# APPLICATION OF COMPLEX ADAPTIVE SYSTEMS IN PORTFOLIO MANAGEMENT

by

Zheyuan Su

A dissertation submitted to the faculty of
The University of North Carolina at Charlotte
in partial fulfillment of the requirements
for the degree of Doctor of Philosophy in
Computing and Information Systems

Charlotte

2017

Approved by:

______________________________
Dr. Mirsad Hadzikadic

______________________________
Dr. Xi Niu

______________________________
Dr. Zbyszek Ras

______________________________
Dr. Wlodek Zadrozny

# ABSTRACT

ZHEYUAN SU. Application of complex adaptive systems in portfolio management. (Under the direction of DR. MIRSAD HADZIKADIC)

Simulation-based methods are becoming a promising research tool in financial markets. A general Complex Adaptive System can be tailored to different application scenarios. Based on the current research, we built two models that would benefit portfolio management by utilizing Complex Adaptive Systems (CAS) in Agent-based Modeling (ABM) approach. Models include performing sector rotations in GICS classified sectors and releasing single stock (Bank of America) trading signals in the US stock market. The multi-agent models are implemented using the Netlogo framework. Both models utilize historical data and produce returns that exceed benchmark returns, which are Buy and Hold strategies on S&P 500 Index and Bank of America stock respectively.

# ACKNOWLEDGEMENTS

In pursuit of the Ph.D. degree, I have received much help, suggestions, and inspirations from many people. Hereby I would like to express my appreciation and gratitude to all of them.

I would like to gratefully and sincerely thank my supervisor Mirsad Hadzikadic for his guidance, understanding, and patience in my research. He created the opportunity for me to bridge the gap between accounting and finance with the techniques in information technology. He also offered me lots of useful suggestions and research ideas. His wisdom, knowledge and commitment inspired and motivated me during the process of my research.

I would also like to convey my appreciation to my dissertation committee members: Dr. Mirsad Hadzikadic, Dr. Xi Niu, Dr. Zbyszek Ras, and Dr. Wlodek Zadrozny for your time and effort on my dissertation.

I would like to thank the faculty members in University Research Computing for providing reliable high performance clusters for our research.

The last but not the least, I would like to thank my parents, parents-in-law and wife, for their support, their faith and allowing me to be as ambitious as I wanted and to do what I thought.

TABLE OF CONTENTS

# LIST OF TABLES

# LIST OF FIGURES

# LIST OF ABBREVIATIONS

| | |
|---|---|
| ABM | agent-based modeling |
| ATS | automated trading systems |
| BAC | Bank of America |
| CAS | complex adaptive systems |
| EBITDA | earnings before interest, tax, dividends, amortization |
| EV | enterprise value |
| EV/EBITDA | enterprise value / earnings before interest, tax, dividends, amortization ratio |
| HPC | high performance computer |
| GDP | gross domestic production |
| GICS | global industry categorization standard |
| MSCI | Morgan Stanley Capital International |
| NASDAQ | National Association of Securities Dealers Automated Quotations |
| NYSE | New York Stock Exchange |
| P/E ratio | price / earning ratio |
| S&P | Standard & Poor's |

# CHAPTER 1: INTRODUCTION

## 1.1 Sector Rotation and Business Cycles

Sector rotation is a ubiquitous phenomenon in the stock market. It refers to the well-known phenomenon of certain sectors outperforming other sectors over a specific period of time. Figure 1 (retrieved from WallStreetCourier.com) illustrates the possible scenarios of both market cycles and economic cycles.

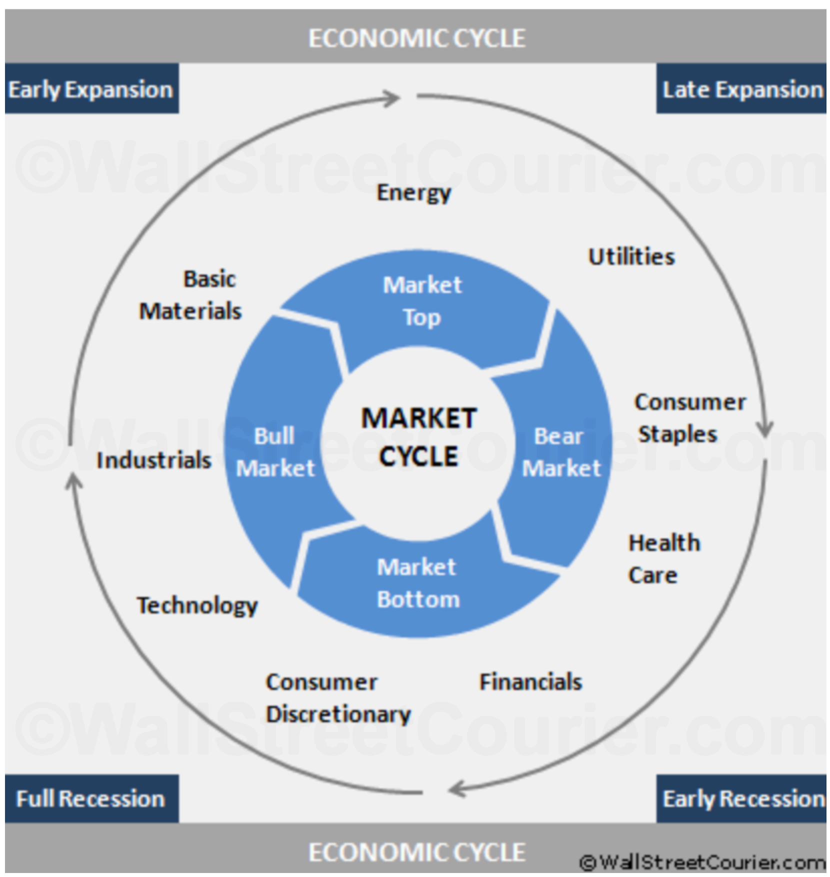


FIGURE 1: Business Cycle vs. Sector Rotation

There are four stages on economic cycles: early expansion, late expansion, early recession, and late recession. Similarly, there are four stages in the market cycles: bull market, market tops, bear market, and market bottoms. Here bull market means the majority of the stock prices increases while bear market denotes the price of the most of the stocks traded in the market are ebbing.

Pring (2010) showed the financial cycle is about one year ahead of the economic cycle. What we know is a full bull and bear cycle is around 10 years. But we don't know is what the current position in the cycle is, such as when exactly the bubble will burst, when the market insanity will disappear and when will the bull and bear market start or end.

In sector rotation strategy, we are interested in how to determine the leading market sectors having the largest price increment, what the preference of the market is and how to select the move of sector follows our expectation most, which in turn will bring the most profits. In the view of market participants, the selection seems to be random, but we believe business cycle plays an important role in it.

## 1.2 Automated Trading Systems

In the past score, more and more computerized automatic algorithm trading mechanisms are put in to the practice in the current world with the fast development in computer science industry. An automated trading system (ATS) is a computer program that automatically creates and submits the corresponding stock exchange. At the end of 2014, more than three quarters of the stock shares traded in NYSE and NASDAQ are originated from automated trading systems. For the underlying assets that are traded by ATSs, they can be stocks, options, bonds, futures, and foreign exchange products. ATSs traded these products based on a predefined set of rules, which determines when to enter the market, liquidate the portfolio, and the amount of money to be put into each investment products. There are various trading strategies used in the ATSs. These strategies differ a lot based on the risk preferences, capital adequacies, sector type favors, market trend simulations, etc.

However, the mainstream trading mechanisms of the ATSs are to analyze a huge quantity of historical data. Based on the historical trading data, pre-defined trading rules are generated for future use. Also the ATSs execute the predefined trading rules and not taking human emotion into consideration. Another disadvantage is ATSs may have over-optimization problem for some time. Over-optimization refers to excessive curve fitting that produces a trading plan that is unreliable in live trading. One possible way to solve the over-optimization is to increase the adaptability of the model in various scenarios.

### 1.3 Traditional Securities Analysis

The traditional way of security analysis (Graham et al. 1934) began to be replaced by the introduction of ATS. Traditional security analysis, also know as fundamental analysis, exams the underlying financial health of companies by inspecting the business's core elements. The major source of information is from the financial statements, including income statements, balance sheets, and cash flow statements. At the same time, the current economic condition is also taken into consideration. The next step is to compute different ratios and compare it with the industry thresholds to see if the performance of the company is on track. In the end, the intrinsic value of the underlying assets will be derived and compare with the current stock price to get the corresponding position when entering the market. If a stock is undervalued, a long position will be taken while a short position will be taken if a stock is overvalued.

## 1.4 Effective Market Hypothesis

In financial world, effective market hypothesis (Malkiel 1970) indicates that the asset prices fully reflect all available information. In order for the stock price to be fully represented in the market, the market should be strong form of efficiency market, which also implies profits exceeding normal returns cannot be made, regardless of the amount of research or information investors have access to. In another words, it is impossible to beat the market when the market has strong efficiency. Since US stock market is semi-strong (Model 1987), indicating there is still chances to outperform the market if correct strategies are utilized.

Since it is an era of big data, simply relying on financial statements is far more than enough to make trading decision based on theoretical value vs. spot market value. Market preference on different sectors will imply the possible explanation for the phenomena of undervalue or overvalue.

## 1.5 Portfolio Management

The concept of Portfolio Management refers to a strategy for investing in a combination of securities such as stocks and other investment instruments. Portfolio management is the art and science of making decisions about investment mix and policy, matching investments to objectives, asset allocation for individuals and institutions, and balancing risk against performance.

With a proper inclusion of sectors in the portfolio, investors can earn above average profits with their capital. This is true even in a financial crisis, which often brings about more investment opportunities. In recent years sector rotation has become a hot strategy in portfolio management, as it can bring extra profits while minimize potential risks.

### 1.6 Agent-based Modeling

Economies are complicated systems encompassing micro behaviors, interaction patterns, and global regularities. During the learning process of economic systems, one usually need take real-world aspects into consideration, such as asymmetric information, strategic interaction, collective learning and possible existence of multiple equilibriums. As fast development in technologies in past decades, analytical and computational tools allow introducing new approaches to the quantitative study of these aspects. One such approach is Agent-based Modeling (ABM), the computational study of economic processes modeled as dynamic systems of interacting agents.

Economies are complex dynamic systems. Large numbers of micro agents engage repeatedly in local interactions, giving rise to global regularities. These global regularities in turn will provide feedback into the determination of local interactions. The result is an intricate system of interdependent feedback loops connecting micro behaviors, interaction patterns, and global regularities.

Although mathematical modeling can give out accurate prediction, it cannot react to the current real-world change. Usually, it needs to be refined based on the current change. At the same time, large numbers of economic agents involved in distributed local interactions. Mathematical modeling cannot provide potential strategic behaviors, as there is no agent in the model. As a result, Tesfatsian proposed a method called Agent-based Modeling to solve this problem and better fit the current condition change to the model.

## 1.7 Two Models

In the research, we developed two agent-based models for portfolio management. One is sector rotation model while the other one is single stock trading signal issuance model. The reason for developing second is single stock will have a more volatile stock price, which means the scale of price change is larger than the index, which is aggregated over a bunch of stocks. Also, in the real world, it will be more realistic to buy stocks rather than to buy indexes.

In sector rotation model, agents will trade Global Industry Categorization Standard (GICS) sectors, which is developed by Morgan Stanley Capital International (MSCI) classifies S&P 500 stocks into ten sectors, based on the public available data. In the single stock signaling model, agents only trade Bank of America stock. The timeframe for sector rotation model is 38 years while the single stock trading signaling model has 19 years horizon. Both these two models significantly outperform the average market returns in the same time period.

## 1.8 Paper Organization

There are many approaches to portfolio management. Chapter 2 discusses the backgrounds of the previous research and the basis of our models. Chapter 3 gives a brief introduction of complex adaptive systems. In chapter 4, the development of sector rotation model is outlined. Chapter 5 describes a derivative model of the sector rotation model – single stock trading signaling model.  Chapter 6 shows some enhancement were made to improve the performance of the single stock signaling model as well as the possible application in interest rate policy determination. Chapter 7 wraps up this research with conclusions.

# CHAPTER 2: BACKGROUND

## 2.1 Investment Methods

Investment methods are usually classified as passive and active portfolio management (Barnes, 2003).

Passive portfolio management does not involve in distinguish favorable from unfavorable securities, or predict future securities prices, or time markets and market sectors. Passive portfolio managers put money in wide range of sectors of the markets, which is also known as asset classes or indexes. The goal of portfolio managers is to make a profit but keep a corresponding risk in corresponding portfolios.

On the information side, passive investment requires less or evens no use of information comparing with the active investment. Instead, the simply rely on long-term historical data and forecast the probable asset class risks and returns. The way they diversify risk is through allocating assets to a wide range of assets instead of put all eggs in one basket.

The frequency of rebalancing portfolio asset class is long. Passive portfolio management only involves limited buying and selling actions. Passive investors typically buy and hold investments, anticipating long-term capital appreciation and limited portfolio maintenance. As a result, passive portfolio management strategies cannot bring investors extra profits simply because they don’t have the possibility of covering a wide range of stock price movements.

An active equity portfolio management (Grinold & Kahn, 1995) requires periodic forecasts of economic conditions and portfolio rebalancing based on foretasted conditions. It might best be described as an attempt to look for good deals in financial markets by utilizing human intelligence. Active portfolio management predominate the investment strategies in the current days. Portfolio managers actively looking for profiting opportunities in the underlying assets, including stocks, bonds, commodities and foreign exchanges etc. They will also find out the best timing to enter and to exit the markets and place corresponding orders. This scenario also applies to the leveraged trading on the futures, options, and other financial derivatives.

While trying to achieve their goals in active portfolio management, portfolio managers will search for the information they believe to be valuable and possibly to be true in the market. At the same time, they have developed complex and effective proprietary methods in the selection of underlying assets. It usually encompasses different analyzing methods, including fundamental analysis, technical analysis, and macroeconomic analysis.

Fundamental analysis is the foundation of solid investing. It involves determining the current health conditions of a company by examining the core numbers in the income statements, balance sheets, earning releases, cash flow statements, and other indicators of economic releases. In fundamental analysis, investors will typically determine whether the stock is undervalued or overvalued. As a result, investors will take corresponding actions such as long or short position and anticipate the market to push the company value to the normal level.

Technical analysis is to evaluate stocks by their statistics generated by market activities, such as the trading prices and volumes in the past. The intrinsic value, which is measured primarily by the fundamental analysis, is not taken into consideration in technical analysis. Instead, charts, indicators, and other tools are actually used in the technically to predict the possible future price moves.

Literally, macroeconomic analysis mainly focuses on the health condition and future trend of economics. There are normal three indicators are monitored, national output (GDP), unemployment and inflation. The macroeconomic analysis aims at understanding how the whole economics functions. As the stock market and the economic are correlated, stock markets usually reflected the future trends in the economic ahead.

All of these methods mentioned above have the same goal of determining the profitability of the underlying assets in the coming future. Portfolio managers usually utilize combined analyzing methods in active investment and anticipate to outperform the average market indexes.

## 2.2 Sector Rotation and Business Cycles Review

The sector rotation model lies on the foundation of business cycles. Based on that, quantitative techniques are applied to predict which sector will stand out and outperform others. Conover investigated the efficacy of an equity allocation strategy that focuses on strategic shifts across U.S. equity sectors. As monetary policy plays a critical role in the capital market, it affects the market liquidity directly (Conover, 2008).

A key factor in determining the success of a sector rotation strategy is selecting indicators that effectively identify when the portfolio should be shifted to a more defensive or a more aggressive posture. Previous research conducted by the author suggests that changes in Federal Reserve monetary policy provide is a good indicator for sector rotation. Specifically, Conover reported empirical evidences showing that Federal Reserve easing has favored cyclical stocks, while Fed tightening has favored defensive stocks.

Establishing the robustness of an investment strategy requires that the strategy be evaluated over an extended period of time. The data used by the author ranged from January 1973 to December 2005. For us, our data ranged from January 1975 to December 2012. As most of the data are overlapped, Conover's result will have prominent impacts on our research.

Daily returns on the 10 U.S. equity sectors: Resources, Non-cynical Consumer Goods, Non-cyclical Services, Utilities, Cyclical Consumer Goods, Cyclical Services, General Industrials, Information Technology, Financials, and Basic Industries. The author also analyzed daily returns the market index that weighted the value across the stocks in the market.

To measure the merits of using monetary policy to guide sector rotation, Conover constructed a sector rotation portfolio by

• Equally weighting the six cyclical sectors during periods of expansive monetary policy

• Equally weighting the four non-cyclical sectors during periods of restrictive monetary policy

To ensure that the sector rotation strategy avoids any look-ahead bias and can be practically implemented on an ex-ante basis, portfolio returns are measured starting two days after an announced policy change and continue until one day after the subsequent policy change.

TABLE 1: Sector performance by monetary periods

| Sector | Expansive Period Returns | Restrictive Period Returns |
|---|---|---|
| Noncyclicals | | |
| Resources | 16.26% | 12.05% |
| Noncyclical Consumer Goods | 15.89% | 10.12% |
| Noncyclical Services | 14.34% | 8.84% |
| Utilities | 12.09% | 9.95% |
| Average for Noncyclicals | 14.65% | 10.24% |
| Cyclicals | | |
| Cyclical Consumer Goods | 22.91% | -5.4% |
| Cyclical Services | 19.6% | 0.57% |
| General Industrials | 19.12% | 5.59% |
| Information Technology | 22.33% | 1.4% |
| Financials | 19.97% | 7.15% |
| Basic Industries | 17.71% | 4.16% |
| Average of Cyclicals | 20.27% | 2.25% |

From Table 1 (Conover, 2008), we can clearly see that average returns for every sector are higher when the Fed is in an expansive period. Also, the portfolio had to be rebalanced only 14 times over the 33-year study period, so a reallocation would have occurred approximately every 2.36 years. In Figure 2, their rotation portfolio confirms the results. The results in Figure 2 (Conover, 2008) also indicate that moving to a more aggressive posture during expansive monetary periods, on average, increased portfolio returns, but at the expense of higher risk. Obviously, the portfolio utilizing sector rotations will be stand out with extra performance.

