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Assignment #6
May 1, 2024
Finance 496

For this assignment, I decided to evaluate how analyzing market sentiment can be integrated into a factor portfolio. It has the beauty of a momentum strategy while adding some advancements to set it apart. For the sentiment, I used Twitter data pulled from Bloomberg's GT function. This shows the number of positive tweets and negative tweets for a given asset. Although the performance of this portfolio surpassed my expectations, I believe that there is more diligence needed to ensure that the codebase is accurately generating returns. Before going into the specific performance of this portfolio, there are a few disclaimers I must make:

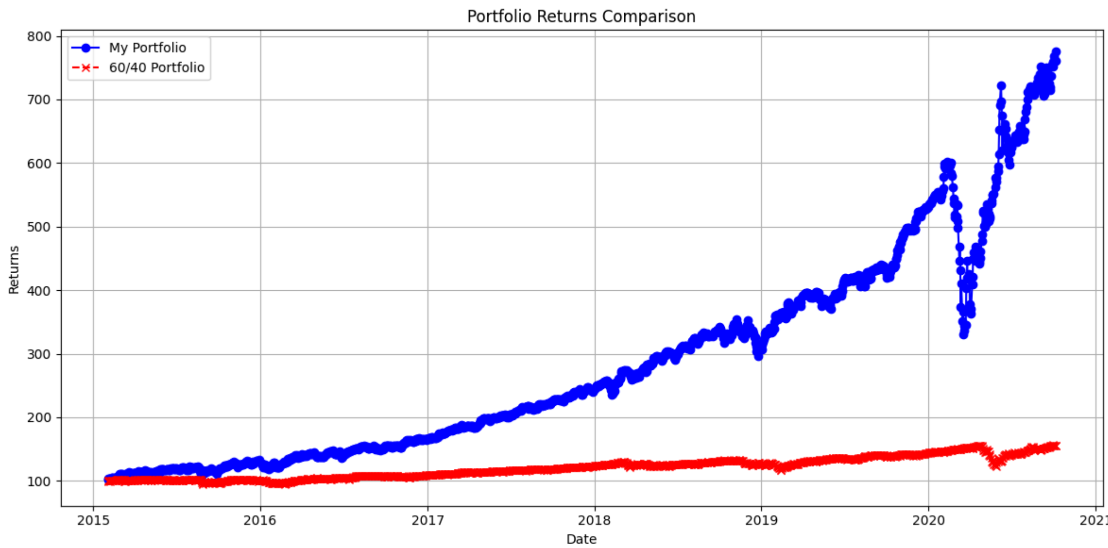
1. The sentiment data was limited to monthly data. Bloomberg offers this data on a 30-minute and real-time basis, but I was constrained by API tokens.
2. The SPX has changed over the past 10 years. A large number of companies have joined it as well as left it. My portfolio is taking the current SPX members and looking back 10 years.
3. Sentiment is calculated using Bloomberg's proprietary model, which I do not have access to view. Therefore, there could be issues with the inputs for my factor portfolio that I wouldn't be able to determine.

4. Twitter is new. It wasn't a thing 20 years ago. Bloomberg only had sentiment data going back to early 2015.

To make this work, I needed to clean the data. This was the longest part of the code. I first took in the positive and negative tweets per asset going back to 2015. I then found the ratio of positive/negative. After that, I looked at the percentage change per month per asset in the sentiment ratio. I then ranked these in descending order, with a filter of 20 tweets minimum using the original csv. After doing this, I made two dataframes, one with the top 10 sentiment assets and one with the bottom 10.

I initially had the intention to do a contrarian portfolio. I would go long on the lowest ranked assets by sentiment and short the highest ranked assets. This did not work at all. I believe this was due to two reasons. (1) There was a significant lack of data. Bloomberg's GT function does not have enough sentiment analysis. The majority of stocks had under 50 tweets in a given month. With the minimum threshold of 20 tweets, there were inaccuracies. (2) There are some assets with no tweets. This means that some months, there weren't even 10 assets with 20 or more tweets. This led to taking a short position in some assets that had fairly positive twitter sentiment.

I ended up keeping just a long strategy in the more positive assets. This led to the returns on the next page compared to the Sixty Forty portfolio. My portfolio significantly outperformed the rebalancing 60/40. This is largely due to how bonds have performed and how concentrated my portfolio was on some top performing assets. If we were to extend this back (somehow pre-Twitter), I think we would see some glaring issues with this strategy, particularly emphasized by the higher volatility and high max drawdown.



Sixty Forty Total Return	54.99%
Portfolio Total Return	649.52%
Sixty Forty Annual Return	7.85%
Portfolio Annual Return	4.15%
Sixty Forty Drawdown	21.15%
Portfolio Drawdown	45.01%
Sixty Forty Volatility	8.27%
Portfolio Volatility	20.08%
Sixty Forty Sharpe Ratio	4.96%
Portfolio Sharpe Ratio	9.59%
Portfolio Beta to Sixty Forty	-0.14

In conclusion, this portfolio performed well, but I would not use it going forward with real money. The issue with it is the short time frame of data I had as well as the lack of data. If I were to scrape the sentiment data myself, using LLMs for robust analysis, this is a strategy that could potentially see success.

Works Cited

https://www.tandfonline.com/doi/abs/10.1080/03085147.2015.1109806

http://dl.fxf1.com/books/english/Mcgraw-Hill,%20The%20Triumph%20Of%20Contrarian%20Investing%20-%20Crowds,%20Manias,%20And%20Beating%20The%20Market%20By%20Goin.pdf