Exploring Stock Market Strategies with Risk and Influence with Complex Networks

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Abstract—This project explores the impact of risk strategies in a complex network of brokers, simulating the stock market over different intervals. It shows how some risk strategies can perform well over typical behavior of the market while others benefit from sudden volatile events. It also explores how influence of broker's friends on the risk assessment can affect the portfolio value over time.

I. INTRODUCTION

This project was designed with the objective of exploring the impact of risk as defined by a power law distribution and networked brokers in the context of neighbor influence on the brokers' portfolio values over different trading intervals. Economic markets are volatile and have been shown to contain many fat-tailed and power law distributions, such as in growth rates and stock returns [1]. Many different models of the market have been created to explore these behaviors, and data is readily available to examine the impacts of different strategies and inter-dependencies on the market. Scholars have examined risk and risk aversion, explored modeling the market as a network of stocks or brokers, attempted to classify and group the networks, and attempted to design models of crashes that resemble the real world. This project combines the study of risk in psychology with the fat tailed distribution of network connections and the volatility of black swan [2] events to evaluate market broker strategies to maximize portfolio value over typical events and through drastic changes in the market.

II. BACKGROUND

This topic has been explored from a variety of perspectives. Most work has been divided into exploring financial markets in terms of complex networks, looking at individuals' perspective on risk, and running case studies with different clustering and strategies in the market. The work in complex networks creates networks with either brokers or stocks at nodes [16], [6], [7]. To create the edges, they have explored the diffusion of information [7], spread of first and rebound shocks [8], and correlation and mutual information of different stocks [10], [11]. This study models the market with brokers at the nodes with influence connecting the brokers.

Further, several models for risk were presented. This involved quantifying the risk with the Chen, Roll, and Ross factors [12] to predict economic activity, assessing the importance of the distribution of risk aversion in the volatility of returns [13], and highlighted the importance of dividends in quantifying the risk level of stocks. These

models provide a basis for developing a model of portfolio risk.

Based on the ideas presented in Taleb's book [2], it has been suggested that some strategies which perform best over typical market moves may not be optimal during sudden volatile events, which characterize the stock market. The idea that these strategies based on risk with the input on risk assessment from neighbors could be what differentiates the quality of the strategies.

III. METHODS

The exploration of the market was designed as a simulation to be run over various time intervals for interconnected brokers that can influence one another and preferred risk levels. This included creating 100 brokers each with a preferred risk level and a number of friends sampled from a power law distribution. The friends also provided their assessment of risk for a given stock which was considered by the broker in their personal assessment. Data for every day in the interval was fed into the simulation, allowing brokers, in a random order, to buy or sell stocks to maintain their preferred level of risk. For interpretation of results, the brokers' indices correspond to the level of preferred risk. Running the simulation over 2003-2012 allows examining the results of strategies both in normal operating and in a drastic events such as the 2007-2008 financial crisis.

A. Data Collection and Filtering

The available tickers were collected from Yahoo Finance's API, yfinance. This API made requests to Yahoo Finance with a request limit being placed on each IP. Fortunaty, the University of Cincinnati offers multiple CPUs in their computer labs. First, all the valid stock tickers were pulled that contained daily stock information from the time peroid of 2000 to 2020, totally 10,000 individual tickers. These tickers were filtered to those with the information needed for the risk calculation in section III-C and 150 stocks were randomly selected from those options to be fed into the simulation. This data was then stored in a pandas dataframe for quick accessbility by the simulations at runtime.

For these stocks, if the price data was missing on a specific day, its price was set to be the most recent value from the time series. Further certain values such as dividend rate and estimated earnings per share were available only as single values instead of time series. This creates inaccuracies in our risk calculation as these single values do flucuate over time, however it is a limitation

of the API. Additionally, Yahoo finance does not record tickers that take their ticker off the public stock market, for reasons such as banrupcy or private buyout. This is a glaring limitation in this simulation as these stocks were not captures in the simulations.

B. Influence and Friend Selection

The number of friends for each broker was selected with a fat tailed distribution with $\alpha = 2.7$ and a minimum value of 2 friends. The set of friends F were selected randomly from a uniform distribution over all the brokers. Each friend started with a set percent $w_i = .04$ controlled of the broker i's risk assessment. Thus, the risk for a stock s was represented with the formula

$$R(s) = (1 - \sum_{f \in F} w_f) R_{broker}(s) + \sum_{f \in F} w_f R_f(s.)$$

C. Risk Calculation

D. Metrics

The portfolio value $V(b_i)$ at any point in time was represented as the sum of the liquid money m_i the broker b_i had and the current value v_s multiplied by the quantity q_s of every stock owned by the broker at the given time: $V(b_i) = m_i + \sum_{s \in stocks} v_s q_s$. Its risk is evaluated as the risk for every stock in the portfolio multiplied by its volume. The portfolio risk was used to quantify the level of risk each broker attempted to maintain while the portfolio value at different times in the interval was used to evaluate the strategy's overall performance.