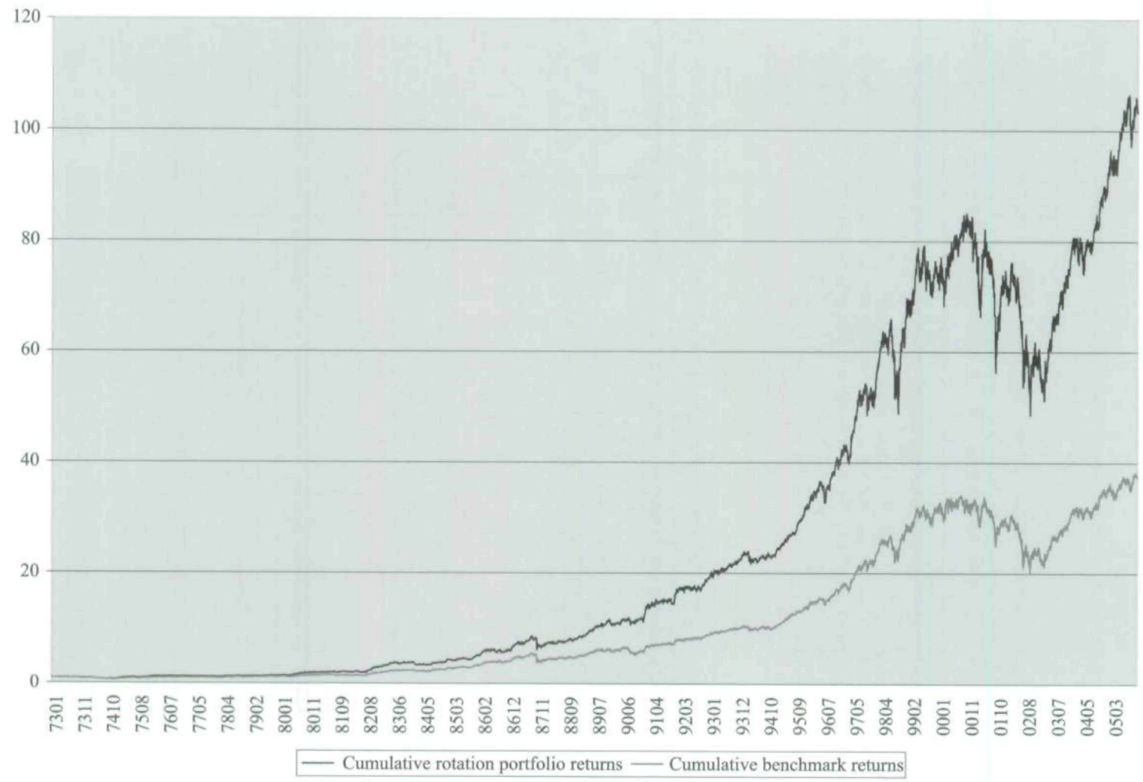


FIGURE 2: Dollar value in the sector-rotation strategy versus the benchmark

However, every cloud has its silver lining. There are limitations over sector rotation strategy. A sector rotation strategy could have been used to improve the portfolio performance in just using 33 years of U.S. equity returns. Using Fed policy changes as indicators of shifting a portfolio to a more aggressive or defensive posture would allow investors to improve their portfolio performance. Specifically, shifting into cyclical stocks following Fed changes that signal a more expansive monetary policy enhances performance, while the appropriate response to a signal of a more restrictive Fed policy is a shift into defensive stocks.

Rasmussen showed different sector will stand out and outperform other sectors under varying business conditions (Rasmussen, 2003), thus creating a cyclical behavior of sector performance. On the cash flow side, sector rotation is the capital flows from one market sector to another as investors pursue sectors that will outperform the market in a given market cycle.

The intuition behind the sector rotation model is the equities go through peaks and troughs based on the expectation of market participants on the business cycles. In business cycles, the economy and the equity markets follows a clearly defined cycle what alternates between favorable and unfavorable market conditions. The equity markets are usually six to nine month ahead of the other. That is how we connect the equity market to the change of status in business cycles.

Sector rotation assumes four stages in the business cycle: early recovery, recovery, early recession, and recession. Some characteristics in these four stages can be described as follows:

- Early recovery (Phase 1): bottoming – expansion in earnings – rising in equity market
- Recovery (Phase 2): improving – peaking in earnings – peaking in equity markets
- Early recession (Phase 3): peaking – peaked out in earnings – falling in equity markets
- Recession (Phase 4): declining – trough in earnings – bottoming in equity markets

Figure 3 (retrieved from todayinsocialsciences.blogspot.com) shows a visualization of these four stages. These four phases are designed so they comprise a full cycle.

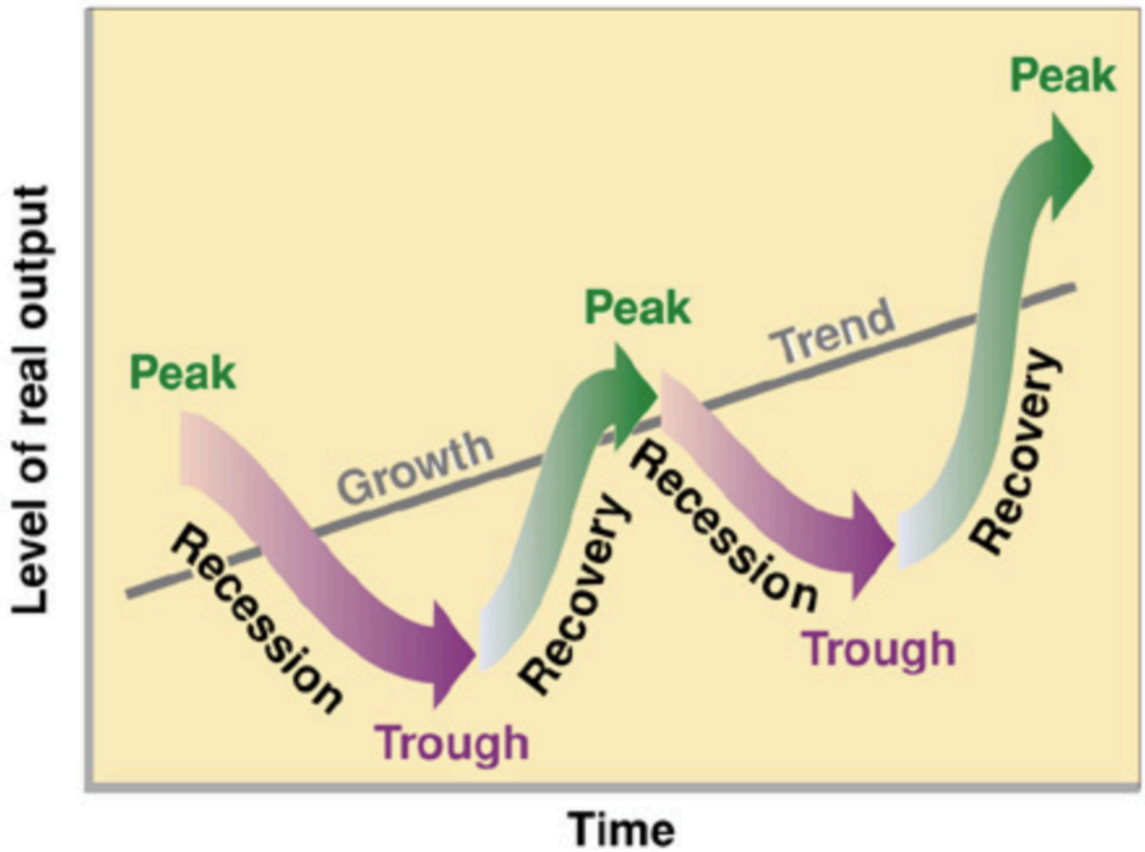


FIGURE 3: Four stages in business cycles

Figure 4 (Rasmussen, 2003) is an illustration of how the economy cycle progress over time in company with corporate earnings, and equity markets. Since business cycles will have a huge impact on corporate earnings, which will also be reflected in the stock prices, there is a strong connection between all these three elements. The black line indicates the status of economy. The dotted line represents the company earnings. The grey line shows the equity markets.

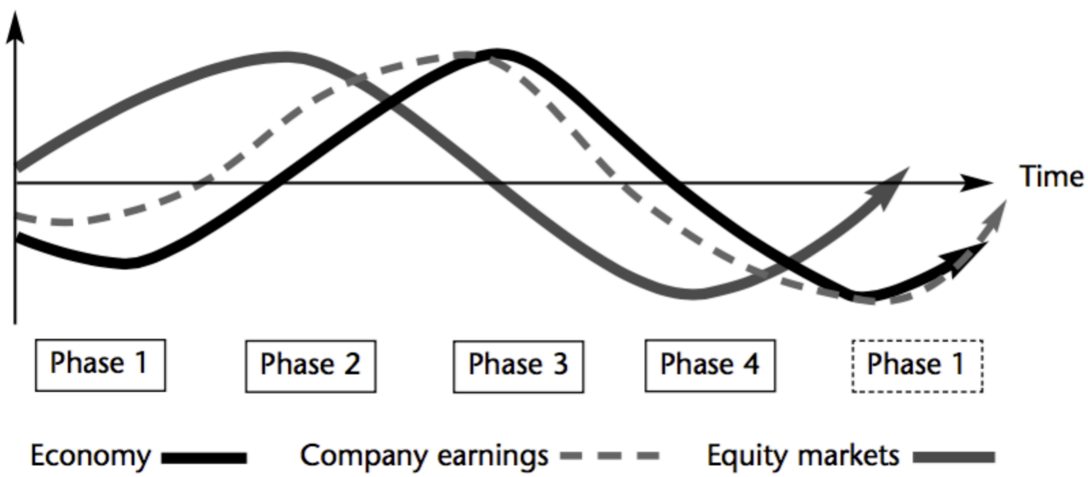


FIGURE 4: Economy, company earnings, and equity markets progress in cycles

The company earnings are assumed to lead the fundamentals of the economy. As economy booms, the amount of business activities will increase correspondingly. In return, the increased business activities feeds back to the economy through the chain reaction but with a short lag. In other words, the businesses are the first one to feel when there is a turn in the economy.

However, company earnings are led by equity markets as investors and analysts are able to obtain information about the business fundamentals before they change. While business cycles progress smoothly, the equity market anticipates the changes in economy before they actually take place. Equity markets predict the possible changes that might occur in the economy.

The table 2 summarizes the changes among economy, earnings, and equity markets.

TABLE 2: Business cycle positions

| | Early Recovery | Recovery | Early Recession | Recession |
|---|---|---|---|---|
| Economy | Low | Medium | High | Medium |
| Earnings | Low | Rising | High | Falling |
| Equity Markets | Rising | High | Falling | Low |

- Early Recovery – Rising in Equity Market

Early recovery is represented as low in macroeconomics. As recession ebbs, the speed of contraction in economy finally slows down. Therefore, the economy bottoms out and business activities started to increase again. In turn, the increases in business activities will be reflected in company earnings over time. On the other hand, one signal of booming in business activities is business investments started to grow. The demands of business activities is picking up again. Inventory begin to decrease and demand of new products grows as well.

Since the stock market is usually seven month ahead of the business cycle conventionally, it often leads the economy indicators in the economy. As a result, stock prices begin to rise. Some stock evaluation factors are driving up as well, such as P/E ratio, EV/EBITDA ratio. In this stage, returns are usually and the market is usually in an upward trend.

- Recovery – Plateau in Equity Market

In recovery stage, the economy has finally picked up the speed. The growth of the economic is high. Business demands are impacted more broadly by the investment in the economy. Inventories in industries are decreasing. Meanwhile, earnings in companies are approaching the peak. As a result, profitability and growth in companies are high, pushing up the valuation of the companies correspondingly. All these above make it possible for equity to stay at plateau for a period of time until the economics transit into next stage.

- Early Recession – Falling in Equity Market

In the end of previous stage, the central banks tend to raise interest rates to prevent the economy overheating, thus controlling the inflation in an acceptable and manageable range. As monetary policy plays a critical role in the capital market, it affects the market liquidity directly (Thorbecke, 1997). As a result, bonds become more favorable when compared with stocks. All these factors started to push the equity markets into a downturn.

At the same time, the economy halted its growth and stopped rising any further. Some sectors are suffering from the contraction in demands. However, due to the increased productivity in the recovery stage, inventory seizes decreasing and starts to climb up again. Company earnings are expected turned into a downshift as earnings level out and started to fall. Profit margins are also ebbing leading to a significant drop in company profits.

As equity market is connected with the company valuations, the majority sectors starts falling because the expectation towards the economy is poor and people are highly uncertain about the potential risk that might come in the down trend in the economy. The returns in the equity market are low or may even be negative in this stage. On the investor side, they will realize the companies' fundamentals are deteriorating and a correction in the market may be needed.

- Recession – Basin in Equity Markets

In the recession phase, the economy is experiencing the trough brought by the previous stage. However, the company earnings will bottom out in the near future. Although the expectation is not an immediate recovery, the time will not take long. Also, the company valuations are still low making it difficult for the equity market to rise up again. Visibility in company financial fundamentals is improving although having depressed earnings. This signal is positive to the equity markets. As a result, the equity market is preparing for it booming in the upcoming early recovering stage.

## 2.3 Sector Rotations and Portfolio Management

In different stages of business cycles, Investors favor different sectors. The basic rationale is that economy will go through the predefined business cycles. Also in any specific timestamp, it is possible to figure out the current location of the economy in the whole cycle. Industries within the economy will be likely to perform better in particular stages of the economic cycle.

Sectors enable investors to potentially take advantage of the status change in the business cycle. Sector rotation is a trading strategy that involves investing in sectors that are expected to perform well at a particular stage in business cycles. Also, the investors are expected to rotate in and out of the sectors as time progress while the economy is moving through different stages of the business cycle.

An investor would essentially increase their asset allocation to industries that are expected to outperform, and under allocate to industries that are not expected to benefit from the stage of the business cycle. This ultimate goal of the sector rotation strategy is to construct an investment portfolio that can perform superior than the overall market with extra rate of returns.

Sector Rotation strategy is similar to the traditional stock investment strategy, which allocates capital into such particular asset class as stocks, bonds, or commodities, it requires investors to construct the portfolios with selected economic sectors or industries with taking advantage of current market conditions. Depending on their risk preference, investors might overweight the sectors that they believe will outperform the market and underweight the sectors that tend to underperform the majority of the industries in the market.

Investment returns on stocks and other securities from companies in the same industry tend to move in similar patterns. Based on this underlying premise, the price in the same industry usually move based on similar fundamental and economic factors that drive a particular industry. The following table shows the best performing sectors in either expansion or recession cycle. New development and use of promising technologies backed the growth in the information technology industry up and usually the IT industry outperform all the other industries when the economy recovers from the recession and started to boom up. Alternately, the most stocks in the financial industry slumped during the recession as the market tends to collapse during the recession. The rational of downtrend is because most stocks in the financial industry experiencing a huge fall in the stock prices.

TABLE 3: Best sectors in expansion / recession cycle

| **Expansion** | **Recession** |
|---|---|
| Information Technology | Utilities |
| Consumer Staples | Financials |
| Energy | Health Care |
| Materials | Telecommunications |
| Industrials | |
| Consumer Discretionary | |

The market outlook is the factor most often used by investors to determine sector allocations. Diversification of risk is considered as one of the most important objective of the portfolio management. Since the price moving direction of all sectors will not be the same, increasing the number of sectors included in the portfolio will reduce the risk but also decrease the returns as well. As a result, it worth the investors to assess the return correlation between sectors and the overall market frequently to determine whether to rebalance investment portfolios.

However, diversification into different sectors will not guarantee against loss. An investor might not be able to diversify the risk by simply allocating capital to each sector evenly. Instead, the risk diversifying process is completed by shifting the weight from one or several sectors to the others based on the latest changes in the economics or market status.

In order to construct an investment portfolio, the global industry classification standard (GICS) is usually used. GICS is an industry taxonomy developed by Morgan Stanley Capital International (MSCI) and Standard & Poor's (S&P) for use in the global financial industry.

GICS is used as a basis of S&P and MSCI financial market indexes. GICS is a four-tiered, hierarchical industry classification system. GICS categorized all S&P major public companies into following four tiers.

- Tier 1 10 Sectors
- Tier 2 24 Industry Groups
- Tier 3 67 Industries
- Tier 4 147 Sub-industries

The first two tiers are shown in the following table.

TABLE 4: GICS sectors (Tier 1 and Tier 2) (Source: MSCI / GICS)

| **Sector** | **Industry Groups** |
|---|---|
| Energy | Energy |
| Materials | Materials |
| Industrials | Capital Goods |
| | Commercial & Professional Services |
| | Transportation |
| Consumer Discretionary | Automobiles & Components |
| | Consumer Durables & Apparel |

Table 4 (continued)

| | |
|---|---|
| | Consumer Services |
| | Media |
| | Retail |
| Consumer Staples | Food & Staples Retailing |
| | Food, Beverage & Tobacco |
| | Household & Personal Products |
| Health Care | Health Care Equipment & Services |
| | Pharmaceuticals, Biotechnology & Life Sciences |
| Financials | Banks |
| | Diversified Financials |
| | Insurance |
| | Real Estate |
| Information Technology | Software & Services |
| | Technology Hardware & Equipment |
| | Semiconductors & Semiconductor Equipment |
| Telecommunication | Telecommunication Services |
| Utilities | Utilities |

Since GICS sector indexes provide overall aggregated performance of each industry with S&P 500, an investment portfolio utilizes the sector rotation strategy will rebalance the weights of capital allocation among these sectors over a certain period of time. The frequency of weight rebalancing and the amount to sectors to be invested are usually depends on the investors' risk preference and expectation towards the future market status change.

## 2.4 Market Momentum

Market momentum is a measure of overall market sentiment (Scowcroft and Sefton, 2005), which refers to aggregated attitude of investors towards a particular stock or the whole market.

Market momentum can be a good indicator of the overall market changes and which are likely to continue in the near future. It considers not only the changes in trading prices but also trading volumes, which is also knows as momentum effect. Jegadeesh and Titman proposed momentum effect back in 1993.

Momentum effect basically indicates the return of stock will like to continue in the same trend within the near future. However, the degree of the trend tends to be weaker as time goes by if there lacks of sufficient support of trading volumes and move in corresponding trading price changes. In another words, the stocks with higher returns in the past will still tend to have high returns in the near future when compared with the stock with low returns.

