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Evaluating Portfolio Performance by Highlighting Network Property and the Sharpe Ratio in the Stock Market

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Abstract—Selecting a portfolio for investing is a crucial decision for individuals and legal entities. In the last two decades, with economic globalization, a stream of financial innovations has rushed to the aid of financial institutions. The importance of selecting stocks for the portfolio is always a challenging task for investors. This study aims to create a financial network to identify optimal portfolios using network centralities metrics. This research presents a community detection technique of superior stocks that can be described as an optimal stock portfolio to be used by investors. By using the advantages of a network and its property in extracted communities, a group of stocks was selected for each of the various time periods. The performance of the optimal portfolios was compared to the famous index. Their Sharpe ratio was calculated in a timely manner to evaluate their profit for making decisions. The analysis shows that the selected potential portfolio from stocks with low centrality measurement can outperform the market; however, they have a lower Sharpe ratio than stocks with high centrality scores. In other words, stocks with low centralities could outperform the S&P500 yet have a lower Sharpe ratio than high central stocks.

Keywords—Portfolio management performance, network analysis, centrality measurements, Sharpe ratio.

I. Introduction

WITH the advent of the new portfolio theory in the late 1960s and the shift of industry owners investing in diversified assets to mitigate the consequences of risk, the competitive environment in the dynamic business world gradually narrowed. In addition, the dramatic growth of the level of communication and rapid exchange of information, along with the various complexities of the coming decades, intensified business competition. The term portfolio is a combination of stocks with other assets that an investor has purchased. In simpler terms, the "portfolio" means forming a combination of different shares and not investing in one share, which is an intelligent measure to reduce the risk of investing in the stock market. To succeed in the corporate stock market, choosing the right approach and maintaining coherence and order, like any other economic market, is important. Without a strategy, investing will only be unplanned buying and selling, affecting the investor's capital and profit or loss. Therefore, portfolio investing is a critical and vital decision for individuals and legal entities, and portfolio diversification is a technique for managing risk and capital. In this research, we used population analysis by employing a correlation network model to extract communities and select a potential portfolio that could outperform the market. Networks play an important role in a wide range of economic phenomena because the economy can be considered as a network in working progress. Using the graph properties and the graph theory results can examine a network or economy conventions. The economy's behavior is not isolated from the behavior of individuals; therefore, the economy as a network works as a state of transformation.

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Analysis of the network involves the recognition of which vertices are connected to others in a graph. Each stock is assumed as the graph's vertices, and edges represent the relationship between vertices. Applying population analysis helps us compare individual data points with other data points in different communities regarding different performance levels. Population analysis allows us to compare two or more communities of companies with respect to one or more enrichment parameters. The result of this analysis enables us to discover the parameters that significantly affect a community [1].

In this study, different correlation networks were created based on the different datasets in different time periods. The potential portfolios were selected based on network properties, centrality measurements, and the Sharpe ratio. In the next step, the performance of the potential portfolios was compared to the S&P500 to check if those potential portfolios can predict the market. This study attempted to evaluate the presented model's ability to identify the stocks with the most diversification in terms of economic sectors and company sizes.

The remainder of this paper is organized as follows; Section II will provide a brief literature review of related studies about the portfolio theoretical framework. The following section (Section III) gives an overview of the methodology and its components (data collection, network and community detection, centrality measurement and Sharpe ratio implication). Section IV addresses the results of section III, and finally, Section V presents the discussion, the limitations, and the future work.

