FINA4350 Group Project

Group 1
Inverse Cramer with Sentiment Analysis

Chan Tsz Hei (3035692060)
Choi Yik Ho (3035685515)
Guo Cheng (3035839955)

Introduction

In recent years, a phenomenon known as the "Cramer Effect" (Dudick 2023) has garnered attention from investors and market analysts. This effect suggests that stocks tend to move in the opposite direction of Jim Cramer's recommendations, a prominent financial commentator and host of CNBC's "Mad Money." (CNBC 2023) While the exact cause of this inverse relationship remains debated, it raises questions about the potential profitability of implementing an investment strategy that capitalizes on the Cramer Effect.

The following sections of this report will present the methodology, results, and analysis of our backtesting process, along with a discussion on the implications of our findings for investors and the broader market. Ultimately, we aim to provide insights for those interested in understanding and potentially capitalizing on the Cramer Effect.

Objectives

This project aims to investigate the validity of the Cramer Effect and explore the potential of using sentiment analysis to test an inverse cramer investment strategy.

We will employ statistical analysis and backtesting to assess the performance of this strategy, by analyzing historical stock data in relation to Jim Cramer's recommendations. By examining various performance metrics, we seek to determine if there is indeed an exploitable pattern in the Cramer Effect and if sentiment analysis can be a valuable tool for implementing the inverse cramer strategy.

Methodology

Data sources

Mad Money Show Stock Picks

We employed a Python script using Playwright and BeautifulSoup libraries to fetch historical stock recommendations from Jim Cramer's "Mad Money" show (TheStreet 2022). The data was saved in a CSV file for further analysis.

The script allowed us to configure the date range, inverse Cramer's calls, and include or exclude "Lightning Round" stock calls. For this study, we collected data from January 1st, 2017, to December 31st, 2021, with the inverse option enabled and Lightning Round calls excluded for consistency.

The extracted data included company name, stock symbol, recommendation date, segment, call (a bullishness spectrum from 1 to 5) and stock price at the time of the recommendation. This dataset served as the basis for our backtesting process and assessment of the inverse Cramer strategy's performance.

After fetching the stock recommendations, we created a sentiment-weighted rank for the stock picks. For example, strong buy recommendations would be 1.5x more important than ordinary buy picks. This was done by aggregating and resampling the recommendations into a monthly frequency, calculating the weighted sum of calls per stock symbol, and then extracting the top 5 and bottom 5 stock symbols based on this ranking. The resulting dataset was saved to a CSV file for further use in backtesting.

Jim Cramer Tweets

By using snscrape, we systematically retrieved Cramer tweets containing stock symbols and their respective timestamps. We have also manually scrapped the tweets from nitter.net, an alternative front-end for twitter as a back-up when Twitter removed their loginless search API in mid April 2023.

After that, we preprocessed and cleaned the data to ensure its usability for further analysis, including the removal of special characters such as '\r' and '\n'. Sentiment analysis is then applied with BERT (Devlin et al. 2019) to generate a sentiment score using the same spectrum as the previous section, from 1 to 5.

Strategy Specification

Quantconnect is chosen as the python backtesting framework for our strategies.

The backtesting period spans January 2017 to December 2021. The primary strategy (**remarC-L/S**) shorts the top 5 picks and goes long on the bottom 5 picks monthly. Weekly rebalancing maintains equal weights for long and short positions, ensuring diversification and minimizing the impact of individual stock performance.

Three strategy variants are also examined. The first (**remarC-L**) goes long on the bottom 5 picks and short on the S&P 500 ETF (SPY), seeking to profit from bottom 5 outperformance. The second (**remarC-S**) shorts the top 5 picks and goes long on SPY, targeting underperformance of the top 5 picks. The last variant (**Cramer-follower**) reverses the initial strategy by going long on the top 5 picks and shorting the bottom 5 picks, evaluating the effectiveness of following or inversing Cramer's recommendations.

Findings

Correlation

After preparing all the useful data, we computed the correlation between Jim Cramer's prediction on the stocks and their actual performance. The correlation is computed by

$$\frac{\Sigma(x_i-\bar{x})(y_i-\bar{y})}{\sqrt{(\Sigma(x_i-\bar{x})^2)(\Sigma(y_i-\bar{y})^2)}}$$

where x denotes the predicted result and y denotes the ground truth.

Correlation measures the strength and direction of the relationship between two or more variables, where a correlation coefficient of -1 to +1 indicates the degree of the linear relationship between the variables, with -1 indicating a perfect negative correlation, 0 indicating no linear correlation, and +1 indicating a perfect positive correlation.

