6. Problems/Challenges/Interesting Findings/Things that didn’t work

There were several compromises that were required in our analysis that potentially introduced bias into our analysis. For a proxy of market performance, we used the constituent stocks of the S&P 500 index. The index is value-weighted which means that the largest companies will have a disproportionate weight in the index. Although it is common practice to do this, there were some biases this introduced that were unavoidable. One of which was the fact that the industry composition of the index is not perfectly balanced. There are some industries that are heavily weighted, while there are some that have a relatively small weighting. The graphic below shows the industry makeup of the stocks that we considered:

As can be seen, consumer discretionary dominates with 16.63% of the stocks belonging to that industry. Industries such as real estate, materials, & telecommunications consist of a dramatically smaller subset of the securities used. Consequently, for industries such as telecommunications, it is reasonable to assume that there is a degree of overfitting for stocks in that industry, and others with a relatively small composition. Although we could have arbitrarily added additional stocks to have a more balanced weighting between industries, this would have resulted in selection bias.

Another natural challenge was due to the fact we are dealing with non-stationarity in our financial time series data. In financial data, this is the case when there are significantly different regimes within the data that may affect how our response variable changes. Although there are many ways the market dynamics changed drastically over the periods that we examined, the most noticeable difference that caught our attention was the difference in interest rates between the three recession periods. As shown in the table below, the interest rates were markedly different during the three periods.



In addition to the biases that we had to contend with, there were issues with access to the appropriate financial data. Having issues on this end further exacerbated some of the previously mentioned problems. For the subsection of our data that included the Great Recession, we were only able to find 60% of the stocks that were in the S&P 500 at the beginning of that period. This inevitably lead to some overfitting for industries that were already thinly represented in the index.

This was also problematic as it prevented us from gaining access to firm specific financial data that we would have then used to compute profitability, liquidity, and leverage ratios. Before we realized that we could not get access to this data, one of our initial hypotheses was that firms with low leverage ratios (such as debt to equity ratio) would be resilient in recessions. It was a very difficult task to gain access to this information however, so we left this out altogether.

Although we used a logistic regression in the end to determine which types of stocks would outperform, we had different ideas initially. We wanted to replace this model with a k-means clustering model. The k-means model would still use the output from the Jensen’s alpha regression. With those results, our plan was to then find categories that distinguished between the groups of underperformers and outperformers and then see if there were any interesting commonalities between the subgroups that the algorithm developed.

As we went deeper into our exploratory data analysis, we noticed that there were some fundamental characteristics of some of our features that we wanted to use that made it difficult to implement this method. When we examined the price to book value ratio variable, we noticed that there was a very severe degree of skewness in its distribution as shown in the boxplot below:

Graphical user interface, chart

Description automatically generated

We delved deeper to see if there were any anomalies with the data that would warrant us removing the two outliers (which were L Brands & Philip Morris, with P/B ratios of 1403.38 & 1318.7, respectively) and there were not.

Using the k-means clustering approach with this issue would have caused the cluster centers to disproportionately be moved by these points. Additionally, with the k-means approach, there would have been some margin for judgment when choosing the appropriate number of cluster centers. We ultimately felt that the logistic regression approach was more definitive, and had the better tools for variable selection, so we went with that approach instead.

7. Other Ideas

The greatest priorities for our group if given more time and resources would have been to incorporate additional firm specific data into the analysis, look at additional time periods of economic downturns, and incorporate a sentiment factor into our analysis.

The end result of our analysis was to include three periods of economic downturns that we calibrated our models on. Although this was the best that we could do with the prohibitive restrictions and resources needed to acquire additional data, including additional data points from more historical periods would have made our model more sound, and less susceptible to possible overfitting.

Including firm specific data proved to be one of the most difficult endeavors for us. Without having access to proprietary databases, or sufficient financial resources, this data was unavailable, and our group was very dismayed by the valuable learning opportunities that were forgone because of this. Some of our inspiration for doing this came from the paper by Guan (2013) where company attributes relating to profitability, leverage, and accounting liquidity were used in his ranking metrics. We would have liked to incorporate measures such as inventory turnover, debt to equity ratio, and profit margin.