II. Literature Review

A portfolio, known as a portfolio of assets or an investment, is a combination of diversified assets that can include investing in housing, banks, stock exchanges, coins, currency, gold, and so on. So far, two approaches to building a portfolio have been adopted: the traditional and modern approach [2]. The traditional approach implies that all investors should have a personal portfolio that is unique and tailored to their needs [3]. This means that investors need to estimate the yield on the securities they intend to invest in before making their portfolios. Then, after estimating the yield, they select the securities that are expected to have the highest returns in the future for investment. American economist Harry Markowitz criticized the traditional portfolio theory [4]. He believed that it was almost impossible to find a share with the lowest risk and highest return, and that if people wanted to build a good portfolio, they need to find a balance between risk and expected return [5]. Markowitz believe that people should not only measure the risk but return of an asset for investing led to Modern Portfolio Theory. The theory was formed on the assumption that investors are inherently risk-averse, but their ultimate purpose is different [6]. In a 2004 study, Roy tried to provide a practical way to determine the best amount of interaction between risk and return. According to Roy, investors initially sought to preserve their original capital, then they would consider the minimum rate of return for their capital [7]. Therefore, they tried to avoid selecting the stocks/assets that had high deviations in their returns. Researchers in 1994 tried to evaluate investment funds' performance [8]. They used the word undesirable deviations for funds with a rate of return below the target rate. Their analysis of monthly data for the previous ten years in December 1992 for two mutual funds and six stock market indexes proved the usefulness of risk to be undesirable in evaluating the performance of capital funds [8]. Designing a framework of eighteen retirement funds for performance assessment based on Sharp ratio showed that undesirable risk in performance evaluation of assets is much better than focusing on the returns' standard deviation [9].

The question now is how do investors optimize their portfolios for the highest expected return with different levels of market risk? Modern Portfolio theory holds that there is no such thing as a full investment. What is important and should be considered is choosing a high-yield strategy, along with proportionate risk. Modern portfolio theory argues that individuals can design an ideal investment portfolio that maximizes returns by considering the optimal amount of risk. By investing in more than one share, the investor can gain the benefits of diversification while reducing their risk. In order to calculate portfolio risk, the variance of each asset along with the correlations between each asset pair can be calculated [10]. The correlation between assets, the percentage of investment in each asset, and the number of different stocks in which they are invested affect the total portfolio risk [10]. With building a diverse portfolio, the risk of high-risk assets will decrease by adding low-risk assets to the portfolio. In fact, by adding securities such as treasury securities and units of investment funds, the risk of the entire portfolio can be reduced.

According to this theory, risk per share consists of two types. The first type is the systematic risk or market risk that cannot be eliminated (such as recession, changes in interest rates on bank deposits, etc.). The second type of risk is an unsystematic risk (risk per share that may result from poor management or sales) [11]. In fact, diverse portfolio is a model for the optimal allocation of an individual's wealth invented between risky assets. This model was focused on only the two factors of expected return and variance. In a 2002 study, Lien examined the relationship between risk and return in investment and creating portfolios. He pointed out the issue of investing. He mentioned that investing in financial institutions in the form of a portfolio needs a precise evaluation of the portfolio performance from several different indicators (i.e., return, share ratio).

III. Methodology

This research is an interdisciplinary work that takes advantage of big data analysis associated with knowledge in the financial domain. In other words, this research is a combination of financial, computational, and statistical analysis. The methodology overview is as shown below:

- Computational analysis: Creating a correlation network model and assessing its property.
- Financial and statistical analysis: Examining the Sharpe ratio focusing on the financial theoretical framework.
- Comparison: Comparing the portfolio performance with the benchmark.

To summarize, first, the centrality measurements (Betweenness, Closeness, Eigen centrality) will be calculated for stocks in communities extracted from the correlation network. Second, based on assessment of centrality scores, a collection of stocks as the potential portfolio will be selected, and finally, the portfolios' Sharpe ratio will be calculated in order to check the portfolio performance against the benchmark.

A. Data Collection and Procedures

The data were collected from ”the Center of Research in Security Prices” (CRSP) for the past 20 years. For analysis, the initial dataset was divided into four datasets for every five years, starting from 2000 and ending with 2019. Different correlation networks were created from different time periods depending on different sets of data. For example, one correlation network was created based on the excess returns of the companies for 2000-2004 inclusively, and another was a network for companies from 2005-2009. To avoid bias selection, all companies existed in each five-year dataset included in the analysis. Therefore, there was a range of 4000 to 6000 companies from different economic sectors and sizes in each dataset. Each dataset contained companies' Ticker, excess return, and companies' economic sectors.