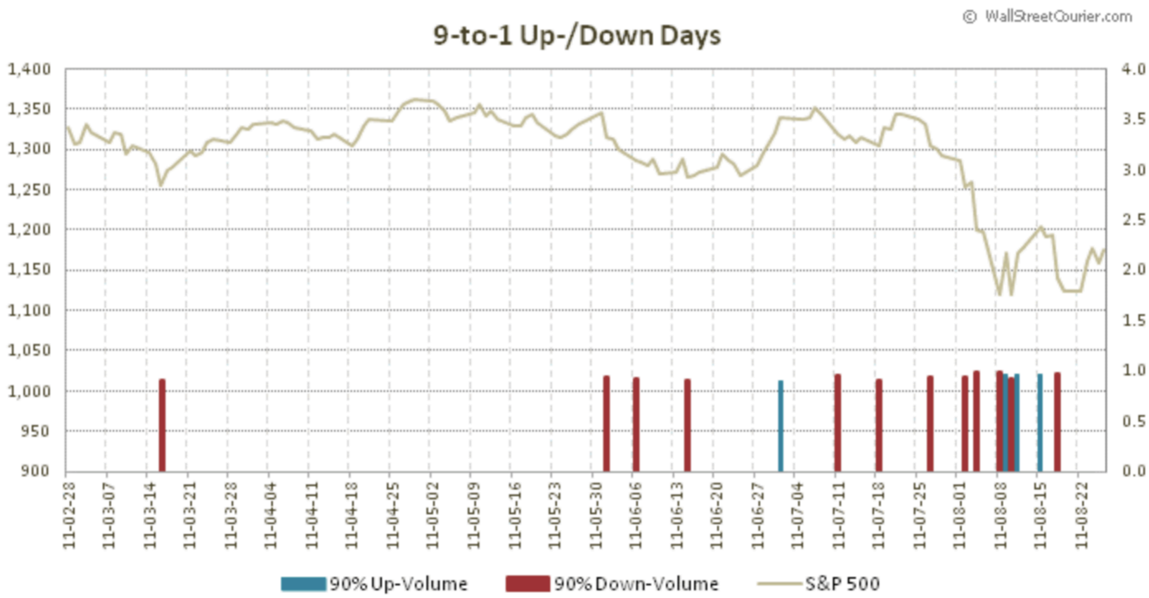


FIGURE 5: Simple illustration of market momentum

Figure 5 (Retrieved from WallStreetCourier.com) shows a simple illustration of the market momentum. 9-to-1 up/down days means if at least of 90% or more stocks in the market move in upward / downward trend, there will be an indicator shows either blue or red. Blue means in that particular day, the majority of the stocks have an increase in price while the red one denotes the opposite way. The rationale of this figure is when an red indicator comes up, the market tends to be low in the next couple of weeks while blue indicator means the market upward trend tends to be strong in the near future. Although it is not always works, market momentum tends to dominate the market most of the time.

Based on the market momentum, investors can take a long position in the stocks that have high returns in the history also take a short position in the stocks have comparably low returns. Jegadeesh and Titman (1993) constructed a similar relative strength portfolio, which contains long position in high return stocks in last three to twelve month and short position in low return stocks in the same period. In the next one to four quarters, this portfolio brought extra market outperforming profits. Jegadeesh and Titman concludes inertia exists in the stock market.

In the next few decades, there were many researchers looked into the market momentum such as Chordia and Shivakumar (2002), Moskowitz and Grinblatt (1999), Hong, Lim and Stein (2000), etc. Although these researchers vary on the degree of momentum in the market, they could not deny the existence of momentum in the stock market. Unlike other effects in the stock market, the degree of strength of market momentum did not weaken after becoming a hot spot in the academics. Jegadeesh and Titman (2001) revisited the market momentum after two years. They found the effect of market momentum is still significant.

However, the market momentum has the following characteristics:

- Market momentum is ubiquitous. Based on the empirical research, market momentum has a vast effect and exists basically everywhere.
- Panel difference in market momentum. The degree of impact from market momentum varies in different markets, even in different stocks.
- The cause of market momentum is complex. Market momentum is found to be related to different factors, such as industries, earnings, trading styles, etc.

# CHAPTER 3: COMPLEX ADAPTIVE SYSTEMS

A complex system is a system that features a large number of interacting components, such as agents, processes, etc. On the aggregate level, their activities offer a novel way of modeling nonlinear systems because of their ability to capture the essence of distributed. The non-linear property indicates it is impossible to derive through the summation of individual activities. Also their activities exhibit self-organization when the interacting components face selective pressures. At the same time, the social and natural phenomena are characterized by feedback loops and emergent properties

## 3.1 Introduction

After entering the new millennium, there is an amazingly fast development in different areas of science and technologies. The improvements are changing people's lives in return. However, it also makes some more people confused about the direction of the new technologies. They might be wondering how will the technologies develop over time and why do we needs such technologies.

All these questions are pointing to the emerging new science: complex systems. Some people predict the complex systems will be the new science of 21$^{st}$ century. Complex systems can be used to not only direct the development of science and technology, but also provide us with a possibility to view the world in another angle. A world of perfection and equilibriums will no longer existed and be replaced by chaotic prosperity. The top-down analytic approach was powerful in the human history of science. But complex systems propose a bottom-up emerging method. Mathematics was once powerful weapons for human to insight into natures. However, when facing huge non-linear systems, simple mathematics apparently cannot do anything. As for complex systems, it will use computer simulations to analyze its targets.

The theory of complexity has been invented in Physics. Its computational counterpart, mostly known as Complex Adaptive Systems (CAS), is a computational paradigm developed in computer science to deal with the issue of complexity in the real world. Computer can act as a simulator of physical and social processes. When a computer simulates behaviors of a system, it can provide us with a unique way of studying the underpinnings of the system that result in observed system behaviors (Holland, 1992).

### 3.2 Definitions of Complex Adaptive Systems

As mentioned above, we can try to derive the definition of complex systems in complex science. Complex system is an intelligent and adaptive system that has medium number of agents that will react to local information. Complex system is a system that is difficult to define, but it exists everywhere in the world. Therefore, we might be able to define it in the following ways.

- It is not a simple system, nor a random system.
- It is a complex system, not complicated.
- Complex system is a non-linear system.
- There are many subsystems in a complex system. The subsystems depend on each other and show interdependence among them. There are different

synergy effects between different systems. The subsystems are multi-level and multi-scale.

We call the elements in complex adaptive systems adaptive agents, or agents for short. The adaptivity here means the agents can interact with other agents in the same environment. Agents will learn and accumulate their knowledge through their lifelong interaction. At the same time, they might change their own structure or behaviors based on the knowledge they retrieve from the system.

Based on this, it makes the evolution possible in the macro system, including the debut of agents' diversification in their properties, emergence of newer and more powerful agents, etc.

Complex adaptive systems treat elements in the system to be target-oriented, active agent. More importantly, CAS believes the active reactions and the interactions with surrounding environments is the key for the macro system to evolve and develop. It is possible to find the root cause from individual prospective for either macro or micro structural changes.

## 3.3 Characteristics of Complex Adaptive Systems

People are living in different complex systems in any moment, such as the economy, ecosystems, neural networks, developing embryos and ant colonies. Among all these systems, independent elements actually have a cohesive effect. The interactions in them actually make the debut of self-organization.

In complex adaptive systems, the environment that an agent lives in is actually constituted by a large set of similar agents. The interaction between agents and the environment follows stimulation – reaction pattern. Therefore, the major effort for an agent to adapt to the environment is to adjust itself and make some corresponding changes to live better or co-exist with other agents in the same environment. This is the major cause for system dynamics to exist in the system.

Although there are different complex adaptive systems existing in different areas and each of the systems actually shows distinct characteristics, they usually shares the following four common properties.

### 3.3.1 Adaptivity

The adaptive agents have human-like functions, such as sensing and reaction. The agents also have their own objectives or goals. They know the fitness function, which is a particular type of functions that is used to summaries, as a figure of merit. Agents are active and positive, as they can interact with other agents in the surrounding environment. Also, agents can adjust their status to the latest changes in the living environment.

Self-interest is another important objective the agents have. Agents might compete or cooperate with others and maximize their objectives and possibility to live. However, everyone makes mistakes, which is the same to agents. Mistakes in expectations and decisions might push agents to death, meaning getting ruled out of the system. Because of this, the adaptivity creates a complex diversified system.

### 3.3.2 Co-evolution

In biology Adaptive agents enhance their existence through positive feedbacks, which also increase the chance of survivability and possibility to change the form they are living. It can change form one unified diversity to another. In other words, that is the evolution of agents.

However, adaptive agents not just evolve, they also co-evolve in the surrounding environment. Co-evolution makes the appearance of all possible kinds of diversified agents, who can live with others perfectly and adapt to different kinds of changes around them. A simple example is the relation between bees and flowers. Flowers got fertilized through the help of bees while bees live on the honey provided by flowers.

Co-evolution lays a solid foundation for any complex adaptive systems to conquer sudden changes and ensure a strong capability for the self-organization.

### 3.3.3 Edge of Chaos

Complex adaptive systems are capable to balance between orders and chaos. The balance point is the edge of chaos. Chaos simply indicates all the elements in a system never stay at any static status. They are dynamic but the degree is far less strong enough to deteriorate the organization of the whole system.

On one hand, the agents will proactively increase the cooperation with other agents in order to boost the possibility of the existence and continuation of themselves. In this way, agents can change their behaviors according to the latest changes of others. They might observe what other people are doing and see if they become better off. If yes, they might mimic the same behaviors and trying to obtain the similar results. Because of this, the whole system actually runs on the edge of chaos.

On the other hand, the edge of chaos is not just simply lying between complete orders and full chaos. The edge also develops over time. With the development, emergence makes its debut.

### 3.3.4 Emergence

The basic characteristic of emergence is the emergence is from small to large and from simple to complex. Complex behaviors do not stem from complex structure. Instead, they emerge from very simple elements. All organisms compete and cooperate in the co-evolution, which leads to a precisely coordinated biological system. One simple example is a molecule emerges from the chemical bond between atoms. Another example is the market, which stems from the trades between people. The trade in turn satisfies people's need for physical goods.

The root of emergence phenomenon is from the interactive effective of the agents, who are under control of several unrelated simple rules. The interaction among agents is actually the agents adapting to the environment. In another words, the interaction is non-linear and depends on a set of agents. Also, it makes the global behaviors are more complex than the local behaviors. Although the rules themselves will not change during the process of emergence, the things determined might change instead. Emergence can also occur based on the results of previous emergence, making the agents and organization more and more complex as the goes by. In another words, emergence in a low level can lead an emergence in high level in the whole organization and emergence is a global level of dynamics in a complex system.

## 3.4 Properties of Complex Adaptive Systems

Complex systems are common results of interaction, co-evolution, and emergence among sets of adaptive agents. Following general properties usually exist in complex adaptive systems: Cluster, Non-linearity, Stocks and Flows, and Multiscale Variety.

### 3.4.1 Cluster

For cluster, there are two meanings. The first one refers to a method to simplify the complexity in the systems. This is to cluster the agents that have similar behaviors and interactions. From this aspect, cluster is the major way to build complex adaptive systems. The second meaning for cluster is the emergence of new complex behaviors after the interactions among simple adaptive agents. The effect of agents clustering is a basic characteristic of the complex adaptive systems.

### 3.4.2 Non-linearity

Non-linearity refers to the changes happen in agents and their properties do not simply follow a linear relationship, especially among the interactions with surrounding environment. The complex adaptive systems believe the effect on individuals is active adaption instead of simple, passive, and one-directional casual relationship. As a result, the behaviors in the complex systems are difficult to predict and the evolutions in the complex systems are tortuous with various different stages.

### 3.4.3 Stocks and Flows

Followings are some example of stocks and flows.

TABLE 5: Stocks and flows examples

| Stocks | Inflows | Outflows |
|---|---|---|
| Population | Births | Deaths |
| Bank Balances | Deposits | Withdraws |
| Water in Bathtub | Water Pouring in | Water Draining out |
| Gas tank | Refueling | Gas burning |

From the examples, we can try to get an idea about the meaning of stocks and flows. Stocks mainly refer to some entities that are accumulated over time by flows. The inflows will increase the stocks while the outflows can decrease them. Also, stocks can only be changed by flows.

Flows are denoted as the behaviors that will change the stocks. It can be seen as changes of resources. Flows can usually be distinguished as inflows, which will increase stocks, and outflows, which will deplete stocks. Flows are typically measured over certain time intervals.

### 3.4.4 Multiscale Variety

The multiscale variety in complex systems is a component in system dynamics. The variety is a result of adaptation in the complex adaptive systems. Every adaption creates new possibilities for further interaction and appearance of new forms of lives in the system. Darwin's theory of survival of the fittest will also kick in to provide supplies of potential species that can come into play and post significant impacts in the future stages. Also, macro systematic structural emergence can happen if multiscale variety is combined with the cluster, and that's the so-called self-organization.

## 3.5 The Application of Complex Adaptive Systems in Business

The first application of Complex Adaptive Systems in the business area is the Santa Fe Artificial Stock Market, which was developed by Palmer et.al (Palmer, 1999). The main purpose of this model is to investigate the development process of bubbles in the stock market as well as the potential causes of market crash.

The model is constituted by various agents with different believes and expectations towards the market. These agents will keep learning based on the latest market changes to update or correct the flaws in their trading pattern. The desires to change become the endogenous variables for the market, which actually depends on the transactions among different investors, either individual or institutional. As a result, the whole ecosystem, constituted by the agents' believes and expectations, evolves over time through the competition to be better off between agents.

The method used to describe the whole ecosystem is based on the cognition, such as faiths, predictions, expectations, and explanations for the current movements in the markets, and all the decisions, strategies made upon their believes. It would be very beneficial to view the economic systems in this way since the systems are founded on the basis of homoeconomicus' behaviors and decisions.

Financial markets are complex systems (Johnson, 2003). In financial markets, there are micro behaviors, interaction patterns, and global regularities (Cappiello, 2006). In order to understand and learn financial systems, one needs to master such concepts as asymmetric information, strategic interaction, and equilibria. Due to the fast expansion of knowledge in computational sciences, the latest analytical tools made it possible to study the above aspects quantitatively.

One of these tools is Agent Based Modeling (ABM), which can model financial markets as a dynamic system of agents. ABM is not the only way to implement a CAS, but it is a way to implement it within a controlled setting in a computational environment. In the past decades, there have been rapid development of ABM applications in fields as diverse as economics, government, military, sociology, healthcare, architecture, city planning, policy, and biology, just to name a few (Tesfatsion, 2006, Johnson, 2013, Dreau, 2009).

In financial market simulations, a large number of agents engage repeatedly in local interactions, giving rise to global markets (Roberto, 2001, Bonabeau, 2002). Stock markets are a good example of financial systems. Local markets will interact with each other, thus contributing to the worldwide momentum of interwoven financial transactions. The momentum here simply implies that all markets closely follow each other through the same bull/bear cycles, although markets can change their status by targeted policy of their respective governments.

# CHAPTER 4: SECTOR ROTATION MODEL

Simulation-based methods are becoming a promising research tool in financial markets. A general Complex Adaptive System can be tailored to different application scenarios. This section documents an application of a Complex Adaptive System approach to modeling in the context of portfolio management, based on the sector rotation strategy in the United States stock market (Su, 2014). Sector rotation is a ubiquitous phenomenon regularly exploited in financial markets.

With a proper sector rotation strategy, investors can outperform the market and achieve extra profits through optimized portfolios. A sector rotation multi-agent model is implemented using the Netlogo framework. The model utilizes historical data and produces returns that exceed Standard & Poor's 500 index returns.

## 4.1 Model Description

In our CAS Agent-Based Model (ABM), we built a sector-trading strategy that implements sector rotation as part of the overall portfolio management. Agents trade sectors based on the publicly available GICS sector data from January 2, 1975 to August 31, 2013. We also include interest in agents' holdings, computed based on their cash on hand, on a daily basis, using data from the Federal Reserve in the same timeframe. In addition, agents know the current status of the stock market, be it bull or bear, based on the recession data available from the National Bureau of Economic Research (NBER). Agents use this information to select their trading rules.

## 4.2 Model Setups

### 4.2.1 Agents

A collection of agents constitutes the “trading world” in this ABM simulation. Agents are given a certain amount of money at the model initialization stage. Agents’ transactions are triggered by their decision rules and the amount of capital they have. As they are aware of the current market status, agents at each time step choose between two sets of trading rules, either bull or bear market trading rules. Here bull market denotes a majority group of securities in which prices are rising or are expected to rise. The bear market however indicates a opposite pattern. Table 2 describes the trading rules assigned to individual agents.

TABLE 6: Trading rules assigned to individual agents

| | |
|---|---|
| Buy-Threshold | Minimum price change required for taking a long position |
| Buy-Period | Time window agents observe before evaluating the Buy-Threshold |
| Sell-Threshold | Minimum price change required for taking a short position |
| Sell-period | Time window agents observe before evaluating the Sell-Threshold |

### 4.2.2 Trading Rules

The following formulas describe agents’ decision rules in detail.

- Basic trading rules: rational + market momentum
- Buy Rule:

– X > Y * (1 - self-confidence * *momentum of buying*) in past Z

– Agents will buy

- Sell Rule:
  - X < Y * (1 – self-confidence * *momentum of selling*) in past Z
  - Agents will sell
- Following are the notations:
  - X – Change in Sector Price
  - Y – Buy/Sell Threshold
  - Z – Buy/Sell Period

For example, if an agent has the following buy related parameters:

- buy-threshold is 0.1
- buy-period is 20

Then the buying rule for this agent is:

IF the stock price goes up 10% in the past 20 trading days,

THEN take a long position on this stock.

Similarly, if an agent has the following sell related parameters:

- sell-threshold is 0.2
- sell-period is 50

Then the selling rule for this agent is:

IF the stock price goes up less than 20% in the last 50 trading days,

THEN agent will take a short position.

Also, short selling is allowed at any point. Short selling in financial market is the sale of a security that is not owned by the seller. Another underlying asset is the security borrowed by the owner. The major motivation of the short selling is the prices of the targeted securities will decrease. The value of the stocks per capita will depreciate over time. The action of short selling enables the market participant to buy back the asset at a lower price to make a profit. Short selling may be prompted by speculation, or by the desire to hedge the downside risk of a long position in the same security or a related one. Since the risk of loss on a short sale is theoretically infinite, in order to control the risk to an acceptable level, an agent can short sell any amount of stock up to the equivalent amount of available cash on hand.