In our initial meeting where we brainstormed and created mind maps of how to approach this problem, we thought that creating a sentiment factor each of the stocks would have been a powerful feature to include. Doing so would have required the application of natural language procession which would have been applied to reports of individual securities to derive an optimistic or pessimistic score for each stock. The score would have then been used as one of the cofactors for the logistic regression. Unfortunately, we were too time restricted to delve into this technique and apply it appropriately

Although recessions are the among the economic events that are often the most costly to investors, there are often other macroeconomic scenarios that can be very disadvantageous to investors that can prevent them from reaching their financial goals. If given more time, we would have liked to do additional stress tests to explore how we could make portfolios that also outperform during other anomalous market conditions.

One additional scenario that we would have likely extended our analysis to would be periods of high market volatility. Periods of high market volatility can be very opportunistic for investors with very long investment horizons and an above average levels of risk tolerance. However, for investors that are on the opposite end of the spectrum such as those that are nearing retirement, there is far less ability to tolerate volatile market conditions given that these individuals need a high degree of certainty in the ending values of their portfolios so that they can properly plan for the drawdown of their funds.

In this extension, we would have begun our analysis in much of the same way as before by looking at approximately the last one hundred years of market data. The main difference in this scenario is that we would use periods of anomalous market volatility instead of recession periods. This would likely be defined as periods where the volatility is above a pre-specified number of standard deviations from the average. Per usual, we would then run our linear regression to see which stocks were above a pre-specified percentile of performance based on Jensen’s alpha. We would subsequently perform a logistic regression as before to see if we could glean into insights that would make stocks more or less likely to outperform in such conditions.

10. Overall Conclusion / Takeaways

Upon completion of this ambitious project, there were many important learning outcomes for us, and important practical applications of this exercise that we will be able to apply to our personal investment portfolios, and the portfolios of others that want to have an edge in turbulent markets. The main learning point that resonated with us through all of our team discussions was the fact that this undertaking was more of an art than a science. Although we had complex models at our disposal, the majority of the value add that we brought to this endeavor was from being able to discern between the strengths and weaknesses of the tools that were available and choose the best combination in-light of the problem that we were facing. Although there were some instances where imperfect information, or lack of information altogether lead us to situations that left us wanting to do more, we were mindful of the business problem with all of our decisions and were able to develop a model that all groups’ members have expressed interest in using in their personal lives.

We can summarize our key findings in two parts. From a macroeconomic level, rising unemployment rates & rising interest rates are indicative of outperformance. From a firm specific level, strong performance and volatility in the period leading to a downturn in addition to being classified as a real estate or financials company are conducive to outperformance. These findings are powerful and have immediate relevance given the growing level of hearsay concerning a potential forthcoming economic downturn.

12. Citations

Dillender M, Friedson A, Gian C, Simon K. Is Healthcare Employment Resilient and "Recession Proof"? Inquiry. 2021 Jan-Dec;58:469580211060260. doi: 10.1177/00469580211060260. PMID: 34873942; PMCID: PMC8655443 ([link](https://journals.sagepub.com/doi/full/10.1177/00469580211060260))

Guan, J. (2013). Estimating the Recession Risk Exposure of Stocks. *S&P Global Market Intelligence Research Paper Series* ([link](https://www.kellogg.northwestern.edu/~/media/Files/Departments/Finance/Guan_JobMarketPaper_EstimatingRecessionRisk.ashx))

Ozkan F C, Xiong Y, 2009, ‘Wise Investing: Analysis of the recession-proof sin stocks’, MBA thesis, Simon Fraser University, British Columbia ([link](https://summit.sfu.ca/item/709))

Woszczyk K, 2019, ‘Do mutual funds invest in recession-proof industries prior to crisis?’, MSc thesis, Erasmus University Rotterdam, Rotterdam ([link](https://thesis.eur.nl/pub/48135/Thesis-final-K-Woszczyk-25.07.pdf))

1 <https://fred.stlouisfed.org/series/JHDUSRGDPBR>

2 Tidyquant, source of stock data (via Yahoo) and macroeconomic times series (via Fred) ([link](https://cran.r-project.org/web/packages/tidyquant/vignettes/TQ05-performance-analysis-with-tidyquant.html))

3 Schwab - Macro-economic factors of fundamental analysis ([link](https://www.cnbc.com/advertorial/2018/06/11/macro-economic-factors-of-fundamental-analysis.html))

- Kaggle, guidance for performing S&P 500 Analysis in R ([link](https://www.kaggle.com/code/paytonfisher/s-p-500-analysis-using-r/notebook))