IV. RESULTS

A. Risk

B. Broker Tendencies

As mentioned in III, the index at which each Broker is labeled as directly correlates with the relative initial risk compared to other indices. From this, information can be gleaned from figures of metrics vs broker ID and how these metrics relate to the risk adversion of the brokers. Notabily, a few tendencies commonly developed. These are the owership of individual stocks, the owership of total stocks, and the value of liquid assets.

Fig 1 shows that both low risk and high risk Brokers both tend to own few stocks compared to that of their medium-risk Brokers. This ownership appears to be parabolic with flat curve defining the maximum. Further tedencies descibe why this shape appears.
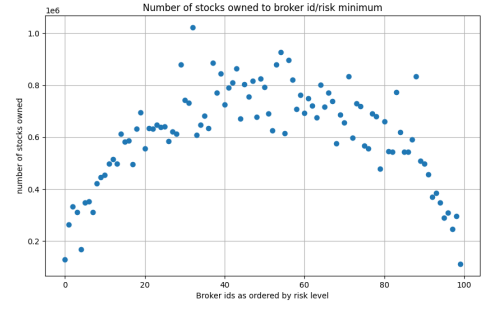

Fig. 1: Total number of stocks owned by Broker Id

Fig 2 assists in describing how the total number of stocks owned has two values. Here, the levels at which unique stocks are owned in inverted compared to Fig 1. Both risk adverse and risky Brokers tend to own a number of unique stocks while those with medium risk tend to own more of the same type of stocks. The ownership of multiple stocks in different industries can be seen as less risky as owning more individual stocks allows certian investments to fail without affecting the total as much. This is compared to a high ownership of a specific stock, which if goes under, results in the entire portfolio going under as well.
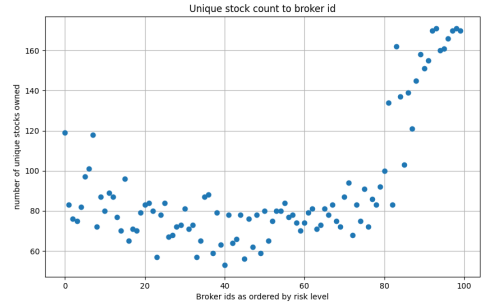

Fig. 2: Unique stocks owned by Broker Id

Finally, the amount of liquid assets of each Broker paints a clear picture of the differing investment strategies of that of low and high risk investors. Fig 3 shows that risk adverse Brokers tend to keep as much as 100% of their assets liquid, that is not invested in the market. Meanwhile, the medium and high risk Brokers tend to invest most of their assests into the market. These three figures paint the various strategies that Brokers with varying levels of risk adversion use.
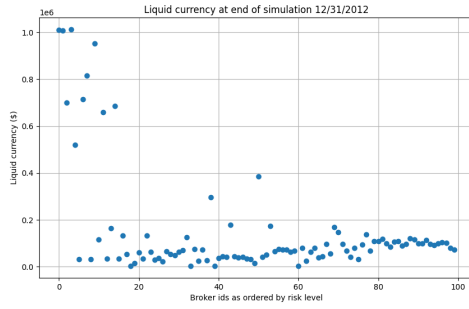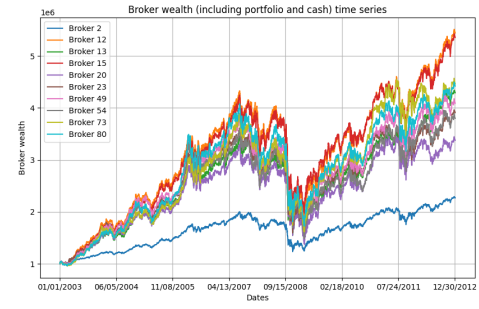
Fig. 3: Liquid currency vs Broker Id

Fig. 5: Timeseries of Broker Wealth

C. Market Strategies

Each strategy is followed throughout the period of 2003 to 2012, with the occurance of the black swan event, the 2008 financial crisis occuring during this time period. Therefore, it is benifical to analyze how different risk stragies performed with and without the black swan event to determine if certian strategies are better given antifragile thinking. Fig 4 shows that pre 2008 both high and medium risk strategies outperformed low risk strategies. However, the most risky Brokers were significantly underperforming their peers. It is important to note that all brokers were able increase their portfolio value over this time.
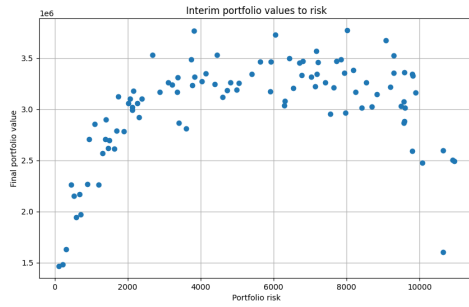
As was the case for the Fig 4, the medium risk brokers appeared to have aquired the most wealth. Fig 6 differs from the pre-black swan event wealth in a few key catagories. First, high risk Brokers were punished significantly worse than before the black swan event. The curve in Fig 6 is very parabolic where both the low and high risk Brokers did not aquire as much wealth as the average risk Broker. This is in comparison to Fig 4, where the curve flattens and stays flat. That is high risk Brokers also perform well.
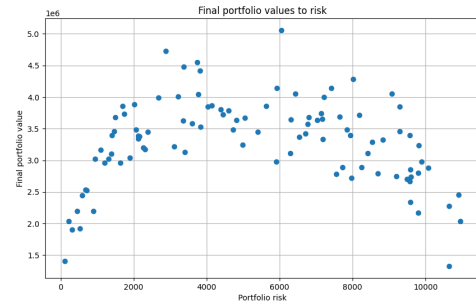