### 4.2.3 Market Momentum

Rationality is not always the real basis for each agent transaction. Panics and frenzies are also driving the trend of the markets. Investors' greedy and panic-prone behaviors amplify regular ups and downs in the market, building up the bubble that inevitably ends in a market crash. Some of the most famous examples are the tulip craze, the south sea bubble, and the great depression. Also, recent market trends in Shanghai Composite Index, shown in the following figure (retrieved from Yahoo Finance), also validate this phenomenon.


FIGURE 6: Shanghai composite index over time

Clearly, market momentum is an important factor that impacts agents' decision-making rules of the agents. Otherwise, there would be no bubbles. Heterogeneous agent models (Hommes, 2006) show that most of the behavioral models with bounded rational agents using different strategies may not be perfect, but they perform reasonably well. With the adaptive trading strategies, agents are able to seek more trading opportunities and boost their profits.

The inclusion of market momentum in the stock-trading model will potentially increase the return of investors, as it allows agents to adjust their trading rules temporarily according to the latest market changes (and anticipation of other traders' behavior). In the stock trading model, momentum was generated by the overall buy/sell behavior of agents, thus creating a bid-ask spread for the stock they are trading. Bid-ask spreads shows the amount by which the ask price exceeds the bid. In this way, the more agents buy stocks, the higher the bidding price. Likewise, the more agents sell stocks, the lower the stock prices, as agents are trying to liquidate their inventories.

As a result, market momentum will impact or even strategically change the agents' decision rules. The more agents are buying sectors, the higher bidding price. The more agents are selling sectors; sector prices will tend to be low as agents are trying to liquidate their inventories.

In our model, the characteristics of market momentum can be described as follows:

– Market Momentum ranges in [0, 1]

– Count how many people intend to buy/sell

– If no one is *buying/selling*, *momentum of buying/selling* will be 0

–If everyone is *buying/selling*, *momentum* of *buying/selling* will be 1

The measurement of market momentum in our model is actually relying on the overall trend of buying and selling. Bid-ask spread in the stock market refers to the difference between the price quoted and an immediate purchase for securities, stocks, future contracts, or options. In order to mimic the bid-ask spread in the real world, the current amount of agents, either hope to sell or buy, is available to all the market participants. Based on this, in each tick, the market momentum can be calculated. The market momentum is unique in every tick as the amount of agents in either buy or sell side varies over time.

### 4.2.4 Degree of Trust

Degree of Trust in our model is denoted as the variable called self-confidence, which is created to control the degree of trust in market momentum. The higher the self-confidence, the stronger the agents believe in their own trading strategies, thus decreasing the impact of the trading environment around them.

Latest market information is available to agents. Consequently, the bandwagon effect plays an important role in transactions. The bandwagon effect simply means that agent behaviors and beliefs, as well as their consequences, spread around. As a result, if there are a lot of agents buying stocks, then agents will increase their buy-threshold. At the same time, if there are many agents who are shorting stocks, then a substantial number of agents will correspondingly decrease their sell-threshold as they try to liquidate their assets as soon as possible. Agents have a variable called self-confidence, assigned randomly at the initial stage, which controls how much each agent trusts other agents. If an agent is totally self-confident, it will only follow its trading rules instead of it being affected by other agents in the market.

### 4.2.5 Genetic Algorithm

The concept of "Survival of the fittest" proposed by Darwin is also applicable to the world of stock transactions. In artificial intelligence, genetic algorithms embody a search heuristic that mimics the process of natural selection. This heuristic mainly generates promising descendants that are more adaptive to the changes in the environment.

A hatch-and-die concept in NetLogo was introduced in the model as a mechanism for likely regenerating the best performers and eliminating underperforming agents. If agents bankrupt in the simulation, newly initialized agents will replace them. This was introduced in order to keep constant the quantity of agents, thus ensuring an active trading environment. On the other hand, ruling out the bankrupt agents helps maintaining a faster simulation speed.

### 4.2.6 Search Space and Mutation

As agents have a lot of parameters, the search space covering all possibilities counts trillions of states. A mutation mechanism is introduced to use a small quantity of agents to simulate agents with all possible combination of parameters. With mutation, agents' parameters are initialized in a small range. However, some agents' parameters are generated in a much larger range. Mutation also takes place in hatch-and-die activity of a NetLogo simulation. With the benefit of mutation, some agents' parameters are randomized far beyond the preset small ranges, thus making it possible to explore the whole parameter search space. At the same time, Monte Carlo simulation was applied in the model to achieve the best result with the minimal number of simulation rounds.

### 4.2.7 Learning and Interaction

In ABM implementations, agents have the ability to learn from each other. The process of learning offers agents the opportunity to refine their transaction decision rules, thus helping them to secure more profits in a complex market (Cui, 2012). Agent learn from the best performers within a certain radius in the NetLogo simulation. The neighborhood structure is introduced to enhance learning efficiency. Learning squeezes the search space from the size of trillions into a much smaller one.

Learning mechanism makes it possible to investigate alternative strategies that have not yet been discovered in the market (Outkin, 2012). In this implementation, to preserve computational time, there is a radius around agents. Agents can only see the other agents in the radius while they are moving around. The introduction of radius makes the learning more sustainable.

The variable aggressiveness indicates to what extent the agents want to adopt their neighbor's behavioral structure. Also, there is a period of time during which the learning process is prohibited in order to allow agents to evaluate their current trading strategies. Contrary to the market momentum-induced changes, according to which agents adjust their trading decision rules temporarily, the changes made through learning are permanent.

### 4.2.8 Benchmarks

Benchmark agents are set to evaluated the performance of the model. There are two benchmarks for the sector rotation model. The first one is the buy and hold strategy for the S&P 500 index. The rationale behind this is the S&P 500 is a composite index of all ten sectors. It will indicate an average return in different portfolio settings. This will be used to compare with the average return of all agents.

The other benchmark is the best possible returns from the same period of time. Initially, this project was primarily created to pilot the agent-based modeling method in portfolio management with a major bank in the US. The best performed model in the bank achieved 250 times of profit in the same timeframe. As a result, the sector rotation model was created to beat the best performing model from the bank.

### 4.3 Global Trading Environment Setup

In the CAS sector rotation model, the world is represented in 2 dimensions. Both X-axis and Y-axis range from -10 to +10. There is a variable called radius defining how far agents can reach out to other agents to both initiate transactions and learn their trading strategies. The Radius has a different value for each agent, making it possible for agents to have diversified trading and differing learning preferences.

However, radius significantly slows down the computing speed. Because of that, we opted to divide the world in four quadrants instead of relying on the radius as the variable that determines what agents see. Agents have the knowledge of where they are and who else is in their quadrant. This replacement of radius with the concept of quadrants was possible due to the preliminary investigations that proved that the final outcome was not significantly different between the two environments.

## 4.4 Implementation Process

This sector trading CAS model was implemented using the Netlogo 5.0.5 programmable modeling environment (Wilensky 2009). Netlogo offers a user-defined grid and the possibility of defining agents, normally called turtles in NetLogo.

Initially, in Version 1(Ver. 1), the transaction types for agents included only the possibility of buying and selling from/to other agents. However, due to the limited number of agents (a computational efficacy limitation), it often happens that there are either no buyers or sellers for a particular sector. Consequently, no transactions happen even though there is an interest in transactions for that particular sector. In order to avoid this situation, in Ver.3, an updated transaction method was created to allow agents to buy or sell any amount of any sectors at any time, this time from the "system/market maker" rather than from individual agents. This updated method provided agents with an unlimited inventory of sector shares and buyers, which is more similar to the real world portfolio management where each agent can buy or sell sector shares almost instantaneously and whenever they want to. Still, we opted to limit the number of shares that can be purchased or sold at any moment (a tick in NetLogo parlance) to 10 shares during each trading day. Later versions of the model explored the possibility of unlimited trading as well.

The prototype of the model used many variables, which significantly increased the search space for finding the best trading rules. Following section will summarize these issues in some details. Consequently, we explored many variants of the reduced search space.

Regarding the mechanism for regenerating or eliminating agents, in Ver.12, a hatch and die concepts of NetLogo were used for introducing new agents and eliminating underperforming ones. Agents who lose all their money are eliminated from the environment. At the same time, new agents are initialized and placed into the environment, thus keeping the number of agents constant. This mechanism makes sure that active trading among agents is maintained.

Interest for cash on hand and transaction costs are two most important factors that impact investors' returns. They are included in the later stages of the model development, which are Ver. 13 and Ver. 15.

In the version of the model that allows for unlimited buying/selling of sectors, agents run out of cash more frequently than in other versions of the model. As a result, in order to get cash to buy new sectors agents have to sell the inventory they have. This creates a new challenge for agents, because now they have to decide whether to sell inventory and buy a new sector.

To solve this problem, Sharpe Ratio was introduced in Ver. 14 to compare the past performance of the sector to be sold and the sector to be purchased. As a result, agents must check Sharpe Ratios for the two sectors they want to buy and sell. The Sharpe Ratio (Sharpe W. 1994) was proposed by William Sharpe in 1994. It is a widely used indicator to inspect past performance of stocks. The formula is given as follows:

$$\mathrm{S} = \frac{\mathrm{E[R]}}{\mathrm{Std.dev(R)}} = \frac{Rewards}{Risk}$$

Here R is the stock that we are inspecting. Sharpe Ratio computes the reward vs. risk in the past (agent specified) number of days. To most people, greater return and lower risk is preferable. As it can be seen from the formula, the higher the Sharpe Ratio the better it is because it means higher reward and lower risk. Therefore, agents swap the long position for the sector with a lower Sharpe ratio with the long position for the sector with a higher Sharpe Ratio when they are running out of cash.

A complete simulation includes two rounds. The first round represents the learning phase. In the second round agents trade with the rules they learned in the first round.

The following table summarizes a complete evolution of our model.

TABLE 7: Model evolutions

| Ver. | Change | Settings | Best Result |
|---|---|---|---|
| 1 | Prototype:<br>• One set of decision rule, long only<br>• *Radius* affects agents transaction and learning process<br>• Agents will buy/sell sector from/to other agents<br>• Agents will buy/sell 10 shares of one sector at a time<br>• 2 rounds simulation | Agent Quantity: 1,000;<br>Thresholds: [-1,1]<br>Step size 0.01;<br>Period: [1,1000]<br>Step size 1; | 35x |
| 2 | Add *self-confidence* | Self-confidence: [-1,1]<br>Radius: [1, 10] | 59x |

Table 7 (continued)

| | | | |
|---|---|---|---|
| 3 | Change radius to unlimited | Radius: Fixed at 10 | 59x |
| 4 | Add short selling mechanism in decision rules | | 112x |
| 5 | Reduced search space and add mutation | Agent Quantity: 1,000;<br>Thresholds: [-0.4,0.4]<br>Step size 0.2;<br>Period: [1,100]<br>Step size 20;<br>Mutation rate:<br>Fixed at 0.1 | 213x |
| 6 | Historical market information available to agents<br>Separate decision rules for bull/bear market | | 245x |
| 7 | Replace *radius* by *quadrant* | | 245x |
| 8 | Introduced 3 rounds simulation<br>• 1st round, learning<br>• 2nd round, no learning, tracking monthly returns<br>3rd round, kill all agents and recreate agents with parameters that have best monthly returns in 2nd round, unlimited | | 225x |

Table 7 (continued)

| | | | |
|---|---|---|---|
| | stock supply; | | |
| 9 | • Go back to 2 round simulation<br>• Agents will no longer buy/sell sector from/to other agents<br>• Agents will have unlimited stock supply | | 249x |
| 10 | Update agent initialization process, no one will buy high and sell low any more | | 257x |
| 11 | Add delay module for market information | Delay: 120 | 191x |
| | | Delay: 250 | 176x |
| 12 | Add die and hatch mechanism. Agents will die when lose all money. New agents will be created copying parameters from best agents in the quadrant or mutation | Delay: 250 | 232x |
| 13 | Historical interest information available to distribute interest for cash on hand | | 248x |
| 14 | Agents will no long buy/sell 10 shares of the sector. Agents will now conduct transaction with maximal possible amount | | 721x |

TABLE 7 (continued)

| | | | |
|---|---|---|---|
| 15 | Add transaction cost | $10 per transaction | 708x |
| 16 | Add Sharpe ratio as a evaluation standard for agent when they are evaluate performance of 2 stocks | | 749X |

## 4.5 The Current Sector Rotation Model

To provide a trade-off between the computing speed and the space exploration, we set the agent number to 1,000. All transaction decision rules are randomized within the [-0.4,0.4] range for required returns and within [0,100] range for the trading periods. *Self-confidence* and *aggressiveness* at set to 0.3 and 0.1, respectively. However, in order to maintain the possibility of exploring the whole search space, a mutation mechanism is added, allowing a subset of agents to mutate from [-0.4,0.4] to [-1,1] for required returns and from [1,100] to [1,1000] for trading periods. Agents are assigned the initial capital in the amount of $50,000. The transaction cost is fixed at $10 per transaction. The mutation rate is fixed at 0.1, which allows 10% of all agents to get buy/sell threshold and buy/sell period generated in [-1,1] and [1,1000] respectively.

During the learning phase, agents wait for 5,000 days/ticks before they start to learn. This gives all agents enough time to prove their initial trading strategies

## 4.6 Model Performance

The benchmark for the evaluation of the performance of the model is the S&P 500 index. The S&P 500 index increased from 70.23 to 1632.97 during the period of 01/02/75 to 08/31/13. If buy-and-hold strategy is used by investors, they receive a 23.25 times return in this time period.

In the Ver. 2, agents had to buy/sell sectors from/to other agents, short selling was not allowed, and there was a global variable called radius defining how far they can reach out to other agents to suggest potential transactions and to learn their neighbor's trading strategies. In this model, agents have only one set of trading rules (no knowledge of bear or bull markets) and they can only buy and sell 10 shares of stock each time. The results are shown in Table 6.

TABLE 8: Initial model performances

| Radius | Period Range | Best Return |
|---|---|---|
| 10 | 200 | 59.154 |
| 10 | 1000 | 58.5825 |
| 5 | 200 | 57.0321 |
| 8 | 200 | 56.1477 |
| 10 | 500 | 53.1203 |
| 3 | 1000 | 36.3485 |

The return numbers indicate how many times agents multiplied their initial capital. It is easy to see that agents gain more return as the radius goes up, because they can reach out for more potential buyers and sellers. At the same time, the computing power limits the model to use only 1,000 agents. As the period ceiling decreases (thus reducing the search space), agents can explore the search space better, resulting in higher return rates.

Then, a reduced sample space is introduced in Ver. 5. The mutation includes only the trading thresholds. Agents are now allowed to short stocks. Agents have publicly available information on market conditions, as well as separate trading strategies for the bull and bear markets. The radius is set to 10, thus allowing agents to have access to all potential transactions and all possible learning targets (10 is the size of the environment). Many step sizes for parameter settings have been evaluated. The best return rate is shown in Table 7.

TABLE 9: Best performances for the updated model

| Radius | Step Size | Best Return |
|---|---|---|
| 10 | 0.01 | 112.415 |
| 10 | 0.2 | 213.257 |

With the step size increasing, it becomes easier to create agents covering the exploration space more readily.

The Ver. 6 of the model makes the historical recession data available to agents. With the historical data, agents will have 2 separate trading rules for bull and bear market respectively. The best agent now achieves a 245x return.

Next, Ver. 7 is created with quadrants replacing radius as the main way to define the extent of agent interactions in the model. This change enables the model simulation to be completed within a day. The best return remains at 245x.

Then, a new simulation model is tested, Ver. 8. This simulation includes 3 phases. In the first phase, learning is turned on. In the second phase, agents use their trading strategies updated by learning from the first phase. Also, the bull and bear trading strategies of the agent who performs best during each month is recorded. In the last phase, a new generation of agents is generated with best parameters recorded in the second phase. However, this time the best return gets reduced to 225x.

Ver. 10 excluded agents who buy high and sell low. This version boosts the best return to 257x.

The goal of the CAS sector rotation model is to simulate real world scenarios. In the current version of the model agents have the privileged information on the changes in the market status (bull vs. bear). However, in the real world there is a delay in understanding when the market actually goes from a recession into a recovery or vice versa. This delay is usually a yearlong. Consequently, a delay mechanism is introduced in the Ver. 11. It is clear that instant market status information offers a big advantage to agents (Table 6).

TABLE 10: Performances with market information delay

| Delay Length | Best Returns |
|---|---|
| 0 | 257x |
| 120 | 191x |
| 250 | 176x |

The latest model Ver. 15 includes the following conditions: interest and transaction cost is added, agents can transact in an unlimited fashion, and agents compare the Sharpe Ratio between two sectors when they are switching position on sectors when running out of cash. As a result of these changes, best performance returns to the 700+x range. Figure 7 shows the return of the latest model.

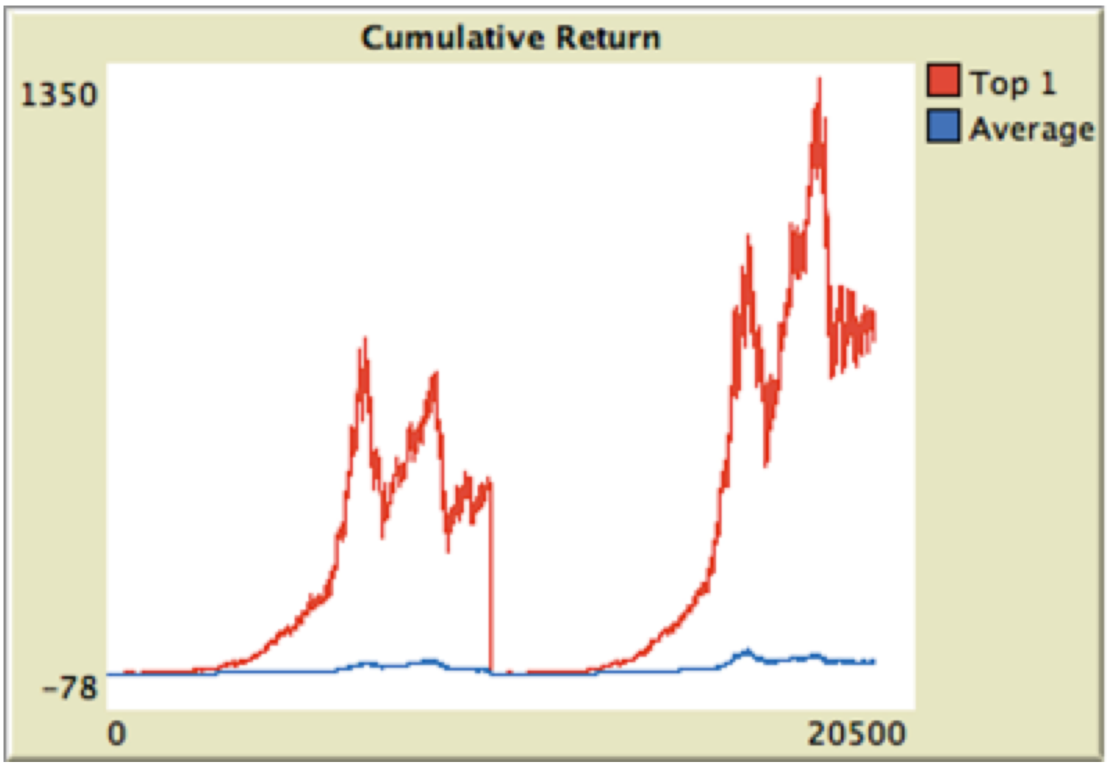


FIGURE 7: Best and average agents performances

After learning, agents perform much better when they repeat a run using the same data. The return is now 749x for the best agent and 24x for average agents.