B. Network and Community Detection

Stock returns and their changes are among the most important factors in assessing the economic value of a company in the stock market, which reflects the investment decisions of individuals in the economic environment. Stock return changes are not independent of each other. Hence, studying the correlation of stock behavior changes provides investors with a greater understanding of market performance. Stock market analysis based on networks provides a study of stock returns' correlations. To test the result of our proposed model and check to see how companies and their returns volatility behave during the time, we divided the data into different sets of 5 years. Companies' returns were subtracted from risk-free to get the excess return parameter. The networks were created based on this excess return parameter. The financial market network is one of the most complex networks, which brings significant challenges to visualization. Creating communities from this complex network consumes considerable time. After constructing correlation networks from input data, hidden knowledge was extracted from the network by using community detection and measuring network centralities. Identifying communities containing highly correlated stocks provides information that can be used along with network properties, such as centrality measurements, to identify optimal portfolios. The Louvain algorithm was applied to the network as a data analysis shortcut tool and grouped different companies with high correlations or similar financial behavior over the period of study [12]. Table I shows the number of nodes in each network following with selected communities' nodes. For example, in 2000-2004, there were 4280 nodes in the network and out of 4280 nodes, 3389 nodes grouped in different communities. Communities 1,2 and 3 selected for further analysis since out of 3389 nodes, 3269 nodes distributed in those three communities.

TABLE I
NUMBER OF NODES IN EACH NETWORK (N.N), NUMBER OF NODES IN SELECTED COMMUNITIES (N.C), SELECTED COMMUNITIES (S.C) AND TOTAL NUMBER OF NODES IN SELECTED COMMUNITIES (T.N.S.C)

Year	N.N	N.C	S.C	T.N.S.C
2000-2004	4280	3389	1,2,3	3269
2005-2009	4083	3590	1,2,3	3539
2010-2014	4489	1495	1,2	884
2015-2019	5211	3481	1,3	2228

This research relies on population analysis based on enrichment analysis on communities extracted from the network. For the robustness of our work, different correlation coefficients, Betweenness, Closeness, and Eigen centralities were examined within each community. Enrichment analysis as the in-depth analysis was applied in each community to get more information about stocks characteristics such as size and economic sectors.

C. Centrality Measurement and Sharpe Ratio Implication

Centrality measurements are the number of direct links between a given node to other nodes. When a node makes many connections in a network, a wide range of relationships are established between this node and others. In this research Closeness, Betweenness and Eigen centrality were measured for each stock. Closeness centrality is the sum of the total distances from one node (v) to all other nodes in a network [13]. The Eigen centrality measures a node's impact based on the number of links to other nodes in the network. The Eigen centrality reflects the importance of nodes connected to the current node because not all nodes are equivalent [14]. Betweenness centrality measures the number of times a node acts as a bridge along the shortest path between two other nodes [15].

After measuring centrality scores, the specific algorithm was constructed based on the equal weightage of the centrality scores came from Closeness, Betweenness and Eigen centrality for this study. As a result of this algorithm, the final centrality score was obtained in order to select the stocks in the portfolio that could outperform the benchmark. Different potential portfolios were selected based on the high and low final centrality score. In the next step, the Sharpe ratio was calculated for all potential portfolios in the manner of low and high central scores.

The Sharp ratio measures risk-adjusted returns and has become the industry standard to examine stock/portfolio performance [16]. Modern Portfolio theory states that adding assets to a diversified portfolio in which the assets are less than one when correlated with each other can reduce portfolio risk without sacrificing returns. Such diversification will help increase the Sharp ratio of a portfolio. The Sharpe ratio can also help explain whether portfolio excess returns are due to smart investment decisions or from additional risk. Although a portfolio can benefit from a higher return than its counterparts, it is only a good investment option if the additional risk does not accompany the higher return. The larger the Sharp ratio of a portfolio, the better its adjusted performance is relative to risk. The performance of each potential portfolio was compared to the benchmark as well as the amount of Sharpe ratio for low and high centrality score.

IV. RESULT

In this study, five correlation networks were created for datasets: 2000-2004, 2005-2009, 2010-2014, and 2015-2019. In the process of creating the correlation networks, different correlation coefficients were tested to find the network containing stocks that had the highest similarities in their excess returns. Since the datapoints were distributed normally, the Pearson correlation coefficient was used in constructing the networks [17, 18]. For avoiding sample bias issues, in the process of filtering and cleaning the data, stocks that existed in each five-year range were selected regardless of presenting in another datasets. Extracting knowledge from complicated networks is not an easy task, therefore the Louvain algorithm was applied in each network and communities with the highest number of nodes selected for the further analysis. After measuring the degree of the centralities, another filtering step was performed for each community. Stocks in each community were divided into subcommunities with high and low degree of centrality. According to the stocks' characteristics in each of the subcommunities, subcommunities with high and low degree of centrality were considered as potential portfolios. Further analysis based on enrichment analysis showed that subcommunities with low degree of centrality contained stocks that had higher diversity in the sense of companies' size and economic sectors, meaning that subcommunities with a low degree of centralities had stocks that belonged to most of economic sectors (range of 12 economic sectors) and a fair range of large and small size of companies.

