really improve the best results we got with the neural network applied only to the lags of the log returns.

The direction predictions only made things worse and in that case not even the lags of the log returns were any better than using an MA 1 model.

In the end, we also considered using the stationary bootstrap to strengthen our conclusions, but our ratios were already bad enough that no amount of robustness checks would get them to magically work. The average R^2 Score we got with our variables was negative so we are already very confident in our conclusion that those ratios are not useful to predict the S&P500.

The 3 Fama French model and the PNLOG model were useful, respectively, at incorporating price agnostic factors including Market Risk Premium, the Size Factor, and the Value Factor and at sentiment indicators to the stocks. Overall, the 3 Fama French model identified stocks and portfolio optimizations that were in line with market conditions at the time, suggesting more risk averse stocks at higher Kappa levels like HSBC and DIS. Meanwhile, the PNLOG model recommends a more diversified portfolio, highlighting any stable sentiments towards a specific stocks. In lower kappa levels, both suggested more risky stocks with a portfolio mostly centered around AMZN.

4 Authors Contribution

All authors contributed equally.

5 Appendix

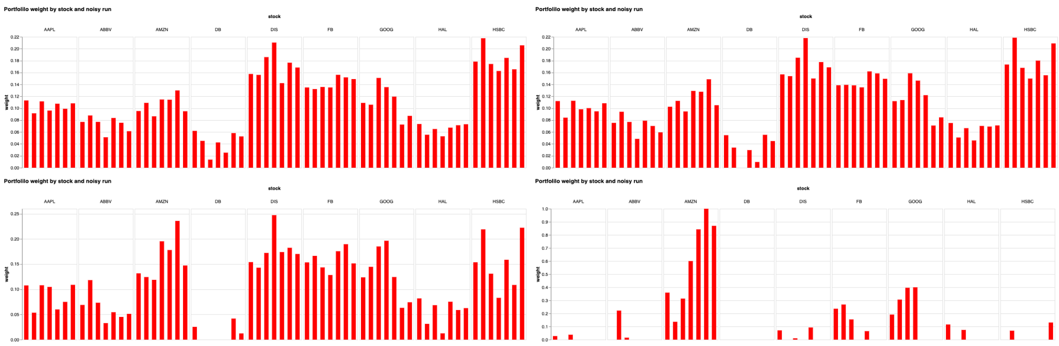


Figure 6: Analysis of sensitivity to noise for each run for each stock

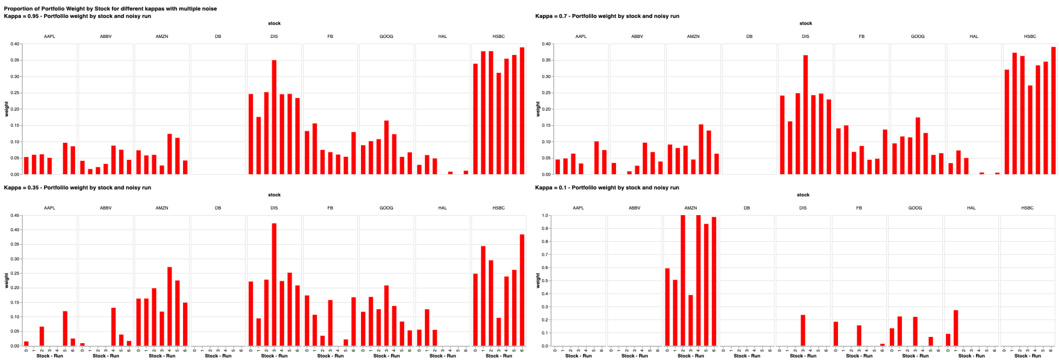


Figure 7: Analysis of 3FF sensitivity to noise for each run for each stock