The following is the best trading rule set at a particular tick:

For bull market:

- If the sector price goes down 4% in last 20 trading days, take a long position.

- If the sector price goes up less than 25% in last 5 trading days, take a short position.

For bear market:

- If the sector price goes down 13% in last 6 trading days, take a long position.
- If the sector price goes up less than 47% in last 5 trading days, take a short position.

The rules above are updated based on the market momentum, which is described in Section 4.2.1. The narrative for the trading rule set basically states that an investor should get in and get out of the market quickly. Once the sector prices deviate from the expectation, investors should clear their positions immediately.

## 4.7 Issues for the Sector Rotation Model

There are several issues that we have encountered during the implementation of the model. The first problem is the exploration space. The following table shows the original range setting for each parameter.

TABLE 11: The initial setting of the parameters

| Parameter | Range | Possibility |
|---|---|---|
| Bull-Buy-threshold | -1 to 1 by 0.01 | 200 |
| Bull-Sell-threshold | -1 to 1 by 0.01 | 200 |
| Bull-Buy-period | 1 to 1000 by 1 | 1,000 |
| Bull-Sell-period | 1 to 1000 by 1 | 1,000 |
| Bear-Buy-threshold | -1 to 1 by 0.01 | 200 |
| Bear-Sell-threshold | -1 to 1 by 0.01 | 200 |
| Bear-Buy-period | 1 to 1000 by 1 | 1,000 |
| Bear-Sell-period | 1 to 1000 by 1 | 1,000 |

TABLE 11 (continued)

| | | |
|---|---|---|
| Aggressiveness | 0 to 1 by 0.01 | 100 |
| Self-Confidence | 0 to 1 by 0.01 | 100 |

Based on the above setting, we have a total search space of 1.6 * 1025, which means we need to create at least 1.6 * 1025 agents to cover the whole space. With the current computing power this is an impossible mission, even if we use high performance computers (HPC) to run the simulation. That is why we created a mutation mechanism. The mutation mechanism allows the agents to mutate and compute new values for their parameters outside of the defined range. Table 7 depicts the search space after mutation was enabled in the model.

TABLE 12: Performances with mutation

| **Parameter** | **Range** | **Possibility** |
|---|---|---|
| Bull-Buy-threshold | -0.4 to 0.4 by 0.2 | 5 |
| Bull-Sell-threshold | -0.4 to 0.4 by 0.2 | 5 |
| Bull-Buy-period | 1 to 100 by 20 | 5 |
| Bull-Sell-period | 1 to 100 by 20 | 5 |
| Bear-Buy-threshold | -0.4 to 0.4 by 0.2 | 5 |
| Bear-Sell-threshold | -0.4 to 0.4 by 0.2 | 5 |
| Bear-Buy-period | 1 to 100 by 20 | 5 |
| Bear-Sell-period | 1 to 100 by 20 | 5 |

TABLE 12 (continued)

| | | |
|---|---|---|
| Aggressiveness | Fixed at 0.1 | 1 |
| Self-Confidence | Fixed at 0.3 | 1 |
| Mutation-rate | Fixed at 0.1 | 1 |

With mutation we successfully reduced the search space to 390,625 possible values. However, this is still higher than expected, and the computation can be performed on an HPC with an extremely low speed, meaning it may take years to run the simulation. Thus, we went further in eliminating the possibility of existence of agents who deploy unreasonable trading strategies. The ranges of Sell-thresholds are changed in the table 13.

TABLE 13: New values for sell-thresholds

| Parameter | Range | Possibility |
|---|---|---|
| Bull-Sell-threshold | Bull-Buy-threshold to 0.4 by 0.2 | < 5 |
| Bull-Sell-threshold | Bear-Buy-threshold to 0.4 by 0.2 | < 5 |

Thus, we finally reduced the search space to 62,500 possible values/cells. With 1,000 agents in the model, we can explore around 1.6% of the search space. At the same time, Monte Carlo simulation (Fisherman, 1995) can be used to repeat experiments on an HPC, in order to get the best parameter set for agents that outperform the market the most.

# CHAPTER 5: ONE STOCK SIGNALING MODEL

Picking winning stocks is hard, sometimes impossible, as both endogenous and exogenous events influence the value of shares in any given moment. However, this has not stopped many investors to try to either time the market or establish strategies that would provide them with long-term gains. Consequently, there are day trading, technical trading, value trading, fundamental trading, and contrarian trading among many other strategies that have been advanced over the years as potential winning strategies in the stock market.

With the advent of computers and sophisticated analytical techniques, many of the previously mentioned approaches have been automated using information technology tools, (Subramanian, 2007, Saad, 1998, Teixeira, 2010) although with limited success. In recent years, complex adaptive systems – inspired methods, primarily using agent-based modeling techniques, have been tried as a way to simulate traders' behavior and capture the intricacies of stock trading (Kodia, Said and Ghedira, 2010). This section introduces an agent-based model (Su, 2015) for signaling the opportune times for stock trading. The system has been evaluated in the context of Bank of America in the period from 1987 – 2013. The model outperformed S&P 500 with buy-and-hold strategy.

## 5.1 Model Setup

In this chapter, we will describe an ABM system that issues stock trading signals (buy, sell, or hold) for a stock (Bank of America in our example). Agents trade stocks based on the publicly available data from January 2, 1987 to December 31, 2013. In addition, agents will have the knowledge of the current status of the stock market, be it bull or bear, based on the recession data available from the National Bureau of Economic Research (NBER). Here bull market indicates a financial market of a group of securities in which prices are rising or expected to rise. Bear market denotes the opposite in financial market terms. Agents use this information to select the corresponding trading rules.

### 5.1.1 Agents

Similar to the sector rotation model, the trading world of one stock signaling model is also constituted by a collection of agents. Although, the investors in the real world can be classified into either institutional investors or individual investors, we decided to look at the individual investors only in order to simplify the model as much as possible. We understand that the institutional investors represent a large component of financial markets.  However, we are trying to investigate the best degree of trust among agents to maximize the profits from the proposed trading strategies.

In the initialization stage, agents are initialized with a certain amount of money. Agents' transactions are triggered by their decision rules, the amount of capital they have, and the current market momentum, based on which agents align their trading strategies with the latest market changes. Based on the knowledge of the latest market status, agents choose the trading rules for the current tick.

Same as the descriptions in the chapter 4, agents will have the following parameters shown in the table 14.

TABLE 14: One stock signaling model agent parameter settings

| **Parameter** | **Settings** |
|---|---|
| Bull-Buy-threshold | Randomized from -0.4 to 0.4 by 0.2 |
| Bull-Sell-threshold | Randomized from -0.4 to 0.4 by 0.2 |
| Bull-Buy-period | Randomized from 1 to 100 by 20 |
| Bull-Sell-period | Randomized from 1 to 100 by 20 |
| Bear-Buy-threshold | Randomized from -0.4 to 0.4 by 0.2 |
| Bear-Sell-threshold | Randomized from -0.4 to 0.4 by 0.2 |
| Bear-Buy-period | Randomized from 1 to 100 by 20 |
| Bear-Sell-period | Randomized from 1 to 100 by 20 |
| Aggressiveness | Fixed at 0.001 |
| Self-Confidence | Fixed at 0.3 |
| Mutation-rate | Fixed at 0.1 |
| Initial Capital | $50,000 |
| Transaction Cost | $10 each |

### 5.1.2 Performance Evaluation Methods

In order to evaluate the performance of the model when comparing to the overall market performance, there are two benchmarks used in the model. Both benchmarks use buy-and-hold strategy, but on BAC stock price and S&P 500 index respectively. The rationale behind the scene is we would like to evaluate the how big the difference will be between active and passive trading methods.

At the same time, we would also like to explore the possible performance when someone is always mimicking the best performers' or top performers' decisions, which also happens in the real world. As a result, we created two benchmark agents in simulation. For benchmark agent 1, labeled as BA1, will always track and replicates the action of the best performer in the model. Benchmark agent 2 (BA2) tracks, weighs, and replicates the top 10% best performers in the whole system. For BA2, if the majority of the agents in the 10% top performers have a preference to buy, then BA2 will take a long position. A short position represents the opposite case. If the number of buy and sell agents is equal, then hold strategy will be applied.

### 5.1.3 Simulation Methods

In contrast to the sector rotation model has two rounds of simulation, the one stock signaling model only has one round. However, the complete simulation timeframe is divided into 2 stages.

In the simulation, stage 1 is the training phase, in which agents learn best individual trading strategies. Stage 2 is a test stage. At the beginning of this stage Agents' capital is reset to the initial value, while agents retain all the rules they learned in the training phase. Agents trade based on the strategies learned in Stage 1, while attempting to maximize their profits.

Learning from other agents is disabled in the first 1,000 ticks, which leaves enough time for agents to evaluate their initial trading strategies. After that, agents learn throughout the rest of the simulation. This mechanism allows agents sufficient time to optimize their strategies throughout the volatilities of the market, i.e. financial crises or huge price volatility periods.

We used a genetic algorithm for regenerating or eliminating agents (Holland, 1975). A hatch and die concepts of NetLogo were used to introduce new agents or eliminating underperforming ones. Agents who lose all of their money are eliminated from the environment. At the same time, new agents are initialized and placed into the environment, thus keeping the number of agents constant. This mechanism makes sure that a robust simulation environment and active trading among agents are maintained.

## 5.2 Model Results

In the stock trading signaling model, S&P 500 and Bank of America (BAC) buy-and-hold strategies were used as performance benchmarks. As the timeframe of the data is from 01/02/1987 to 12/31/2014, different settings of training/test experiments were conducted during the simulation. Table 15 shows three typical experiments.

TABLE 15: Experiment setups

| | | | |
|---|---|---|---|
| Experiment 1 | Training | From | 01/02/1987 |
| | | To | 12/31/2014 |
| | Test | From | N/A |
| | | To | N/A |
| Experiment 2 | Training | From | 01/02/1987 |
| | | To | 12/31/2004 |
| | Test | From | 01/02/2005 |
| | | To | 12/31/2014 |

TABLE 15 (continued)

| | | | |
|---|---|---|---|
| Experiment 3 | Training | From | 01/02/1987 |
| | | To | 12/31/2011 |
| | Test | From | 01/02/2012 |
| | | To | 12/31/2014 |

In experiment 1, agents are trading all the time from 1987 to 2014. There is no test period, as agents' capital is not reset during experiment. It indicates how well agents perform in the maximum timeframe.

In experiment 2, the whole timeframe is divided into 75% training and 25% testing tranches. In other words, training stage is from 1987 to 2004, while the test stage starts in 2005 and ends in 2014. This cut is inspired by best practice in supervised learning.

As the underlying stock in the model is Bank of America, which is in financial sector that was the major cause of recent financial crisis, experiment 3 creates a bull market period for the testing stage in order to test how well the model performs in a bull market with less volatility in stock prices. As a result, the training period is from 1987 to 2011, and the testing period is from 2012 to 2014.

The results of the experiments are shown as below in Table 16

TABLE 16: Experiment results in percentage

| | | | |
|---|---|---|---|
| Experiment 1 | Benchmark | S&P 500 Buy & Hold | 735.42% |
| | | BAC Buy & Hold | 664.53% |
| | Benchmark Agents | BA1 | 358.33% |
| | | BA2 | 581.12% |
| | Model | Best Performer | 1,189.71% |
| | | Top 10% Best Performers | 718.44% |
| Experiment 2 | Benchmark | S&P 500 Buy & Hold | 73.3 % |
| | | BAC Buy & Hold | - 50.4% |
| | Benchmark Agents | BA1 | 37.16% |
| | | BA2 | 71.29% |
| | Model | Best Performer | 540.46% |
| | | Top 10% Best Performers | 88.89% |
| Experiment 3 | Benchmark | S&P 500 Buy & Hold | 61.88% |
| | | BAC Buy & Hold | 28.61% |
| | Benchmark Agents | BA1 | 71.85% |
| | | BA2 | 61.51% |
| | Model | Best Performer | 374.02% |
| | | Top 10% Best Performers | 105.34% |

It is obvious that the performance of the stock trading signaling model is much better than a buy-and-hold strategy on Bank of America stock. It even outperforms the S&P 500, which shows an ascending trend in the long term. As the Bank of America stock has not recovered from the downfall of the last financial crisis, it is a good test for evaluating the performance of a simulation model, especially when compared to S&P 500 index. Figures 1 through 3 show the comparisons between the model's performance and the buy-and-hold (BAH) strategy on BAC and S&P 500 in a more intuitive way.

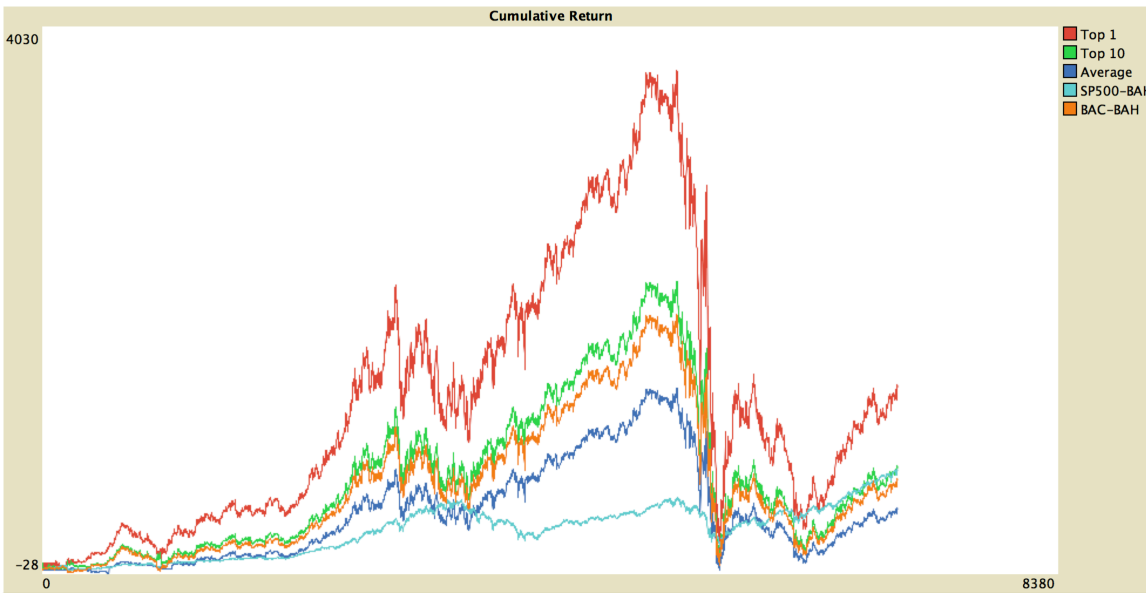


FIGURE 8: Experiment 1 simulation results

Figure 8 shows the result of experiment 1. Experiment 1 indicates how well agents can perform in the maximized timeframe. Agents are trading based on their experience that accumulated overtime. There is no capital reset during the experiment 1, as we are trying to mimic the trading situation in real life and give out a sense of the maximum possibility of agents' profitability. At the same time, experiment 1 allows us to observe the full story that happened during the whole timeframe while agents are trading. In Figure 8, the best performer achieved the profit of 3,450% in 2007, right before the beginning of the subprime mortgage crisis. All agents suffered huge losses during this crisis and they have not recovered even by the end of the simulation.

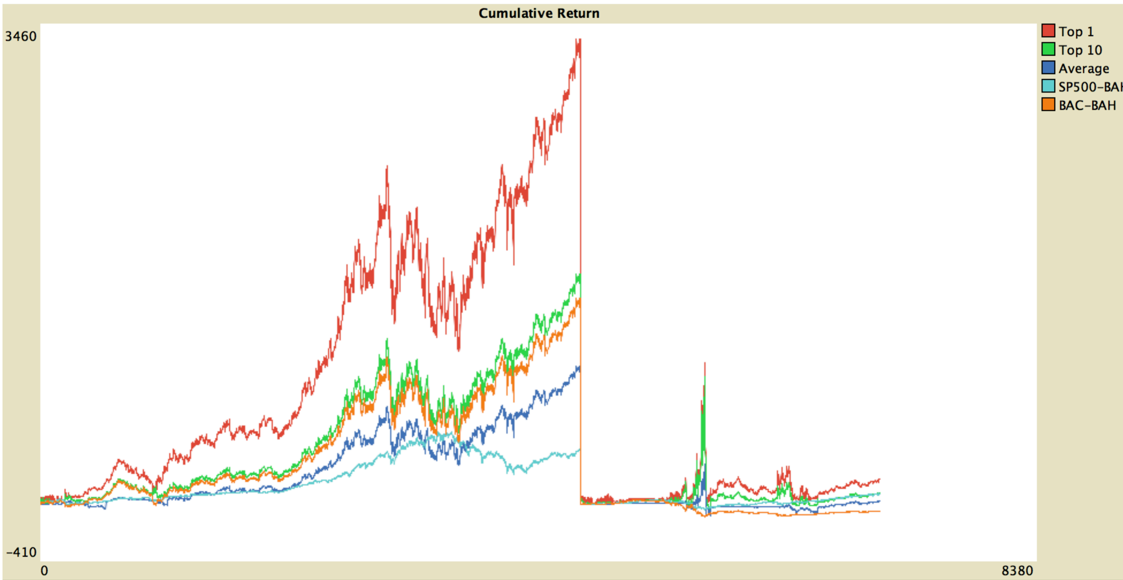


FIGURE 9: Experiment 2 simulation results

Experiment 2, shown in the figure 9, resets agents' capital in the first trading day of 2005. Agents did well in the training stage. In the test phase, agents secured significant profits until the crisis happened. It took agents about 3 years to recover from the downfall incurred by the crisis.