The potential portfolios were compared against the market. The results showed that portfolios containing stocks with low degree of centrality could outperform the benchmark compared to higher-central stocks. Fig. 1 shows that portfolios containing stocks with low degree of centrality could outperform the benchmark compared to portfolios containing stocks with high degree of centrality (Fig 2). In Figs. 1 and 2, Blue Line is potential portfolio and red line is benchmark. This result was consistent for all potential portfolios selected from correlation networks for the time periods 2005-2009, 2010-2014 and 2015-2019 and their communities.

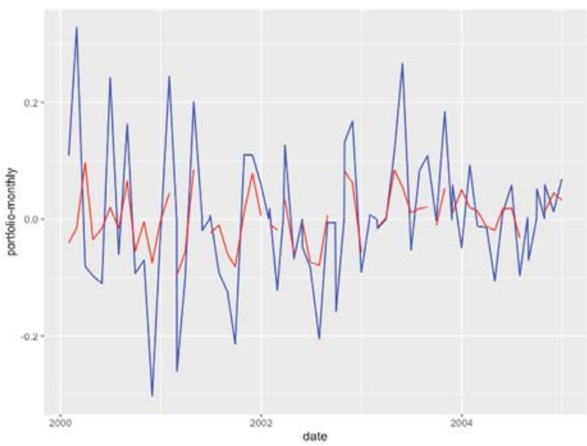

Fig. 1 Low-central stocks-2000-2004

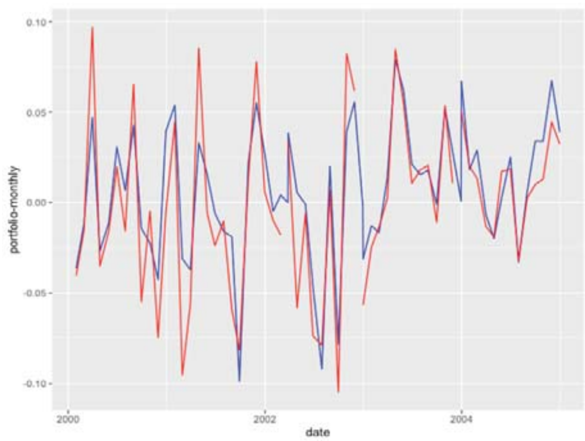

Fig. 2 High-central stocks-2000-2004

In the next step, portfolios' Sharpe ratios were measured for each high- and low-central subcommunity. The result showed that the Sharpe ratio for low-central stocks was slightly lower than high-central stocks; meaning that they were less profitable than higher-central stocks. However, they could outperform the market with less deviation from market movements.

V. Discussion and Conclusion

Applying population analysis employing correlation networks, community detection algorithms, and enrichment analysis proved that this model could predict the benchmark trend. Different centralities were measured for stocks in each community, and a specific algorithm was constructed based on the equal weightage to create the final centrality score for each stock. We examined different portfolios categorized based on low and high final centrality scores. Enrichment analysis showed that low central stock portfolios had higher diversity in size and economic sectors. Our model identified portfolios with low final centrality scores and greater diversity as candidate portfolios that could predict the market trend better than portfolios with high final centrality. This research concludes that the general statement about the meaning of centrality measurements is not always correct, meaning that nodes with high centrality scores are not always the important entities. This study found that the importance of nodes does not rely on high centrality measurement but also on the network model structure. In this regard, to reduce the risk of portfolio profitability and be able to predict the market, we must choose stocks for the portfolio that have a low degree of centralities. Since the Sharp ratios for portfolios containing stocks with high degree of centrality are slightly higher than portfolios containing stocks with low degree of centrality, future research should focus on the optimization strategy as it changes the weight of stocks in low-end portfolios to increase Sharpe's ratio. Therefore, the portfolio will predict the market well and have a good amount of profitability.

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