	30 days return	90 days return	180 days return
Correlation	0.00231	0.00626	-0.00338

The table above displays the correlation between Jim Cramer's sentiment (from 1 to 5) and the actual stock performance in the 30th, 90th, and 180th days. Figures show that Cramer's prediction has a slightly positive correlation with the ground truth in the short and medium term, while they have a negative relationship when we expand the time horizon.

Accuracy

Although correlation is a useful tool for identifying linear relationships between variables, it cannot provide a complete picture of the situation. For example, a positive correlation may suggest that the stocks recommended by Cramer performed better than those he opposed, but it still does not guarantee that they outperformed the market average. Therefore, it is important to establish a benchmark to accurately evaluate the absolute performance of the stocks.

In order to calculate the benchmark, we initially gathered the annual return and standard deviation data for the S&P index over a period of 20 years. Using this data, we then computed the confidence interval for the stock performance based on the t-distribution. It can be obtained by

$$Range = [\bar{x} - (t\_critical \times (s/sqrt(n))),\ \bar{x} + (t\_critical \times (s\ /\ sqrt(n)))]$$

where t_critical is the t-value corresponding to a given confidence level with n-1 degrees of freedom. We set the confidence level to 95%, with n of 20, $\bar{x}$ of 9.93%, and s of 14.67%. Using this information, we calculated a confidence interval of [0.031, 0.168], which is considered the normal range for the annual return of a stock. If a stock's annual return falls within this range, it is considered normal. However, if a stock's annual return is less than 0.031 or greater than 0.168, it is considered underperforming or outperforming.

We then design a new criterion to evaluate the accuracy of Jim Cramer's predictions. The prediction will only be considered accurate if and only if both conditions stated below are met.

Conditions of an accurate result

Sentiment	< 3 (bearish)	3 (neutral)	> 3 (bullish
Actual return	< 0.031	> 0.031 & < 0.168	> 0.168

Accuracy by time frame

	30 days	90 days	180 days
Accuracy	0.414	0.390	0.366

From the table above, we can see the correlation between the sentiment scores and the returns were slightly positively correlated that sizzles out as time goes on.

Accuracy by sector

Best performing sector

Sector	Health Care REITs	Health Care Services	Personal Products	Hotels
Accuracy	0.571	0.542	0.534	0.532

Worst performing sector

Sector	Life Sciences Tools & Services	Interactive Media & Services	Electric Utilities	Oil & Gas Equipment & Services
Accuracy	0.235	0.243	0.277	0.281

From the tables above, the accuracies are lackluster across sectors, with the best performing ones merely better than random probability of 0.5.

Relatively speaking, Cramer's predictions on stocks from traditional sectors, such as the health care sector, are more accurate.

Backtest results

Strategies	Sharpe	CAGR %	Drawdown %	Net Profit %	Win Rate %
Cramer-follower	-0.484	-8.136	38.5	-34.119	44
remarC-L/S	**0.389**	**5.245**	26.8	**28.582**	55
remarC-L	0.342	3.792	31.5	20.088	49
remarC-S	0.309	2.075	**10.2**	10.628	**57**

The performance of the strategies is assessed using several metrics, including Sharpe ratio, compound annual growth rate (CAGR), drawdown, net profit over the 5 year period, and win rate (percentage of winning trades over losing ones). The table above provides a summary of the results for each strategy.

The Cramer-follower strategy underperformed, with a negative Sharpe ratio of -0.484 and a CAGR of -8.136%. The maximum drawdown was 38.5%, and the net profit and win rate were also unfavorable, both suggesting that following Cramer was not profitable.

Among the three inverse cramer strategies, the original variant (Long Bottom 5, Short Top 5) performed best with a CAGR of 5.245%. However, it still significantly underperformed the S&P 500 benchmark, which achieved a 15% CAGR during the same period.

In conclusion, following Cramer's recommendations was unprofitable, and inverting them did not yield alpha.

Future work

In terms of portfolio construction, integrating a sentiment weighted ranking system could be a direction for future improvements. Further hyperparameter optimization could also enhance the alpha of the inverse strategy, for example to change the rebalancing period, stop-loss threshold or better trade timing with technical indicators.

Regarding data processing, more work could be done to properly filter relevant tweets, without relying solely on the appearance of cashtags. We could further explore the extraction of stock tickers by fine tuning pre-trained transformers on our specific use case to carry out named-entity recognition.

Conclusion

In conclusion, our analysis did not reveal a substantial correlation between Jim Cramer's recommendations and stock returns, nor did we identify alpha by inverting his stock picks. These findings suggest that the Cramer Effect may be attributed to confirmation bias rather than a consistent market anomaly.

The results of our analysis indicate that media-driven narratives, such as the Cramer Effect, may not always hold true in practice. Investors should approach such claims with skepticism and rely on their own research and due diligence to make informed decisions.

References

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