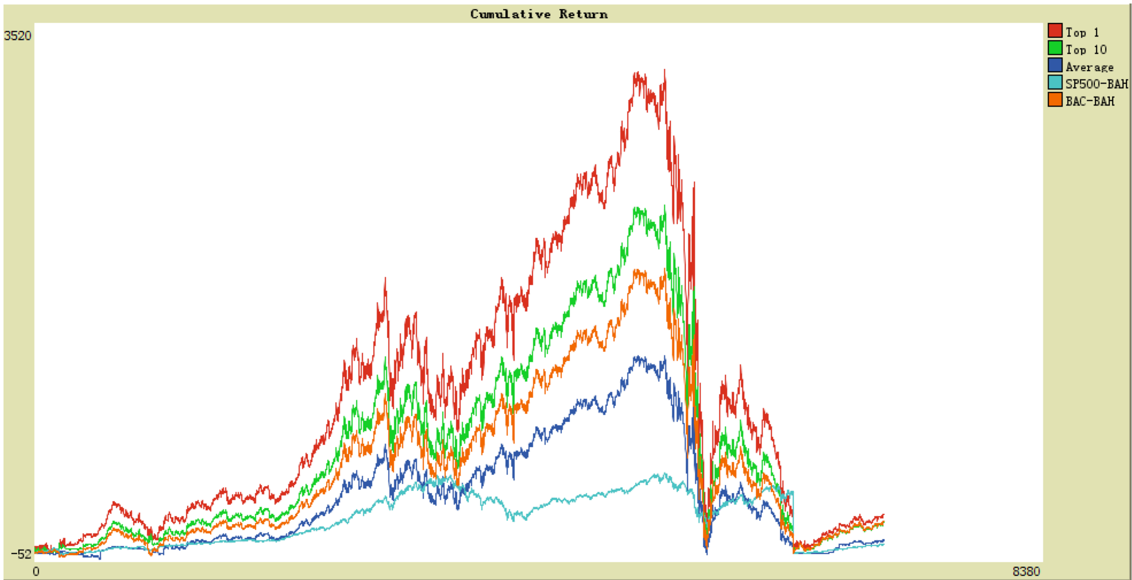


FIGURE 10: Experiment 3 simulation results

In the last experiment, agents' capital was reset at the beginning of 2012. In a pure bull market, the best agent gained around 374% profit, which was 13.34 times more than the simple buy-and-hold strategy on Bank of America stock.

However, it's interesting to see that benchmark agents (BA1 and BA2) underperformed their tracking targets, the best performer and top 10% best performers respectively. BA1 always replicates the current market best performer's action. BA2 mimics the top 10% best performers' action in the market. One possible explanation is that the trading frequency in bear market is much higher than that in the bull market, as the higher transaction frequency enables agents to secure the slight profit room in small price changes. Although this strategy comes with higher transaction costs, the extra profit can offset this drawback. Table 17 shows this phenomenon through the trading volumes.

TABLE 17: Trading volumes in shares

| | | |
|---|---|---|
| Experiment 1 | BA1 | 293,162 |
| | Best Performer | 12,686 |
| Experiment 2 | BA1 | 113,770 |
| | Best Performer | 6,851 |
| Experiment 3 | BA1 | 57,070 |
| | Best Performer | 4,802 |

Following shows the best trading decision rule set derived from the experiments for a particular agent in the simulation

For bull market:

- If the stock price goes down 37% in last 87 trading days, take a long position.
- If the stock price goes up less than 20% in last 71 trading days, take a short position.

For bear market:

- If the stock price goes down 20% in last 10 trading days, take a long position.
- If the stock price goes up less than 40% in last 61 trading days, take a short position.

The strategies above are the core decision rules for issuing stock trading signals. However, the market momentum turns the decision rules to actual transaction thresholds, which are then used to help agents make their moves.

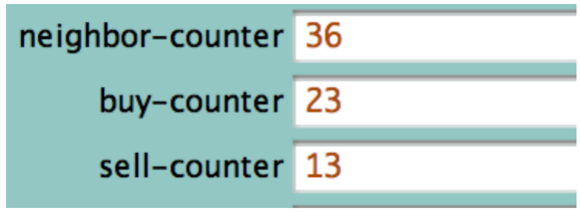


FIGURE 11: Agent's built-in variables for market momentum

For example, the above figure (Figure 11) shows an agent's built-in variable for momentum. There are 36 agents around it. Out of these 36 agents, 23 want to buy and 13 want to sell. As the confidence is 0.3, Table 7 shows the actual decisions in that particular tick.

For bull market:

- If the stock price goes down 29% in last 87 trading days, take a long position.
- If the stock price goes up less than 18% in last 71 trading days, take a short position.

For bear market:

- If the stock price goes down 18% in last 10 trading days, take a long position.
- If the stock price goes up less than 34% in last 61 trading days, take a short position.

The following figure (Figure 5) is an example of the actual stock trading signaling over time. When the green line hits 1, the system advises a long position. When the red line hits -1, then the model advises a short position. If both lines stay at 0, then hold strategy is applied.

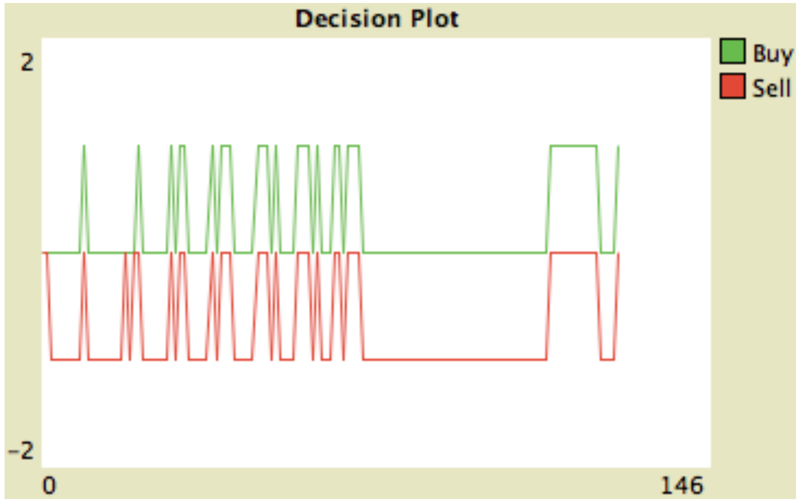


FIGURE 12: Decision plot overtime

In the experiment, agents' learning too quickly was one of the key issues. There is a variable called aggressiveness which controls the degree of agents learn from the difference between its and the best agent's performance. The aggressiveness was set to 0.1 while we introduced the learning component. That is in each tick, each agent will learn the 10% of the difference of trading rules between it and the top performers in radius. As a result, uniformity spread throughout the simulation. The best trader's performance was much less than 500%. This result was way below the BAC buy-and-hold strategy.

Therefore, aggressive was decreased to eliminate the uniformity among agents. Since the whole simulation has only 7,053 ticks, if aggressiveness is set too low then learning is not that effective in changing agents' decision rules. After several hundred simulation runs aggressiveness was finally set to its more optimal value of 0.001, in order to reconcile the problem of diversity, learning speed, and limited learning time. However, we will put more effort in the chapter 6 to explore the optimal level for the learning aggressiveness in the simulation.

What's more, reducing aggressiveness increase the correlation of return distribution between stock trading signal issuing model and historical S&P 500. Table 18 shows the correlation of annual returns between stock trading signaling model and historical S&P 500 with different settings of aggressiveness.

TABLE 18: Correlation of annual returns

| Aggressiveness | 0.1 | 0.01 | 0.001 |
|---|---|---|---|
| Correlation | 0.43 | 0.46 | 0.54 |

# CHAPTER 6: ONE STOCK SIGNALING DISCUSSIONS

In this chapter, we will discuss the efforts we had to enhance the performance of the one stock signaling model. The first part of the chapter will emphasize the optimization of degree of trust and learning aggressiveness. The second part of this chapter will cover the potential application in the setting of interest policy.

## 6.1 Model Enhancements

In the agents' trading decision rules, trust metrics and learning aggressiveness are fixed in the previous simulations in order to reduce the sample space in the simulation. In the model described in chapter 5, we have to sacrifice the total space exploration, which is in trillions, for computing speed. However, the single stock laid a solid corner stone for our further investigation of the parameters with fixed values. In the next step of model development, we started to explore the possibility to find the optimal level of either trust metrics and learning aggressiveness will maximize agents' profit in the same time frame.

### 6.1.1 Trust Metrics

The decision-making process in stock investment requires not only the rational trading rules practices, but also faith that market information is reliable. A trust metric is an indication of the degree to which one social actor trusts another. Picking the right time and position is hard, as both endogenous and exogenous factors impact stocks' intrinsic value at any given moment. With the advantage of asymmetric information, which is what happens when one party in a transaction has more or superior information compared to others, some investors will benefit from utilizing it. However, trust metrics will alleviate this impact by simply following the market's trend. Investors with the highest degree of trust in others can adapt their trading rules to the latest market changes, thus making it possible for them to outperform the market and maximize their profit.

The concept of risk control involves the method of identifying potential risk factors and takes actions to reduce or eliminate such threats. It plays a key role in portfolio management, as it can stop the potential loss in the unexpected stock price changes. Risk control methods make it possible for a dynamic portfolio management strategy to outperform the market (Browne, 2000). A degree of trust impacts the stock trading activities and risk control strategies (Asgharian et al., 2014). The use of trust metric can be beneficial in portfolio risk control, allowing investors to see the unanticipated changes in the market and take counter actions to prevent further loss.

#### 6.1.1.1 Degree of Trust

Degree of Trust is a parameter that we are interested in exploring. In the model, a variable called self-confidence is created to control the degree of trust to other agents' trading strategies (Su, 2015). The higher the self-confidence, the stronger the agents believe in their own trading strategies, thus decreasing the impact of the trading environment around them.

Agents have access to the latest market information. All agents conduct transactions based on the current stock price. They can track all the past prices, starting with Jan 2, 1987. At the same time, the bandwagon effect, which is characterized by the possibility of individual adoption increasing with respect to agents who have already done so, plays an important role in transactions. As a result, if there are a lot of agents who are buying stocks, then agents will increase their buy-threshold. At the same time, if there are many agents who are shorting stocks, then a substantial number of agents will correspondingly decrease their sell-threshold, as they try to liquidate their assets as soon as possible.

As a result, self-confidence captures the agents' degree of trust among all the other agents. In the self-confidence exploration stage, this parameter changed from fixed values to randomly assignment at the initial stage, making it possible to explore the best degree of confidence one should adopt in order to outperform the market.

#### 6.1.1.2 The Connection between Market Momentum and Self-Confidence

The overall trend of buying and selling constitutes the market momentum, according to which agents adjust their trading strategies correspondingly. With the adaptive trading strategies, agents are able to seek more trading opportunities and boost their profits.

However, agents cannot completely trust the market momentum. The degree of trust will affect the participation rate in stock trading (Guiso, 2008). Therefore, the variable self-confidence bridges the gap between market momentum and agents' rational trading strategies. Each agent has a randomly initialized degree of trust and the simulation tracks the best performer's self-confidence.

In the agent's buy and sell rules, self-confidence plays a key role in setting the real trading threshold. In some extreme scenarios, agents with the self-confidence of 1 do not listen to the latest market trends, while agents with the self-confidence of 0 follow market trend makers.

Rational investors are risk-averse in transactions. These investors prefer the lower risk choice when facing two investments with similar expected returns. Risks can be categorized into non-systemic risk and systemic risk, which cannot be diversified. As a result, following the market trend alleviates the non-system risk and lets agents keep the systemic risk only.

#### 6.1.1.3 Simulation Setups

The table below shows the basic model parameter setups to explore the best degree of trust among agents.

TABLE 19: Degree of trust exploration model setups

| **Parameter** | **Settings** |
|---|---|
| Bull-Buy-threshold | Randomized from -0.4 to 0.4 by 0.2 |
| Bull-Sell-threshold | Randomized from -0.4 to 0.4 by 0.2 |
| Bull-Buy-period | Randomized from 1 to 100 by 20 |
| Bull-Sell-period | Randomized from 1 to 100 by 20 |
| Bear-Buy-threshold | Randomized from -0.4 to 0.4 by 0.2 |
| Bear-Sell-threshold | Randomized from -0.4 to 0.4 by 0.2 |
| Bear-Buy-period | Randomized from 1 to 100 by 20 |
| Bear-Sell-period | Randomized from 1 to 100 by 20 |
| Aggressiveness | Fixed at 0.1 |
| Self-Confidence | **Randomized from 0 to 1 by 0.01** |

TABLE 19 (Continued)

| | |
|---|---|
| Mutation-rate | Fixed at 0.1 |
| Initial Capital | $50,000 |
| Transaction Cost | $10 each |

Similar to the setups for one stock signaling model, the exploration space for all possible trading strategy combinations exceeds trillions of possibilities. As the combination is extreme large, it has a huge impact on the computing speed of the simulation. In order to provide a trade-off between the computing speed and the space exploration, we set the agent number to 1,000. All transaction decision rules are randomized within the [-0.4,0.4] range for required returns and within [0,100] range for the trading periods. Aggressiveness is set to 0.001. Self-confidence is randomized from 0 to 1 by 0.01. The small range used in the simulation is to decrease the search space, thus boosting the coverage of each run. However, the full search range will be close to the real world trading. Mutation is introduced to allow a subset of agents to mutate from [-0.4,0.4] to [-1,1] for required returns, and from [1,100] to [1,1000] for trading periods. Agents are assigned with the initial capital in the amount of $50,000. The transaction cost is fixed at $10 per transaction, thus forcing agents to trade off for the opportunity costs. The mutation rate is fixed at 0.1, which allows 10% of all agents to get buy/sell threshold and buy/sell period generated in [-1,1] and [1,1000] respectively. Also, interest is distributed at the end of each tick, based on the amount cash held on hand.

Unlike the sector rotation model, the whole simulation to explore best degree of trust only has one round. The simulation was built based on the one stock signaling model. However, it will be based on the experiment 1 of the one stock signaling model. In that setup, agents are trading all the time from 1987 to 2014. There will be no test period in the simulation. As a result, agents' capital will not be reset during experiment. In this setup, it will be possible for us to explore how well agents perform in the maximum timeframe.

One major difference is learning from other agents is disabled in the first 1,000 days, which leaves enough time for agents to evaluate their initial trading strategies. After that, agents learn throughout the rest of the simulation. This mechanism allows agents sufficient time to optimize their strategies throughout the volatilities of the market, i.e. financial crises or huge price volatility periods.

6.1.1.4 Results

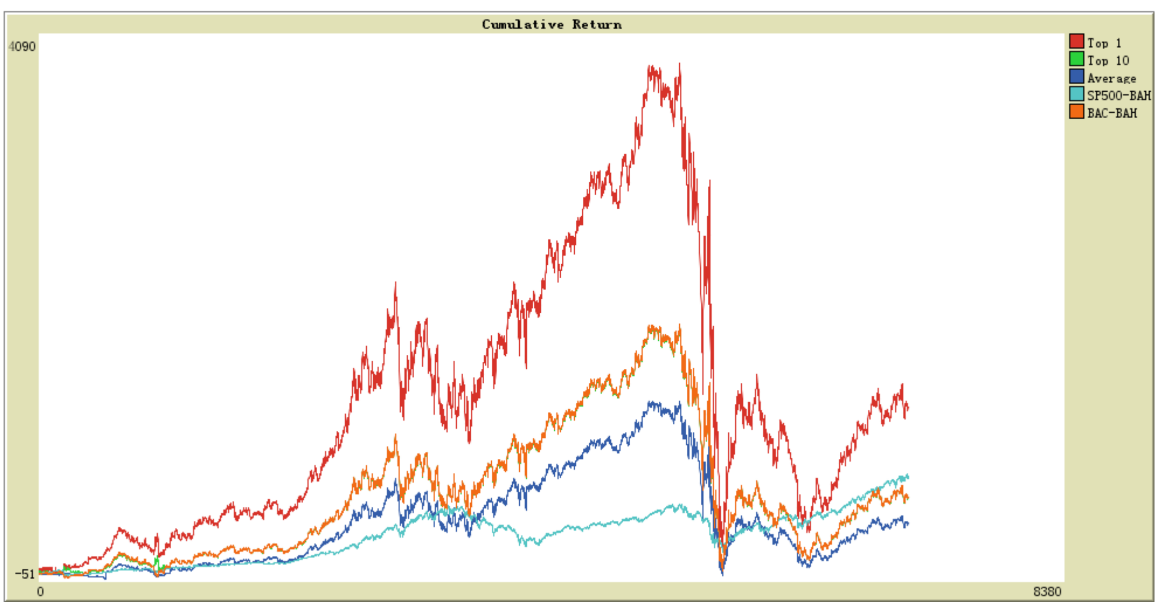


FIGURE 13: Cumulative returns in degree of trust exploration simulation

In the degree of trust exploration, S&P 500 and Bank of America (BAC) buy-and-hold strategies were used as the performance benchmarks. The S&P 500 index increased from 246.45 to 2059.9 during the period of 01/02/87 to 12/31/13. The Bank of America stock price increased from 2.34 to 17.89 in the same period. If investors use buy-and-hold strategy, they will receive 735.82% and 664.53% respectively. Figure 13 shows the cumulative return for different agents in the simulation. The best performer in the simulation achieved 1607.52% profit, which is 2.18 times better than the SP500 benchmark. Also, the top 10% performers achieved 678.75% profit, which is slightly better than the BAC benchmark. The reason for it is that the SP500 is related to banking industries, which were the main cause for the last financial crisis. As a result, BAC stock price is still 60% below its historical high but SP500 was surpassing its historical highs again and again in the past few years. Table 20 shows the summary of the results.