Fig. 6: Value of Portfolios by Broker Id

Fig. 4: Value of Portfolios before Black Swan event

D. Antifragile Strategies

Both Fig 5 and Fig 6 show the resultant wealth of Brokers throughout the simulation. Fig 5 shows the time-series of each of the portfolios. A few tends are of note. Firstly, the total wealth of the Broker's assets all appear to follow the general market trendline, and therefore all follow eachother. All of the brokers hit a significant loss due to the 2008 financial crisis, however it is import to note that all the Brokers "road out the wave" and kept their assets. This resulted in, by 2012, the Broker's regaining the wealth that they aquired before 2008. Other Brokers rebounded significantly well as compared to their peers, specificly those brokers with medium risk.
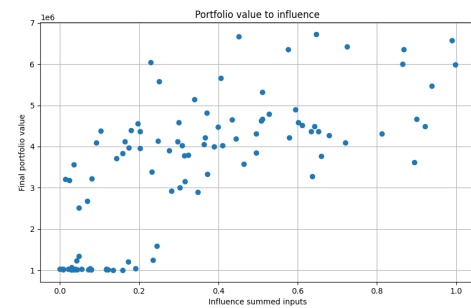
E. Influence

Fig. 7: Plot of portfolio values to percent of decision made based on friends' recommendations on risk
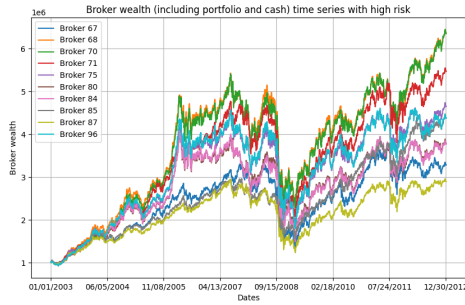
Fig. 8: Time series of portfolio values of brokers with high risk ordered by number of friends providing input on risk assessment for stock purchases
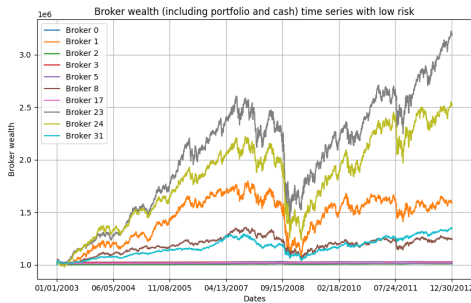

Fig. 9: Time series of portfolio values of brokers with low risk ordered by number of friends providing input on risk assessment for stock purchases

The simulation examining the impact of influence assigned the brokers to either a low, medium, or high risk level. Within each group, the brokers were ordered from lowest amount of initial friends to greatest quantity, sampled from the fat-tailed distribution discussed in III-B. The plot in Figure 7 shows that allowing a large 50-100% portion of the purchase assessment to be made with input from neighbors improves the portfolio value. While there is a wide range of values coming from a given influence, it generally improves up to around 50% of the risk assessment being provided by friends. This is likely because taking multiple neighbors' input highlights stocks that are doing well for multiple different brokers, making the decision easier and capturing the change in value directly that the risk assessment did not capture. Further, it can be seen that this benefit of influence was consistent across the different risk levels by examining Figures 9 and and 8. It is notable that basing the influence connections of the network around the risk assessment provides an expansion on a single broker's understanding of the stocks behavior but did not entirely capture the additional benefit of accessing partial information as desired.

V. CONCLUSION

This project explored the value of different risk strategies in a simulated market of networked brokers with power law assumptions for risk and connectivities between brokers.

It demonstrated the value of taking some input from neighbors' assessments on risk to filter which stocks are actually performing well and showed ...

A. Future Work

Given the scope of time for the project, only limited aspects of market strategies could be explored. One open area in which limited advances were made was exploring the impact of the influence of neighbors' assessment of risk on the success of a strategy. Because all neighbors used the same information and formula, except for the accounting of their personal status, the impact of influence could be expanded. Further, the risk assessment would be modified to vary more between brokers based on partial information and stocks without full information available to better represent the real world and better account for the interconnections between stocks.

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