TABLE 20: Simulation results

| | | |
|---|---|---|
| Best Performer | Cumulative Return | 1,607.52% |
| | Self – Confidence | 0.42 |
| Top 10% Performers | Cumulative Return | 678.75% |
| | Self – Confidence | 0.46 |
| Benchmarks | Benchmark Agent 1<br>S&P 500 Buy-and-hold | 735.82% |
| | Benchmark Agent 2<br>BAC Buy-and-hold | 664.53% |

From the Monte Carlo simulation of the model, the best level of degree of trust is at the level of 0.42. It indicates that the best performer will change its decision rules 58% according to the market changes, and keep the 42% of its initial decision rules settings. The best decision rule set was described as follows.

- If the stock price goes down 52% in last 234 trading days, take a long position.
- If the stock price goes up less than 40% in last 42 trading days, take a short position.

However, these rules are subject to 58% with respect to the degree trust to the market momentum. As market momentum changes everyday, agent will change their decision rules correspondingly. Following shows a particular trading rules set are actually put into practices on Dec. 31 2014.

- If the stock price goes down 20% in last 234 trading days, take a long position.
- If the stock price goes up less than 18% in last 42 trading days, take a short position.

The narrative for the trading rule set basically states that an investor should track the past performance for a particular stock and then decide whether to get in. For the exit strategy, if the stock's performance deviates from the expectations, investors should clear their positions immediately.

#### 6.1.1.5 Discussions

From the simulation results in the previous section, we can see that the momentum, a measure of the overall market sentiment (Scowcroft and Sefton, 2005), plays an important role in the CAS stock stock-trading model. All the rules are adjusted based on the market momentum in a specific time tick.

With the benefit of the momentum, the performance of the stock-trading model is far better than a simple buy-and-hold strategy for both S&P 500 and BAC. In the current model, momentum is generated by the agents' desire to conduct transactions. Future refinements in the momentum component will play a key component in improving the performance of the model. Agents should change their rules at a level of 0.42 to the market changes in order to outperform the market.

### 6.1.2 Learning Aggressiveness

Although trust plays an important role in stock markets, learning is also an inseparable part of stock trading. It is an act of acquiring new or modifying existing knowledge, behaviors, or skills. Learning builds upon the previous knowledge over time. Similarly to trust metrics, learning investment strategies involves mimicking the behavior of top market performers, copying their philosophy of stock trading. However, unlike trust metrics, learning is a continuous lifelong process, enabling a person's ability to adapt to the changes in the environment. Investors are constantly aware of the latest market changes, and they possibly benefit from the current state of the market (Linn, 2007).

A learning curve captures the progress of learning over time. It is a graphical representation of the increase of learning with experience. The slope of learning reflects how aggressive (eager, motivated, or capable) the learner is in attempting to become a better performer over time. A typical learning curve is shown in figure below. A more aggressive learner tends to copy more from the market best performers, and consequently has a much steeper learning slope. Less aggressive learners, however, tend to use best performers' behavior only as a minor correction to update their own trading rules.

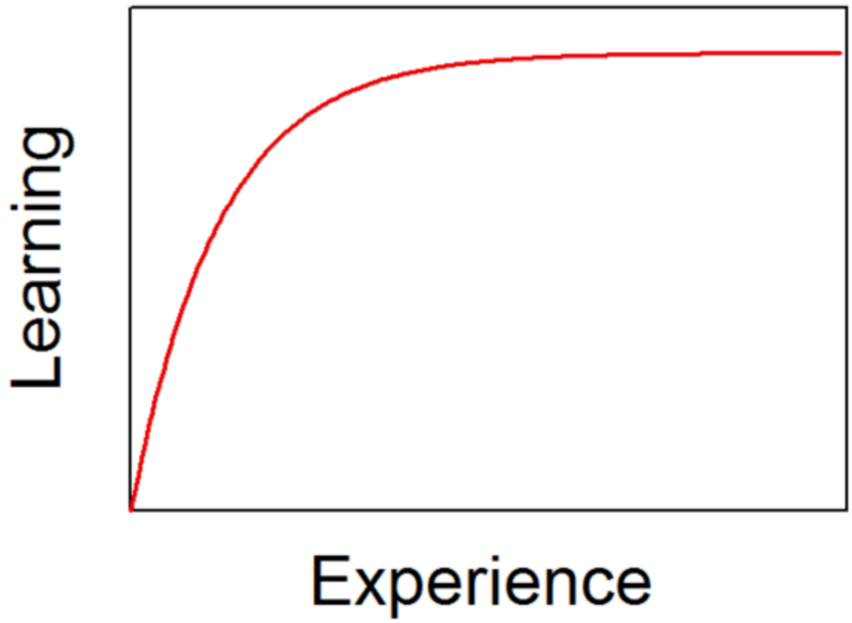


FIGURE 14: Learning curve

Similarly, learning plays an important role in investment. Learning from past performance and from actions of others makes investors become better through their accumulated expertise (Seru, 2010). This is, in turn, reflected in their actions in the market place. A simple way of learning in investment is to mimic behaviors of top market performers, copying their philosophy of stock trading. By doing so investors become aware of the latest market changes and possibly benefit from the current state of the market (Linn, 2007). The progress of learning over time is captured in what is frequently referred to as a learning curve, which is a graphical representation of the increase of learning with experience. The slope of learning reflects how aggressive (eager, motivated, or capable) the learner is in attempting to become a better performer (investor in this case) over time. A more aggressive learner tends to copy more from the market best performers, while a less aggressive ones tend to only use best performers' behaviors as a minor correction in updating its own trading rules.

This section introduces an agent-based model for finding the optimal value of aggressiveness in learning when maximizing stock trading returns (Su, 2015). The model is based on the single stock signaling model, which is derived from our multi-sectors trading model. The system has been evaluated in the context of Bank of America stock performance in the period of 1987–2014. The model significantly outperformed the buy-and-hold strategy on both S&P 500 and Bank of America stock.

#### 6.1.2.1 Learning Aggressiveness Backgrounds

In agent based models agents interact with each other. Learning is one of such interactions. In our model, learning offers agents the opportunity to check and compare their decision rules with those of the best performers, thus making it possible for them to refine their rules and secure more profits in the future similar market trends (Cui, 2012). The major simulation method is still utilizing the agent based modeling. ABM models combined with artificial intelligence-based reinforcement learning provide a plausible way of stock modeling (Ramanauskas, 2008).

Unlike the degree of trust, which only changes the agents' decision rule temporarily based on the latest market trends, learning has a permanent impact on agents' trading strategies. The learning mechanism makes it possible to investigate alternative strategies that have not yet been discovered in the market (Outkin, 2012). In this implementation, to preserve computational time and to maximally alleviate the constraints of the limits of available computing power, a radius is introduced in the simulation. Agents can only see other agents within their own radius while moving around, which helps with avoiding the homogenization of agents. Agents have the opportunity to learn from the best performers within their radius, thus within their neighborhood, which helps with improving the learning efficiency as well. With the ability to learn and to decide how much they want to learn from their neighbors (i.e., how close they want to get to their neighbor's value on a particular variable), the size of the exploration space of optimal decision rules is reduced from the size of trillions of combinations into a much smaller one.

The variable aggressiveness defines the extent of neighborhood best performers' behavioral structure the agent wants to adopt. It ranges from 100% to nothing, with most cases being somewhere in the middle. Prior to the learning phase, agents' original decision rules will be given sufficient time to evaluate their performance. The learning process starts only after this evaluation period.

6.1.2.2 Model Setups

Following table shows basic parameter setups to explore the optimized learning aggressiveness.

TABLE 21: Learning aggressiveness exploration model setups

| **Parameter** | **Settings** |
|---|---|
| Bull-Buy-threshold | Randomized from -0.4 to 0.4 by 0.2 |
| Bull-Sell-threshold | Randomized from -0.4 to 0.4 by 0.2 |
| Bull-Buy-period | Randomized from 1 to 100 by 20 |
| Bull-Sell-period | Randomized from 1 to 100 by 20 |
| Bear-Buy-threshold | Randomized from -0.4 to 0.4 by 0.2 |
| Bear-Sell-threshold | Randomized from -0.4 to 0.4 by 0.2 |

TABLE 21 (continued)

| | |
|---|---|
| Bear-Buy-period | Randomized from 1 to 100 by 20 |
| Bear-Sell-period | Randomized from 1 to 100 by 20 |
| Learning Aggressiveness | Randomized from 0 to 1 by 0.0001 |
| Self-Confidence | Randomized from 0 to 1 by 0.01 |
| Mutation-rate | Fixed at 0.1 |
| Initial Capital | $50,000 |
| Transaction Cost | $10 each |

In this model, the exploration space for all possible trading strategy combinations is in the size of trillions. As the combination is extreme large, a huge quantity of agents needs to be created to cover all possibilities. This is theoretically doable, but it has a huge impact on the computing speed of the simulation. It may take decades to get the result if trillions of agents are used in the model.

In order to provide a trade-off between the computing speed and the space exploration, the number of agents in the model is capped at 1,000, while taking advantage of the mutation mechanism to explore the possibility of exploring the whole space of parameter dimensions. The settings of parameters are listed in the table above.

All transaction decision rules are randomized within the reduced sample space along with mutation enabled. As a result, the 4 minimum required returns will be randomized with [-0.4,0.4] range with 0.2 step size. The 4 trading period parameters will be initialized within [0,100] range with 20 step size.

Learning aggressiveness is randomized between 0.1 and 0.0001, with step size 0.001. The rationale behind this setting range is that there are 7,110 trading days in the whole simulation. This range will prevent all agents from learning too fast, and ensuring that all agents have identical trading rules.

Self-confidence is randomized between 0 and 1, with the step of 0.01. The small range and large step sizes are used in the simulation as a mechanism for decreasing the size of the search space, thus boosting the coverage of each run. However, the full search range will be closed to the real world trading.

Mutation is used to allow a subset of agents to mutate from [-0.4,0.4] to [-1,1] for required returns, and from [1,100] to [1,1000] for trading periods. The mutation rate is fixed at 0.1, which allows 10% of all agents to get buy/sell threshold and buy/sell period generated in [-1,1] and [1,1000] respectively. Mutation also works in the hatch-and-die stage, indicating there will be 10% of all the newly generated agents' parameters will be initialized in the [-1,1] and [0,1000] ranges.

Agents are assigned the initial capital in the amount of $50,000. The transaction cost is fixed at $10 per transaction. Also, interest is distributed at the end of each tick, based on the amount cash held on hand and the current tick interest rate. The interest rate we used for interest distribution is derived from the Federal Reserve Web site.

In the simulation, learning from other agents will also be disabled in the first 1,000 days. As a result, agents will have sufficient to test their trading strategies they are born with as well as evaluating other's rules. After that, agents learn until the end of the simulation. This mechanism allows us to test the durability and profitability of agents' initial trading rules throughout the volatile market movements.

There will only be one round of simulation without test period. The reason behind this setup is to give agents maximal time to trade and achieve the maximal profits in their life frame.

### 6.1.2.3 Results

In the stock trading model, S&P 500 and Bank of America (BAC) buy-and-hold strategies were used as the performance benchmarks. The S&P 500 index increased from 246.45 to 2059.9 during the period of 01/02/87 to 12/31/13. The Bank of America stock price increased from 2.34 to 17.89 in the same period. If investors used the buy-and-hold strategy, they would earn 735.82% and 664.53% of their initial investment respectively. Following figure shows the cumulative return for different agents in this simulation.

The best performer in the simulation achieved 1,363.36% profit, which is 1.85 times better than the SP500 benchmark. Also, the top 10% performers achieved 697.94% profit, which is slightly better than the BAC benchmark. The main reason for this is that the S&P500 is a weighted index including stocks from all industries. The main cause of the last financial crisis is related to banking industries. Therefore, the banking industry suffered more downturn than the S&P 500. This resulted in BAC stock price being still 60% below its historical high, while SP500 was surpassing its historical highs again and again in the past few years. The table below shows the summary of the results.

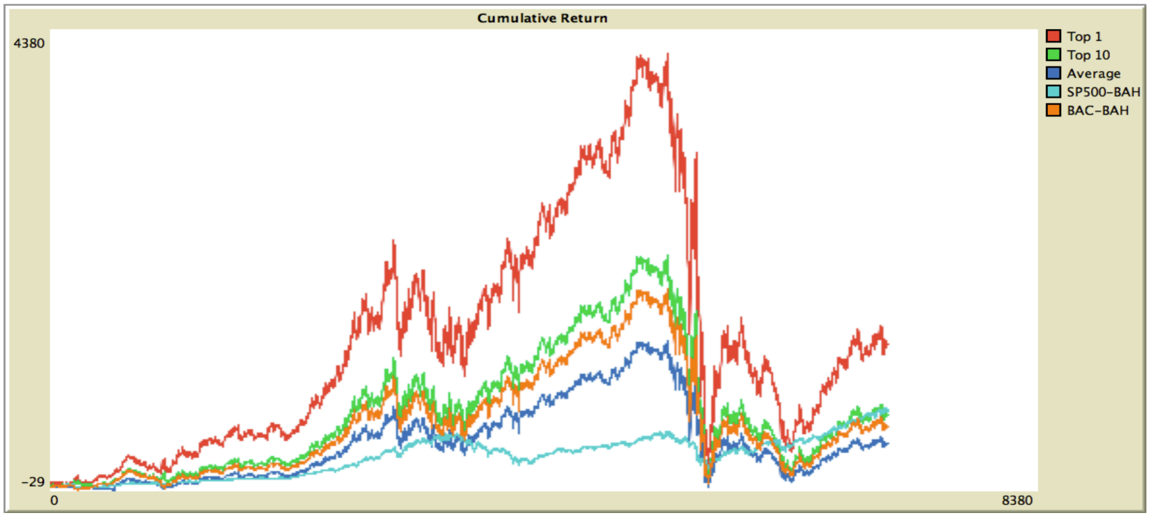


FIGURE 15: Learning aggressiveness exploration simulation results

TABLE 22: Simulation results

| Agent | Strategy | Experiment 1 | Experiment 2 |
|---|---|---|---|
| Best Performer | Cumulative Return | 1363.36% | 556.75% |
| | Aggressiveness | 0.07 | 0.025 |
| Top 10% Performers | Cumulative Return | 678.75% | 544.12% |
| | Aggressiveness | 0.05 | 0.03 |
| Benchmark Agent 1 | SP500 Buy-and-hold | 735.82% | |
| Benchmark Agent 2 | BAC Buy-and-hold | 664.53% | |

From Monte Carlo simulations, two typical experiments results are selected for demonstration of model performance with different final aggressiveness results. Experiment 1 represents the one of our best results while the experiment 2 has below average performance. It's obvious that the best level of learning aggressiveness was at the level of 0.07. It indicates that the best agent tended to accept 7% of the difference between its and the best performer's (within the radius) decision making parameters. After that, agents move around and seek others that are better off still. As the aggressiveness was randomized between 0.1 and 0.0001, 0.07 indicates a significantly fast learning speed. Comparing the results between these two experiments, higher aggressiveness tends to bring higher results. The preference for high speed of learning indicates that agents tend to mimic the best performer's trading behavior and learn as quickly as possible during the whole simulation process, without actually committing to early to mimic the first few more successful agents that they actually see. Because of the permanent effect of learning, the best agents are able to mimic all the best rules within a shorter period of time with faster learning speed.

#### 6.1.2.4 General Discussion

Compared with the return of the S&P 500, the CAS model with optimized learning aggressiveness presented here has achieved a much higher return, around 1.8 times, than the S&P in the same timeframe.

Best agent and agents with the top 10% performance show a very aggressive learning style, with 0.07 and 0.05 derived values respectively. With a fast learning speed, agents can use the trial-and-error method to get trading rules that works best in the current market environment. However, one problem we face is the inability to run the simulation with a large amount of agents. If we could put more agents into the simulation, then we would be able to supply more randomly initialized decision rules into the pool. With a larger pool, agents could mimic the best set of rules immediately instead of waiting for a long time to get the best rules available to them.

On the trading strategies side, the narrative basically states that an investor should track the past performance for a particular stock and then decide whether to get in. For the exit strategy, if the stock's performance deviates from the expectations, investors should clear their positions immediately.

## 6.2 Application in Policy Determination

In this part, we will try to explore the possible application of the model in the traditional monetary policy setting, i.e. interest rate.

### 6.2.1 Interest Rate, Monetary Policy and Market Liquidity

Interest rate, is the price the borrower pays to the lender based on the proportion of the money owed. The total amounts of interest on the borrowed capital will depends on the principal sum, the interest rate, the frequency of interest compounding, and the length of time the capital is borrowed.

Monetary policy is the process implemented by such national authorities, as central banks or currency boards, to control the supply of money. The usual methods of monetary policy are interest adjustment, bank reserve ratio adjustment, and open market operations.

The ultimate goal of monetary policy is to control the inflation in the real economy. The inflation goal set by most central banks in the world is between 2% to 3% each year. Further goals of a monetary policy are usually targeted at contributing to a stable growing economic, low unemployment rates, and predictable exchange rates with other currencies.

Monetary policy is usually referred as contractionary or expansionary. Expansionary policy is normally used to stimulate the economy by monetary authorities.

The supply of money is usually increased to a much higher level during the expansionary monetary policy implementation. It is usually used to confront with the high unemployment rate during a economy recession by lowering the interest rate and expecting business started to grow as a result of easy credit retrieval. On the other hand, the aggregate demand, the overall demand for goods and services in the economy, will increase as the unemployment rate lowers and boost the gross domestic product. However, the currency will depreciate during the expansionary policy, resulting in the slump of corresponding currency rate.

In contrast, contractionary monetary will usually increase the interest rate. This action will slow down the economy in return. In some worse scenario, the economy might experience deflation. Also, contractionary monetary policy can lead to increased unemployment and depress the money borrowing and spending by individuals and companies.

Interest rate adjustment is used as the most commonly used tool by the central bank. The most impact in the monetary is the open market operations. This comes with the management among the overall money circulating in the economy with the means of buying and selling of multiple financial instruments. Examples are company bonds, municipal bonds, treasury bills, foreign currencies, exchanging for money on deposit at the central bank. The deposits in the central bank can be converted to currency. As a result, the change of the quantity of the money on deposit in central bank can lead to the change of amount of the money into market circulation.

One example is central bank tends to take expansionary monetary policy. It will tend to decrease the interest rate. At the same time, central bank will purchase government debt and releasing tons of cash in the circulation. As a result, commercial banks will have more money available to lend. On the other hand, they tend to lower the lending rate, pushing down the overall price of the loan, and making the loan more attractive. At the same time, low interest for credit cart will increase spending for most consumers. What's more, lower interest makes the borrowing cheaper and stimulates the business owners to expand and increase the supply to meet the surging demands. In order to expand, more workers will be hired as well as an income hike. In return, higher income also increases the demand.

Liquidity preference refers to the demand for money (Keynes, 1936). It explains the determination of the interest rate by the supply and demand of the money. In other words, the more quickly an asset can be converted to money the more liquid it is. According to Keynes, demand for liquidity is usually determined by the following three motives.

- The transaction motive. People prefer liquidity for basic transactions because their income is not always available. The required liquidity is proportional to the income. The higher the incomes, the more liquidity will be required.
- The precautionary motive. People need liquidity for some unexpected situations, which will incur uncertain expenses. Same as the transaction motive, the higher the income, the more liquidity will be required.
- Speculative motive. People hold money to speculate in either bond or stock market. When the interest rate decreases, people will usually demand more money to hold until the interest started to increase again. In other worlds, the lower the interest, the more money will be required to hold on hand for possible speculative opportunities.

### 6.2.2 Possible Application in Interest Rate Policy Setting Application

Since the speculative motive is one of the most important factor for the demand of money, which will also be impacted by the interest rate set by monetary policy. The one stock trading model or even the sector rotation model is possible to test people's behaviors among different interest settings.

In the model, since interest rate will impact agents' cumulative return overtime in the model, the model could be used to inform policy makers on the setting of interest rate in the context of anticipated investor reactions. This is due to the fact that government open-market operations induce liquidity effects that lead to interest rate behaviors (Lucas, 1990), and market liquidity also affects the trading activities (Chordia, 2001).

Liquidity is one of the most important properties and the foundation of the stock markets. The information will be reflected in the prices more quickly in a highly liquid market, resulting in better effect of capital redistribution. Also, investors can rebalance their portfolio rapidly since the demand and supplies are actually in equilibrium. With quick portfolio rebalancing, it will be easier for investor to diversify the risk and make sure the weight of the portfolio is in the optimal level.

In this simulation, investors have to decide between Bank of America shares and money with a fixed interest rate. Since interest will be given to agents at the end of each day, they will need to balance off the pursuit of profit through investment or interest through cash. Although higher returns come with higher risk, but the uncertainty towards future still plays an important part in people's decision-making processes (Su, 2015). As a result, policy makers could try to test various options using this model to see the market reactions to differing scenarios. With varying interest settings, agents may exhibit preferences towards the stock or money. As the preferences change, the liquidity in the market will also act correspondingly.

Rationality also plays an important role in the stock price determination, because rationality is affected by the supply and demand of the stocks. Although stock market participants believe that they are rational in their decisions on stock purchasing, panics and frenzies also drives many market trends. This phenomenon is usually happens a lot in economic booming period, while the price of underlying asset, such as real estates, stocks, bonds, to levels that are well above the historical norms. On the other hand, the economic boom is driven by the usual low interest rate brought by the expansionary monetary policy, which aims to drag the economics out of the pace of recession.

In the economic boom, investors' greedy and panic-prone behaviors amplify regular ups and downs of the market, thus building up a bubble that inevitably ends up in a market crash. The most recent experience is the real estate bubble in the states. As the population in the states grown in a fast speed, people believe there will be higher need for housing. As a result, the housing price will never decrease, making them a much safer asset class. The index of US housing prices nearly doubled from 1996 to 2006. Although, the index only increased 1/3 in the first 5 years, the second half of the decade actually experienced a much higher rocketing speed. However, even the house prices were going up at a record fast pace, this phenomena were piled up through an unsustainable frenzy, such as mortgage fraud, houses were mainly bought by the subprime borrowers, instead of prime borrowers. The plateau of the housing price was in 2006. Three years later, 1/3 of the value evaporated. Leading to the bankruptcies of Fannie Mac and Freddie Mac, as well as some major investment banks in the Wall Street. The federal government will have to use multiple stages quantitatively easy policy, which is actually expansionary monetary policy, to bail out the big banks and ensure the economic stability.

The boom and the burst of bubble in the US real estate market and the ripple effect it had on the mortgage-backed securities, led to a global economic contraction, which surpassed the great depression we had back in 1930s.

As a result, since Irrational markets occasionally display bubble phenomena. The correct interest rate setting may be able to control the formation of bubbles and indeed ensure that economy is healthy.

# CHAPTER 7: CONCLUSIONS AND FUTURE WORKS

Complex Adaptive Systems is a computational paradigm developed in computer science to deal with the issue of complexity in the real world. Computers can act as simulators of physical and social processes. When a model simulates behavior of a system, it provides us with a unique way of studying the underpinnings of the system that result in observed system behaviors.

Financial markets are complex systems. In financial markets, there are micro behaviors, interaction patterns, and global regularities. At the same time, the agents' behaviors also try to uncover the irrational decision rules. Due to the fast expansion of knowledge in computational sciences, the latest analytical tools made it possible to study the above aspects quantitatively.

In this dissertation, we showed two models, which were built on the method of agent based modeling, used the concept of complex adaptive systems. Both models actually outperformed the market and significantly exceeded the assigned benchmarks. These promising results proved complex adaptive systems and the method of agent based modeling can be applied to the real world markets. Computer simulations allow us to see behind-the-scene actions of agents, and to make possible forecasts on possible futures of the markets.

First, for the sector rotation models, comparing with the return of the S&P 500, the CAS model presented here has achieved a much higher return, around 800x in the same timeframe as the S&P. However, although the CAS sector rotation model achieved a much higher return than the S&P 500, the best achievement relies heavily on the interaction among agents. Momentum is a measure of the overall market sentiment (Scowcroft and Sefton, 2005). It is the desirability of buying or selling among all agents. Agents change their threshold based on the market momentum. With the benefits of momentum, the model achieves a much higher return than the S&P 500. However, we are aware that the best return is probably just an outlier, because it happens if and only if the market contains the same momentum as the one in the model.

Second, for the single stock signaling model, it showed a much higher return on a single stock trading in the same timeframe, when the model performance was compared with the buy-and-hold strategy of S&P 500 and BAC stock. We conducted three experiments with different test and training period settings. The model we built stood out in all three experiments and produced promising results and possibly profitable trading rules. Since one stock signaling model was built on the sector rotation model, the market momentum once again impacted the performance of agent. In the initial testing of the model, momentum is generated by the agents' desire to conduct transactions. Future refinements in the momentum component will lay a key component in improving the performance of the model.

Third, the decision-making process in stock investment requires not only the rational trading rules practices, but also faith that market information is reliable. A trust metric is an indication of the degree to which one social actor trusts another. As a result, we explored the optimal degree of the trust should agents gave to the market momentum in the later stage. We tried to figure out the degree of trust can bring agents' highest degree of returns in their trading activities. Compared with the return of the S&P 500, the CAS model with optimized self-confidence presented here has achieved a much higher return, around 2 times, in the same timeframe as the S&P. The Monte Carlo simulation was conducted to run the model thousands of times to make sure we covered the search space as much as possible.  From the Monte Carlo simulation of the model, the best level of degree of trust is at the level of 0.42. It indicates that the best performer will change its decision rules 58% according to the market changes, and keep the 42% of its initial decision rules settings.

Fourth, learning plays a key role in stock investment. It enables people to mimic the best performers' strategies in the real-world market. Aggressiveness (or eagerness) in learning determines the degree of learning activity, or the degree to which one trader decides to mimic another during every opportunity to learn. In our agent-based model we built a stock-trading model that issues a daily stock trading signal. Through the result, we found the following general learning pattern in the agents who stood out to be the best performers in the market. Best agent and agents with the top 10% performance show a very aggressive learning style, with 0.07 and 0.05 derived values respectively. With a fast learning speed, agents can use the trial-and-error method to get trading rules that works best in the current market environment. However, one problem we face is the inability to run the simulation with a large amount of agents. If we could put more agents into the simulation, then we would be able to supply more randomly initialized decision rules into the pool. With a larger pool, agents could mimic the best set of rules immediately instead of waiting for a long time to get the best rules available to them.

Fifth, we squeezed out another possible application of the models – in monetary policy, specifically interest rate, setting. Similar to the concept that market was built upon investors, both models we built are constituted with agents. As a result, agents' reactions and behaviors can be a good reference and provide relevant information to policy maker regarding interest rate settings. Policy makers may then use this model to test the impact of different interest rate settings in various market conditions, in order to confirm or disprove the desired changes in the financial markets. When used in this way, the model may be able to work as a new tool for policy makers, and help them improve the effectiveness of their recommended policies.

Sixth, we figured out a way to solve the exploration of search spaces. Initially, when we launched the model, the total search space of all agents is 1.6 * 1025, which means we need to create at least 1.6 * 1025 agents to cover the whole space. With the current computing power this is an impossible mission, even if we use high performance computers (HPC) to run the simulation. It will take at least multiple scores before we know the experiment results. In order to reduce the overall search space, we proposed a small search range with mutation mechanism, which successfully reduced the sample space to 62,500. With 1,000 agents in the model, we can explore around 1.6% of the search space. The significant reduction of sample space makes the experiment become doable with Monte Carlo simulation. Although 1.6% of the search space was explored in each simulation run, we can explore the whole search space with dozens run with HPC and get the results in several days.

The last but not the least, as for future works and continuation model refinement, we will use multiple underlying assets, selected from different sectors of the S&P 500, in order to test the performance of this model and evaluate different market reactions to the change in interest rates. Also, we might work on several strategies for improving the computation of the momentum component. One possibility is to extract the real time tweets from Tweeter and to run a sentiment analysis on those tweets. Then the signals from Twitter will be attached to the current momentum component. The other possibility is to use the transactions volume to deduce the historical drive in the market and plug it into the current momentum mechanism, leading to a more precise forecast about the upcoming market movements. In return, agents can anticipate the changes in the future investors' actions and adjust their transaction strategies to maximize profits. The trading of single stock can also be extended to multiple stocks, which are selected from different sectors. In that way, the multiple stocks trading model will give out a better sense of different degree of trust across different sectors.

REFERENCES

Asgharian, H., Liu, L., & Lundtofte, F. (2014). Institutional Quality, Trust and Stock-Market Participation: Learning to Forget. *Trust and Stock-Market Participation: Learning to Forget.*

Barnes, J. (2003). Active vs. Passive Investing. *CFA Magazine.* Jan 2003: 28-30.

Bonabeau, E., 2002. Agent-based modeling: Methods and techniques for simulating human systems. *Proceedings of the National Academy of Sciences of the United States of America, 99(Suppl 3),* 7280-7287.

Browne, S. (2000). Risk-constrained dynamic active portfolio management. *Management Science, 46(9),* 1188-1199.

Cappiello, L., Engle, R. F., & Sheppard, K. (2006). Asymmetric dynamics in the correlations of global equity and bond returns. *Journal of Financial econometrics, 4(4)*, 537-572.

Chordia, T., & Shivakumar, L. (2002). Momentum, business cycle, and time-varying expected returns. *The Journal of* Finance, 57(2), 985-1019.

Conover, M., Jensen G., and Mercer J., (2008). *Journal of Investing, Sector Rotation and Monetary Conditions*. 34–46.

Cui, B., Wang, H., Ye, K., &Yan, J. (2012). Intelligent agent-assisted adaptive order simulation system in the artificial stock market. *Expert Systems with Applications, 39(10)*, 8890-8898.

Dreau, D. Stanimirov, D.; Carmichael, T.; Hadzikadic, M. (2009), Bioinformatics and Computational Biology. *An agent-based model of solid tumor progression. Vol. 5462;* Rajasekaran, S., Ed.; Springer: New York; pp 187–198.

Darley, V., and Outkin, A., 2007. NASDAQ market simulation: insights on a major market from the science of complex adaptive systems. *World Scientific Publishing Co., Inc.*

Faber, M., 2010. *Relative Strength Strategies for Investing.* Cambria.

Farmer, J., Patelli, P., and Zovko, I., 2005. The predictive power of zero intelligence in financial markets. *Proceedings of the National Academy of Sciences of the United States of America, 102(6),* 2254-2259.

Fishman, G., 1995. *Monte Carlo: Concepts, Algorithms, and Applications.* Springer.

Graham, B., Dodd, D. L. F., & Cottle, S.1934. Security analysis. New York: McGraw-Hill.

Grinold, R., & Kahn, R.  (1995). *Active portfolio management (pp. 367-8).* Probus Publ.

Guiso, L. (2008). Trusting the stock market. *Journal of Finance, 63(6),* 2557-2600.

Holland, J., (1992). *Daedalus. Vol.121. No.1. A New Era in Computation*, pp. 17-30.

Hommes, C. H. (2006). Heterogeneous agent models in economics and finance. *Handbook of computational economics, 2*, 1109-1186.

Hong, H., Lim, T., & Stein, J. C. (2000). Bad news travels slowly: Size, analyst coverage, and the profitability of momentum strategies. *The Journal of Finance, 55(1),* 265-295.

Jegadeesh, N., & Titman, S. (1993). Returns to buying winners and selling losers: Implications for stock market efficiency. *The Journal of finance, 48(1),* 65-91.

Jegadeesh, N., & Titman, S. (2001). Profitability of momentum strategies: An evaluation of alternative explanations. *The Journal of Finance, 56(2),* 699-720.

Johnson, L., Hadzikadic, M., Whitmeyer, J., (2013). International Journal of Humanities and Social Science. *The Future Engaging Complexity and Policy: Afghanistan Citizen Allegiance Model. Vol.3. No.10*.

Johnson, N. F., Jefferies, P., & Hui, P. M. (2003). *Financial market complexity*.

Malkiel, B. G., & Fama, E. F. 1970. Efficient capital markets: A review of theory and empirical work. *The journal of Finance, 25(2),* 383-417.

Keynes, J. M. (1936). *The general theory of interest, employment and money*.

Kodia, Z., Said, L., and Ghedira, K., 2010. A study of stock market trading behavior and social interactions through a multi agent based simulation. *Agent and Multi-Agent Systems: Technologies and Applications* (pp. 302-311). Springer Berlin Heidelberg.

Linn, S.C., & Tay, N.S.(2007). Complexity and the character of stock returns: Empirical evidence and a model of asset prices based on complex investor learning. *Management Science, 53(7),* 1165-1180.

Lucas, R. E. (1990). Liquidity and interest rates. *Journal of economic theory, 50(2)*, 237-264.

Model, A. P., Diversification, I. I., & Roll's, C. A. P. M. 1987. *Investment Analysis & Portfolio Management.*

Moskowitz, T. J., & Grinblatt, M. (1999). Do industries explain momentum?. *The Journal of Finance, 54(4),* 1249-1290.

Outkin, A. V. (2012, Sep). An agent-based model of the NASDAQ stock market: Historic validation and future directions. *In CSSSA Annual Conference*, Santa Fe, New Mexico (pp. 18-21).

Palmer, R. G., Arthur, W. B., Holland, J. H., & LeBaron, B. (1999). An artificial stock market. *Artificial Life and Robotics, 3(1),* 27-31.

Pring, M. 2010. *The Investor's Guide to Active Asset Allocation: Using Technical Analysis and ETFs to Trade the Markets.* McGraw Hill Professional.

Raberto, M., Cincotti, S., Focardi, S. M., & Marchesi, M. (2001). Agent-based simulation of a financial market. *Physica A: Statistical Mechanics and its Applications*, 299(1), 319-327.

Rasmussen, M. (2003). *Quantitative portfolio optimization, asset allocation and risk management.* Palgrave Macmillan.

Ramanauskas, T. (2008). Agent-Based Financial Modelling as an Alternative to the Standard Representative-Agent Paradigm. *Pinigø studijos*, 2, 5-21.

Saad, E., Prokhorov, D., and Wunsch, D., 1998. Comparative study of stock trend prediction using time delay, recurrent and probabilistic neural networks. *Neural Networks, IEEE Transactions on, 9(6),* 1456-1470.

Scowcroft, A. and Sefton, J. (2005). Understanding momentum. *Financial Analysts J.,* 64-82.

Seru A., Shumway, T., & Stoffman, N(2010). Learning by trading. *Review of Financial Studies, 23(2),* 705-739.

Sharpe, W. (1994). The Sharpe Ratio. *The Journal of Portfolio Management 21 (1):* 49–58.

Subramanian, H., Ramamoorthy, S., Stone, P., and Kuipers, B., 2006. Designing safe, profitable automated stock trading agents using evolutionary algorithms. *Proceedings of the 8th annual conference on Genetic and evolutionary computation* (pp. 1777-1784). ACM.

Su, Z., & Hadzikadic, M. (2014). Applications of Complex Adaptive Systems in Portfolio Management. *In 5th. World Congress on Social Simulation* (p. 6).

Su, Z., Hadzikadic, M. (2015). An agent-based system for issuing stock trading signals. *SIMULTECH* 2015.

Su, Z., Hadzikadic, M. (2015, October). Trust Metrics Exploration in Optimizing Stock Investment Strategies. *In International Symposium on Methodologies for Intelligent Systems* (pp. 331-340). Springer International Publishing.

Su, Z., Hadzikadic, M. (2015) Optimizing Aggressiveness in Stock Trading Simulations. *The Computational Social Science Society of the Americas* 2015.

Su, Z., Hadzikadic, M. (2015) Enhancing Stock Investment Returns with Learning Aggressiveness and Trust Metrics. *Journal of Policy and Complex Systems, Volume 2, Number 2*, 2015

Tesfatsion, L. 2006. Agent-based computational economics: A constructive approach to economic theory. *Handbook of computational economics*, 2:831–880.

Teixeira, L., and De Oliveira, A., 2010. A method for automatic stock trading combining technical analysis and nearest neighbor classification. *Expert systems with applications, 37(10)*, 6885-6890.

Thorbecke, W. (1997). On stock market returns and monetary policy. *The Journal of Finance, 52(2),* 635-654.

Wilensky U: NetLogo. (1999), ccl.northwestern.edu/netlogo. Center for Connected Learning and Computer-Based Modeling. Northwestern University, Evanston, IL.